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Modelling and optimization of Industrial Prosumers with Renewable Energy Sources

by

Eva María Urbano González

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Supervisors:

Dr. José Luis Romeral Martínez

Dr. Konstantinos Kampouropoulos

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A mi familia.

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Abstract

The current energy transition fosters the insertion of renewable energies and system decentralisation intending to achieve a more secure, sustainable and efficient energy market. The industry can play a key role in this transition due to the digitalization resulting from the industrial revolution 4.0 and the current revolution 5.0, which encourages its renewal through resilient and human-centred solutions. Of all industrial entities, SMEs are particularly interesting as they consume more than 13% of global energy and find it more difficult than large companies to adopt new energy management strategies. Intending to favour energy transition and improve industrial competitiveness, this thesis addresses the energy situation of industrial SMEs to transform their consumer infrastructures into prosumer infrastructures capable of exchanging green energy with the utility grid, boosting also market decentralisation.

To do so, the present thesis proposes a complete framework for the optimization of the investment in energy equipment to be made by industrial SMEs, aiming to improve their performance by adopting a prosumer role in the electricity market. This framework is based on the development of a methodology that includes the modelling of the energy infrastructure of the industrial plant, the modelling of quantitative and qualitative factors together with their uncertainties, and the solving of a two-stage optimization problem. This two-stage optimization problem analyses the costs and benefits of the investments, as well as the prosumer operation of the infrastructure over its expected lifetime. Uncertainties in both quantitative and qualitative parameters are also introduced into the problem and the risks faced by the industrial SME in upgrading its energy system are assessed and minimised.

The proposed methodology has been applied to several case studies, the results of which show the benefits of transforming an industrial SME from a consumer to a prosumer. The optimization of the investment, considering quantitative and qualitative factors, risks, and the prosumer operation of the system throughout its lifetime, results in technically and financially robust solutions. Therefore, it has been possible to verify the usefulness of the proposed methodological framework to be applied to industrial SMEs, promoting their transformation into active entities in the energy markets and increasing their competitiveness.

Keywords – Industrial SMEs, prosumer, investment optimization, quantitative-qualitative, optimization considering risks

Resumen

La actual transición energética fomenta la inserción de energías renovables y la descentralización del sistema con el objetivo de conseguir un mercado energético más seguro, sostenible y eficiente. La industria puede desempeñar un papel clave en esta transición debido a la digitalización resultante de la revolución industrial 4.0 y a la contemporánea revolución 5.0, que promueve su renovación mediante soluciones resilientes y centradas en el ser humano. De todas las entidades industriales, las PYMES son especialmente interesantes, ya que consumen más del 13% de la energía mundial y tienen más dificultades que las grandes empresas para adoptar nuevas estrategias de gestión energética. Con la intención de favorecer la transición energética y mejorar la competitividad industrial, esta tesis aborda su situación energética para transformar las infraestructuras de consumo de las PYMES industriales en infraestructuras prosumidoras capaces de intercambiar energía verde con la red eléctrica, impulsando también la descentralización del mercado.

Para ello, la presente tesis propone un marco completo para la optimización de la inversión en equipos energéticos que deben realizar las PYMES industriales, con el objetivo de mejorar su rendimiento adoptando un papel de prosumidor en el mercado eléctrico. Esta optimización se basa en el desarrollo de una metodología que incluye la modelización de la infraestructura energética de la planta industrial, la de los factores cuantitativos y cualitativos junto con sus incertidumbres, y la resolución de un problema de optimización de doble etapa. Este problema de optimización analiza los costes y beneficios de las inversiones, así como la operación prosumidora de la infraestructura a lo largo de su vida. También se introducen en el problema incertidumbres en los parámetros cuantitativos y cualitativos, y se evalúan y minimizan los riesgos a los que se enfrenta la PYME industrial al actualizar su sistema energético.

La metodología propuesta se ha aplicado a varios casos de estudio, cuyos resultados han demostrado los beneficios de transformar una PYME industrial de consumidora a prosumidora. La optimización de la inversión, teniendo en cuenta los factores cuantitativos y cualitativos, los riesgos y el funcionamiento prosumidor del sistema a lo largo de su vida, da lugar a soluciones técnica y financieramente sólidas. De esta manera, se ha podido comprobar la utilidad del marco metodológico propuesto para ser aplicado a las PYMES industriales, promoviendo su transformación en entidades activas en los mercados energéticos y aumentando su competitividad.

Palabras clave – PYMEs industriales, prosumidor, optimización de la inversión, cuantitativo-cualitativo, optimización considerando riesgos.

Abstract

L'attuale transizione energetica sostiene l'introduzione di fonti rinnovabili e la decentralizzazione del sistema energetico con l'obiettivo di realizare un mercato più sicuro, sostenibile ed efficiente. L'industria può giocare un ruolo chiave in questa transizione grazie alla digitalizzazione derivante dalla rivoluzione industriale 4.0 e dall'attuale rivoluzione 5.0, che ne incoraggia il rinnovamento attraverso soluzioni resilienti e centrate sull'uomo. Tra tutte le entità industriali, le PMI sono particolarmente interessanti in quanto consumano oltre il 13% dell'energia globale ma hanno più difficoltà delle grandi aziende ad adottare nuove strategie di gestione energetica. Con l'intento di favorire la transizione energetica e migliorare la competitività industriale, questa tesi analizza situazione energetica delle PMI industriale per trasformare le loro infrastrutture di consumo in infrastrutture *prosumer,* in grado di scambiare energia *green* con la rete di distribuzione, favorendo in aggiunta il decentramento del mercato.

Per fare ciò, questa tesi propone un quadro completo per l'ottimizzazione degli investimenti in attrezzature energetiche da parte delle PMI industriali, con l'obiettivo di migliorare le loro prestazioni adottando un ruolo di prosumer nel mercato elettrico. Questa ottimizzazione si basa sullo sviluppo di una metodologia che include la modellazione dell'infrastruttura energetica dell'impianto industriale, la modellazione di diversi fattori quantitativi e qualitativi e le loro rispettive incertezze, e la risoluzione di un problema di ottimizzazione in due fasi. L'ottimizzazione in due fasi analizza i costi e i benefici degli investimenti, nonché il funzionamento dell'infrastruttura nel corso della sua durata prevista. Vengono inoltre introdotte nel problema incertezze nei parametri quantitativi e qualitativi per valutare e minimizzare i rischi che la PMI industriale affronta nell'ammodernamento del proprio sistema energetico.

La metodologia proposta è stata applicata a diversi casi di studio, i cui risultati mostrano i benefici della trasformazione di una PMI industriale da consumatore a *prosumer*. L'ottimizzazione dell'investimento, che tiene conto di fattori quantitativi e qualitativi, dei rischi e del funzionamento *prosumer* del sistema durante il suo ciclo di vita, porta a soluzioni tecnicamente e finanziariamente solide. Pertanto, è stato possibile verificare l'utilità del quadro metodologico proposto per la sua applicazione alle PMI industriali, promuovendo la loro trasformazione in entità attive nel mercato dell'energia e aumentandone la competitività.

Parole chiave - PMI industriali, prosumer, ottimizzazione degli investimenti, quantitativo-qualitativo, ottimizzazione considerando i rischi.

Table of contents

List of Figures

List of Tables

Nomenclature

List of abbreviations

AHP	Analytic Hierarchy Process
ANFIS	Adaptive Neuro-Fuzzy Inference System
ANN	Artificial Neural Network
CHP	Combined Heat and Power
COE	Cost of Energy
COP	Coefficient of Performance
CVaR	Conditional-Value-at-Risk
DA	Day-ahead
DG	Distributed Generation
DNN	Deep Neural Network
DR	Demand Response
DS	Direct Search
DT	Decision Tree
EC	European Commission
EE	Elementary Effect
EH	Energy Hub
ESS	Energy Storage Systems
EU	European Union
FIS	Fuzzy Inference System
GA	Genetic Algorithm
GHG	Greenhouse Gas
IoT	Internet of Things
LHS	Latin Hypercube Sampling
LP	Lineal Programming
LSTM	Long Short-Term Memory network
MADM	Multi-attribute Decision Making
MF	Membership Function
MILP	Mixed-Integer Lineal Programming

MLP	Multilayer Perceptron
MODM	Multi-objective Decision Making
MOO	Multi-Objective Optimization
MS	Member States
NECP	National Energy and Climate Plan
NPV	Net Present Value
OAT	One-at-a-time
PDF	Probability Density Function
PMI	Piccole e Medie Imprese
PSO	Particle Swarm Optimization
PV	Photovoltaics
PYME	Pequeña Y Mediana Empresa
RES	Renewable Energy Sources
RF	Random Forest
RRP	Recovery and Resilience Plant
RT	Real-time
SA	Sensitivity Analysis
SME	Small-and-medium enterprise
SVM	Support Vector Machine
ToU	Time of Use
TP	Transparency Platform
TYNDP	Ten-Year Network Development Plant
UA	Uncertainty Analysis
VaR	Value-at-Risk
VPP	Virtual Power Plant

Parameters, variables and indices

A	Subset of the real space containing optimization constraints
C	Cost
E	Energy stored
$E(x)$	Expected value of x

ec	Economic
en	Environmental
f	Objective function
$g(x)$	Equality constraints of an optimization problem
$h(x)$	Inequality constraints of an optimization problem
lb	Equipment lower operation bound
$norm$	Normalized
P	Energy inputs of the EH
p	Levels in uncertainty parameters
$p(x)$	Probability distribution of x
q	Vectors for the creation of trajectories in the Morris method
ql	Qualitative
qt	Quantitative
r	Hurdle rate
S	Firs-order Sobol index
S_T	Total-order Sobol index
so	Social
T	Optimization horizon
t	Time
ub	Equipment upper operation bound
v	Dispatch factor
VAR_{level}	Confidence level for VaR computation
$V(x)$	Variance of x
w	Criteria weight in a multi-objective optimization problem
x	Variable in a problem
η	Coupling matrix
μ^*	Morris index
Δ	Increase or step in a variable or parameter

1. Introduction

This chapter settles the scope of the research, the problem addressed and the thesis objectives, together with the starting hypothesis that have guided the developments done.

1.1. Research topic

Climate change is a global phenomenon whose effects must be stopped or slowed down as far as possible to prevent further damage to the environment. The Paris Agreement, signed by 195 nations, specifically addresses the mitigation of Greenhouse Gas (GHG) emissions, calling for holding the increase in the global average temperature to well below 2°C above pre-industrial levels and pursuing efforts to limit the temperature increase to 1.5°C above pre-industrial levels [1]. For this to happen, a general change is needed.

Among other technical and social approaches, solutions can be provided by the energy sector, which should undergo a transition towards zero CO_2 emissions to assure system sustainability. Decarbonisation of the sector is achievable if clean renewable energy sources (RES) are further inserted, electrifying the market and increasing the efficiency of transmission and distribution systems [2]. Although this massive electrification can be achieved by the integration of RES, the current market structure presents barriers to their inclusion, as market mechanisms are based on high marginal costs and power dispatchability, whereas RES offer low marginal costs and are intermittent and nonprogrammable [3]. To overcome these and other barriers, a change of paradigm is required, switching from a centralised dispatchability-based energy market to a distributed and hybrid system in which small RES located at consumption points such as industries and households together with demand flexibility are key for success. To support this energy transition, governments around the world are enhancing the access of these distributed non-large producers and active consumers of clean electricity to the grid and introducing financial incentives, disincentives and market mechanisms for decarbonisation by businesses, industry, transportation and consumers [4].

To support this change of paradigm from a centralised structure to a distributed one enhancing the inclusion of RES closer to consumption points and therefore system decarbonisation, the European Commission (EC) has created an energy planning framework based on six energy packages: “Energy Union Strategy” (2015), “Clean Energy for all Europeans” (2016), “European Green Deal” (2019), “Fit for 55” (2021)”, and “REPowerEU” (2022). These energy packages focus on the energy transition by encouraging and setting targets for the reduction of emissions through increasing system decentralisation, decreasing the use of fossil fuels, deploying renewable energies, increasing supply diversification, and generating alternative green fuels. RES represented 22.1% of total energy consumed in the EU in 2020, 2 percentage points above the target for that year [5]. Beyond 2020, new targets have been stated for 2030 and 2050. The main objective – decarbonisation - has been set to a reduction of GHG emissions to at least 80% below 1990 levels for 2050 [6]. Renewable energy targets have been increasing over the years, being the current target the achievement of a share of 45% of renewables by 2030 [7]. As stated before, one crucial action to achieve these targets is the participation of consumers, both industrial and tertiary, in the market. This can be done through the incorporation of RES in their energy infrastructures or by adopting an active energy role purchasing energy and inserting surplus energy from RES into the market. Prosumers, who are these entities capable of managing energy systems to exchange energy with the external market, are therefore acquiring global importance as fundamental actors in the achievement of an energy market with high penetration of distributed energy sources [8].

Due to the industry's energy characteristics, the digitalization impact of the Industry 4.0 revolution [9], and the current Industry 5.0 revolution which tries to renew and transform them into more future-proof, resilient, sustainable and human-centred entities [10]; the industry has great potential for the incorporation of flexibility. For these reasons, it is a suitable actor to undergo a transition towards a prosumer model. However, for the adequate transformation of industrial entities into active energy actors it is required to assess both their energy operation strategy as well as the investment which may be required to align their energy infrastructure with market opportunities. Among the different industrial entities, small-and-medium enterprises (SMEs) are especially interesting due to their importance in energy-related issues, as they consume more than 13% of total global energy and account for more than half the energy used in the industrial and commercial sectors [11]. However, industrial SMEs face more difficulties than larger enterprises in adopting novel energy management strategies [12], and programmes for the incorporation of RES and flexibility require further research [13]. Although some scientific research has been carried out into energy efficiency improvements in the SME sector such as [14], there are no publications on SMEs adopting prosumer behaviour and, as stated in [15], there is a need to adjust sustainable development practices to the SME framework.

In this framework, the research topic of this thesis lies in the creation of suitable techniques and methodologies for the transformation of industrial SMEs into prosumers, addressing the operation of their energy equipment as well as the investment in new energy assets to improve their competitiveness and promote energy transition.

1.2. Research problem

1.2.1. Prosumer industrial SMEs

The conversion of industrial SMEs into active energy actors requires an upgrade of their energy strategy, including investment in new equipment and improving their energy flow management. Until now, energy monitoring and management in industries have focused on operational energy planning, energy audits, energy efficiency measures, energy accounting, measurements and development of reports [16]. However, with the rise of digitalization technologies related to Industry 4.0, energy management methods can change drastically. The growth of the virtual world with the development of the Internet of Things (IoT) facilitates the creation of a digital model that resembles the real world. With this model, which considers the energy consumption, energy generation and the situation of the external energy market and internal energy assets [17], it is possible to forecast future energy situations and take decisions to optimize the performance of the industrial plant.

Until now, the Energy Hub (EH) concept, which models the energy infrastructure that connects inputs and outputs from different carriers directly or through conversion equipment, has been widely used to represent the energy infrastructure of industries. In recent years, the EH has been considered not only to manage energy carriers aiming to meet internal demand efficiently but also as a base to create flexibility and participate in Demand Response (DR) programs. A DR operation of the EH suppose a temporal change in consumer's energy demand as a reaction to the market status. DR has as an objective the empowerment of consumers to adjust their demands at strategic times and promote the efficient use of energy resources [18]. Scientific publications have deeply analysed DR concepts and applications. [19] presents an optimization model for the scheduling of RES based on pricing notifications from the utility grid, and [20] exposes a system model aiming to optimize its performance based on day-ahead (DA) and real-time (RT) market status. From these studies, it can be concluded that the incorporation of EH structures in industrial SMEs with DR capabilities can increase the energy efficiency of the plant, diminishing energy use and operating costs by taking advantage of the tools provided by the market.

Legislation is taking a step forward, opening up the possibility for EHs to not only adopt DR behaviour but also to insert energy into the grid, becoming prosumers. This allows a higher insertion of RES and an overall decrease in electricity prices, decongesting the distribution and transmission networks and improving energy efficiency. Thus, prosumers are likely to become major actors in the electricity market. The term prosumer was first introduced in [21] as a person or entity who consumes and produces a product. Translated into the electrical market, a prosumer demands electricity and has also the capability to sell it to the grid. In order to transform an industrial SME into a prosumer, smart management of energy flows is

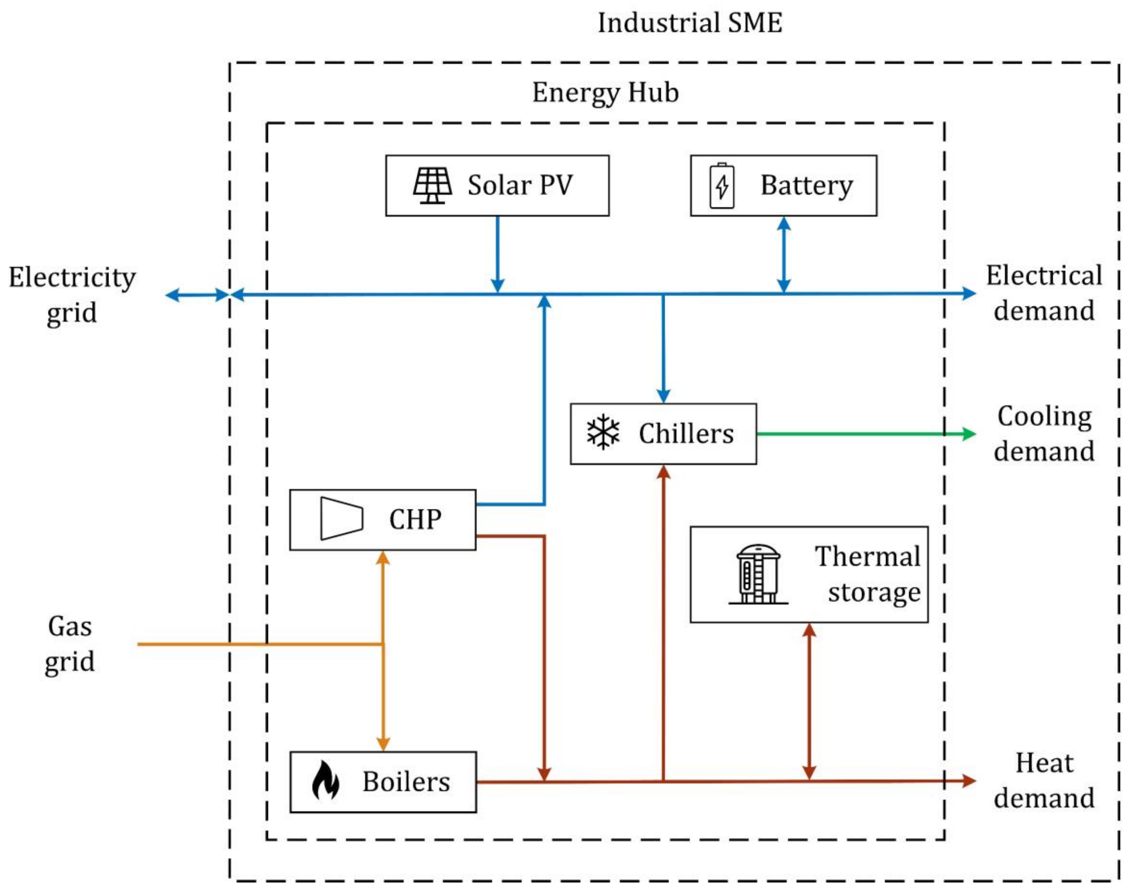

Figure 1: Schematic of the potential infrastructure of a prosumer industrial SME.

required, evaluating the internal and external energy situation to perform optimal decisions regarding energy generation, consumption, and storage.

The implementation of a prosumer, as that of DR capabilities, is commonly based on the EH model of the energy system. Figure 1 exposes an example of a potential energy infrastructure of a prosumer industrial SME, with a bidirectional flow with the electricity grid and an internal EH enhancing robustness and interconnectivity. The optimal management of energy lies in the knowledge of the costs and emissions of the system, the current state of the EH, and the future status regarding demand, RES availability, prices, and external utility grid energy mix. In recent literature, the implementation of prosumer capabilities in EHs has been a focus of interest. The first research dealt with energy management systems that enabled the sale of electricity to the grid in a short-term scheduling concept. [22] optimizes the operation of the EH considering an exchange of energy with the ancillary service market. [23] also presents short-term scheduling of small and medium-scale consumers under Time of Use (ToU) DR programs, where the energy assets of the EH are scheduled bearing in mind the possibility to sell electricity to the grid. Although these types of studies considered prosumer capabilities, they aimed mainly at the delivery of surplus energy without considering energy trading as a potential interest to be included in the business model of the consumer.

> **In order to obtain maximum profit from being a prosumer, there is a need to consider energy trade as a potential benefit bearing in mind not only current variables but also future situations regarding both the internal and the external situation, creating a time-aware EH operation strategy.**

Also, prosumer EH optimizations such as [24], [25] evaluated home energy infrastructures, not considering industrial characteristics. Indeed, nearly all studies evaluating consumer capabilities to support the energy transition focus on the tertiary sector. In most cases, only electricity consumption is considered, overlooking the thermal side of the problem [26]. This can also be seen in [27], which considers only tertiary end-users that consume electricity. Although [28] describes the thermal side of the energy infrastructure for a tertiary building, only energy sources that provide electrical energy are included in the optimization problem. Thus, no interconnection is generated through the different energy carriers present in the system. Industrial SMEs have a strong thermal side [29] that cannot be overlooked when evaluating their prosumer potential, and, as described in [30], their demand pattern differs drastically from that of the tertiary sector.

> **Although there have been developments in consumer EH to foster energy transition, most of them focus on the tertiary sector, which is radically different from the industrial sector. To convert industrial SMEs into prosumers, it is still required to create a tailored methodology for their optimal energy prosumer operation.**

1.2.2. Energy sizing optimization

Despite the opportunities provided by the market, the industrial framework, and the available techniques, nowadays most industrial plants are still not equipped with RES or ESS. However, the potential benefits of the adoption of a prosumer behaviour incentive the investment in energy equipment to improve the profitability of actively managing energy flows. For this reason, there is a requirement to suitable design and size the energy assets of factories. SMEs select investments with short payback periods and favourable economic parameters; once the investment has been made, the infrastructure is maintained in operation until another relevant event occurs that requires new investment, thus exploiting the equipment for its whole lifetime [31]. Up to date, optimal energy equipment sizing studies in the literature focus mainly on considering islanded mode operation to support the energy transition by acting as independent entities to the market, thus not adopting a prosumer approach. In [27], an ESS is sized for an isolated grid to minimise total system cost. In [28], distributed energy resources are sized for a building considering islanded performance, and in [32], an isolated hybrid wind-hydrogen system is designed for a house. In this type of optimization, the infrastructures are not connected to the main grid, so the objective is to assure the security of supply.

There are also papers dealing with sizing strategies for non-islanded mode, such as [33], which assesses the sizing for a factory with the aim of minimising the energy purchased from the utility grid. In the cited study, ESS and buffer stocks are sized for a whole year although the cycles of energy prices in the external market are not considered. In [30], RES and ESS are sized for an industrial facility and a residential complex, with the possibility to deliver – but not commercialise – energy. This study considers seasonal characteristic days as representative time intervals for system operation. [34] employs a Genetic Algorithm (GA) to size the ESS in a microgrid to find the energy and power capacities to minimize the operation cost of the microgrid. A similar approach is found in [35], which presents a methodology for sizing a combined PV-wind RES to apply it to a power plant in an industrial area. This work considers load requirements, physical and geometric constraints for the installation, operation and maintenance cost and the possibility to deliver energy surplus to the grid. Although in these studies there is an exchange of energy with the grid, none of them evaluates the economic impact of energy exchange on the value of the investment and its return, which is crucial for investment decisions in SMEs.

> **Therefore, it is required to create an optimization approach for the sizing of energy infrastructures in industrial SMEs considering a prosumer optimal operation that benefits from the exchanges with the external grid.**

In addition, the optimizations performed to date consider mainly a typical year represented by a set of characteristics days and do not evaluate the effect of weekly cycles into the operation nor the evolution over time of external and internal parameters. There are a few papers that consider this for some parameters in the sizing problem. In [36], different time scenarios are analysed, although a long-term horizon strategy is not implemented. Similarly, [37] addresses the potential variation of demand creating different outcomes for the problem. [38] presents an optimization model for long-term, multi-stage planning of a general decentralised multi-energy system. The optimal investment is addressed from a multi-stage perspective, i.e., distributing the investment over years and performing retrofitting, which could be suitable for urban planning applicable to large government entities or districts where buildings are added in multiple phases. SMEs, however, do not plan energy investments to take place gradually; rather, decisions are taken based on immediate investment return and maximisation of profit along the lifetime of the equipment. Also, although [38] evaluates multiple years to perform the investment at different time points, the cost of the energy carriers and the technology degradation are discretised and considered constant during entire years. This fact discerns from reality, as input parameters are subject to important seasonal and hourly variations [39]. This is especially true for the industrial sector, where the production is maintained constant during week-days and is diminished during weekends to perform minor activities such as adopting new plant configurations and maintenance [40], making it essential for industrial SMEs to consider the continuous weekly operation to capture production and costs patterns and properly size their energy infrastructure.

Free software tools are also available for sizing energy sources to meet specific design criteria. DER-CAM is a popular software solution for designing distributed energy resources for the tertiary sector. Users have access to several key features, in particular the possibility of varying their load and deciding based on economic and environmental criteria. To perform this optimization, DER-CAM considers three typical days per month over one year [41], leading to a simplified idealization of the decision-making process [42]. REopt is another software tool which serves as a technical-economic decision-support model for RES. REopt is focused on the tertiary sector, specifically on buildings, campuses and communities. It assesses the optimal mix of energy sources and the optimal dispatch of equipment separately, and only one year is modelled explicitly, which is assumed to repeat throughout the analysis [43]. However, neither of these tools accounts for the multiple years in the lifetime of the energy equipment or the evolution of market parameters, both of which are crucial factors when assessing the real value of an investment operation. In addition, the optimization horizon for energy equipment operation is daily and, as other research works, does not capture the characteristic industrial load and market weekly cycles.

> **To adequately size the energy equipment of industrial SMEs, their long-term performance should be evaluated, including the variation in external parameters as well as the degradation of internal equipment over years and considering relevant operative timeframes, in this case, weeks.**

This sizing optimization approach will allow industrial SMEs to decide on investments bearing in mind long-term perspectives. However, the inclusion of the variation over time of parameters supposes the uncertain assumption values, which create in turn uncertainty in the investment output. [44] performs an analysis considering investment trends in firms during the last years and raises the point that entities tend to intuitively invest less if the uncertainty in the energy market increases to avoid unexpected results.

> **Therefore, as important expenses are to be performed in energy equipment investments, it is crucial to optimize not only the plant design and operation but also to analyse and evaluate the risk of these actions.**

To do so, it is essential to understand the risk in the design problem output and the inputs that cause it. When evaluating the optimal decision for an energy investment to be performed in an industrial SME, a complete Uncertainty Analysis (UA) has to be done to properly analyse the risk linked to the investment and its robustness, and Sensitivity Analysis (SA) is required to identify the parameters that cause this risk.

This identification allows SMEs to decide if they put an effort into better defining the most critical factors, thus reducing the epistemic uncertainty and the investment risk; and also provides them with a framework to identify the points in time at which the investment perspectives are better due to a clearer evolution of key parameters.

To date, some studies have been presented addressing uncertainty for energy infrastructure design and operation. Most of them analyse uncertainty employing uniquely a basic SA to evaluate the variation of the output of the system according to a set of selected inputs. This is the case of [45], which optimizes an energy system for rural electrification and carries out a SA. In this study, the proposed SA methodology is not clear and the selection of the inputs' uncertainties is subjective, not presenting their probability distributions. Similarly, [46] evaluates a set of pre-defined system combinations and their sensitivity in front of different parameters, without providing details on the methodology. [47] optimizes a hybrid system employing commercial software and performs a SA. In this case, it is mentioned that the SA is carried out by changing only one parameter at a time once. This procedure is also followed in [48], in which appears an optimization of a trigeneration system considering the variation of load and energy carriers' prices through analysing potential occurrence scenarios. The one-at-a-time (OAT) strategy employed in these studies, where each input parameter is modified in an isolated manner while the others remain the same, is common in the literature due to its ease of implementation and logical analysis of results. The OAT approach has also been used in [49], which addresses the optimal design of a stand-alone hybrid energy system for a rural area. This study pre-states the configuration of the system and conducts a SA based on scenarios to appreciate the influence of environmental policy on the total system cost. Similarly, [50] exposes a techno-economic analysis of a standalone hybrid energy system and does a SA through OAT strategy to see the effects of costs of energy in the system's economic performance, [51] tests four hybrid power system scenarios for a household application and carries out a SA employing three wind speeds and solar radiation possibilities. The work in [52] presents a sizing energy model optimization considering yearly performance and proposes a SA. In contrast with other studies, in this work, the SA is carried out considering 3 different scenarios combining subjectively distinct values of the uncertain inputs. In none of these works, however, the probabilities of the analysed uncertain inputs are considered. Moreover, the performed SA strategies do not provide the required insights to properly evaluate the output statistically, as they only consider a small number of scenarios and the interrelation of different energy inputs is most of the time overlooked. A slightly different approach is presented in [53], which performs an OAT methodology employing several samples of a uniform distribution, improving the consideration of only a few scenarios. However, the use of uniform distributions is a simplification of reality, as it is common to have specific scenarios with a higher probability of occurrence rather than intervals where the probability of all values is equal [54]. Therefore, the employment of uniform distributions limits the capacity of obtaining suitable insights into the investment problem faced by industrial SMEs.

Few studies with improved SA strategies have been published, such as [55], where a SA is applied for zero/low energy buildings aiming to obtain the design parameters that affect the performance. In this case, the SA is formed in a two-stage approach, using global and local methods as the first and second stages, respectively. However, this analysis does not carry out a UA and thus despite sensitivity being addressed to evaluate the inputs that most affect the performance, the output uncertainty is not known. [56] performs both UA and SA for the optimal design of a distributed energy system to supply energy to a tertiary demand. The objective is the minimisation of total system cost while meeting CO_2 emissions restrictions. The UA is performed using the Monte Carlo simulation while the SA consisted of a two-step global SA. Despite the existence of different market prognoses, the uncertainty linked to energy market costs is modelled as uniform, without considering the higher probability of some scenarios above others. Furthermore, in all the above studies the proposed optimization models employ only one year as a representative time frame, simplifying the decision-making process and not evaluating the time evolution of parameters. According to [57], the fact of solving this optimization problem using single "typical-year" approaches produces results that become suboptimal after a short time due to the changing framework where the energy systems are integrated. In the mentioned studies, the proposed inputs' probability distribution functions are static, i.e., they do not vary with time, which does not allow for evaluation of the future costs probabilities and simplifies their consideration. This uncertainty handling is methodologically erroneous and does not enable obtaining a realistic framework for energy investment analysis.

> **To evaluate the risk industrial SMEs are undertaking when performing an energy investment, it is required to carry out both UA and SA. These UA and SA should be based on a time-continuous probability distribution characterisation of the inputs and should be performed in a statistical approach considering the cross-influences of inputs in the output.**

Once the uncertainty of the investment is known, if it is significant it may be possible that the industrial SME requires to reduce it before investment. This can be done by incorporating the uncertainty spectrum in the optimization process. In most of the current studies dealing with energy investment, optimization is presented without considering uncertainties. As seen before, some papers analysed energy investment's uncertainty after obtaining the solution, without optimising it concerning uncertainties. These approaches enable the investor to know the risk assumed when investing, although they do not propose an adaptation strategy for unacceptable risk levels nor incorporate the uncertainty analysis inside the optimization problem.

> **For further enhancement of energy equipment investment in situations with high uncertainty, it is useful to incorporate this uncertainty in the optimization problem.**

The literature on energy investment optimization that considers risks within the decision-making problem is scarce. [58] develops an optimization model for regional energy systems. The presented methodology includes degrees of fulfilment for the uncertain constraints, which provides decision-makers with alternatives under different violation parameters. [59] addresses an optimal energy system by minimizing total annual cost while limiting the average worst-case emissions. Both of the aforementioned studies do not consider risk as an optimization objective, but rather as a limitation, creating a strategy that is robust in front of uncertainties. Although robust optimizations provide a simple framework for dealing with uncertainty, they are conservative and trade off the performance of the system for its robustness [60]. Another strategy commonly employed in the literature for optimization under uncertainty is two-stage stochastic optimization, in which the decision parameters are selected in the first stage and all possible scenario realisations are considered in the second stage, optimising the mean resultant value. This is used in [61], which applies a two-stage stochastic model to a district energy system optimization under uncertainty on the demand side, and in [62], which employs a two-stage stochastic search for the optimal sizing and placement of energy storage. Even though two-stage stochastic methods incorporate uncertainty in the optimization problem, they do so from a risk-neutral perspective not providing a clear measure of the risk taken by the investor [63]. [64] presents an improved method including a risk-aversion strategy. In this study, the planning of an integrated energy system incorporates the Conditional-Value-at-Risk (CVaR) as part of the objective function. Following the same approach, [65] proposed a sizing methodology assessing risk through the computation of the mean-variance. In all the above works, the risk is expressed by employing quantitative-only approaches, focusing mainly on economic parameters.

> **The energy equipment optimization should explicitly incorporate risk, evaluating and optimising them and thus improving robust and risk-neutral strategies.**

Some of the studies mentioned in this section consider social and environmental objectives. When they are considered, quantitative parameters, such as emissions or job creation, are chosen to measure them. However, there are qualitative criteria of importance for industrial SMEs, i.e. social acceptance and alignment of the investment decision with the administration; that are usually not considered in energy optimization problems due to difficulty in their measurement. Also, the studies discussed above that include uncertainties within the optimization problem deal mainly with economic uncertainties, leaving aside the uncertainty associated with the measurement of environmental and social spectra. These economic and quantitative-focused models are insufficient for the energy sizing problem as there are criteria and uncertainty dimensions that can only be addressed through qualitative approaches which can equal or dominate quantitative ones [66].

> **Therefore, it is essential to incorporate qualitative considerations in energy investment decision-making** [67]**. This will enhance a better evaluation of the suitability of the energy investment and of the uncertainties faced, improving the competitiveness of the enterprise and creating significant positive outcomes** [68]**.**

To date, qualitative parameters inside the decision-making process have been considered in the literature for non-energy optimization problems. In [69], a generic methodology for assets management decision-making considering quantitative and qualitative factors is presented where qualitative factors are crisply measured. In [70], country energy planning strategies are proposed where qualitative criteria are employed, although they are not optimized. [71] considers both quantitative and qualitative parameters for uncertainty assessment in the design of a building although qualitative attributes are set as crisp numerical values without considering judgemental vagueness. Even though these studies incorporate qualitative parameters, they do not account for the uncertainty linked to their subjectivity. Thus, currently, there is no study in which qualitative parameters are measured assessing also their uncertainty and thus transforming their abstract value and quantifying it so they can be incorporated into an optimization problem.

> **To suitably include qualitative parameters in the optimization problem and minimise risks, their evaluation from a mathematical point of view and their uncertainty should be addressed considering their vague definition and subjectivity inherent to their measurement.**

The incorporation of both quantitative and qualitative parameters and their uncertainties in the optimization problem supposes a suitable framework for the energy investment decision-making of industrial SMEs, supporting them on their path to becoming an active part of the energy market.

Therefore, research and developments in this thesis will be carried out in the fields of energy infrastructure modelling, prosumer operation optimization, uncertainty assessment and quantitative and qualitative factors measurement in order to elaborate a complete **risk-informed energy investment optimization methodology** suitable for transforming industrial SMEs into prosumers. Figure 2 presents an overview of the exposed research problem. Energy equipment investments are evaluated by considering long-term perspectives and the effect of qualitative and quantitative parameters and uncertainties on the performance of the industrial SME as a prosumer. This prosumer operation is obtained through the optimization of energy flows, which is based on the EH model of the industry and considers current and future internal and external energy situations to decide when to trade energy with the utility grid and which equipment to use. The assessment of these aspects in this thesis and their inclusion in a single strategy will enable the creation of a methodological framework that will support industrial SMEs in their transformation towards active players in the energy market, supporting energy transition while capturing the opportunities that it presents.

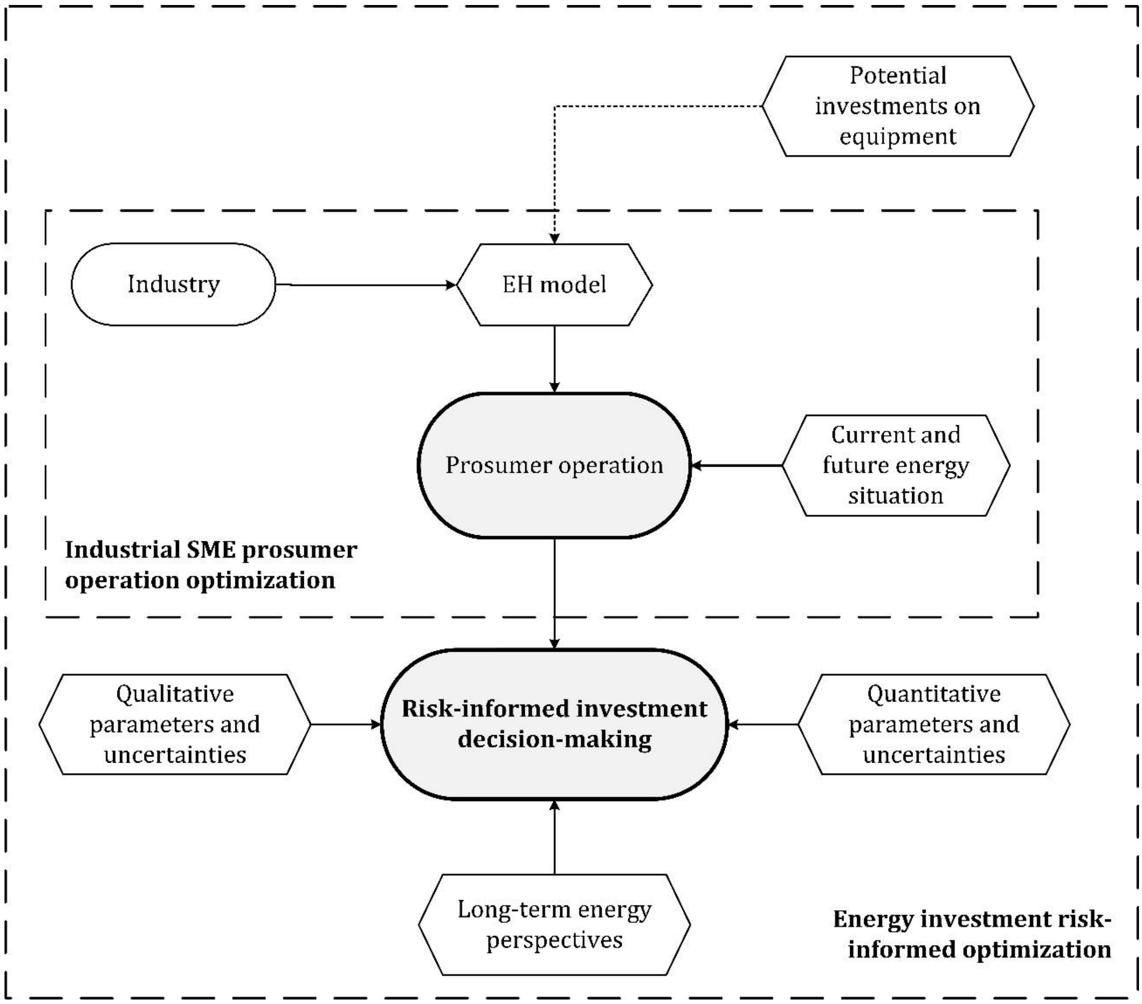

Figure 2: Research problem overview.

1.3. Aim and objectives

The aim of the proposed thesis is to progress the state of the art on energy management and equipment optimization in the new prosumer context for industrial SMEs. In this aspect, the basis of analysed approaches will be based on: energy modelling, internal energy flow and external exchange optimization, energy equipment investment optimization, and risks assessment and consideration in the investment problem.

In order to achieve the thesis aim, the following objectives should be fulfilled:

1. Modelling

   The modelling of the industrial energy infrastructure should be addressed, together with the model of input quantitative and qualitative parameters and their uncertainty.

2. Optimization

   The optimization of the energy infrastructure of the industrial SME and of its operation should be carried out. The operation optimization has to consider prosumer behaviour whereas the optimization of the energy infrastructure should evaluate the lifetime suitability of energy equipment for the industrial SME to act as a prosumer.

3. Risk-informed decision-making

   Uncertainties of qualitative and quantitative inputs parameters should be incorporated in the investment optimization and decision-making process of industrial SMEs, evaluating the risk associated with investment decisions and minimising it.

1.4. Hypotheses

The foundation of the identified research problem is represented by the following hypotheses:

- The prosumer operation of an industrial energy infrastructure creates a benefit for the industry by decreasing the cost of energy, reducing emissions and improving social benefits.

- The optimization of the energy investment considering the lifetime operation of the equipment enables to account for future external and internal situations, reaching a solution able to provide benefits over a long period.

- The incorporation of quantitative and qualitative parameters and criteria in industrial SMEs' decision-making process improves the economic, environmental, and social benefits of the obtained solutions.

- The final overall profit obtained by industries is more reliable if the risk is evaluated and incorporated into the industrial decision-making problem.

1.5. Thesis outline

This thesis is presented as a compendium of publications. Firstly, chapters 2, 3, and 4 discuss the developments carried out and reproduce the thesis discursive line. Specifically, chapter 2 deals with the modelling and optimization of the operation of the industrial plant as a prosumer. Chapter 3 introduces the optimization of energy sizing and assesses the risk assumed by the company, and chapter 4 uses previous chapters' developments to generate an investment optimization methodology considering quantitative and qualitative risks within the mathematical optimization.

Each chapter includes an explanatory part exposing the techniques and methodologies used and a section where the publications that detail the developments are shown. Partial conclusions are also done for each of them.

Chapter 5 is the compendium itself. The publications included are the following:

- E. M. Urbano, V. Martinez-Viol, K. Kampouropoulos, and L. Romeral, "Future european energy markets and industry 4.0 potential in energy transition towards decarbonization," *Renew. Energy Power Qual. J.*, vol. 18, no. 18, pp. 190–195, 2020.

- E. M. Urbano, V. Martinez-Viol, K. Kampouropoulos, and L. Romeral, "Renewable energy source and storage systems sizing optimization for industrial prosumers," in *IEEE International Conference on Emerging Technologies and Factory Automation, ETFA*, 2020, vol. 2020-Septe.

- E. M. Urbano, V. Martinez-Viol, K. Kampouropoulos, and L. Romeral, "Energy equipment sizing and operation optimisation for prosumer industrial SMEs – A lifetime approach," *Appl. Energy*, vol. 299, no. July, p. 117329, 2021.

- E. M. Urbano, A. D. Gonzalez-Abreu, K. Kampouropoulos, and L. Romeral, "Uncertainty analysis for industries investing in energy equipment and renewable energy sources," Renew. Energy Power Qual. J., vol. 19, no. 19, pp. 126–130, 2021.

- E. M. Urbano, V. Martinez-Viol, K. Kampouropoulos, and L. Romeral, "Risk assessment of energy investment in the industrial framework – Uncertainty and Sensitivity analysis for energy design and operation optimisation," Energy, vol. 239, p. 121943, 2021.

- E. M. Urbano, V. Martinez-viol, K. Kampouropoulos, and L. Romeral, "Energy-Investment Decision-Making for Industry : Quantitative and Qualitative Risks Integrated Analysis," *Sustainability*, vol. 13, no. 6977, 2021.
- E. M. Urbano, V. Martinez-viol, K. Kampouropoulos, and L. Romeral, "Quantitative and Qualitative Risk-informed energy investment for industrial companies," *Energy Reports*, vol. 9 p. 3290-3304, 2023.

In addition to these, Annex A exposes another publication which has not been included in the compendium but which is mentioned in chapters 2, 3, and 4 to support the understanding of the entire thesis work. This publication is:

- E. M. Urbano, V. Martínez-Viol, and L. Romeral, "Optimization of industrial plants for exploiting energy assets and energy trading," in *IEEE International Conference on Emerging Technologies and Factory Automation, ETFA*, 2019, vol. 2019-Septe.

Chapter 5.7 then presents other research activities that support the main line of the thesis. The publication resulting from these activities, shown below, has also been included in Annex A:

- E. M. Urbano, K. Kampouropoulos, and L. Romeral, "Energy crisis in Europe: the union objectives and countries' policy trends: New transition paths?" *Under review.*

Finally, Chapter 7 exposes the discussion and conclusions for all the developments carried out.

2. Modelling and operation optimization

This chapter exposes the model of the industrial energy infrastructure and its operation as a prosumer, including also a section for the forecasting of relevant input parameters to consider current and future energy situations.

2.1. Industrial energy infrastructure modelling

Industrial energy infrastructures are characterized by the presence of different energy carriers and equipment to transform and store them in order to meet demand requirements. In the past, different energy systems with different energy carriers were planned and managed independently [72]. Nonetheless, to improve system efficiency and reliability it is required to model these energy infrastructures and their correlations as a whole. This multi-carrier energy system model can be obtained by applying the EH concept. The EH was first introduced in [73], [74] as an interface between consumers and producers which were connected directly or through conversion equipment that could handle one or more energy carriers. [75] defines the EH as a unit where multiple energy carriers can be converted, conditioned, and stored; and [76] considers it as a unit that provides the functions of input, output, conversion and storage of multiple energy carriers. Figure 3 and equation 1 depict the general EH concept, which relates inputs and outputs through a coupling matrix. L represents the demand or output vector, P the input vector of the system and η the coupling matrix which can contain direct connectivity parameters, converters efficiency, and coefficients of performance of equipment (COP) [77]. The EH equation can also be written as appears in equation 2.

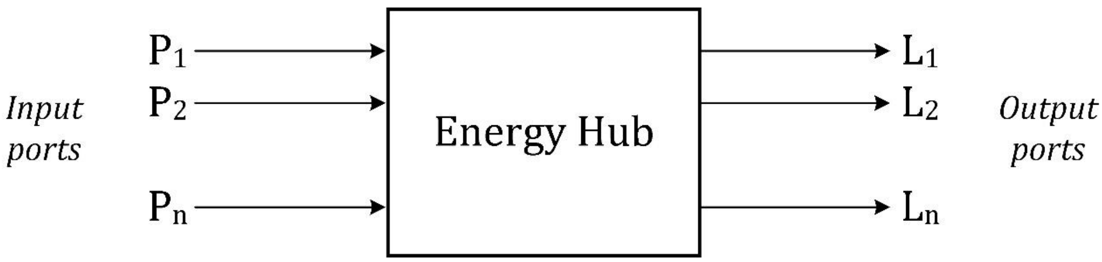

Figure 3: EH concept.

$$\begin{bmatrix} L_\alpha \\ L_\beta \\ \vdots \\ L_\theta \end{bmatrix} = \begin{bmatrix} \eta_{\alpha\alpha} & \eta_{\alpha\beta} & \cdots & \eta_{\alpha\theta} & \cdots \\ \eta_{\beta\alpha} & \eta_{\beta\beta} & \cdots & \eta_{\beta\theta} & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ \eta_{\theta\alpha} & \eta_{\theta\beta} & \cdots & \eta_{\theta\theta} & \cdots \end{bmatrix} \begin{bmatrix} P_\alpha \\ P_\beta \\ \vdots \\ P_\theta \end{bmatrix} \tag{1}$$

$$L = \eta\, P \tag{2}$$

To obtain the EH model of an industrial energy infrastructure it is required to obtain the coupling matrix relating inputs with outputs and also the operational constraints that apply to the system. This model can be obtained by applying the following rules that guide the development of an EH and that can be expanded for their application to diverse energy infrastructure types:

- Relationship between a single input and single output of an energy converter

  The converter that transforms input energy P_α into output L_β is modelled as exposed in equation 3. The converter has a performance of $\eta_{\beta\alpha}$, which can be either efficiency or COP, depending on the specific equipment considered.

$$L_\beta = P_\alpha \eta_{\beta\alpha} \tag{3}$$

- Existence of energy converters in series

  In this case, called multi-stage conversion, all the output of one energy converter goes directly to another converter. The final output is therefore the transformation, through all the converters, of the initial inputs. This is expressed mathematically by multiplying the performance of the converters in the chain:

$$L_\theta = P_\alpha \eta_{\beta\alpha} \eta_{\theta\beta} \tag{4}$$

- Converters with more than one input and output

  Converters can be connected, either in the input, output or both, to one or more other sources, converters or demand points. Figure 4 exposes an example of this situation.

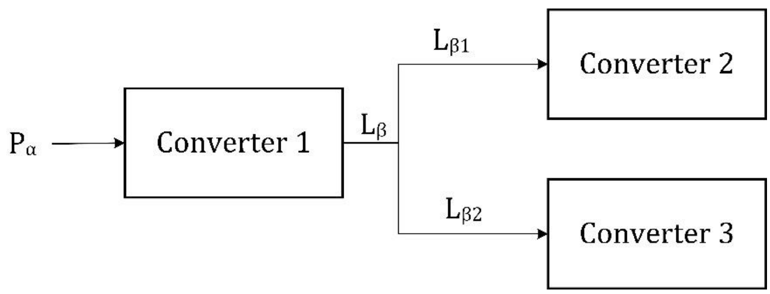

Figure 4: Converter output connected to more than one converter.

  To assure the proper operation of the system, it is required that the inputs and outputs of the system are correctly distributed without exceeding the power transacted. This is done by introducing the dispatch factors, v_i, which represents the fraction of an input or output that comes or is directed to other converters, inputs or outputs. The formulation is here expressed taking as reference the nomenclature in Figure 4:

$$L_\beta = P_\alpha \eta_{\beta\alpha} \tag{5}$$

$$L_\beta = \sum_{i=1}^{n} L_{\beta i} \tag{6}$$

$$L_{\beta 1} = L_\beta v_1 \tag{7}$$

$$0 \leq v_i \leq 1 \tag{8}$$

$$\sum_{i=1}^{n} v_i = 1 \tag{9}$$

- Equipment and transactions operational bounds

  Energy converters have operational bounds which have to be fulfilled to guarantee the correct functioning of the system. This can also happen for transactions where connexion lines are limited to a specified capacity. These bounds are expressed as inequalities:

$$lb_\alpha \leq P_\alpha \leq ub_\alpha \tag{10}$$

  For the case of storage systems, operational bounds include the maximum and minimum power that can be introduced and extracted from the storage as well as the minimum and maximum energy stored. To compute the energy stored, the following time-dependent expression is employed:

$$E_\beta^t = E_\beta^{t-1} + \Delta t\left(P_\beta - L_\beta\right) \tag{11}$$

From the logic depicted in these rules, it is possible to infer the EH model of more complex energy systems. In order to assure the success of the process, the methodology presented in [78] has been considered and upgraded to adapt it to the prosumer problem:

- Step 1: Identification of input and output port groups.

  Identification of input and outputs of the EH. Due to the prosumer nature of the infrastructure – and the bi-directional connectivity of the EH with the electricity grid – some inputs appear also as outputs of the system.

- Step 2: Identification of energy converters.

  Identification of energy converters and energy storage systems together with the energy carriers that they treat and convert.

- Step 3: Determination of the energy flow inside the hub.

  In this step, the coupling matrix is defined by analysing the connectivity between all inputs, outputs and energy converters.

- Step 4: Determination of the system's restrictions.

  Determination of all system restrictions, including connectivity between converters, gathering and use of inputs, and generation of outputs.

- Step 5: Determination and calculation of the converters' operation bounds.

  Identification of bounds applicable to energy converters in the EH and determination of their formulation.

This process enables to obtain the EH model of complex industrial SMEs' energy infrastructures, which serves as a basis for its transformation into a prosumer.

2.2. Forecast of the future energy situation

The prosumer operation of an industrial SME should consider not only current parameters and variables but also future situations over a specified operational time horizon. For the industrial sector, these operational cycles are weeks, as production is maintained constant during week-days and diminished during weekends to perform other activities, e.g. maintenance [40]. Therefore, to obtain the optimal prosumer operation of the plant it is required to know the evolution of parameters that influence it considering a weekly time horizon. These parameters depend on the specific industrial SME analysed and can be, among others, solar irradiation, electricity price in the market, and demand. The forecast of some of them can be obtained from external sources. For example, market electricity prices can be gathered from market operators and solar irradiation from meteorological entities. Nonetheless, the prediction of internal demand depends uniquely on the industry's characteristics and has therefore to be carried out internally to evaluate the operation of the plant. The industry is a sector where the demand can have irregular and infrequent behaviour depending on several conditions and that is constantly under improvement processes. For this reason, a method that enables periodically auto-adjustment and high accuracy is required.

In recent times, artificial intelligence methods used for demand or load forecasting include mainly Artificial Neural Networks (ANN), expert systems and Support Vector Machines (SVM). An ANN approach for short-term load forecasting is introduced in [79], in which a Deep Neural Network (DNN) is developed. Its performance is compared with other algorithms commonly used for load forecasting, specifically SVM, Random Forest (RF), Decision Tree (DT), Multilayer Perceptron (MLP) and Long Short-Term Memory network (LSTM), reaching the conclusion that the DNN developed has the lowest forecast error of the studied methods. Despite the suitability of ANN, nowadays researchers are focusing on developing hybrid methods combining ANN with other techniques. [80] proposes an extreme learning machine technique with the Levenberg-Marquardt method and [81] explores the possibility to use ANN to create a hybrid method with other techniques such as back propagation, fuzzy logic, Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). [82] also presents a hybrid approach, in which a clustering method together with ANN and SVM is used for load forecasting. It is shown that the forecasted consumption has a lower error than in the case of using ANN and SVM alone. Nonetheless, it is suggested that the creation of a forecasting method with fuzzy methodology together with ANN will produce better and more accurate results. In this path, a fuzzy logic model for load forecasting was tested in [83]. This paper uses only fuzzy techniques intending to extract rules and predict energy demand. This methodology can be improved by combining ANN with fuzzy logic. Adaptive Neuro Fuzzy Inference System (ANFIS) is a forecasting technique which employs both ANN and fuzzy logic [84]. ANFIS aims at mapping input to output for highly non-linear processes and has been tested for general demand forecast applications [85], [86] and also for industrial predictions providing promising results [87]. Therefore, ANFIS is used here to forecast the demand of prosumer industrial SMEs.

ANFIS is based on the combination of ANN and Takagi-Sugeno type fuzzy logic and was first presented in [88]. Figure 5 exposes the ANFIS architecture, which has 5 layers. In the first layer, the fuzzification of the inputs takes place. To do so, membership functions are consulted and the degree of fulfilment of inputs is computed. The parameters that appear in this layer and that are required to carry out the fuzzification are called premise parameters. In the second layer, the neurons compute the fire strength rule by performing an AND operation of the incoming signals. Then, layer 3 normalises the received input and sends the result to layer 4, where the Takagi-Sugeno fuzzy reasoning method is applied employing the consequent parameters. Finally, layer 5 computes the single output by adding the inputs received. For the proper functioning of the ANFIS method, it is required to train it to adjust the premise and consequent parameters. Once it has been trained, it is possible to use it to forecast the energy vector of interest and employ the result as input for the prosumer operation optimization.

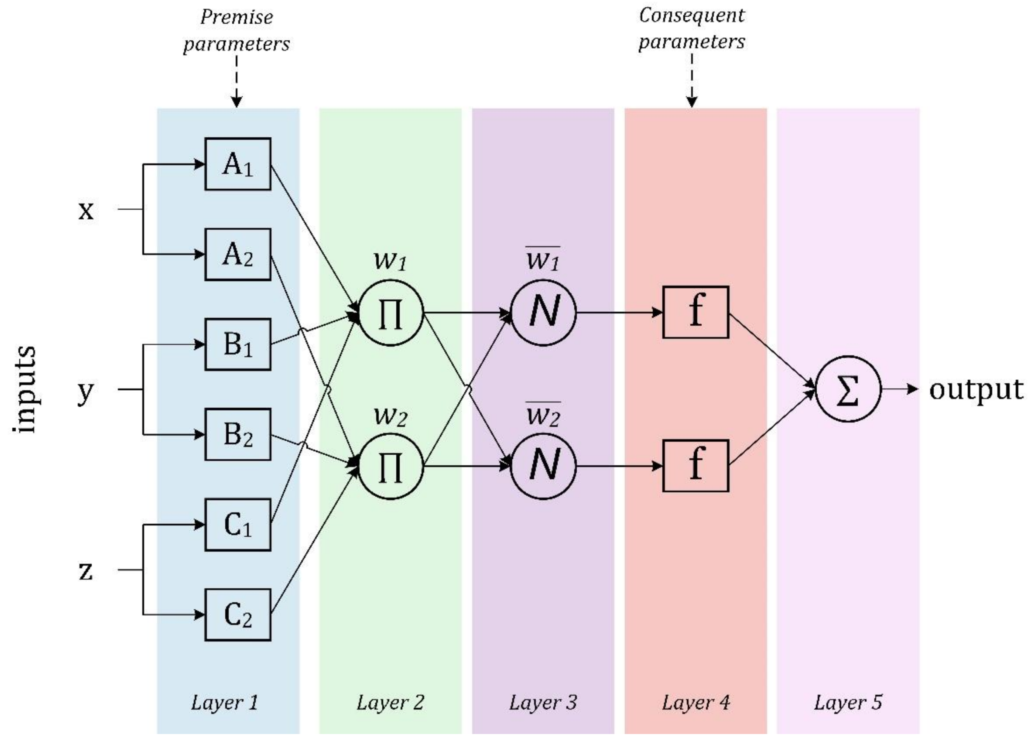

Figure 5: ANFIS architecture.

2.3. Prosumer operation

The purpose of the EH industrial model and the forecast of the energy vectors is the optimization of the energetic operation of the plant considering a prosumer behaviour that can provide benefits both for the enterprise and for the electricity market. The optimization, which is carried out with a weekly time horizon to capture demand and market cycles, has to be performed considering internal and external parameters to decide the best energy management strategies, deciding on which equipment to use, when to buy and sell electricity from the utility grid and when to charge and discharge energy storage systems either to sell it to the utility grid or to use it to fulfil internal demand. The objective of this operation depends on the interests of the enterprise and can be, for example, the minimisation of energy costs and emissions. Generally, an optimization problem is defined mathematically as:

$$\text{Given: } f: A \rightarrow \Re \tag{12}$$

$$\text{Find: } x_0 \in A \text{ such that } f(x_0) \leq f(x) \text{ for all } x \in A \tag{13}$$

Where f is the objective or fitness function of the problem that can contain the cost of energy purchased from the utility grid, the benefit obtained when selling energy, the levelized cost of employing energy converters within the EH, and the emission caused by the use and conversion of specific energy carriers. A, in contrast, represents a subset of the real space which can be understood as the constraints that need to be achieved or fulfilled. It can be a group of equalities and inequalities, which in the framework of the prosumer optimization problem should contain internal EH restrictions as well as prosumer operation restrictions related to energy exchange with external entities. The parameters to optimize are represented as x, which are for the prosumer optimization problem the equipment set points and energy transactions of the EH with external grids. Considering that the prosumer optimization problem is represented as a minimisation over time, it can be formulated as:

$$\text{Minimise: } \sum_{t=1}^{N} f^t(x) \quad (14)$$

$$\text{Subject to: } g^t(x) = 0 \;\forall\; t \quad (15)$$

$$h^t(x) \leq 0 \;\forall\; t \quad (16)$$

Where $g(x)$ is the set of equality constraints and $h(x)$ is the set of inequality constraints that have to be fulfilled at all times. For the studied problem, these constraints are:

- Equality constraints:
  - EH equilibrium, which can be expressed employing the general EH formulation as:

$$L - \eta\, P = 0 \quad (17)$$

  - Use of all energy to/from an energy converter or input by another energy converter or output, which is assured by the dispatch factors:

$$\sum_{i=1}^{n} v_i - 1 = 0 \quad (18)$$

- Inequality constraints:
  - Equipment conversion upper and lower bounds.
  - Transaction restrictions, such as maximum energy that can be traded with external grids, which can be electricity, gas, or others.
  - Maximum and minimum energy stored in the storage systems.

The fitness function f can be formed by one or more functions depending on the objectives pursued by the industrial SME. In the literature, most studies addressing energy optimizations have as a unique objective the economic profit maximisation, such as [89], although some of them also consider environmental and social implications. From these, the most common approach is to combine economic and environmental objectives, including emissions as a constraint or as an objective [90]. As the decisions taken by industrial SMEs have great environmental and social impacts, it is beneficial in the formulation of the optimization problem to consider the possibility to treat more than one objective. There are several ways to handle Multi-Objective Optimizations (MOO). MOO problems can be broadly divided into Multi-attribute Decision Making (MADM) and Multi-objective Decision Making (MODM) problems. MADM refers to optimization problems in which the optimization space is discrete and, before the optimization process begins, there exists a limited set of predefined criteria. MADM is often used in finite selection or choice problems [91]. In contrast, MODM is mostly used for solving engineering problems expressed mathematically and is therefore more suitable for the problem here presented. MODM are often classified according to the handling of the preferences for the different criteria considered [92]:

- Methods with a priori articulation of preferences: In these methods, the preferences for the different criteria are computed before the search for the solution is performed, which makes it possible to obtain a single optimal solution.
- Methods with a posterior articulation of preferences: In these methods, no preferences are specified and the algorithm performs the search for a set of solutions that are considered optimal for the optimization problem. Once the set of solutions is obtained, the decision-maker can evaluate it and perform the selection of the best alternative.
- Methods with no articulation of preferences: This method usually considers setting the weights of all criterions equal to one or setting specific goals, so no preference for one over another is specified.

The prosumer operation optimization problem searches for the best energy management strategy considering the enterprise's preferences. This problem has diverse optimal solutions where a trade-off between the different criteria exists. Nonetheless, this optimization is designed to be carried out repeatedly on an industrial SME to compute its operation and it is therefore unfeasible and unproductive for decision-makers or supervisors to continuously evaluate the best trade-off alternative. Thus, an MODM methodology with a prior articulation of preferences is preferred. Inside this category, the Weighted Sum Method (WSM) represents the core and most used approach for selecting weights to compose a unique objective function such as [93]:

$$f = \sum_{j=1}^{N} f^i w_j \tag{19}$$

Being w_j is the weight assigned to the j-ith objective. Since different objectives have different values and ranges, f^i should have been previously normalised before being introduced into the final fitness function. The mathematical formulation of the optimization problem results in a multi-objective, multi-period problem, which may contain integer or continuous parameters depending on the case under analysis. In [94] Mixed-Integer Lineal Programming (MILP) and evolutionary algorithms are tested for multi-objective optimization of complex energy systems. The results show that MILP is suitable for generating a list of ordered solutions with short resolution time while evolutionary algorithms, such as GA, work with a population of potential solutions each representing a different trade-off between objectives and is particularly advantageous for multi-objective optimizations. [94] formulates the mixed integer nonlinear problem for a multi-objective scheduling of EV and solves it using a Benders decomposition and transforming the large-scale optimization problem into one master MILP problem and one non-linear problem. A similar problem exposes [95], which solves it using multi-objective evolutionary algorithms and MILP. The optimization technique used depends on the characteristics and complexity of the industrial SME analysed as well as on the computational resources; being GA and MILP or LP adequate techniques.

2.4. Publications

The techniques and methodologies exposed in this chapter have been presented and published in the articles detailed in this section. These articles, therefore, deal mainly with energy modelling, forecast, and operation optimization of industrial SMEs as prosumers. In all of them, case studies are presented to evaluate the suitability of the proposed techniques and methodologies for industrial SMEs and the advantages of becoming prosumers. A complete version of the second and third articles is available in section 5 whereas the full version of the first article can be consulted in Annex A.

- E. M. Urbano, V. Martínez-Viol, and L. Romeral, "Optimization of industrial plants for exploiting energy assets and energy trading," in *IEEE International Conference on Emerging Technologies and Factory Automation, ETFA*, 2019, vol. 2019-Septe.

  This article presents an overview of the **energy and industrial framework** which promotes the creation of prosumers from industrial entities. The article exposes the **detailed EH model** for a specific industrial site, the **load forecast using ANFIS**, and the **optimization of the prosumer behaviour**.

- E. M. Urbano, V. Martinez-Viol, K. Kampouropoulos, and L. Romeral, "Future european energy markets and industry 4.0 potential in energy transition towards decarbonization," *Renew. Energy Power Qual. J.*, vol. 18, no. 18, pp. 190–195, 2020.

  The objective of this article is to establish the **current and future frameworks for the energy market and industrial developments**. The transformation to a prosumer is evaluated by **analysing the economic benefit of operating as so**.

- E. M. Urbano, V. Martinez-Viol, K. Kampouropoulos, and L. Romeral, "Energy equipment sizing and operation optimisation for prosumer industrial SMEs – A lifetime approach," *Appl. Energy*, vol. 299, no. July, p. 117329, 2021.

  Although this article already exposes developments that will be addressed in the next chapter of this thesis, it includes the development of the **EH for the energy infrastructure of and industrial SME** and the **prosumer operation optimization considering weekly energy patterns**.

2.5. Conclusions

This chapter has presented the modelling of the industrial energy infrastructure, the forecast of the energy vector, and the prosumer operation optimization problem. As commented in the previous section, to evaluate the suitability of the proposed techniques and methodologies, case studies have been defined and analysed; and the results published in the exposed articles. The case studies reflect standard SME plants with a bi-directional connection to the electrical utility grid and a connection to the gas grid. They have to fulfil electrical and thermal demands and account with the following energy equipment: PV generators, batteries, Combined Heat and Power (CHP) units, and boilers. Their energy infrastructure has been modelled and the forecast of both electrical and thermal demand has been carried out using ANFIS. The ANFIS methodology enables to obtain forecast error between 5.1% and 7.6% by employing as inputs the day of the week, the time of the day, the scheduled production, the external temperature, and the demand 1 day and 1 week before.

With the EH model and the energy forecasts, the prosumer operation of the plant is optimized. The results expose that power from the renewable energy source is injected into the utility grid in the time intervals where generation is high and electricity costs in the external market are also high. In contrast, when costs in the market are low, this power is used for internal demand or to charge the battery. It has also been possible to appreciate that, due to the fact that gas is significantly cheaper than electricity, it is employed not only to fulfil thermal demand but also to operate the CHP unit and generate electricity to cover electrical demand. The optimization of a plant without electricity exchanging capabilities has also been done for comparison purposes to evaluate the benefits of becoming a prosumer. The economic spectrum of the prosumer operation has been evaluated and savings between 7% and 20% have been observed.

These developments demonstrate the feasibility of trading energy with the utility grid by controlling the operation points of energy equipment to benefit from the state of the external market, injecting green energy at high-cost periods. Due to the economic profitability of becoming a prosumer, the proposed energy management strategy is likely to be included in the current business models of industrial SMEs, promoting the decentralisation and flexibility of the energy system.

3. Infrastructure sizing and risk assessment

This chapter addresses the energy sizing optimization problem and assesses the investment risk related to it. Firstly, the sizing problem itself is defined and the techniques and methodologies employed to solve it are presented. Secondly, the risk industrial SMEs undertake when performing the energy investment to upgrade their plant is addressed.

3.1. Sizing optimization

The purpose of this optimization is to obtain the sizes of energy equipment in which to invest. The objective of the optimization should be aligned with industrial interests and consider the lifetime performance of the new equipment. Currently, the interest of industrial enterprises lays mainly in the achievement of profitable economic outputs. Cost of Energy (COE) is an output often employed when optimally sizing energy equipment [96]. This parameter serves to analyse the cost of the energy generated considering the repeatability of the performance of the energy resources during their lifetime. However, to suitably address energy investment performance, variations according to external and internal changes that occur over the lifetime of the equipment should be addressed. For this reason, the Net Present Value (NPV) is a more suitable parameter for evaluating investments, as it considers the different cash inflows and outflows for different periods and transforms them into current value; evaluating lifetime profitability [97]. NPV can be computed as:

$$NPV = -C_0 + \sum_{(i=1)}^{T} \frac{C_i}{(1-r)^i} \tag{20}$$

Where C_0 is the initial investment cost, C_i is the cash flow of year i, and r is the hurdle rate used by the enterprise. A positive NPV announces that the obtained benefits are higher than the costs, resulting in a good investment option. To compute the NPV, it is required to obtain the costs and benefits of operating the energy equipment and thus to carry out the prosumer operation optimization introduced in section 2.3. Therefore, the sizing optimization problem can be formulated as a two-stage optimization problem in which equipment sizes are selected in the first-stage and their prosumer operation is evaluated in the second-stage. A similar approach is also used in [98], which proposes a two-stage optimization for the sizing of an ESS. In the first stage, the ESS capacity and inverter rating are selected, and in the second stage, the dispatch schedule is optimized. [99] follows this same strategy for the design and planning of a microgrid with a combined cooling, heat and power system, and [100] does so for the optimal sizing and operation of a CHP unit. For the sizing optimization problem of an industrial SME, the energy equipment to install are selected in the first stage while in the second stage the prosumer operation based on weekly time horizons is computed. Figure 6 depicts the proposed methodology. First of all, relevant data is extracted from databases. This data can include, among others, meteorological information, market costs, internal demands, and equipment parameters. As the optimization is carried out for the complete lifetime of the investment and considering weekly operational periods, weeks are selected over the optimization horizon. Then, the operation of a reference plant is optimized. This reference plant represents a "Do-nothing" scenario in which the industrial SME

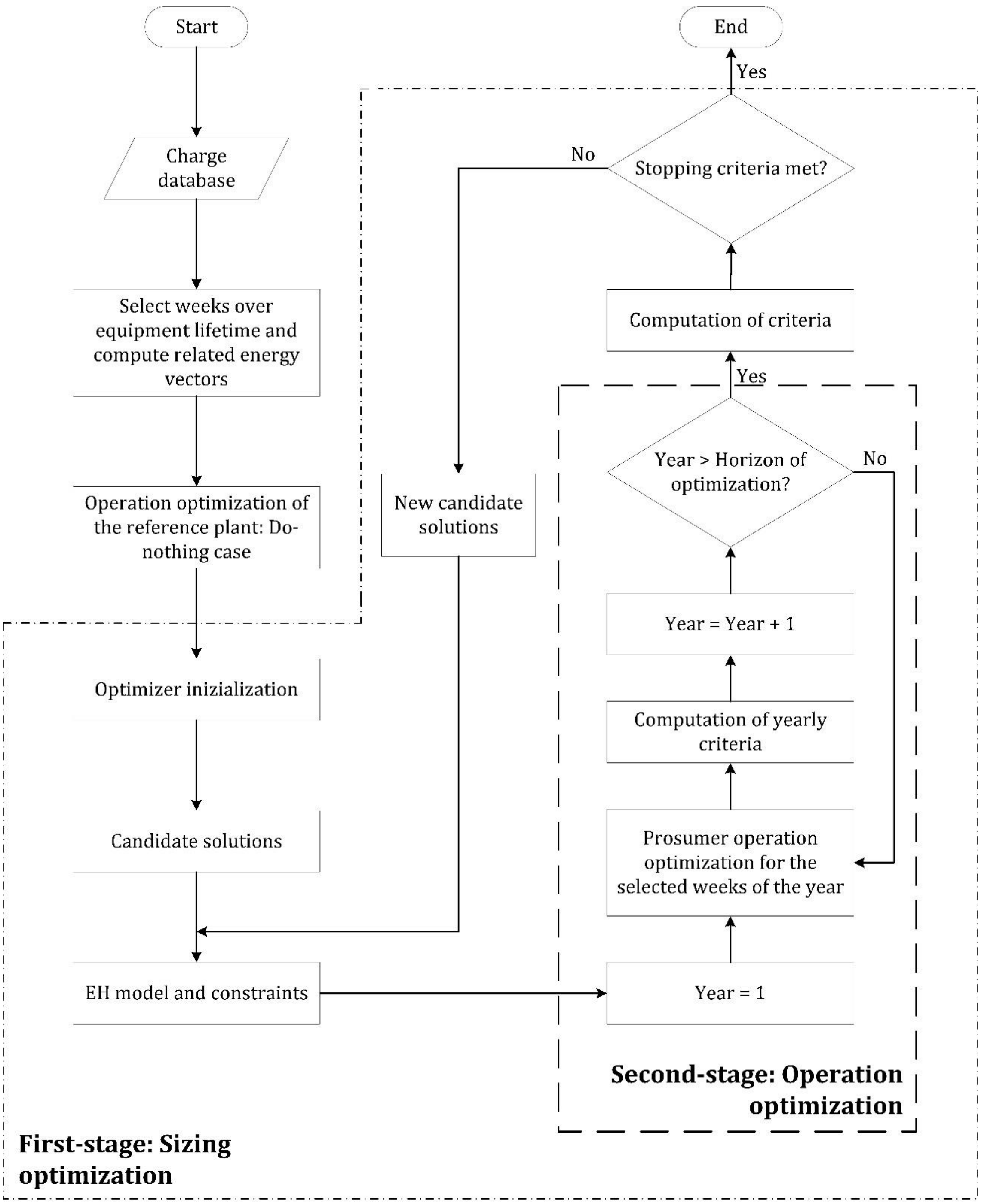

Figure 6: Energy equipment sizing optimization methodology.

operates as a prosumer but does not modify its energy infrastructure. This optimization will be used for comparison purposes to evaluate the benefits of upgrading the industrial plant equipment. Once this step is performed, the algorithm continues to the two-stage optimization. In the first stage, candidate solutions are selected for evaluation. These candidate solutions are the possible sizes of energy equipment to install in the industrial SME. With these data, the EH model of the potential upgraded industrial plant is constructed and related constraints are generated. This model moves to the second stage of the optimization in which the prosumer optimal operation is obtained. This optimization is carried out by analysing selected weeks per year and considers long-term variations in external and internal parameters such as changes in the cost of energy carriers or industrial demand growth perspectives. The optimal operation is compared per year with that of the reference plant to evaluate the costs and benefits produced by upgrading the plant with the analysed candidate solutions. If NPV is used as a criterion, these costs and benefits represent the cash inflows and outflows. When the evaluation of the operation along the optimization horizon is completed, the chosen criteria that comprise lifetime performance are computed. At this point, the global optimizer checks whether the near-maximum global has been obtained or not through its stopping criteria, which deal with the result tolerance, number of iterations without improvement, time constraints, etc. If a near-maximum global has been reached, the algorithm finalizes its operation. Otherwise, new potential solutions are created and the process is repeated.

To successfully carry out the proposed optimization, an important amount of data is required, which can include:

- energy carriers' current and future costs,
- feed-in tariff,
- meteorological information such as solar irradiation and wind,
- emissions cost,
- internal demand,
- industrial SME expected growth ratio,
- equipment initial cost,
- equipment operation and maintenance costs,
- equipment degradation,
- equipment efficiencies, and
- investment restrictions such as maximum investment or payback period.

The optimization problem formulated presents unconnected complex feasible areas, so gradient-based and local optimization algorithms are not suitable for its resolution as they tend to reach local maximums close to the starting point. For this reason, the use of global optimization algorithms is in this case preferred, as they have a better chance of finding the global optimal and do not require information from the derivative of the objective function [101]. For the specific situation considered, the optimization problem is solved using Direct Search (DS), a derivative-free global optimization algorithm based on branching techniques that performs successfully in front of practical problems with complex search areas [102] and that provides global convergence as proven in [103]. The second-stage of the problem contains also an internal optimization procedure. This optimization is solved through LP to minimize computational cost and assure the achievement of the global operational optimum.

3.2. Risk analysis

The optimization problem addressed in the previous section requires employing data on current parameters and their evolution in upcoming years. This data is considered deterministic, assuming that their value is known and certain. However, the real values of these inputs are uncertain and so is their evolution. This creates uncertainty in the output of the optimization problem which represents a risk for the industrial SME performing the investment. To improve the investment perspectives of industrial SMEs, this section analyses the risk related to it. To do so, it is required to:

- model the uncertainty of input parameters,
- perform a UA to measure the uncertainty in the output and therefore the risk assumed by investors, and
- perform a SA to identify where the risk is coming from.

Figure 7 shows the methodology to carry out this risk analysis. First of all, the results from the sizing optimization are gathered and the model of the upgraded plant is obtained. The uncertainty in input parameters is then characterized and a UA analysis is performed to obtain the output uncertainty. Lastly, the SA is carried out to identify the most influential inputs in outputs' uncertainties and rank them.

3.2.1. Uncertainty characterization

The inputs considered deterministic in the optimization stage are inherently uncertain. To evaluate the uncertainty of the optimization output, it is indispensable to consider the uncertainty in the input. Uncertain parameters that influence the investment decision can be characterized through different strategies, such as scenarios, numerical ranges or Probability Density Functions (PDF). The latter is more suitable for energy investment optimization problems, as it enables the

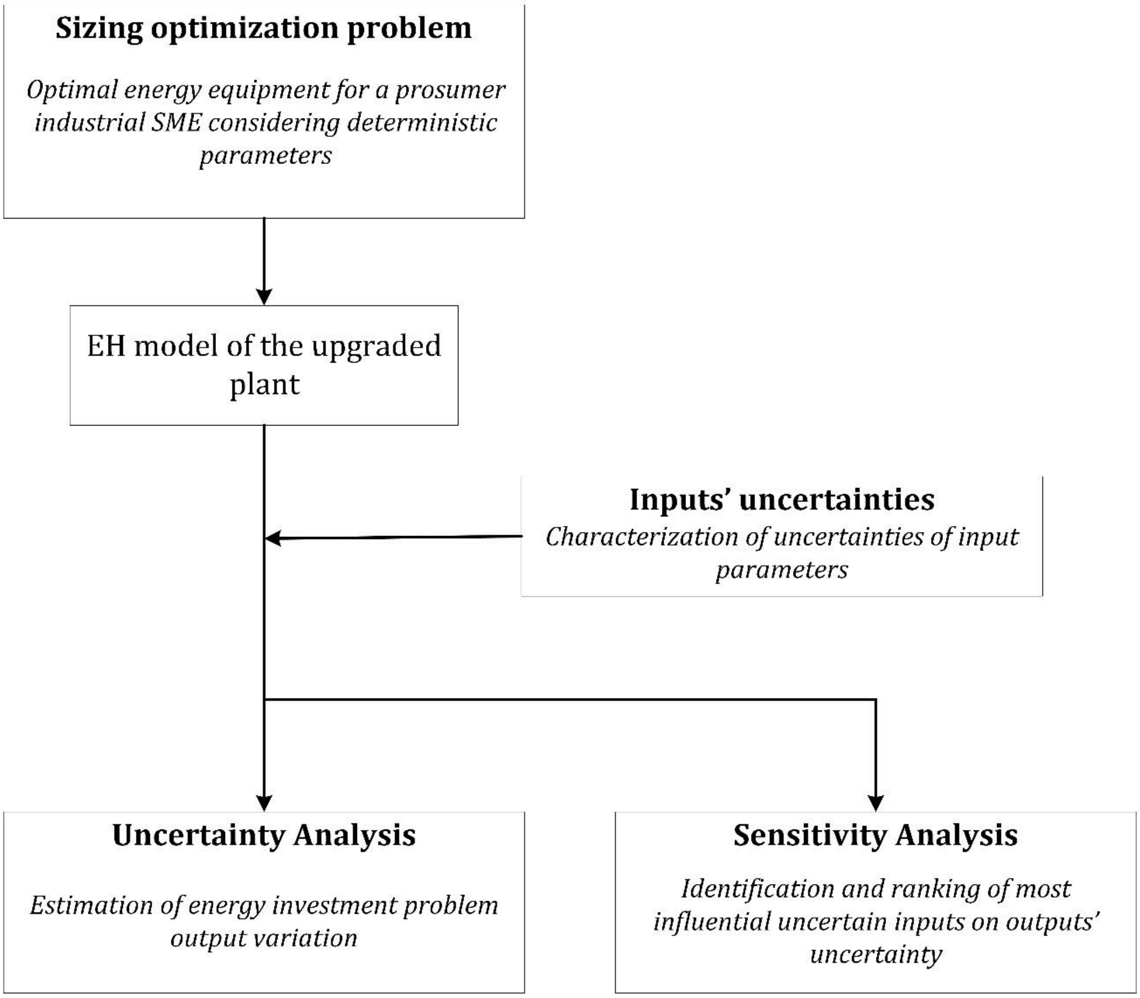

Figure 7: Risk analysis methodology.

application of sophisticated UA and SA methods that provide robust results [104]. To obtain the PDF of an uncertain input, a literature search is performed to gather the possible current and future values for the analysed parameter. Once data gathering is completed, several potential PDFs are tested on it and the one that fits better is chosen to characterize its uncertainty. In the case that the analysed parameter presents uncertainty in its current value and also in its evolution over time, the uncertain evolution is included in the problem by adapting the PDF to the changing trends. The goodness of the PDF fit is evaluated through the loglikelihood function, which evaluates the joint probability distribution of the random vector resulting from the PDF to be the provided input data sample. The distributions considered for characterizing the inputs are the BirnBaurn-Saunders, the exponential, the extreme value, the gamma, the generalized extreme value, the half-normal, the inverse Gaussian, the Kernel, the logistic, the log-logistic, the lognormal, the Nakagami, the normal, the Weibull, and the uniform distributions.

3.2.2. Uncertainty Analysis

With PDFs assigned to input parameters, a method that generates samples according to these PDFs is a suitable UA strategy that allows obtaining a reliable output for the energy infrastructure problem analysed [105]. Although Monte Carlo is a commonly used statistical sampling method [106], its high computational cost suggests the employment of quasi-random sampling methods such as the Latin Hypercube Sampling (LHS), which provides results efficiently at a low computational cost [107] and has been proved to perform well in energy models [108]. Therefore, in this thesis, LHS is used for UA. LHS divides the uncertainty spectrum into subsets of equal probability and draws samples randomly from each of the subsets [109]. Once N samples are obtained for each of the inputs' PDFs, they are combined to obtain N uncertain scenarios to analyse [110]. The energy equipment in which to invest has already been selected during the deterministic optimization problem and in this UA the objective is to know the uncertainty in its performance. Although the equipment itself does not change, its operation can be modified to adapt to external and internal deviations. Therefore, for each uncertain scenario, the operation of the industrial SME is computed again. With this process, the output distribution is obtained, making it possible to evaluate the robustness of the deterministic problem solution in front of uncertainties and the expectable costs and benefits.

3.2.3. Sensitivity Analysis

Once the uncertainty in the output is known, the risk becomes more tangible for investors, although it is convenient to perform a SA to know the inputs that cause most of this uncertainty. Among other approaches, statistical global SA methods are the ones that provide the most model insights [104]. Due to the complexity of the optimization problem and its high computational cost, a two-stage SA methodology is considered for the study here presented. The first stage aims at reducing problem dimensionality, identifying and discarding less-influential inputs through a screening technique. The most widely used screening methodologies for energy models are Sequential Bifurcation, Nominal Range Sensitivity and, particularly, the Morris method [111], [112]. Among the different screening techniques for energy models, the Morris method is the most suitable one as it does not require hypotheses regarding the nature of the model and thus can be applied to a wide range of problems [113]. The second stage of the SA methodology is selected to be formed by a statistical variance-based global SA method, applicable to non-monotonic and non-linear models [114]. Among the variance-based methods, Sobol, FAST and e-FAST have been widely used for energy systems, providing stable results. The Sobol method presents more robust results than FAST and e-FAST and allows for a suitable sample size to capture the behaviour of the problem [115]. Considering this robustness and that a previous screening stage is employed to reduce problem dimensionality, the Sobol method is the one chosen as the second-stage for the SA. The combination of Morris and Sobol has already been used in the literature to assess complex uncertain problems, such as in [116]; and has been proved to provide results efficiently while quantifying the sensitivity effectively.

3.2.3.1. Morris method

The Morris method is a global approach that can be considered an extension of local OAT techniques which enables the discrimination of less influential inputs employing a small sample size and low computational cost [117]. The uncertainty range of all the inputs is divided into p levels. Then, q base vectors are obtained from sampling one random level per uncertain input. These base vectors are recommended to be between 4 and 10 [118] and serve as the starting point for the creation of trajectories, which enable the analysis of the influence of the inputs in the output. In each trajectory, the inputs' values are consecutively increased or decreased a step Δ. The Elementary Effect (EE) of input x_i in the trajectory can be computed as:

$$EE_i = \frac{f(x_1, \dots, x_i + \Delta, \dots x_k) - f(x_1, \dots, x_i, \dots x_k)}{\Delta} \tag{21}$$

Where f represents the deterministic model. To ensure a desirable symmetric treatment of inputs [119], it is convenient to employ a value of p even and a step value of:

$$\Delta = \frac{p}{2(p-1)} \tag{22}$$

With the EE obtained, it is possible to rank parameters through the index μ_i^*:

$$\mu_i^* = \frac{1}{q}\sum_{j=1}^{v} |EE_i| \tag{23}$$

3.2.3.2. Sobol method

Once the less influential inputs are discarded, the Sobol method is applied, which aims to calculate two metrics per parameter named first-order Sobol index and total-order Sobol index. These metrics indicate the portion of the output variance that is explained by a parameter alone and the portion of the output variance that is explained by a parameter and its interactions with others [56].

On the one hand, the first-order index of the parameter x_i is defined as:

$$S_i = \frac{V_{x_i}\left(E_{X_{\sim i}}(Y|x_i)\right)}{V(Y)} \tag{24}$$

Where Y is the output of the system, $V(Y)$ is its total variance and $E_{X_{\sim i}}(Y|x_i)$ is the mean value of Y considering the variation of all model inputs except x_i, which remains fixed. This term is evaluated for all values of x_i, and its variance computed, which is expressed by the term V_{x_i}. On the other hand, the total-order index is defined as:

$$S_{Ti} = \frac{E_{X_{\sim i}}\left(V_{x_i}(Y|x_{\sim i})\right)}{V(Y)} \tag{25}$$

Where $V_{x_i}(Y|x_{\sim i})$ is the variance of the output over all the possible values of x_i when the rest of the inputs are fixed. This variance is computed for all the values of the inputs, which is represented by the $E_{X_{\sim i}}$ term. To compute the Sobol indices for complex energy problems considering the entire distribution of inputs, repeatedly running the model is required. To minimise the computational cost while maintaining the method's robustness, the best practices exposed in [120] are employed. These practices establish the use of two different sampling matrices A and B with rows equal to the number of simulations and columns equal to the number of considered uncertain inputs, the matrix $\boldsymbol{A}_{\boldsymbol{B}}^{(\boldsymbol{i})}$ is constructed for all factors with all the columns from A except the i-th column, which is obtained from B. Then, the numerical estimators of the sensitivity indices are computed as:

$$V_{x_i}\left(E_{X_{\sim i}}(Y|x_i)\right) = \frac{1}{N}\sum_{j=1}^{N} f(\boldsymbol{B})_j \left(f\left(\boldsymbol{A}_{\boldsymbol{B}}^{(i)}\right)_j - f(\boldsymbol{A})_j\right) \tag{26}$$

$$E_{X_{\sim i}}\left(V_{x_i}(Y|x_{\sim i})\right) = \frac{1}{2N}\sum_{j=1}^{N} \left(f(\boldsymbol{A})_j - f\left(\boldsymbol{A}_{\boldsymbol{B}}^{(i)}\right)_j\right)^2 \tag{27}$$

3.3. Publications

This section exposes the publications done related to energy sizing optimization and risk assessment addressed in this chapter. The publications include case studies in which energy equipment is optimized and risks are evaluated to verify the suitability of the proposed techniques and methodologies. For each of the publications, a brief text is included with the objective to ease the consultation of the thesis' developments. Chapter 5 includes the full version of all of them.

- E. M. Urbano, V. Martinez-Viol, K. Kampouropoulos, and L. Romeral, "Renewable energy source and storage systems sizing optimization for industrial prosumers," in *IEEE International Conference on Emerging Technologies and Factory Automation, ETFA*, 2020, vol. 2020-Septe.

  This article **optimizes the size** of renewable energy and energy storage systems for an industrial plant considering a **prosumer operation**. It compares the performance of the industrial plant considering different energy equipment and operation scenarios and exposes the **advantages of optimally sizing energy equipment for prosumer purposes**.

- E. M. Urbano, V. Martinez-Viol, K. Kampouropoulos, and L. Romeral, "Energy equipment sizing and operation optimisation for prosumer industrial SMEs – A lifetime approach," *Appl. Energy*, vol. 299, no. July, p. 117329, 2021.

  This paper presents the detailed **optimization methodology** to adequately solve the **energy equipment sizing problem** for industrial SMEs. The energy and economic profiles of SMEs are analysed and the mathematical formulation of the **two-stage optimization** problem including **sizing and operation** is exposed in detail.

- E. M. Urbano, A. D. Gonzalez-Abreu, K. Kampouropoulos, and L. Romeral, "Uncertainty analysis for industries investing in energy equipment and renewable energy sources," Renew. Energy Power Qual. J., vol. 19, no. 19, pp. 126–130, 2021.

  In this paper, the **two-stage optimization of the energy investment** is performed and the risk of the investment is analysed. Energy carriers' **uncertainty is characterized** and investment risk is evaluated through an **uncertainty analysis**.

- E. M. Urbano, V. Martinez-Viol, K. Kampouropoulos, and L. Romeral, "Risk assessment of energy investment in the industrial framework – Uncertainty and Sensitivity analysis for energy design and operation optimisation," Energy, vol. 239, p. 121943, 2021.

  This article exposes in detail the **deterministic two-stage energy investment optimization** and the **risk assessment**, including **uncertainty analysis** and **two-stage sensitivity analysis**

3.4. Conclusions

The current chapter has addressed the energy sizing optimization problem and the assessment of energy investment risks. The energy sizing or investment problem has been presented as a two-stage deterministic optimization, in which energy equipment is selected in the first-stage and the prosumer operation of the equipment over its lifetime is optimized in the second-stage. For risk assessment, a methodology based on uncertainty characterization of inputs, uncertainty analysis, and two-stage sensitivity analysis has been defined. These techniques and methodologies have been applied to different industrial case studies aiming to explore the benefits of optimally sizing the equipment and evaluate the uncertainty in the investment performance in front of inputs' variabilities. These case studies and related results have been published in the articles mentioned in the last section: [121]–[124].

The obtained results show that optimally sizing energy equipment for prosumer purposes can produce energy-related savings of approximately 45% compared to a "Do-nothing" scenario in which no new equipment is included and the plant does not operate as a prosumer. Regarding the economic performance of the investment, the payback period for a prosumer lays between 4 and 8 years, which supposes a significant reduction compared to the self-consumption case, with a payback period between 10 and 11 years. It has also been possible to verify that, although the optimal investment for a prosumer can be higher as it is preferable to have, for example, more renewable energy capacity, this does not affect negatively the payback period as yearly returns are also higher and the investment is quickly recovered.

The final value of the investment in the case studies analysed – measured through the NPV – multiply by 10 that of the initial cost, a fact that enhances the investment of industrial SMEs in new equipment and energy management strategies. Regarding the specific equipment selected in the investment optimization, the solutions are highly dependent on the plant demand type and the evolution of external parameters. Nonetheless, in all the studied cases an upgrade of the energy infrastructure improves the energy performance of factories and permits trading with the external utility grid as a prosumer, boosting the profitability of the investment and contributing to the decarbonisation of the energy sector.

The results of the exposed deterministic energy sizing optimization have been improved by analysing also the risks related to the related investments. The UAs carried out in the different case studies expose that the variation of the economic output is moderate in front of current system uncertainties. For the case study analysed in [123], the final NPV value has a 68% chance of laying around 2.4% of the mean value and a 95% chance of lying around 4.8% of the mean. With the obtained values, it can be concluded that despite variations in the inputs of the system, the optimization methodology to size energy infrastructures for prosumers is robust and the risk can be acceptable by enterprises. SA has also been performed, indicating that for the cases studied the inputs that most influence the performance of the investment is the uncertainty in the cost of energy carriers – electricity and gas – and their evolution.

The proposed framework for energy sizing optimization and investment risk assessment is useful to the industrial sector and specifically to SMEs, enabling them to better analyse the energy and economic perspectives of the investment to perform.

4. Risk-informed investment

The current growing uncertainty in the energy markets [125], [126] advises not only to evaluate the risk of investing in energy equipment but also to incorporate uncertainty in input parameters – and especially uncertainty in the cost of energy carriers – in the energy investment optimization problem. Also, the Industry 5.0 revolution is enhancing the renewal of industries to transform them into more value-driven, sustainable, and human-centred entities [127], making it indispensable to consider qualitative criteria and their uncertainty in the decision-making process.

For these reasons, this chapter exposes a risk-informed investment optimization approach that incorporates both quantitative and qualitative parameters and uncertainties in the energy sizing problem. Figure 8 shows an overview of the proposed methodology, which is based on the developments carried out in the previous chapters of this thesis. First of all, input data is selected and collected and quantitative and qualitative parameters and their uncertainties are modelled. The process to model quantitative inputs and their uncertainties has been exposed in section 3.2.1. This chapter deepens these previous considerations to expose how quantitative inputs and uncertainties are treated to be included in the optimization problem. Also, qualitative criteria values and uncertainties are analysed, modelled and incorporated into the problem. Once input data has been characterized, the two-stage energy sizing optimization process takes place. This two-stage process is an extended version of that previously presented in section 3.1. In this case, the first and second stages of the optimization consider both quantitative and qualitative parameters, their uncertainties, and their effect on the perception of the energy equipment and on the operation of the prosumer industrial SME. The fitness function is also computed bearing in mind these parameters and the risk caused by the uncertainty in the inputs, as well as the preferences of the investor.

The follow sections detail the process to model and incorporate quantitative and qualitative parameters and uncertainties in the investment problem as well as the extended two-stage optimization process to support industrial SMEs in adopting new energy equipment to become prosumers.

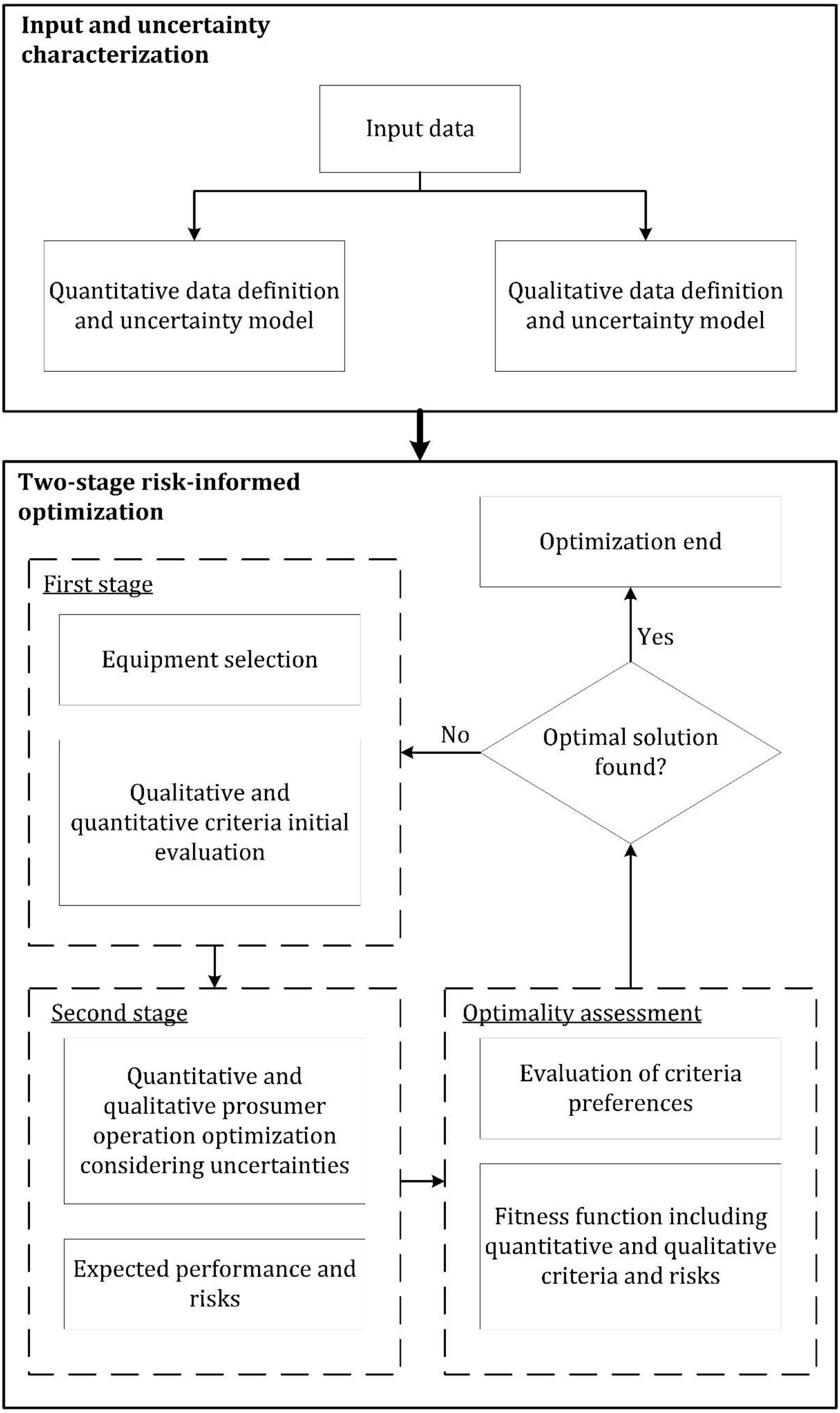

Figure 8: Risk-informed investment optimization methodology.

4.1. Input and uncertainty characterization

Before carrying out the optimization of the energy investment, it is necessary to identify the risks influencing the investment and model them for their incorporation into the problem. As discussed above, these parameters and risks can be both qualitative and quantitative.

4.1.1. Qualitative data

Qualitative data are those required to take the decision but are not measurable in a quantitative manner. Qualitative parameters are used, as shown in Figure 8, both in the first and second stages of the energy investment optimization. In the first stage, qualitative parameters or criteria directly linked to the equipment analysed, such as social acceptance, alignment with the administration, or ecological influence; are evaluated. In the second stage, the qualitative cost of using specific technologies is included in the operation optimization to prioritize the use of technologies with favourable qualitative consequences.

Due to the difficulty in their measurement, the value of qualitative parameters is commonly assigned by an expert or decision-maker based on their knowledge about, for example, the community where the industry is placed and the governmental framework [128]. To improve using single values to measure qualitative parameters, its consideration can be done by evaluating two parameters which enable addressing a value for the parameter itself and for its uncertainty. These two new parameters are *impact* and *probability. Impact* is the effect or the degree of fulfilment of a qualitative parameter and *probability* the likelihood that this *impact* occurs [129]. For the energy investment optimization in industrial SMEs, Table 1 exposes an example of the definition of *impact* and *probability* to measure the qualitative parameter "social acceptance".

Table 1: Qualitative parameter *impact* and *probability* definition example.

Qualitative parameter	Social acceptance
Impact	How strongly does the analysed solution affect the social acceptance of the industrial SME?
Probability	How likely is it that the mentioned impact occurs if the analysed solution is adopted by the industrial SME?

To include qualitative parameters in the energy investment optimization problem, it is required to assign a numerical value to *impact* and *probability.* For the case of qualitative evaluation in the first stage of the energy investment optimization, *impact* and *probability* depend on the mix of technologies considered for upgrading the energy infrastructure as well as on their social, environmental and technical influences. Therefore, the values of *impact* and *probability* are different for each candidate solution and decision-makers and experts have to estimate them for the whole continuous search space of possible solutions. These estimations are subject to a judgemental vagueness that generates uncertainty inherent to the definition process. To cope with this uncertainty, it is important to avoid considering qualitative parameters as crisp values not to lose relevant judgemental information. A suitable strategy to incorporate this vagueness in the energy investment optimization problem is the employment of fuzzy logic [130]. [131] explores the usefulness of the fuzzy set theory as a tool to express uncertainties inherently associated with human opinions and concludes that it can be successfully used together with multi-criteria optimization problems to get a more sensitive, concrete and realistic result. Therefore, in this thesis, a Fuzzy Inference System (FIS) is employed to consider the vagueness in the definition of the qualitative parameter and obtain a measure of it that encompasses its value and uncertainty dimensions. Two FIS are widely accepted and employed in the literature; the Mamdani and the Takagi-Sugeno [132]. Here, the Mamdani method is selected as it performs better in extracting experts' opinions on risk factors and thus it is more suitable for decision-making problems [133]. Figure 9 illustrates the functioning of a max-min

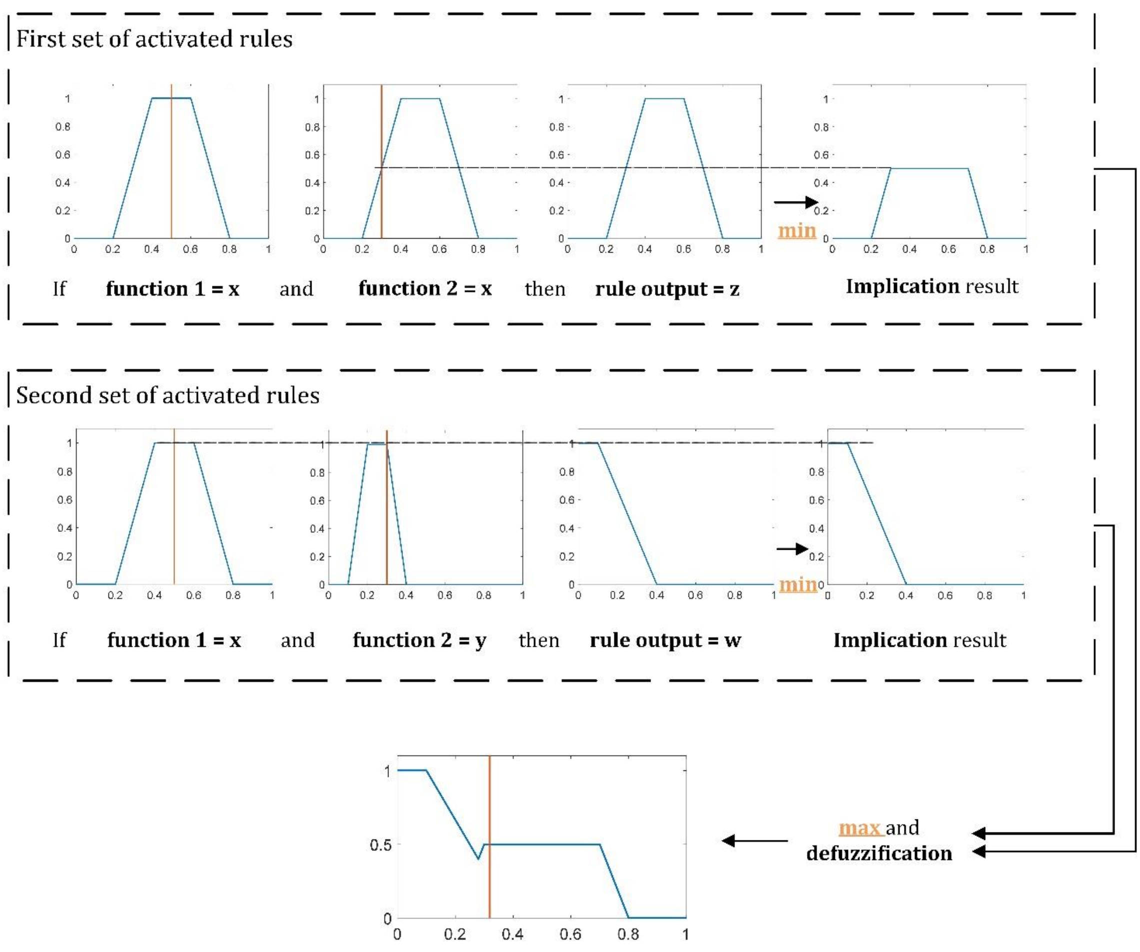

Figure 9: Mamdani FIS reasoning example.

composition Mamdani FIS through an example in which there are two input parameters, one with value 0.5 which activates membership function (MF) *x* and the other with value 0.3 which activates MFs *x* and *y*. These input parameters generate therefore two sets of activated rules. For each one, *if-then* reasoning is used to obtain the fuzzy output. *If-then* rules are defined by decision-makers and reflect their judgemental knowledge to evaluate the system output [134]. *Min* implication process is then applied to account for the level of fulfilment of MFs by input parameters. Following, the fuzzy outputs of each of the activated rules are aggregated through a *max* process, and the final fuzzy set is obtained. To compute as an output a unique value, the fuzzy set is defuzzified. This defuzzification can be carried out by employing the centroid strategy, which provides solutions that naturally and smoothly respond to the created rules [135].

The Mamdani FIS is the base of the fuzzy system proposed in this thesis to evaluate qualitative parameters in the two-stage extended risk-informed energy investment optimization process. Figure 10 exposes the complete fuzzy system for the evaluation of qualitative parameters and their uncertainty in the first stage of the optimization problem. First of all, the capacities of the technologies selected to upgrade the infrastructure are fuzzified and MFs are assigned to them. Gaussian MFs are preferable as they describe the continuity of opinions better than other common types of MFs due to their smoothness and naturality [136]. MFs can be directly defined by decision-makers through their expertise in the field or obtained through opinion mining [137]. *Probability* and *impact* are then computed through two separate Mamdani FIS that consider the *if-then* rules reflecting the judgements of decision-makers. *Impact* and *probability* functions are then aggregated to obtain the qualitative perception fuzzy set which is defuzzified to obtain a single output value.

The exposed analysis supports a non-only quantitative process that adjusts the solution to the enterprise's interests by including qualitative parameters in the first-stage of the optimization. Nonetheless, the socio-political framework is susceptible to changes and therefore these parameters have also to be included in the second-stage of the problem to adapt the prosumer operation of the plant according to the qualitative preferences of the enterprise. To do so, decision-makers should analyse the potential socio-political changes and the eventual positive or negative influence that the employed technologies would have on investments' performance considering the new context. This analysis reflects the alignment of the chosen technologies on the enterprise's interest over time and can be translated to dynamic qualitative cost for its inclusion in the operation optimization, creating a qualitative-aware operation strategy. As these dynamic costs are also subject to vagueness, fuzzy logic is also employed. Figure 11 expose the reasoning flow for this case. Technologies are evaluated in an isolated manner to compute the cost of employing them and therefore *probability* and *impact* can be directly assigned. Once *probability*

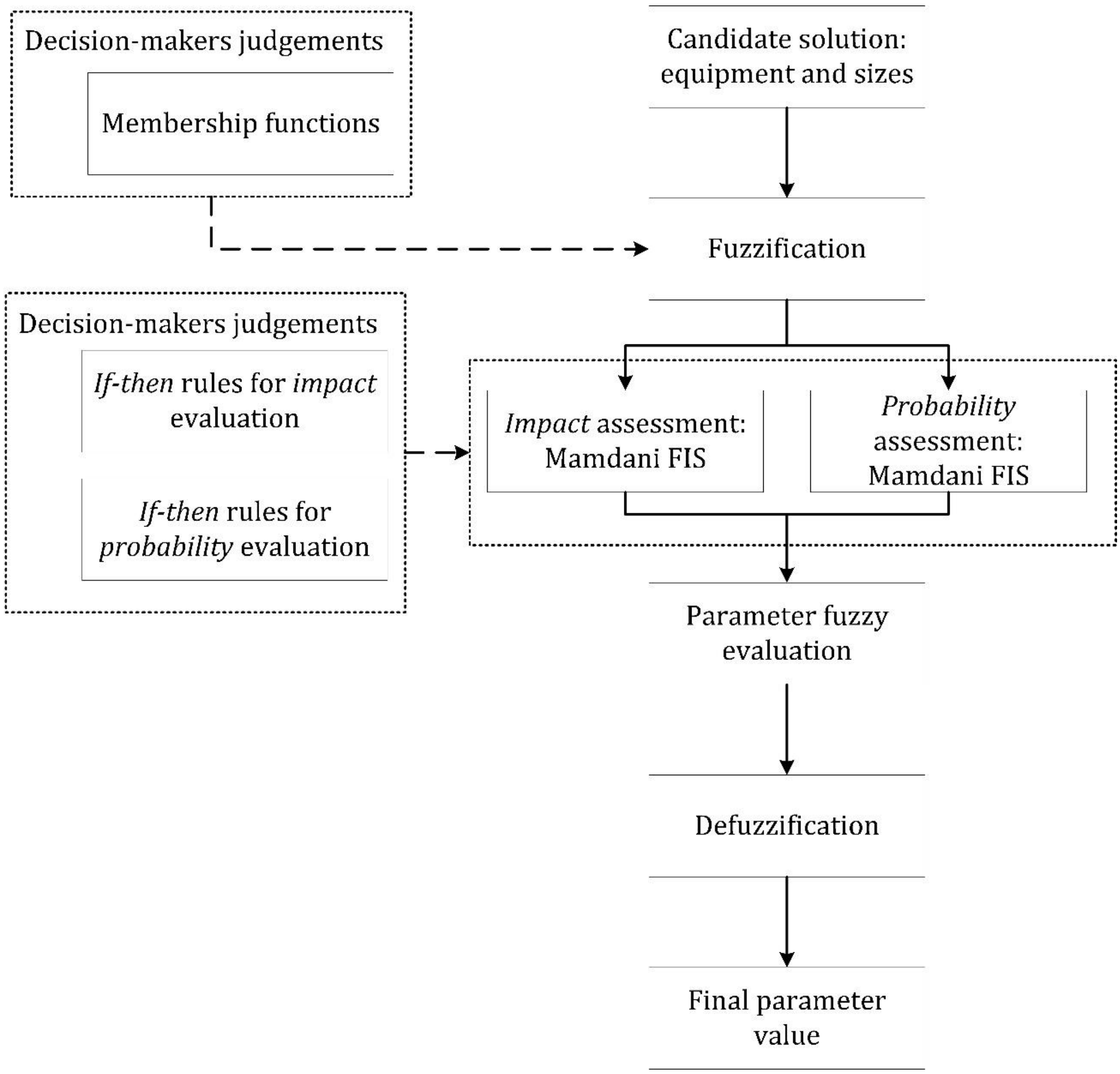

Figure 10: FIS for the evaluation of qualitative parameters in the first stage of the optimization process.

and *impact* are obtained, the qualitative dynamic cost is computed through the Mamdani FIS.

4.1.2. Quantitative data

Quantitative data are those that can be directly measured numerically and which are required to perform a technical and economic analysis of the solution. The model of quantitative data uncertainty has been exposed in section 3.2.1 for the evaluation of the quantitative risk assumed by the industrial SME when performing an investment. In this chapter of the thesis, however, this model is included in the optimization problem.

As with qualitative parameters, quantitative parameters can be characterized through *probability* and *impact*. On the one hand, *probability* refers to the values the parameters can take and how likely they are. This probability is reflected in PDFs.

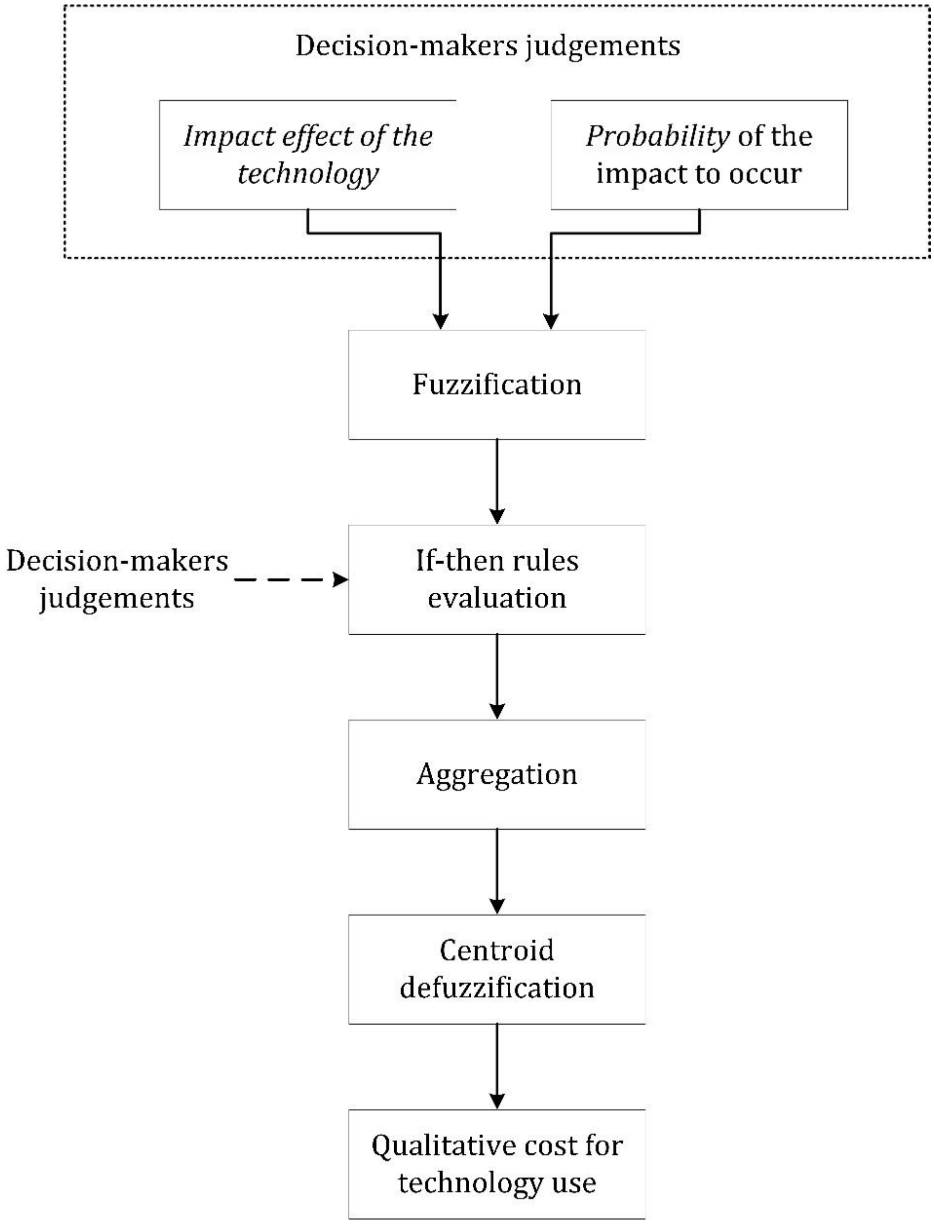

Figure 11: FIS for the evaluation of the qualitative cost of employing a technology

On the other hand, *impact* refers to the influence that the different probable values have on the resultant performance of the investment – which is measured according to a set of criteria defined by the enterprise. To compute this *impact*, the enterprise's criteria should be evaluated for the possible quantitative parameters' values, using the samples of the PDFs obtained through the LHS method. Therefore, it is required to repeatedly run the optimization model that computes the performance of the investment for all the samples of input quantitative parameters to evaluate the *impact* that their potential variations have on the output of the system. This process enables to obtain a PDF for the quantitative criteria of interest for the enterprise. Once this output PDF is constructed, it is useful to extract risk measures for their inclusion in the final fitness function. [138] proposes the use of variance as a measure of risk for the optimal scheduling of a battery system. However, variance measures the dispersion of the output, without specifying in which direction this dispersion is occurring and therefore not identifying if uncertainty is producing a positive or a negative deviation from the mean value. In contrast, [139] considers the uses of Value-at-Risk (VaR) for the risk management of energy portfolios. VaR represents the worst expected case for a pre-defined confidence level. That is, VaR is the PDF point which presents a cumulative probability equal to the confidence level, which is normally 1%, 5% or 10%. VaR allows risk to be assessed by considering only the negative impact of uncertainty and is therefore a better risk measure than the variance. Even so, it is a frontier value that does not assess the distribution in the left tail, omitting information from the worst-case scenarios that could be relevant in the decision-making process. An improved risk measure index is the Conditional-Value-at-Risk (CVaR). CVaR computes the mean of the worst-case scenarios for a pre-defined confidence level, which avoids the selection of solutions with undesirable profit distributions [140]. CVaR is computed as:

$$CVaR(x) = \frac{1}{1 - VaR} \int_{-1}^{VaR_{level}} xp(x)dx \tag{28}$$

Where $p(x)dx$ is the probability of the value x according to the obtained PDF, and the VaR level is the confidence level for which the VaR and CVaR are computed. In this thesis, CVaR is proposed as a risk measure for quantitative parameters. Apart from this measure, the mean of the obtained output PDF is also considered to evaluate the statistically expected investment performance.

4.2. Two-stage risk-informed optimization

This section exposes the methodology for the optimization of the energy investment of industrial SMEs considering quantitative and qualitative parameters and uncertainties both in the first and second stages of the optimization procedure. This optimization is an extended and more complete approach of that developed for the deterministic energy sizing optimization presented in section 3.1.

In the first stage of the optimization procedure, candidate solutions are selected for evaluation. The EH model and constraints are constructed and also qualitative parameters directly related to the equipment analysed are computed through the FIS exposed in section 4.1.1. These qualitative parameters can be, for example, the social acceptance of the technologies evaluated or the job creation potential. Then, the EH model moves to the second stage of the optimization where the prosumer operation of the plant is computed. This operation is affected by both quantitative and qualitative costs. Qualitative costs include in their value, which is computed through fuzzy logic, their uncertainty dimension. However, for the consideration of quantitative data uncertainty, it is required to repeatedly optimize the prosumer operation of the plant. Figure 12 illustrates this second stage process. Once the EH model is received and the qualitative costs of employing technologies computed, the

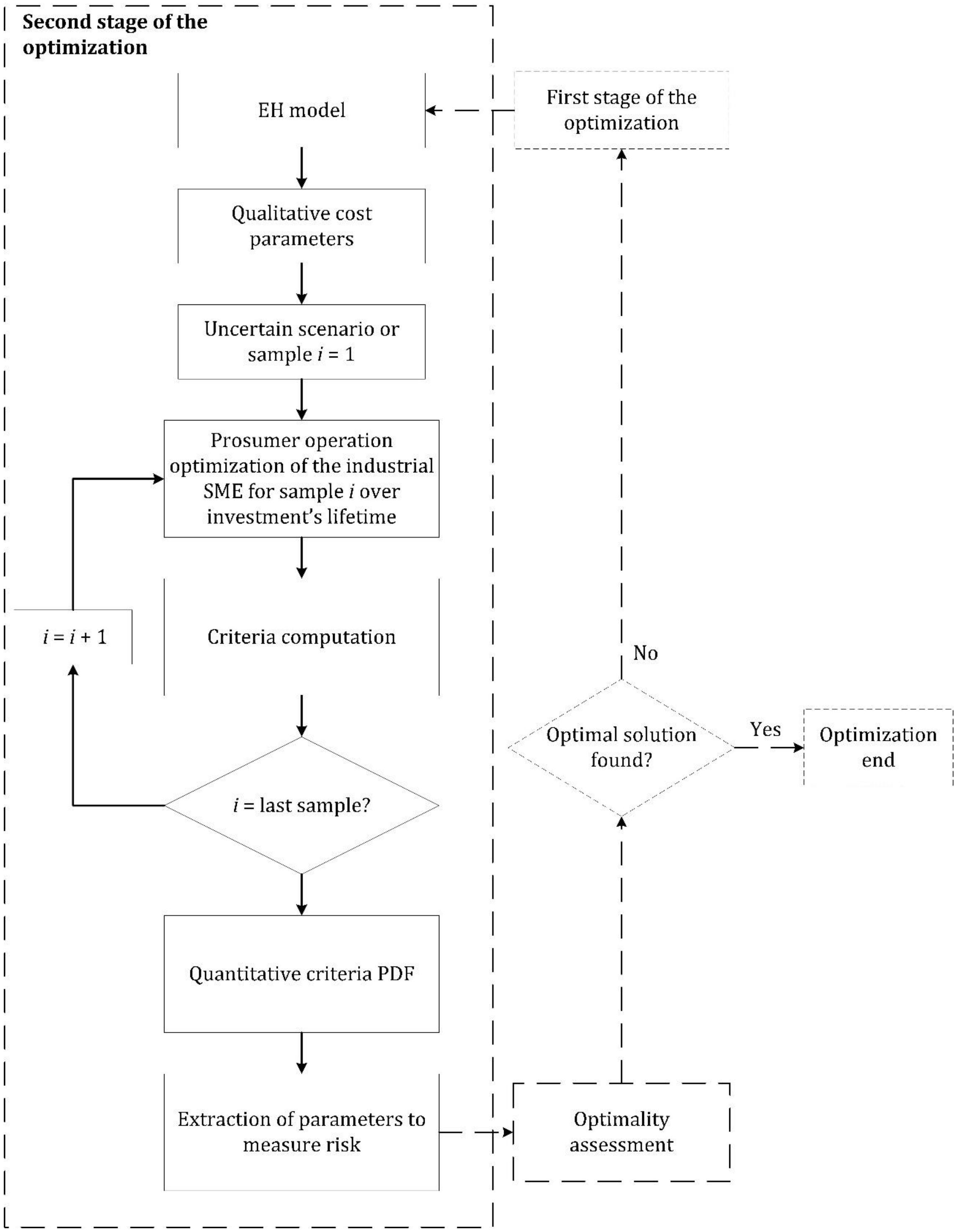

Figure 12: Workflow for the second stage of the risk-informed optimization.

first uncertain scenario is selected for its analysis. Uncertain scenarios are generated from samples of input PDFs which are randomly combined. It is worth mentioning that both quantitative and qualitative parameters are dynamic from a time point of view and therefore change over the optimization horizon to better reflect the growing uncertainty in the energy situation as time passes. The prosumer operation over the expected lifetime of the energy investment is optimized considering the possible quantitative data reflected in the evaluated scenario. At the end of the lifetime optimization, the quantitative criteria of interest for the enterprise, which can be, among others, NPV and emissions, are computed. Then, this operation optimization process is repeated for all the uncertain scenarios born from the PDFs' samples. When all uncertain scenarios have been analysed, the results from their evaluations are put together and the PDF of the criteria is obtained. At this point, it is possible to compute the mean and the CVaR for each of the criteria.

Once the second stage of the optimization is completed, it is time to assess the optimality of the candidate solution and decide if the optimal solution has been found or if the process is to be repeated from the first stage. This decision is reached based on the quantitative and qualitative criteria computed through the two stages of the optimization process, which have to be included in a single fitness function. The criteria's union can be performed through aggregation or multiplication. In this case, it is better to employ aggregation as it considers positive and negative criteria and deals better with outliers, limiting their influence on the final function value. Qualitative criteria measured in the first stage of the optimization include their uncertain definition and risk in their value. In contrast, for quantitative criteria, there are two differentiated measures: expected value and CVaR. In this paper, these values are unified in a single measure by employing the VaR level which defines CVaR as:

$$X_{measure\ with\ risk} = E(x) + VAR_{level} CVaR(x) \tag{29}$$

The aggregation of quantitative and qualitative criteria requires the assignation of weights. In this extended two-stage risk-informed investment optimization, the computation of weights is improved to better reflect the opinion of decision-makers by employing an Analytic Hierarchy Process (AHP). AHP is a tool to methodologically determine the weights based on subjective decision-makers' preferences. It decomposes the problem into a hierarchy, having the goal on top and structuring the criteria and risks into levels. In classic AHP applications, the set of studied alternative solutions are included in the hierarchy, and they are analysed in a bottom-up perspective, from sub-criteria to criteria preceding them in the hierarchy until reaching the overall goal. In this thesis, as the evaluation of solutions is performed through a continuous optimization problem, the AHP is employed to select the weights which are later incorporated into the fitness function to optimize. The goal of the problem, located at the top of the hierarchy, is in this case the investment to upgrade the energy infrastructure and become a prosumer, improving the competitiveness of the enterprise. Immediately below the goal, a set of criteria appears which designate the aspects considered by the enterprise to reach the decision, such as economic and environmental aspects. Then, the next level details the criteria linked to these aspects and the relevant risks that apply.

After generating the hierarchy, each of the items in a level is compared to the rest in the same level and under the same hierarchy branch in a pairwise manner. This process is reflected in a paired comparison matrix, in which the element a_{ij} denotes the importance of parameter i in front of parameter j following the Saaty scale definition [141], exposed in Table 2. This matrix definition process is done for the upper or lower diagonal part, being the parameter in the opposite part, a_{ji}, equal to $1/a_{ij}$. Based on this matrix, the weights can be computed using the geometric mean and multiplying the results of the matrix from the lower levels of the hierarchy until reaching the goal [142].

Table 2: Saaty fundamental AHP scale.

Intensity of importance	**Definition**
1	*i* and *j* are equally important
3	*i* is moderately more important than *j*
5	*i* is strongly more important than *j*
7	*i* is very strongly more important than *j*
9	*i* is extremely more important than *j*
2 , 4 , 6 , 8	Intermediate values between two adjacent judgements employed when compromise is needed

Therefore, following the AHP, quantitative and qualitative criteria are structured under the main decision-making criteria employed for investment evaluation. These criteria in enterprises are usually economic, social and environmental [143]. The main criteria are computed as the arithmetic means of the criteria under them. To avoid numerical illness, remove dimensions, and obtain a realistic measure of the criteria, all parameters are normalized previous to the balance. The mathematical formulation is, for the case of the economic criteria:

$$X_{ec} = \frac{\sum_{k=1}^{n} X_{ec,qt,norm,k} + \sum_{z=1}^{m} X_{ec,ql,norm,k}}{m+n} \tag{30}$$

Where m is the number of qualitative sub-criteria and n is the number of quantitative sub-criteria. Main criteria are then incorporated into a single function reflecting the preferences of decision-makers. This fitness function can be formulated as:

$$f = w_{ec}X_{ec} + w_{so}X_{so} + w_{en}X_{en} \tag{31}$$

This fitness function is computed and the global optimizer checks its stopping criteria. If the optimal solution has been reached, the optimizer finalizes its operation. Otherwise, the result is returned to the first stage where new potential solutions are created and the process is repeated.

4.3. Publications

This section exhibits the publications related to the developments exposed in this chapter of the thesis, detailing the methodological framework for the optimization of the energy infrastructure considering risks and quantitative and qualitative factors. Chapter 5 includes the full version of all of them.

- E. M. Urbano, V. Martinez-viol, K. Kampouropoulos, and L. Romeral, "Energy-Investment Decision-Making for Industry : Quantitative and Qualitative Risks Integrated Analysis," *Sustainability*, vol. 13, no. 6977, 2021.

  This article presents the **risk-informed energy investment optimization** problem and addresses both **quantitative and qualitative** parameters in an integrated approach. **Qualitative** parameters and uncertainties are incorporated in the first-stage of the optimization and evaluated employing **fuzzy logic**. **Quantitative** uncertainties are also considered in the **prosumer operation** by evaluating several **possible scenarios** and computing their **mean and variance.**

- E. M. Urbano, V. Martinez-viol, K. Kampouropoulos, and L. Romeral, "Quantitative and Qualitative Risk-informed energy investment for industrial companies," *Energy Reports*, vol. 9 p. 3290-3304, 2023.

  In this paper, the **complete extended two-stage risk-informed energy investment optimization** is addressed. **Qualitative** parameters and uncertainties are considered through **fuzzy logic** both in the **first and second stages** of the optimization. **Quantitative** parameters are modelled through **PDF and sampled using LHS**, and quantitative criteria are considered by computing their **mean and CVaR**.

4.4. Conclusions

The risk-informed energy investment optimization has been developed and applied to case studies whose results have been reflected in the articles mentioned above: [144], [145]. These case studies deal with the energy investment optimization of industrial SMEs to become a prosumer under uncertainties on both quantitative and qualitative inputs and considering economy, technology, social and environmental parameters as decision criteria. In order to compare the benefits of incorporating the risks into the decision-making problem, baseline optimizations aiming at maximizing the economic return without considering risks have also been carried out.

In the optimizations carried out, it has been verified that the selected investment depends on the parameters considered, among which the qualitative ones play an important role. Specifically, in the case studies analysed, the size of the CHP system is significantly affected by the incorporation or not of qualitative factors related to social acceptance, alignment with the administration, and ecological impact. The size of the CHP is larger when risks and qualitative parameters are not considered. On the other hand, when these are incorporated into the optimization problem, a more complete preconception of the CHP is achieved and its size is decreased. In the same way, the incorporation of qualitative costs in the optimization of the operation makes the use of the CHP more moderate, limiting it, while in the risk-free case the CHP is used to maximise mainly the economic benefit. Therefore, it can be concluded that the incorporation of quantitative, qualitative and risk parameters in the optimization process does indeed affect the resultant energy infrastructure. When these criteria are not considered, equipment which is economically feasible but with possible strong negative social and environmental impacts is selected for installation. However, when qualitative criteria and risks are considered, the equipment is selected considering a trade-off between different criteria and reaching an overall less qualitative risky solution. Therefore, the selection of criteria is crucial and affects drastically the resultant solution of the optimization problem.

In terms of maximising investment performance, the case in which no risks are assessed presents better deterministic performance criteria. Even so, in these cases, the variability and risk assumed in order to achieve such performance are higher than in the case where risks are incorporated in the optimization problem, and thus the obtained solution is less robust. Taking a decision considering only the deterministic and risk-free criteria can lead to a situation with high exposure to strictly non-economic risks with great impacts on the enterprise. By incorporating risks in the evaluation of investment performance, it is possible to reduce the variability and CVaR of the criteria analysed, reaching a smarter initial investment that achieves an economic performance comparable to the obtained without analysing risks while minimizing negative risks and profiting from the positive ones.

The methodology presented in this chapter presents a large practical value as it opens the way to a new strategy for the energy investment decision-making process of industrial SMEs. It fits their requirements, considering diverse criteria intrinsically different and searches for long-lasting low-risk investments. The proposed methodology can be adopted by decision boards to analyse energy-investment problems, enhancing the incorporation of criteria characterized by different natures in a single optimization function, and modifying the input parameters to adjust the solution to the requirements of the enterprise. The inclusion of this procedure into investment decision-making can lead to the achievement of more robust energy-investment decisions, enhancing the participation of consumers in the energy market and increasing their competitiveness.

5. Compendium of publications

5.1. Future European energy markets and Industry 4.0 potential in energy transition towards decarbonization

Reference:

E. M. Urbano, V. Martinez-Viol, K. Kampouropoulos, and L. Romeral, "Future european energy markets and industry 4.0 potential in energy transition towards decarbonization," *Renew. Energy Power Qual. J.*, vol. 18, no. 18, pp. 190–195, 2020. Available on: http://www.icrepq.com/icrepq20/268-20-urbano.pdf.

Publication framework:

This article establishes the base for the study of industries as prosumers. It analyses the current energy situation and the potential changes that may occur due to the ongoing energy transition. It also reviews some of the most recent legislation and policies in the energy field and evaluates the possibility of the industry becoming a prosumer. The industry potential is then assessed by developing a prosumer operation optimization and the suitability of the industrial sector to actively participate in the energy transformation is verified.

Main contributions:

- Analysis of current and future energy market scenarios.
- Review of electricity market legislation.
- Analysis of the role of industrial entities in the energy transition.
- Prosumer operation optimization of industrial entities.

Key words:

Electricity markets, flexibility options, renewable energy sources, smart factories.

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Future European energy markets and Industry 4.0 potential in energy transition

Eva M. Urbano[1], Victor Martinez-Viol[1], Konstantinos Kampouropoulos[2] and Luis Romeral[1]

[1] MCIA Research Center, Department of Electronic Engineering
Universitat Politècnica de Catalunya
Rambla de Sant Nebridi 22, 08222 Terrassa (Spain)
Phone:+34 937 98519, e-mail: eva.maria.urbano@upc.edu, victor.martinez.viol@upc.edu, luis.romeral@upc.edu

[2] Fundació Eurecat, Centre Tecnològic
Plaça de la Ciència 2, 08242 Manresa (Spain)
Phone: +34 938 777 373, e-mail: Konstantinos.kampouropoulos@eurecat.org

Abstract. Climate change, economic growth and fossil fuel price volatility are forcing governments and thus society to adopt economical and technical measures in the energy sector to reach sustainability. These actions can be seen as opportunities for the stakeholders that form the energy market and also for new actors that may enter as a consequence of the energy transition that is taking place. In this paper, a description of the energy targets and potential market scenarios in Europe is carried out, together with a review of the policies implemented to achieve these objectives. Within this framework, the possibility of the industry to adopt a crucial role in the development of the new energy market is also analysed. The potential tools for its achievement are also presented, together with some of the techniques and mechanisms that make it feasible. From this study, it can be concluded that the industrial sector will become a major distributed prosumer, providing services to the energy market and facilitating the energy transition.

Key words. Electricity markets, flexibility options, renewable energy sources, smart factories.

1. Introduction

Climate change has become a critical issue with worldwide implications which is taking special attention by several governments around the globe. The effects of climate change have to be stopped before they cause irreversible impacts on the environment. Global energy use has been increasing along with economic growth. According to several studies, such as the one shown in [1], there is a strong relationship between energy consumption, energy prices and economic growth, concluding that economic growth tends to increase energy consumption and usually energy supply from other countries. In the European case, external energy supply is mainly based on fossil-fuels and the incrementation in its dependence will cause vulnerability of the energy market due to the price volatility of the fossil-fuel sector [2]. Intending to reach a more secure and sustainable energy system without scarifying economic growth, it is crucial to increase energy efficiency, decrease energy use and perform a decarbonization of the society. The increase in energy efficiency and the reduction of emissions coming from the energy sector will suppose a change in the deterioration trend of the environment and a step ahead towards the self-sufficiency of energy markets.

The European Commission has already started the transition to a new energy market. Since 2000, several energy policies, subsidies and founds have been implemented to achieve the clean energy objectives stated for 2020. Regarding decarbonization, it has been possible to verify that economic growth and low-carbon transition are compatible, as it was concluded by the European Commission in [3]. The implementation of Renewable Energy Sources (RES) has also been a focus of attention during this period. In 2016, the consumption from RES represented 17% of the total consumption, approaching the 20% target for 2020. Beyond 2020, new targets have been stated for 2030 and 2050. The main objective, decarbonization, has been set to a reduction of greenhouse gas (GHG) emissions to 80-95% below 1990 levels for 2050 [4]. The measures implemented until now are still showing their effects and will probably continue delivering benefits past 2020. However, their advantages will not be enough to achieve 2050 targets. For this reason, new energy strategies and potential scenarios are being studied, and the impact of several measures in the energy market are being further analysed.

In this paper, a vision of these future energy markets is presented, together with an assessment of their different environmental implications. A review of the measures that are being applied or that will be available in the close future is also exposed and their real impact in the energy market studied. These measures englobe the use of RES, the energy efficiency of the system, the use of flexibility sources and the improvement on the connectivity of the electrical market. Although these measures would provide clean energy, the market would probably need other technologies to support them, such as Energy Storage Systems (ESS) or enhanced use of nuclear energy. Furthermore, new technologies for Carbon Capture Storage (CCS) will also be studied. These measures must include the industrial sector, which nowadays accounts for more than 25% of total European energy consumption [5] and will probably become a key actor in the future energy market. Therefore, the potential benefits of creating new energy roles in the market from industrial sites are studied in this paper, considering them as a potential source of flexibility, introducing RES in the system, increasing internal and external system efficiency and becoming a distributed prosumer.

This paper is structured as follows. Firstly, the possible main characteristics of the future energy market are drawn in Section 2. Secondly, in Section 3 the current legislation is studied together with the impacts that it causes in the energy transition. Furthermore, some solutions to the problems raised by these legislations are proposed in the same section. Thirdly, in Section 4, the potential of the industry is discussed, presented as a tool for the energy transition by applying several of the ideas shown in the previous sections. Fourthly, in Section 5 a use case is shown in which the possible behaviour of the Industry 4.0 in upcoming energy market is analysed. Lastly, in Section 6 the work's conclusions are drawn.

2. Future energy markets scenarios

Several strategies and measures to reach 2020 sustainable scenario have already been implemented, expecting to keep providing results past this year. According to the last European Commission report [6], the 2020 environmental and energy targets were already achieved or close to its objectives by 2016. However, these measures will not provide enough decarbonization to achieve 2050 targets, making fundamental the modernisation of the energy system. Similarly, actions related to the investment in realistic technological solutions, empowering citizens and aligning action in key areas such as the industry are necessary to reach the established goals [3]. The objective of 80-95% reduction in GHG emissions will only be possible if a major change in the market structure and the role of stakeholders and end-users is performed. Thus, the development and implementation of past-2020 strategies and measures are urgent. In [4], the potential decarbonisation scenarios that can take place in Europe during the next years are analysed. They include scenarios with high energy efficiency, diversified supply technologies, high implementation of RES, CCS and nuclear scenarios. The study concludes that the decarbonization scenario is achievable, reducing also the import dependency and thus the exposure to fossil-fuel price volatility, although their implications vary depending on the followed path. Despite this fact, it is necessary to define new legal and market instruments to practically deploy these new scenarios.

The main implication and the one that is common in all the scenarios is that there will be a transition from high fuel operational costs to low fuel costs but high capital expenditure. This variation in the location of costs will force energy markets to adapt its pricing structure. It will also suppose an opportunity for industry and service providers to innovate in the generation, storage and consumption management technology. Another common implication is the electrification of the system, increasing the use of electricity despite the general decrease in carbon-based energy use. This is because electrical energy can be generated through RES on a high percentage and it will contribute to the decrease in emissions of other sectors, such as transport, heating and cooling.

Apart from these implications, the final structure of the energy and specifically the electrical market will be different depending on the predominant scenario. Two of the strategies that have been considered to decrease GHG emissions are CCS and nuclear power. It is well known that by increasing the presence in the market of CCS and nuclear power, the GHG emissions can be significantly diminished. In fact, in [7] several benefits of the commercial deployment of this technology are exposed, presenting the capability of the net removal of CO2 from the atmosphere. However, both CCS and nuclear power have strong negative environmental impacts. In [8], the environmental impacts of the usage of nuclear power are identified, concluding that developments related to the ecological safety of the technology should be performed. Regarding CCS, in [9] it is shown that it can cause acidification and human toxicity, which contributes to global warming. Moreover, the future of CCS and nuclear power crucially depends on social acceptance and, especially in the case of CCS, its viability has to be demonstrated in large scale before a CO2 infrastructure, which does not currently exist, is developed.

In the case that CCS and nuclear power become a restricted resource due to its collateral effects on the environment and society, the increase in the share of RES and energy efficiency of the system becomes not only advisable but essential. Storage technologies are key aspects for this to happen. However, storage is currently more expensive than other solutions such as gas backup generation. Although the need for energy efficiency solutions with renewable energy implementations is clear; the installation of ESS can be decreased if smart grids are implemented. With the inclusion of smart grids, the power system will change from a centralized structure to a decentralized and hybrid structure, allowing to decongest the transmission and distribution networks and minimize losses. A decentralized structure will only be possible if the adequate infrastructure for distribution, interconnection and long-distance transmission is performed, to effectively connect the flexibility resources, which includes demand management, ESS, Distributed Generation (DG) and prosumer entities. Up to date, the EU has targeted to eliminate electrical islands and to create a single integrated European energy market [10], pointing to an increase in the transmission capacity of all member countries to 10% of their internal power generation capacity by 2020 [11]. However, measures should assess not only transmission capacity between member countries but also connectivity in local networks and smart grids [12].

The exposed scenarios and assumptions lead to the delimitation of a future energy market in which RES, energy efficiency and smart flexible resources play a significant role. Their impact in the market due to the change in the location of the capital has to be studied and changes in the pricing mechanism and market legislation will need to be adopted.

3. Electricity market legislation

The primary focus of the climate and renewable energy legislation in Europe is to reduce energy import dependence and decrease environmental harm caused by the energy sector. To do so, there is a will to decrease energy consumption, increase the share of RES and reduce GHG emissions. The measures implemented to achieve the previously stated targets will affect not only current producers and distributors but also consumers, including industries.

The current energy market was designed, due to historical reasons, for a power system based on dispatchable energy sources. This market, which is being liberalized, is based on high positive marginal costs and dispatchability of power. The nature of RES supposes a challenge for the integration of low-carbon energy sources into the market due to its main characteristics: variability and uncertainty, which produce technical issue that still needs to be solved nowadays regarding grid balance and stability. There are also barriers regarding investment and cost management of RES installation. These types of installations suppose high capital and integration costs. However, the marginal costs of RES, which are the ones considered at the wholesale market, are usually close to zero [13]. These facts present an incompatibility between electricity liberalization and renewable policy, making high share of RES not possible due to the fact that owners of RES plants would be unable to earn and return on their investment with the current energy pricing mechanisms [14]. One of the main measures adopted by the EU to increase the use of RES and decrease GHG and energy use is to actuate on the energy costs. However, a modification of the energy price based on taxes or levies to enforce policies influences negatively the competitiveness of energy intensive sectors [15], which produces a contrary result to other targets of the EU. The legislation implemented to carry out the energy transition has to be carefully studied and analysed to avoid negative effects in the competitiveness, sustainability and security of supply of the system. It is crucial to stablish climate policy using market mechanisms instead of modifying the price of the energy, and for this to happen there is a requirement to redesign the market clearing mechanism to be able to accommodate RES. The redesign should lay in the modification of the pricing structure to better capture the full renewable cost structure, as well as the incorporation of higher time resolution and later gate closure time to fit RES behaviour [16].

The previously mentioned measures would enable the incorporation of large-scale RES into the market, supporting business models for plant owners. However, a complete renewable energy scenario is not possible without accompanying RES with other capacity measures to solve intermittency issues. The electrical system should be able to adapt itself to the requirements imposed by the variability of RES, making flexibility a key requisite for a renewable based energy system [17]. This flexibility can mean flexible generation, storage, Demand Response (DR) and interconnection. The measures that are being studied for this point, such as the deployment of smart grids, Energy Hubs (EH), Virtual Power Plants (VPP) and of conveniently distributed generation together with a more active role of the Distribution System Operator (DSO), could help not only in creating flexibility but also in improving the efficiency of the transmission and distribution systems, enabling and overall energy use without compromising the competitiveness of the system. In this path, Europe is moving towards a market with multiple types of new actors and where interconnection and flexibility are key factors for the improvement in energy efficiency and decrease in harmful emissions. Prosumer aggregation policies are gaining interest by Member Countries, creating communities able to extract and introduce energy to and from the utility grid at specific time intervals, overcoming the challenges introduced by RES [18].

The implemented legislation until now will need to be modified and adapted to the outlined trends, enabling the creation of smart grids, DG and prosumer entities without scarifying the competitiveness of the system. The basis for new energy trading mechanisms are also to be settled in order to enable an increase in the share of RES as well as the possibility of new actors to enter into the electrical market.

4. Industry 4.0 in the energy transition

The previous section described the modifications that will need to be performed in the electrical market to allocate RES, decrease GHG and improve energy efficiency. The presented trends together with recent scientific publications show that the main streams to achieve EU targets are the creation of Smart Grids, Energy Hubs (EH), Virtual Power Plants (VPP), DR capabilities and prosumer actors, who are able to produce and consume energy; creating flexibility in the demand side to increase the incorporated share of RESs, providing local generated energy to the distribution network to improve its efficiency and decreasing general energy cost in the electrical grid. Until now, the focus has been the tertiary sector, creating communities of small individuals and RES that can be aggregated to obtain a significant exchange of energy. However, in the EU 25% of the total energy consumption happens in the industrial sector, where programs for the incorporation of RESs, DR and prosumers can also be implemented although they have still not been assessed.

The potential of the Industry 4.0 to adopt efficiency measures and decrease their environmental impact on the society should be considered when stablishing the baselines for the future energy markets, as the energy consumption, energy equipment, ESS and RES present in industrial sites or communities enable the establishment of novel energy management strategies that could take into account the state of the external market to optimize their internal operation and interaction with utility grids. Several industrial facilities account with multi-carrier energy systems coupled between them. The integration and operation of the energy infrastructure can be done through the creation of an EH, a novel concept which optimally links the available energy sources in an energy infrastructure [19]. The implementation of an EH in a factory leads to an increase in energy efficiency which supposes direct economic and environmental benefits for the consumer [20]. This idea can be broadened considering the external market. The first approach historically contemplated has been to adopt DR capabilities, scheduling load according to the market needs and thus creating flexibility in the electrical network. DR is added to EH optimization through price signals send by the energy supplier and the results of this optimization show gains for the consumer and assistance to the electricity grid, leading to a flatter demand curve [21]. Although this strategy already demonstrates important benefits for both industry and electricity market, it does not implement the recent advances in legislation which enables the creation of self-consumption communities and prosumer microgrids.

Prosumer industrial sites can be created from single manufacturing plants or through the aggregation of several entities together with close-placed RES generation plants. The result of this aggregation would act as a single entity in front of external energy structures, creating a VPP able to introduce energy in the utility grid when required. An internal energy market could be settled for peer-to-peer energy trading and the bidding optimization with the utility grid could be performed by an aggregator, an actor who will potentially appear in upcoming years in the market [22], [23]. These new energy management strategies will lead to higher economic savings than in previous cases due to the exploitation of the internal energy assets against the external market [24]. The EU has recently opened the legislation path for this solution to be implemented and Member Countries are developing policies for the inclusion of these prosumer smart grids and VPP into the energy infrastructure established [25], [26].

5. Use case

Industry 4.0 will be a powerful tool during the energy transition to achieve the targets that have been set by the EU. As seen in the previous section, industrial sites can integrate RES and support energy market adopting prosumer capabilities, either alone or aggregated. The objective of the use case developed in this section is to verify the economic viability of the creation of a prosumer entity out of an industrial plant, corroborating then the potential interest by manufacturing site owners to invest in the creation of VPPs, including energy management strategies into the existing business model. The use case shown here is based on an automotive manufacturing plant connected to the electrical and gas energy networks with a total amount of primary energy purchased of 9.5MWh per month. The demand can be divided into electrical and thermal, and the conversion equipment of the plant is formed by a boiler and a cogeneration plant, which interconnects the electrical and the thermal sides of the energy structure. With the aim of verifying the economic viability of the implementation of prosumer capabilities, two days of the year for this plant are studied in this section. To implement a smart energy management system able to decide when to share energy with the utility grid and when to store it, there is a requirement to implement RES and ESS systems. A Photovoltaic (PV) system is selected as the RES to be implemented in the factory, which will cover an available space of 15000m^2, and the ESS is sized to supply energy to critical loads during a predefined interval of time. With this information, the comparison between electrical load and energy generated by the PV system for the studied days can be seen in Fig. 1 and Fig. 2. The electricity price at the wholesale energy market has ben added to the graphs to visualize the potential benefits of including the PV system together with an ESS.

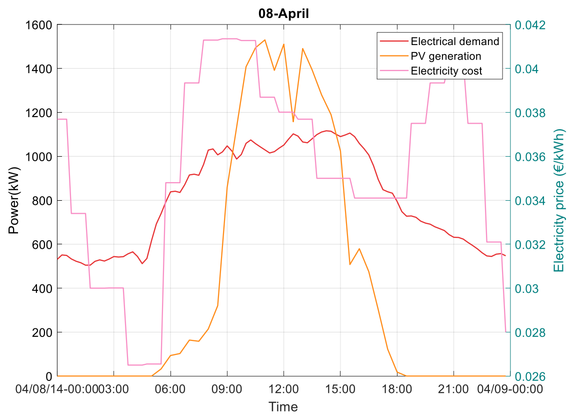

Fig. 1: Electricity cost and electrical load and generation for the 8th of April.

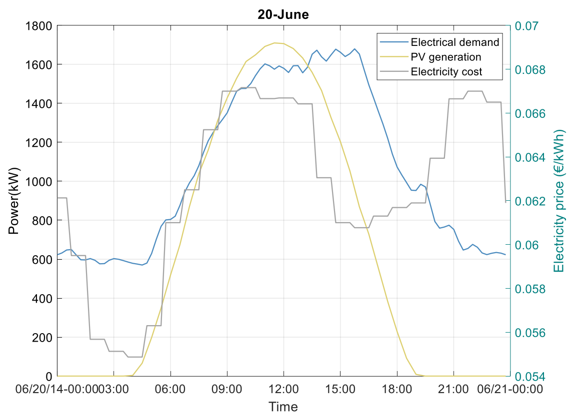

Fig. 2: Electricity cost and electrical load and generation for the 20th of September.

It can be seen that in one of the cases, the energy generated by the PV system overcomes the electrical load of the system at some time intervals, although these do not necessary coincide with the time intervals at which the electricity cost is higher. Until now, the energy generated by the PV system in factories has been used internally or sold directly in its totality. However, with the arise of self-consumption legislations that enable prosumer capabilities, the energy management system can buy and sell electricity depending on their operation points and the state of the external market. An optimization is performed considering this last approach in which the installation, operation and maintenance cost of energy equipment is considered, together with the possibility to exchange energy with the utility grid. The results of the optimization can be seen in the following figures for the first day under study:

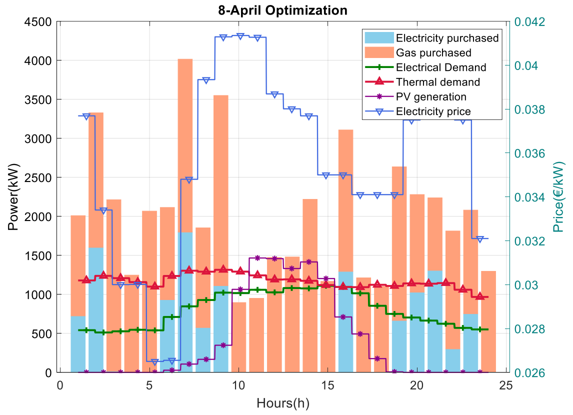

Fig. 3: Optimization for the 8th of April showing the energy purchased.

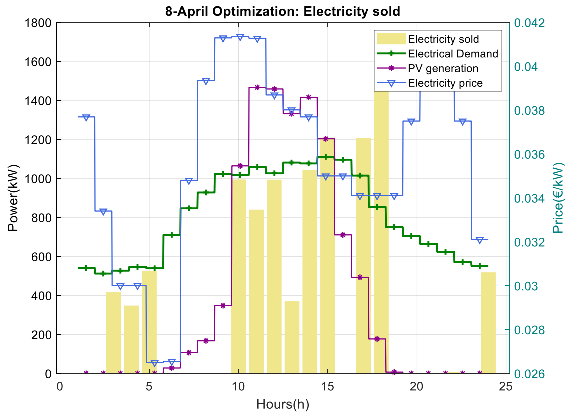

Fig. 4: Optimization for the 8th of April showing the energy sold.

In Fig. 3 is possible to appreciate that between 10h and 15h, when the energy cost is high, electrical energy is not being purchased. It is also detectable that gas is being bought at a higher rate than the needed to fulfil electrical demand due to the existence of a cogeneration plant which operates close to its maximum power capability and generates electricity to be consumed or stored at the electrical site of the factory. The prosumer behaviour of the factory can be seen in Fig. 4. Here it appears that what happened between 10h and 15h is that electricity is being sold taking profit from its high value. The same optimization is carried out for the second day under study, and the results can be observed in Fig. 5 and Fig. 6.

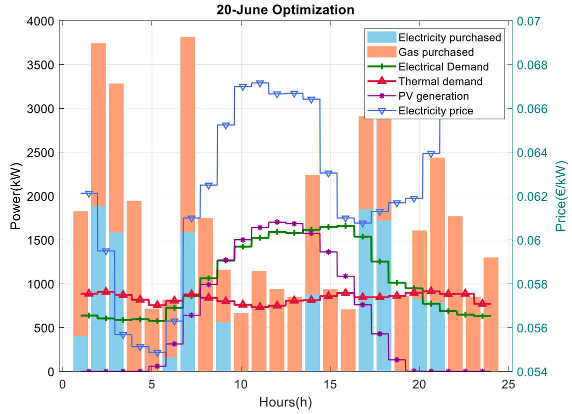

Fig. 5: Optimization for the 20th of September showing the energy purchased.

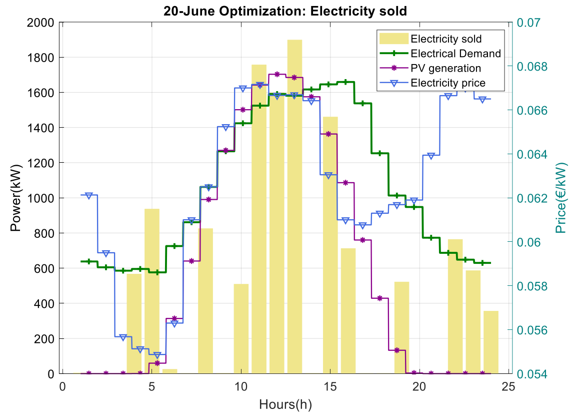

Fig. 6: Optimization for the 20th of April showing the energy sold.

The same type of behaviour can be seen in this case. During the hours of maximum price at the wholesale market, the optimal decision is to sell electricity to the utility grid instead of purchasing it. In Fig. 7 it appears that the electricity being sold is higher than the generated by the PV system during the time interval between 11h and 14h. This means that other source of electrical power, such as the cogeneration system and the ESS, are being used to fulfil the electrical demand and also to increase the amount of energy sold to the utility grid.

In the previous figures, specially in those related to the energy inserted into the utility grid, it is significant that the moments at which the energy is being sold are relatively separated from the peak-electricity cost. For this optimization problem, the electrical battery was set to a predefined value at the beginning of each day and there is no thermal storage. For this reason, there seems to be an initial part of the day at which gas and electricity is purchased at higher rates than the rest of the day although the demand is at its minimum. This process seems to delay the reaction to the peak-electricity cost, probably due to capacity terms of ESS to fulfil the demand while at the same time preparing its state for high electricity price periods.

In the use case developed it has been possible to see that when there is a possibility to trade energy with the utility grid, the optimal operation points, under an economic point of view, of the energy equipment are modified to profit from the state of the external energy market, introduced green energy to the energy infrastructure when demand and electricity cost is high. Due to its economic viability, this energy management strategy can be added to the current existing business models of manufacturing plants, enabling the creation of a huge number of prosumer industrial sites promoting the decentralization of the electrical grid.

6. Conclusions

In this paper, the energy targets, potential market scenarios and energy legislation in Europe has been exposed showing a clear trend towards the inclusion of RES and flexibility sources. The policies implemented until now and the ones presented as a draft enable the possibility to create aggregated entities, smart grids, energy hubs and demand responsive consumers. Within this framework, the possibility of the industry to adopt a crucial role in the development of the new energy has been analysing by showing its ability to create prosumer aggregated entities exploiting its internal energy equipment for market purposes. The use case developed has shown the economic viability of this strategy as well as the benefit that the utility grid can obtain from the energy transactions performed. With this information it can be said that the energy prosumer will become a key actor during the energy transition and that industries are suitable to adopt this role as they present a complex and smart energy infrastructure with high energy transactions potential.

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5.2. Renewable energy sources and storage systems sizing optimization for industrial prosumers

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Publication framework:

This article initiates the thesis research on the sizing of energy equipment for a prosumer industrial plant. It models the energy infrastructure of the industrial plant and optimizes its operation considering four different energy management strategies to evaluate the benefits of optimally sizing the energy equipment considering prosumer behaviour.

Main contributions:

- Energy equipment sizing considering a prosumer operation.
- Prosumer operation optimization considering weekly demand and energy market patterns.
- Evaluation of the prosumer investments' benefits compared to other energy management strategies.

Key words:

Prosumer, Decarbonisation, Sizing optimization, Genetic Algorithms

Renewable energy source and storage systems sizing optimization for industrial prosumers

Eva M. Urbano
MCIA Research Center
Universitat Politècnica de Catalunya
Terrassa, Spain
eva.maria.urbano@upc.edu

Víctor Martinez-Viol
MCIA Research Center
Universitat Politècnica de Catalunya
Terrassa, Spain
victor.martinez.viol@upc.edu

Konstantinos Kampouopoulos
Eurecat, Centre Tecnològic de Catalunya
Manresa, Spain
konstantinos.kampouropoulos@eurecat.cat

Luis Romeral
MCIA Research Center
Universitat Politècnica de Catalunya
Terrassa, Spain
luis.romeral@upc.edu

Abstract—In this paper, the size of the renewable energy sources and energy storage systems for an industrial plant will be optimized considering a prosumer behaviour that actively bids energy with the utility grid. The energy infrastructure of the industrial plant is modelled and the sizing optimization problem is mathematically defined and solved using Genetic Algorithms. Four scenarios are considered regarding energy management strategies: Do-nothing, self-consumption, prosumer with non-optimal installation and prosumer with the optimal installation. Results show that the prosumer with optimal installation outperforms other scenarios achieving total energy savings of 47% and a payback period of 8 years, enhancing the participation of industry in the upcoming energy market where distributed energy sources and flexible active clients will have a significant role towards decarbonisation.

Keywords—Prosumer, Decarbonisation, Sizing optimization, Genetic Algorithms

I. Introduction

Climate change is a worldwide issue whose effects are to be stopped or slowed down as much as possible to avoid further consequences in the environment that could put today's society life quality at stake. Among other technical and social approaches to avoid global warming, solutions can be provided by the energy market, which should undergo a transition towards zero CO2 emissions to assure system sustainability. This decarbonisation of the sector will only be achievable if clean Renewable Energy Sources (RES) are further inserted and the efficiency of transmission and distribution systems is improved [1], [2]. However, the energy sector and its market mechanisms are based on high marginal costs and power dispatchability, while renewable technologies offer low marginal costs and are intermittent and nonprogrammable, inhibiting a high penetration of them into the market [3]. A key step to be performed by the market to allow for a better integration of variable RES is the creation of flexible resources such as flexible plants with demand response; as well as the decentralization of the energy sources [4].

Self-consumption is a current solution to integrate distributed energy sources and system's flexibility, as well as to improve the economic competitiveness of energy market end-users. For consumers willing to include self-consumption in their energy structure, the installation of a RES is needed, having the option to consume energy directly from the on-site generation when it is available or purchasing it from the utility grid when the RES is not producing energy. The cost performance of the system can be improved when installing Energy Storage Systems (ESS), which provides the possibility to decide when to use energy generated on-site and when to purchase it from the grid according to an energy cost indicator [5]. This adaptation of the energy demand by end-users depending on the market situation does not only imply benefits for the end-user but also for the whole electrical system, avoiding consumption when electricity cost is high, indicating high marginal cost and thus a major presence in the market of non-clean and fossil fuel energy sources.

The inclusion of self-consumption is currently ongoing for the tertiary sector, providing promising results [6]. However, to increase the share of RES and the efficiency of the system, the existence of other flexible sources that inject energy in the market is needed. Prosumers are being presented worldwide as fundamental actors in the achievement of an energy market with high penetration of distributed energy sources [7], [8]. They can manage RES, ESS and energy systems to interact with the utility grid considering current and future market status, bidding with the wholesale market at the most interesting time intervals. There are already some studies that deal with the energy bidding optimization of prosumers with RES and ESS, such as [9], [10]. However, an issue that remains unexplored is the proper design of energy equipment installations to fit prosumer purposes for exploiting RES and ESS to supply power to internal demand and also to obtain and extra benefit from optimally bidding with the utility grid.

Up to day and although self-consumption approaches are spreading rapidly, most energy end-users are not considering the design of installations for its exploitation against external energy market opportunities. In most research papers dealing with energy optimal sizing, an islanded mode is considered, such as in [11], [12]. In this type of optimization, the smart grids where RES and ESS are applied are not connected to the main grid and thus the focus of the sizing is to assure the security of supply and grid stability. A sizing strategy for non-islanded mode is presented in [13], where the sizing for a factory is assessed having as objective the minimization of energy purchased from the utility grid. This approach can also be seen in other works such as [14], [15]. Although in some of these studies there is an exchange of energy with the grid, excess energy is directly delivered without considering active energy bidding as a potential economic benefit. It is also noticeable that most of research and applications for energy management systems are aimed at the tertiary sector. However, the industrial sector is the most energy-consuming sector worldwide with 54% of the total energy delivered [16]. Therefore, conversion from industrial consumers to industrial prosumers by incorporation of RES and ESS and adoption of energy active profiles requires further research [17].

In this paper, the energy equipment sizing for an industry aiming to adopt a prosumer behaviour is assessed. To do so, the industrial energy infrastructure is modelled and the optimization problem defined considering different restrictions regarding plant operation and installation capabilities. The sizing problem is solved using a Genetic Algorithm (GA) approach, which enables the resolution of complex and non-smooth problems with multi-objective fitness functions. Four different scenarios for a typical industrial plant are analysed and compared between them to evaluate their economic benefits. The first scenario is the “Do-nothing”, which represents the current situation for most of the factories that do not have RES nor ESS. In the second scenario, the factory accounts with RES and ESS sized for a typical self-consumption case, without the possibility to sell energy surpluses to the utility grid. The third scenario accounts with the same factory model as the previous one with the difference that in this case, the plant acts as a prosumer, contemplating an active exchange of energy with the utility grid and, lastly, in the fourth scenario the plant has a RES and ESS system optimally sized for prosumer purposes and acts as an active customer, exchanging energy with the utility grid. The payback periods and energy savings for each of the scenarios are obtained and compared to evaluate the suitability of the optimal energy infrastructure for industrial prosumers.

The paper is structured as follows. First of all, in section II the legal and economic framework of the system will be exposed. Secondly, the problem will be defined in section III, where the energy model, optimization problem and methodology to follow will be defined. Thirdly, in section IV the use case will be presented and in section V the results of this exposed. Lastly, conclusions will be drawn in section VI.

II. Future energy market and costs

The energy market is undergoing a transition towards decarbonisation which is empowering consumers to adopt new roles and benefit from the changes that will take place in upcoming years. One of the main issues to assess during this period is the increasing share of RES and distributed energy sources in the electrical market that due to its intermittency, which forces the creation and incorporation of flexible energy actors. Up to day, the legislation and the costs of the energy equipment have been a barrier for the instauration of prosumer facilities that would lead to a decarbonisation of the energy sector.

As the fight against climate change and reduction of CO2 emissions is a main commitment by governments around the globe, the barriers related to grid access, administrative procedures and techniques development are being progressively removed to facilitate the creation of a smart and flexible energy structure. As an example, nowadays the EU has updated its energy policy framework to facilitate a transition to clean energy. Specifically, the Clean Energy Package directive [18] stipulates the importance of:

- Granting demand side resources access to all markets at all timeframes.
- Empowering the consumer to participate in DR without the consent of the supplier and to switch aggregation service provider without penalty.
- Empowering independent aggregators by ensuring that they can enter the market without the consent of other actors and without compensating generator/supplier.

This directive, which also encourages to analyse the regulatory framework to allow the entry of prosumers in the market, has already been adopted by several Member Countries such as Germany and Netherlands, where premium tariffs for energy insertion are available; and Portugal, where the remuneration for surplus energy is paid at 90% of market price [19].

The favourable legislation framework supports the incorporation of prosumers in the electrical grid, but it is also essential to assure the cost-competitiveness of the technological solutions to obtain feasible business strategies regarding energy management systems. Although the cost of energy equipment for adopting self-consumption and prosumer approaches was prohibitive until few years ago, it has been decreasing exponentially [20], achieving payback periods of 10 years [21]. A useful cost parameter to be used when computing the suitability of RES and ESS for an application is the Levelized Cost Of Energy (LCOE). This parameter considers not only capital cost, but also installation and operation costs and degradation of the ESS through its lifetime. It can be considered as the cost of using the energy equipment, taking into account its amortization and maintenance expenses. For Photovoltaics (PV), which is the most common RES installed in self-consumption facilities, the installation cost is around 1€/W, decreasing as the installed capacity increases; while the LCOE was 0.08€/kWh in 2018, expecting a decrease to 0.05€/kWh by 2030 [22]. For the case of ESS, the most mature technology is the Li-ion battery, whose current LCOE is $187/MWh, presenting a decrease of 76% compared to 2012 values [23] and which will continue dropping by 54-61% for years to come. Due to its expected mass production caused by an increase in electric vehicles, its LCOE is forecasted to reach a value of $70/MWh by 2030 [24].

Apart from the increasing competitiveness of energy equipment, it is worth mentioning that the decarbonisation of the energy sector will undoubtedly lead to its electrification, which will increase the overall electrical energy demand. This will cause a rise in energy prices of at least a 30% by 2030 [25], achieving and average cost of $85/MWh and thus increasing the profit margin for energy actors willing to perform as prosumers.

III. Problem definition

The objective of this paper is to study, develop and apply a design model to optimize the energy equipment of a factory to be used for meeting the internal demand and to exploit them against the external energy market. This exploitation consists on purchasing and selling electrical energy at strategic points in time that would create an extra benefit for the facility owner. In this section, a generic industrial plant model, used as a basis for further developments, is presented together with constraints regarding its operation, as well as its RES and ESS installation capacities. Then, the optimization problem and its characteristics are defined and finally the methodology for the resolution of the problem is shown.

A. Industrial plant model

The energy infrastructure of industries varies depending on its activity and size, being big and energy-intensive enterprises the primarily ones taking action towards a deep decarbonisation through the inclusion of RES and energy efficiency measures [26]. However, industrial SMEs, which represent the 99.2% of the total enterprises in the manufacturing sector [27], are slower in the adaptation to the new energy scenario. With the objective of enhancing decarbonisation procedures in SMEs and improving the energy infrastructure and economic benefits of this kind of manufacturing plants, in this paper the company profile considered resemble the energy infrastructure of a generic SME.

The model, which represents the internal energy assets of the industrial plant and its connectivity, considers the existence of a RES and ESS, a specified power demand and a bi-directional connection with the utility grid. The inputs and outputs of the energy system are:

- Inputs: Energy from the utility grid, energy produced by the RES and energy obtained from the ESS.

- Energy outputs: Demand of the industrial plant, energy to be sold to the utility grid and energy to be stored in the ESS.

The energy balance for this problem is represented in the following equation:

$$\eta_g I_e + \eta_R I_R + \eta_{db} I_b = \eta_m D_m + \eta_{cb} D_b + \eta_g D_e \quad (1)$$

Where I_e, I_R and I_b are energy inputs from the utility grid, the RES and the ESS respectively; D_m, D_b and D_e $a$re energy outputs to internal load, the ESS and the utility grid and $\eta_g, \eta_R, \eta_{db}, \eta_m$ and η_{cn} are the efficiencies of the system for exchanging energy with the utility grid, discharging the battery. Equation (1) represents an ideal scenario and its direct application could cause working behaviour outside feasible areas for the equipment of the plant. In order to obtain a model that resembles real world, restrictions regarding energy flow should be considered. The first constraint applicable to the problem is the limitation of power exchange with the utility grid, provided by the contract with the energy supplier:

$$0 \le I_e, D_e \le P_{grid,max} \quad (2)$$

Where $P_{grid,max}$, is the maximum power contracted by the prosumer. The other constraints of the problem deal with the maximum power transferred to and from the ESS and its capacity, which should be between specified thresholds at all time frames. This is represented by the following equations:

$$0 \le D_b \le C_c C \quad (3)$$

$$0 \le I_b \le C_D C \quad (4)$$

$$C_{min} \le E_b^t \le C \quad (5)$$

$$E_b^t = E_b^{t-1} + \Delta t [D_b^t - I_b^t] \quad (6)$$

Where C is the capacity of the battery and C_C and C_D the charge and discharge ratio, respectively. C_{min} is the minimum capacity acceptable and E_b^t is the energy stored in the ESS at the moment t.

Industrial plants offer limited space for the installation of RES and ESS. As the size of these equipment is unknown, it is important to consider a maximum size for its installation in a given manufacturing plant, which is represented by:

$$0 \le RES_{size} \le RES_{max,size} \quad (7)$$

$$0 \le ESS_{size} \le ESS_{max,size} \quad (8)$$

There are also constraints regarding the impossibility to simultaneously buying and selling electricity to and from the utility grid and charging and discharging the ESS at the same time. The performance of these actions always lead to under-optimal points of performance due to the fact that the selling price of energy is always lower than the buying price and that there is an inherent cost for using the battery. For these reasons, there is no need to add the mentioned constraints to the problem as the optimizer will not lay in these non-optimal areas.

B. Optimization problem

The aim of the proposed optimization problem is to size the RES and the ESS to transform an industrial plant into a prosumer, obtaining a benefit through energy bidding with the utility grid while meeting its internal demand. For the solution to be feasible and attractive to industry, it is crucial to assure a fast payback period and low operational costs of the energy system, which are the two objectives that will be considered in this problem. Thus, the objective function can be formulated as follows:

$$f = w_1 PB^{trans} + w_2 OC^{trans} \quad (9)$$

Where PB^{trans} is the normalized payback period, OC_{trans} is the normalized cost of the energy system considering the cost of energy, the amortization of equipment and the maintenance operations; and w and w are the weights assigned to each of the objectives. The normalization is performed in order to assure the independence of the objective function from the dimensions and numeric imbalance of the two criteria. To obtain these values, the following equations are used:

$$PB^{trans} = \frac{PB - PB^0}{PB^{max} - PB^0} \quad (10)$$

$$OC^{trans} = \frac{OC - OC^0}{OC^{max} - OC^0} \quad (11)$$

Where the superscript 0 and max represent the minimum and maximum values for the corresponding criteria. The value for the OC is computed analysing the current and future state of the energy market, RES availability and internal demand with the aim of obtaining the energy purchased and sold and energy charged and discharged in the ESS along a predefined horizon. Its value comes from (12), which represents the cost of acting as an active consumer. In order to assure an optimal performance as a prosumer, this is solved using linear programming optimization techniques to decide ideal points to exchange energy with the grid.

$$OC = \Delta T \sum_{t=1}^{n} E_c - E_b + RES_c + ESS_c \quad (12)$$

$$E_c = C_{be}^t I_e^t \quad (13)$$

$$E_b = C_{se}^t D_e^t \quad (14)$$

$$RES_c = C_{RES} I_{RES}^t \quad (15)$$

$$ESS_c = C_{ESS} \times (I_b^t + D_b^t) \quad (16)$$

Where C_{be}^t and C_{se}^t are the cost for buying and selling electricity at the time interval t and C_{RES} and C_{ESS} are the LCOE of the RES and ESS, computed based on capital, installation and maintenance cost.

The PB criteria is computed considering the initial investment needed for the RES and ESS and the economic savings resulting from the energy that is not being purchased from the utility grid and the benefits of selling energy at specific time intervals, being formulated as:

$$PB = \frac{C_0}{S_{PC} - N_{PC} + S_B} \quad (17)$$

Being C_0 the initial investment, S_{PC} the cost of purchasing energy in the Do-nothing scenario, N_{PC} the cost of purchasing energy in the new scenario with RES and ESS and S_B the benefit obtained from selling energy at the utility grid.

This optimization problem is multi-objective and non-smooth, being not possible to assure the performance of derivative resolution methods. As the variables to optimize are the size of RES and ESS, it is possible to handle the optimization problem through an evolutionary algorithm, such as GA, that enables the surveillance of the different feasible areas without relaying in decreasing directions and is particularly advantageous for multi-objective optimizations. This methodology has been used in [28], [29] for the optimization of energy management systems. The GA optimization methodology creates a population of potential individual solutions which is tested against the problem to be solved, verifying the fulfilment of constraints and computing the fitness function for each of them. If the stopping criteria are not met, which deal with the result tolerance and the number of generations without improvement, a new generation is created and tested. This new generation is the result of selecting the individuals with best performance, keeping, crossing and mutating them to obtain a new population that could potentially outperform the previous one.

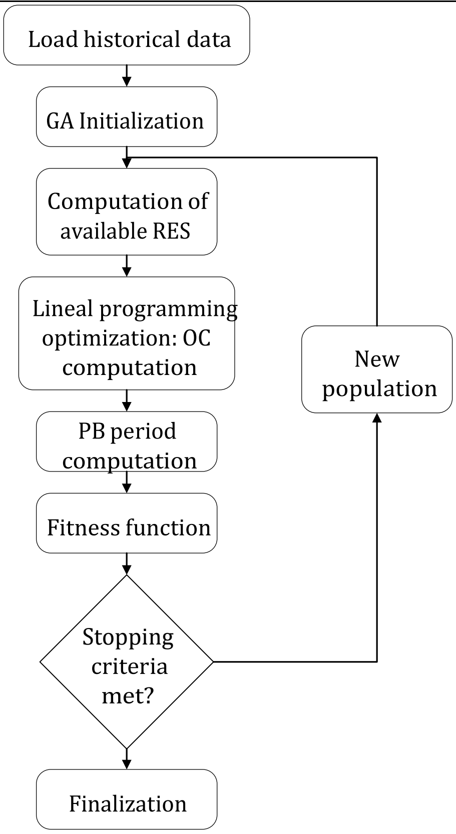

Fig. 1: Methodology used to solve the optimization problem

C. Methodology

To solve the aforementioned problem, the methodology shown in Fig. 1 is applied. The first step is to load historical information, which includes internal demand of the factory, meteorological parameters needed to compute RES energy production based on its size and electricity prices at the wholesale market. Once this is performed, the GA is initialized and the first individuals obtained. From this population, it is possible to compute the available RES. With this information, an optimization of the prosumer behaviour for each of the individuals is done, deciding when to purchase energy for consumption or storage and when to sell it according to internal and external market status with the aim to obtain maximum benefit. This optimal energy bidding strategy leads to the computation of operation cost of the energy assets, the energy cost and the benefits from selling electricity, obtaining also the payback period. The fitness function is then evaluated and this process is repeated with new populations while the stopping criteria are not met.

IV. USE CASE

In this section a use case is developed at which the optimization of energy equipment sizing for energy bidding as a prosumer is applied. In order to assure the general validity of the obtained results for a broad range of SMEs, data from an average real manufacturing plant has been used to create a use case that resembles the reality of industrial SMEs worldwide.

A. Industrial plant under study

The industrial plant under study is assumed to be a medium factory size with plastic transformation processes with a total consumption between 128 kWh and 480 kWh per day and a maximum power exchange with the utility grid of 36kW. The electrical demand is higher in the summer period than in the winter period due to the existence of electric chillers, as can be seen in Fig. 2, and there is no consumption of thermal energy. It has a surface of 10000m2, 30% of which is available for the installation of PV panels and there is available space for a 1GWh Li-ion ESS. Its location, in Barcelona, Spain (41.488º, 1.919º), presents a solar irradiance profile over a year that shown in Fig. 3. Optimization is performed along the whole year, by taking four representative weeks of the seasons of the year that will be used to compute operation costs of energy equipment, energy use and payback periods.

As said previously, four scenarios are considered. The first scenario is the "Do-nothing", which represents the current situation for most of the factories that do not have RES nor ESS. This energy scenario presents the energy costs shown in Table I for the selected weeks.

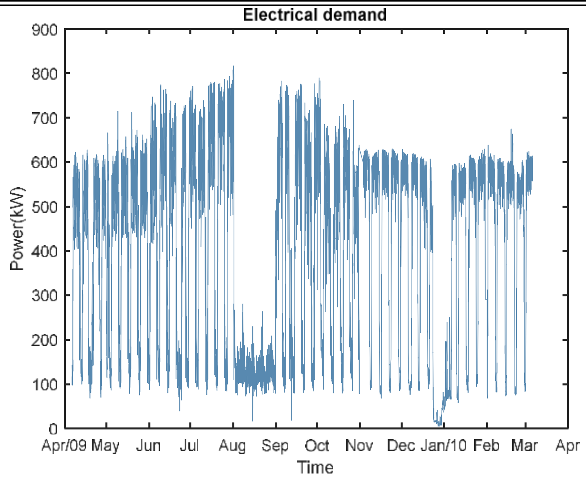

Fig. 2: Electrical demand

TABLE I: ECONOMIC COST FOR SCENARIO 1

Season	Cost (€)
Spring	263
Summer	413
Fall	335
Winter	201

In the second scenario the factory accounts with RES and ESS sized for a typical self-consumption case, without the possibility to sell energy surpluses to the utility grid. This sizing is easily provided through tools from enterprises selling self-consumption approaches, such as [30], [31]. For the use case performed here, the self-consumption solution given by these tools consists of a PV installation of 2500m2 and a battery capacity of 37kWh. The third scenario accounts with the same factory model as in the second scenario but with the difference now the plant acts as a prosumer contemplating an active exchange of energy with the utility grid. Lastly, in the fourth scenario the plant has a RES and ESS system optimally sized for

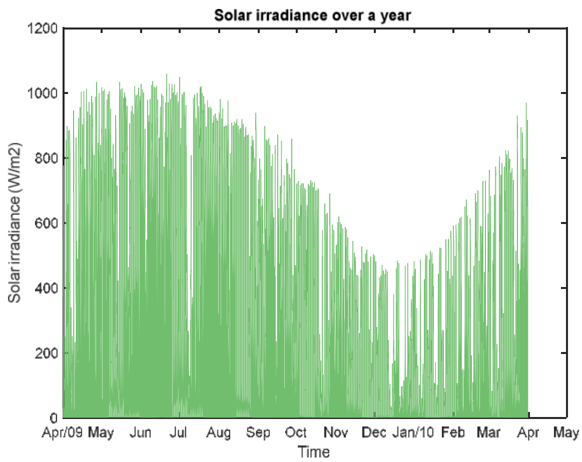

Fig. 3: Annual profile of solar irradiance in Barcelona, Spain

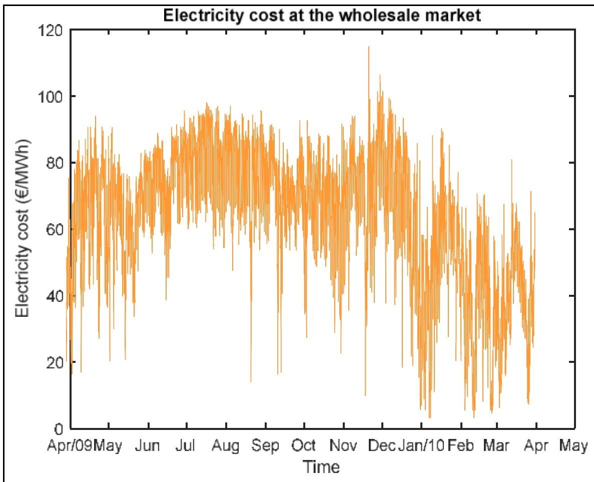

Fig.4: Electricity price at the wholesale market

prosumer purposes and acts as an active costumer exchanging energy with the utility grid. The energy price patterns correspond to those at the wholesale market in Spain and Portugal [32]. To account for energy cost increase, an average increment of 30% during the studied period has been considered according to [25]. The difference of the cost between buying and selling electricity at the wholesale market has also been considered of 30% in consonance with new legislations being developed by several countries [19]. The resultant energy purchasing cost is shown in Fig. 4.

B. Optimization problem formulation

In this section the optimization problem for the energy equipment sizing is applied to the use case defined above. In this case, the energy balance is represented by:

$$\eta_g I_e + \eta_R I_R + \eta_{db} I_b = \eta_m D_m + \eta_{cb} D_b + \eta_g D_e \quad (18)$$

The RES considered to be installed in the factory is a PV system, and its input can be expressed according to its size as:

$$I_R = \frac{A_{PV} P_{nom} G}{1000} \quad (19)$$

Where A_{PV} is the area of the PV system, P_{nom} is the nominal power per area and G is the solar irradiance. The constraints of the problem, defined in section III, are:

$$0 \leq I_e, D_e \leq 36\ kW \quad (20)$$

$$0 \leq D_b \leq C \quad (21)$$

$$0 \leq I_b \leq C \quad (22)$$

$$0.1C \leq E_b^t \leq C \quad (23)$$

$$0 \leq A_{PV} \leq 3000\ m^2 \quad (24)$$

$$0 \leq C \leq 1000\ kWh \quad (25)$$

Considering that industry prioritizes a fast return on investment, the objective function is:

$$f = 0.7PB^{trans} + 0.3C^{trans} \quad (26)$$

V. Results

The results for the use case are exposed here. First of all, the results for scenarios 2, 3 and 4 are shown and then the comparison of the payback and the energy cost for each of them is analysed.

A. Scenario 2

In this scenario the industrial plant accounts with a PV installation of 2500m2 and a battery with 37kWh of capacity. The behaviour of the plant and the charge cycles of the ESS for a spring representative week can be seen in Fig. 5 and Fig. 6, while the operational cost and the savings in energy purchase are available in Table II. In this case, as it is not possible to sell energy to the utility grid, the energy from RES is consumed as it is generated and the excess is stored in the battery for its later use.

TABLE II: Economic cost for Scenario 2

Season	Operational cost(€)	Energy purchase savings(€)	Savings with respect to scenario 1
Spring	228	107	40%
Summer	327	183	44%
Fall	285	113	34%
Winter	184	52	26%

B. Scenario 3

With the same energy equipment as scenario 2, in this case there exist the possibility to obtain a

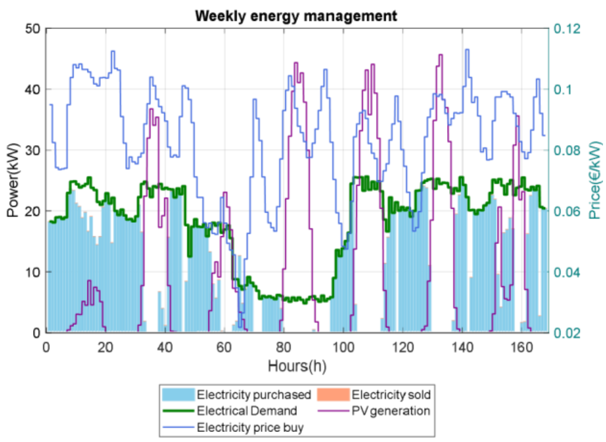

Fig. 5: Plant performance in scenario 2

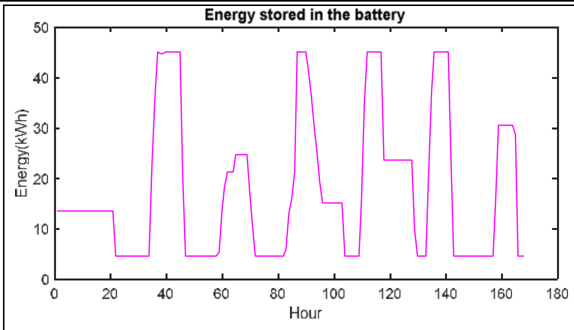

Fig. 6: ESS charge profile in scenario 2

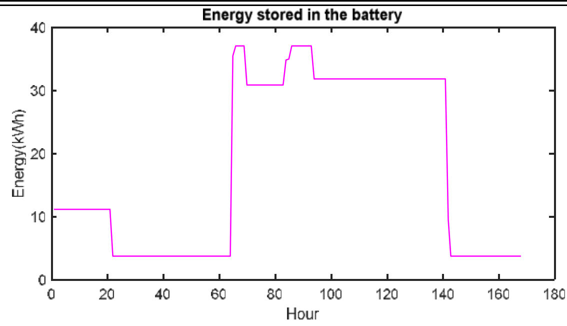

Fig. 8: ESS charge profile in scenario 3

benefit from the energy sold to the utility grid. The behaviour of the plant and the charge-discharge cycles of the ESS for the spring representative week can be seen in Fig. 7 and Fig. 8. The economic benefits are available in Table III. As the PV energy is generated at the daily time intervals with highest energy cost at the wholesale market, this energy is most of the time used for self-consumption and export it to the utility grid.

TABLE III: ECONOMIC COST FOR SCENARIO 3

Season	Operational cost(€)	Energy purchase savings(€)	Savings with respect to scenario 1
Spring	196	130	49%
Summer	272	229	55%
Fall	268	125	37%
Winter	181	54	27%

However, during a week the variation of the electricity price makes feasible to purchase energy for its direct storage to be sold at a latter point of time. It can also be seen that in this case the ESS effectuates less charge cycles, inducing a longer battery lifetime.

C. Scenario 4

In this scenario the energy equipment is optimized considering a prosumer behaviour. The result for the optimization can be seen in Table IV. The energy trading and the behaviour of the plant can be seen in Fig. 9 and Fig. 10, and the economic performance in Table V. The behaviour is similar to the one already exposed for scenario 3, as both of them are prosumers. However, in this case the energy exchange is higher, supposing lower operational costs and higher energy savings.

TABLE IV: RESULTS OF THE SIZING OPTIMIZATION

PV Size	ESS SIZE
2670m2	45kWh

TABLE V: ECONOMIC COST FOR SCENARIO 4

Season	Operational cost(€)	Energy purchase savings(€)	Savings with respect to scenario 1
Spring	193	143	54%
Summer	262	245	59%
Fall	263	136	41%
Winter	179	60	30%

D. Comparison and evaluation

The comparison of the results for the 3 scenarios exposed above and the "Do-nothing" one is done here. To do so, the economic impact of the different solutions along the lifetime of the energy equipment system is studied, which is taken to be 25 years, a value easily achieved by PV systems [33].

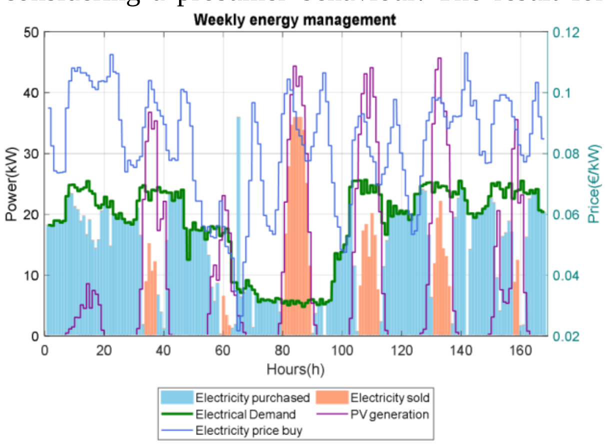

Fig. 7: Plant performance in scenario 3

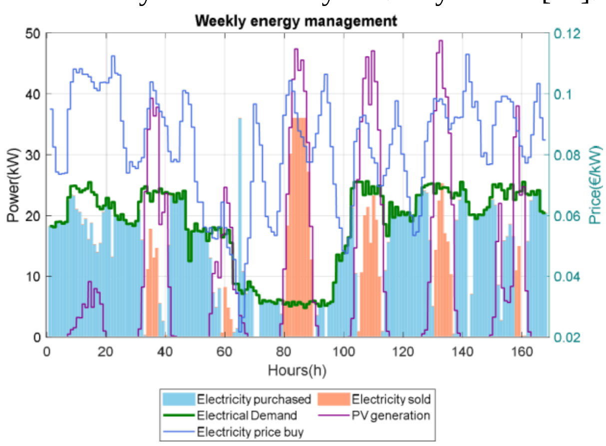

Fig. 9: Plant performance in scenario 4

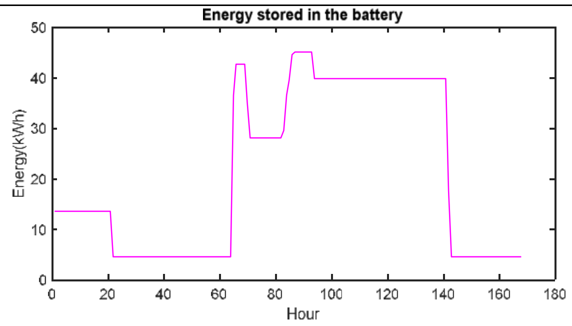

Fig. 10: ESS charge profile in scenario 4

However, the lifetime of the ESS varies strongly depending on charging cycles, going from 10 to 20 years [34]. According to the results, for scenario 2 the ESS performs a charging cycle per day while for scenarios 3 and 4, the charging cycles are 12 per week. For this reason, it can be considered that during the expected lifetime of the installation, two ESS replacements should be done for scenario 2 and only 1 for scenarios 3 and 4. In Fig. 11 the accumulated value of the energy management system considering initial investment and replacements is shown. The payback period for scenario 2, which is the self-consumption approach, is 10.5 years, a common value for this type of installation as has been shown in section II. In contrast, scenarios 3 and 4 present an energy management system that allows for a payback period of 8 years. It is noticeable that although scenario 4 requires higher initial investment, the payback period is achieved at the same time as in scenario 3, leading to the fact that choosing optimal energy equipment size does not influence in the return of investment, a critical point to be considered for industrial enterprises.

The total energy savings along the lifetime of the equipment are also computed for each of the

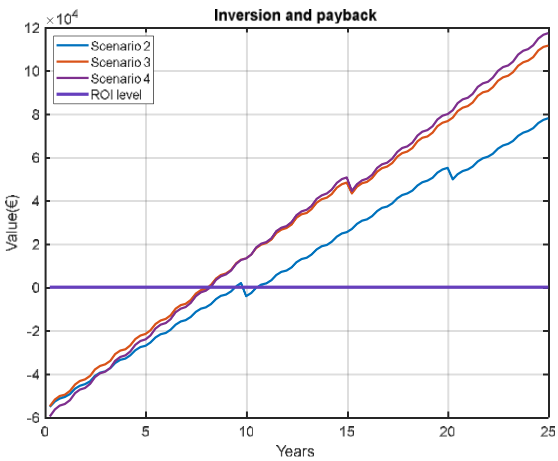

Fig. 11: Amortization and payback period

analysed scenarios and can be seen in Table VI. The adoption of a self-consumption behaviour already represents a considerable saving, although it is clearly surpassed by the prosumer approach. It can be seen that through the sizing optimization of the RES and ESS, the energy savings represent almost half of the total energy use, improving also the prosumer behaviour of scenario 3 without influencing in the return of investment.

TABLE VI: Scenario comparison

Scenario	Payback period	Accumulated energy cost during system lifetime	Energy savings along lifetime compared to "Do nothing"
1	-	476099€	-
2	10.5 years	297258€	38%
3	8 years	264589€	44%
4	8 years	250042€	47%

VI. Conclusions

In this paper, the energy equipment sizing for an industry aiming to adopt a prosumer behaviour has been assessed. To do so, a general SME industrial energy infrastructure has been modelled and the optimization problem defined and solved using a GA approach. Several scenarios have been considered representing different energy management strategies that are likely to be implemented in industrial plants. The self-consumption is a well-known energy solution already accepted by the legislation which provides a high rate of energy savings and a payback period acceptable by industries. Based on this and considering social and governmental trends that enhance system flexibility, the prosumer is proposed as a key factor in the future energy market. The prosumer actively exchanges energy with the utility grid optimizing the energy bidding according to market status. In this paper, the suitability of optimizing the energy equipment to produce excess energy and storage capability to sell it to the utility grid at ideal moments has been shown. A methodology to suitable size RES and ESS for an industrial prosumers has been defined an applied to a use case. In this use case, the prosumer with optimal energy equipment size presents energy savings of 47% respect the "Do-nothing" scenario and also surpasses the performance of self-consumption and prosumer with nonoptimal energy equipment. The payback periods obtained are also reduced, enabling and enhancing the adoption of these measures by SMEs willing to incorporate smart energy management systems into their business models participating in the decarbonisation of the market.

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5.3. Energy equipment sizing and operation optimisation for prosumer industrial SMEs – A lifetime approach

Reference: E. M. Urbano, V. Martinez-Viol, K. Kampouropoulos, and L. Romeral, “Energy equipment sizing and operation optimisation for prosumer industrial SMEs – A lifetime approach,” *Appl. Energy*, vol. 299, no. July, p. 117329, 2021. Available on: https://doi.org/10.1016/j.apenergy.2021.117329

Publication framework:

This article exposes the complete energy sizing methodology for industrial SMEs aiming to transform themselves into prosumers. The deterministic two-stage optimization approach is detailed. In the first stage, the potential equipment to install is analysed. In the second stage, the prosumer operation of the potential upgraded plant is optimized for the complete expected lifetime of the investment.

Main contributions:

- Continuous global optimization of energy equipment operation throughout its lifetime, considering yearly, seasonal and hourly cost evolutions and equipment degradation.
- Realistic one-week active energy bidding optimization to capture weekly energy cost and production cycles.

Key words:

Energy transition, prosumers, renewable energy sources, optimal sizing, industrial sector.

Energy equipment sizing and operation optimisation for prosumer industrial SMEs - A lifetime approach

Eva M. Urbano*[a], Victor Martinez-Viol[a], Konstantinos Kampouropoulos[a] and Luis Romeral[a]

[a] MCIA Research Center, Department of Electronic Engineering

Universitat Politècnica de Catalunya

Rambla de Sant Nebridi 22, 08222 Terrassa (Spain)

*Corresponding author. E-mail address: eva.maria.urbano@upc.edu

Abstract

The market is searching for solutions to reduce emissions in the energy sector by increasing the consumer efficiency and flexibility and integrating renewable sources. Prosumers are suited to this role and are increasingly considered crucial to any such solution, being industries suitable to adopt this role. Small-and-medium enterprises (SMEs) that need to upgrade their energy infrastructure, due to equipment obsolescence or external pressures to adopt greener technologies, face difficulties in integrating new energy management strategies given the investment required and the payback periods. Industrial SMEs traditionally seek to make on-off investments with fast returns, exploiting the obtained equipment for its whole lifetime. Therefore, this paper presents a novel methodology to determine the optimal sizing and operation of the energy infrastructure for an industrial SME transitioning to a prosumer model to improve its economic perspectives, considering the exploitation of the infrastructure for its complete lifetime. The energy and economic profiles of SMEs are analysed and their energy infrastructure modelled in order to define the sizing and operation optimisation problem. Operation of the equipment is optimised considering weekly cycles along multiple years, obtaining the net present value of the investment. The proposed methodology, which employs direct search and linear programming techniques, enable industrial SMEs to undertake informed energy investment actions. A real manufacturing plant is described, characterized and used as the basis for a case study. The results show the economic feasibility of installing new energy equipment in SMEs, obtaining payback periods less than five years and final investment value of more than ten times the initial expense.

Keywords

Energy transition, prosumers, renewable energy sources, optimal sizing, industrial sector.

1. Introduction

Climate change is a global phenomenon whose effects must be stopped or slowed down as far as possible in order to prevent further damage to the environment. The Paris Agreement, signed by 195 nations in December 2015, specifically addresses the mitigation of greenhouse gas (GHG) emissions, calling for limiting the increase in global average temperature below 2 K above pre-industrial levels [1]. For this to happen, a general change is needed. Among other technical and social approaches, solutions can be provided by the energy market, which should undergo a transition towards zero CO_2 emissions to assure system sustainability. Decarbonisation of the sector is only achievable if clean renewable energy sources (RES) are further inserted, performing an electrification of the market and increasing the efficiency of transmission and distribution systems [2]. Although this massive electrification can be achieved by the integration of RES, the current market structure presents barriers to their inclusion, as market mechanisms are based on high marginal costs and power dispatchability, whereas RES offer low marginal costs and are intermittent and nonprogrammable, inhibiting high penetration of them into the market [3]. To overcome these and other barriers, a change of paradigm is required, switching from a centralised dispatchability-based energy market to a distributed and hybrid system in which distributed small RES and consumer flexibility are key for success. To support this energy transition, governments around the world are enhancing the access of distributed non-large producers of clean electricity to the grid and introducing financial incentives, disincentives and market mechanisms for decarbonization by business, industry, transportation and consumers [4]. In Europe, the transition to a new energy market has also started. Several energy policies, subsidies and funding routes have been implemented to achieve the clean energy objectives stated for 2020. RES represented 17% of total production in 2016, approaching the 20% target for 2020. Beyond 2020, new targets have been set for 2030 and 2050. The main objective – decarbonisation – has been set at a reduction of GHG emissions to 80-95% below 1990 levels for 2050 [5]. One of the main focuses for achieving these targets is through the participation of small consumers in the market. Prosumers, who are capable of managing energy systems to exchange energy with the external market considering its current and future status, are acquiring global importance as fundamental actors in the achievement of an active energy market with high penetration of distributed energy sources [6].

Due to the industry's energy consumption, energy infrastructure and the current Industry 4.0 revolution [7], the industry has great potential for the incorporation of flexibility through digitalisation and it is therefore suitable for the transition to a prosumer model. Among the different industrial entities, small-and-medium enterprises (SMEs) are especially interesting due to their importance in energy-related issues, as they consume more than 13% of total global energy and account for more than half the energy used in the industrial and commercial sectors [8]. However, industrial SMEs face more difficulties than larger enterprises in adopting novel energy management strategies [9], and programmes for the incorporation of RES and flexibility require further research [10]. In this type of enterprise, most costs, especially those related to energy, are deemed necessary and are largely overlooked; as a result, little analysis is made of energy management and its impact on the company. Although some scientific research has been carried out into energy efficiency improvements in the SME sector such as [11], there are no publications on SMEs adopting prosumer behaviour and, as stated in [12], there is a need to adjust sustainable development practices to the SME framework. SMEs could face the problem of having to invest in energy infrastructure when their existing equipment becomes obsolete or governmental, social or market pressures require them to upgrade. This investment gives added value to industrial enterprises, supporting the achievement of their primary goal, which is to maintain or increase productivity. The investment process in industrial SMEs differs from that of larger enterprises due to the access to finance and the existent managerial system. Industrial SMEs selects investments with short payback periods and favourable economic parameters; once the investment has been made, the infrastructure is maintained in operation until another relevant event occurs that requires a new investment, thus exploiting the equipment for its whole lifetime [13]. When upgrading the energy infrastructure, it may be beneficial to evaluate the possibility of adopting smart energy management strategies such as prosumer behaviours. However, the intrinsic characteristics of industria l SMEs are not compatible with standard prosumer approaches and specific energy investment selection strategies are required for them, as addressed in this paper.

Nearly all studies evaluating consumer capacity to support the energy transition focus on the tertiary sector. In most cases, only electricity consumption is considered, whereas thermal side is overlooked [14]. This can also be seen in studies focusing specifically on energy sizing, such as in [15], where only tertiary end-users which consume electricity are considered. Indeed, in [16], the thermal side of the energy infrastructure for a tertiary building is described but only energy sources providing electrical energy are optimized. Thus, no interconnection is generated through the different energy carriers present in the system. However, industrial SMEs have a strong thermal side [17] that cannot be overlooked when evaluating their prosumer potential, and, as described in [18], their demand pattern differs drastically from that of the tertiary sector. For these reasons, together with the specific investment characteristics of SMEs, a scientific approach must be taken to determine the optimal energy sizing strategy for the transition of SMEs to prosumers.

Optimal energy equipment sizing studies are present in the literature. The mainstream considers operation in islanded mode to support the energy transition by acting as independent entities to the market. In [15], an energy storage system (ESS) is sized for an isolated grid with the objective of minimising the total system cost. In [16], distributed energy resources are sized for a building considering islanded performance, and in, [19] an isolated hybrid wind-hydrogen system is designed for a house. In this type of optimisation, the infrastructures are not connected to the main grid, so the objective is to assure the security of supply and grid stability. There are also papers dealing with sizing strategies for non-islanded mode, such as [20], where the sizing for a factory is assessed with the aim of minimising the energy purchased from the utility grid. In this study, energy storage systems and buffer stocks are sized for a whole year without considering the variation cycles of energy prices in the external market. In [18], the RES and ESS are sized for an industrial facility and a residential complex, to – but not commercialise – energy. In this paper, seasonal characteristic days are considered as representative time intervals for system operation. In [21], RES are sized for large industrial sites, considering the possibility of supplying energy to the grid without profit. The sizing is performed without evaluating the optimisation and operating costs of internal equipment. In [22], the operational optimisation of thermal and electrical equipment to supply energy to a residential complex is performed and the effects of uncertainty on the optimal system size are assessed. The optimisation accounts for environmental aspects but does not translate the emission of GHG into economic parameters, which are the primary consideration for enterprises. Although in these studies there is an exchange of energy with the grid, either the economic impact of this energy is not analysed or only a delimited time interval is considered. None of the studies evaluate the impact of energy exchange on the value of the investment and its return. In addition, the optimisations performed to date consider a typical year represented by a set of characteristics days and do not take into account the effect of weekly cycles into the operation optimisation nor the evolution over time of external and internal parameters. The few papers that consider the evolution of certain parameters include [23], where different time scenarios with different parameters are analysed, without implementing a long-term horizon strategy. Similarly, in [24], the potential variation of demand is addressed. However, none of these studies evaluates the cost evolution of energy parameters, and the methodologies are not suited to optimising an energy investment considering its value along lifetime. In [25], an optimisation model is presented for long-term, multi-stage planning of a general decentralised multi-energy systems. The optimal investment is addressed from a multi-stage perspective, i.e., distributing the investment along years and performing retrofitting, which could be suitable for urban planning applicable to large government entities or districts where buildings are added in multiple phases. SMEs, however, do not plan energy investments to take place gradually; rather, decisions are taken on the basis of immediate investment return and maximisation of profit along the lifetime of the equipment. Also, although multiple years are evaluated in [25] to perform the investment at different time points, the cost of the energy carriers and the technology degradation are discretised and considered constant during the year. This does not reflect reality and can lead to suboptimal decisions, as technology degrades continuously and external costs are subject to important seasonal and hourly variations [26], which should be taken into account in the investment analysis of SMEs.

Free software tools are available for sizing energy sources to meet specific design criteria. DER-CAM is a popular software solution for designing distributed energy resources for the tertiary sector. Users have access to several key features, in particular the possibility of varying their load and deciding on the basis of economic and environmental criteria. To perform this optimisation, DER-CAM considers three typical days per month over the course of one year [27], leading to a simplified idealization of the decision-making process [28]. REopt is another software tool which serves as a technical-economic decision-support model for RES. REopt is also clearly focused on the tertiary sector, and specifically on buildings, campuses and communities. It assesses the optimal mix of energy sources and the optimal dispatch of equipment separately, and only one year is modelled explicitly, which is assumed to repeat over the period of analysis [29]. However, neither of these tools take into account the multiple years in the lifetime of the energy equipment or the evolution of market parameters, both of which are crucial factors when assessing the real value of an investment operation. In addition, the optimisation horizon for energy equipment operation is daily and does not capture the characteristic weekly energy cycles.

Research has also been carried out into optimisation techniques for the sizing and operation of energy infrastructures. In [19], the sizing and dispatch problems are solved using a set of pre-defined rules that indicate where the energy should come from depending on the different situations that may arise. In [18], the sizing is performed through a parametric analysis considering the different options of component sizes, while in [30], different meta-heuristic algorithms are employed. A robust optimisation framework is proposed in [31], together with hybrid modelling, which is used to develop a model based on historical data. Linear programming (LP) and mixed-integer linear programming (MILP) are also commonly applied to energy system sizing. In [20], a MILP algorithm is presented to improve the matching between energy source generation and flexible demand, and in [21] MILP is used to compute the optimal size of a RES. For problems in which optimal design and operation strategy are sought, the non-linear relationship between the equipment selection and capacity and their operating lifetime operation requires the use of simplification techniques to obtain a linear resolution. Simple energy systems such as the one presented in [15] apply MILP to sizing and hourly operation problems of an ESS. However, in the current state of the art, and for the evaluation of complex energy systems with several time operation evaluations, a two-stage optimisation approach is also proposed in which the capacity and equipment variables and the operation variables remain unconnected during the resolution, the optimisation to be performed without simplification strategies. This two-stage methodology is employed in [16], where the dispatch problem is nested within the sizing problem of a RES for an islanded microgrid and solved using a combination of PSO and MILP. In [32], a two-stage stochastic optimisation problem is also proposed for ESS sizing. In the first stage, the ESS capacity and inverter rating are selected, and in the second stage, the dispatch schedule is optimised. This same strategy is also followed in [33], where a two-stage planning and design method is applied for a microgrid with a combined cooling, heat and power system, and in [34], where the optimal sizing and operation of a CHP system is studied.

Bearing in mind the evolution of the energy market and the current situations of industrial SMEs, there is a need to develop a global vision on how to transform SMEs into prosumer entities through investment in energy equipment for smart energy management. Therefore, this paper aims to assess the optimal design of the energy infrastructure for an SME to enable an equipment upgrade, evaluating the possibility of exchanging energy with the external grid and the business opportunities that this presents. Considering the economic priorities and requirements of industrial enterprises, the analysis is carried out for the whole lifetime of the energy equipment, considering market time evolution, emission taxes and expected internal growth. Also, in order to capture the energy cost and production cycles, a weekly operation horizon is considered to maximise the bidding profits while the optimal size and the optimal operation of the equipment are assessed. This work makes the following contributions to the state of the art:

- Continuous global optimisation of energy equipment operation along its lifetime, considering yearly, seasonal and hourly cost evolutions and equipment degradation. This procedure improves the single-year operation and extrapolation of results used until now in the literature and the consideration of fixed energy costs, increasing the robustness and accuracy of the results.
- Realistic one-week active energy bidding optimisation to capture weekly energy cost and production cycles, which are determining factors of SMEs' equipment operation, improving current single- or isolated-day methodologies.

This problem is addressed through a two-stage global sizing optimisation adapted to the case of energy equipment for industrial prosumers, which differs from previous works as it addresses the entire energy infrastructure of the studied entity. Direct search (DS) is well suited to the first stage, which is characterised by few design variables and defined boundaries, while LP is employed in the second-stage, quickly reaching the operation that leads to the global minimum. The presented framework is applied to the novel field of industrial SMEs as prosumers. Active energy bidding of industrial SME energy infrastructures with the utility grid is considered, taking into account the latest legislation streams, which make provision for industry to participate in the electricity market and transition to a prosumer model. This approach can also be considered a contribution of this paper to the state of the art.

The paper is organised as follows. Section 2 describes the energy framework and background, specifying the equipment, energy and emissions costs for prosumers over the coming years. Section 3 defines the problem and presents the mathematical formulation and the two-stage global DS-LP optimisation methodology for its resolution. Section 4, presents a case study to verify the assumptions of this paper, while the results are discussed in detail in Section 5. Finally, Section 6 presents the conclusions of the study.

2. Energy framework and background

The energy infrastructure of industries varies depending on its activity and size, being big and energy-intensive enterprises, the primary ones taking action towards deep decarbonization through the inclusion of RES and energy efficiency measures [35]. However, industrial SMEs, which dominate the industrial landscape, are slower in the adaptation to the new energy paradigm.

SMEs can be defined as enterprises with 10 to 249 employees with sales not exceeding 50 million euros and an annual balance sheet lower than 43 million euros. As an example, the average SME in Europe employs 32 people and has a value-added of 1.418 million € [36]. Its specific electricity consumption and final energy consumption are considered to be 1.449 kJ/€ and 4.512 kJ/€ respect the value-added [37] with peak power ranging from dozens of kW to units of MW [38]. With these data, the annual final energy consumption of the average SME is 1.777 MWh, being the consumption of electricity 570MWh.

Current SMEs base their energy behaviour in the direct purchase of electricity from the utility grid to satisfy their electrical load and the use of gas for combustion to cover the thermal load, although district heating is also employed when available [38]. Even though cogeneration is widely used in large-industrial sites [39], it is not established for SMEs, which mainly use boilers for the combustion of natural gas [40].

Even though self-consumption is being widely applied to the tertiary sector as can be seen in several works, such as in [41], where the optimal sizing and power schedule of PV for household prosumers is analysed; it is not yet established in the industry. As the energy transition and the newest legislation to tackle it leads to a switching trend from self-consumption to active consumers with prosumer capabilities, the industry is likely to incorporate energy equipment for prosumer purposes instead of for self-consumption. In fact, several countries around the world propose different strategies for enhancing the emergence of prosumer entities [42]. As an example, a review of policies implemented in several European countries is available in [43], including feed-in tariffs, premium tariffs and tax reduction when RES are utilized.

These trends and the technological advances and cost reduction of energy equipment enable SMEs to expand their energy capacities through dimensioning and diversifying their internal energy infrastructure. The spreading use of RES, and Photovoltaic (PV) systems specifically, is leading to a drastic decrease in their costs. According to the study on the levelized cost of electricity from different sources developed by Fraunhofer ISE [44] and the PV status report by the European Union [45], the Levelized Cost of Energy (LCOE) for PV systems, from 0,0371 to 0,11€/kWh in 2018, is forecasted to be reduced to 0,02-0,065€/kWh in 2035. Regarding its investment cost, from 600-1.400 €/kWp in 2018, it is expected to be decreased to 350-815 €/kWp by 2035. The operation and maintenance cost of 9,5€/kW-year is also likely to be decreased by 50% to 2035, reaching a value of 4,75€/kW-year.

Electrochemical ESS will also lower their cost to due to their wide adoption as ESS in electric vehicles. The most mature application for energy storage is the Li-ion battery. As exposed by the Fraunhofer ISE [44] and also considering the values obtained in the research article [46]the LCOE of electrochemical ESS was 0,05-0,2€/kWh in 2018, presenting a decrease of 76% compared to 2012 values, and which will likely continue dropping by 50-60% until 2030. The capital cost of Li-ion batteries, 380-480€/kWh; and its operation and maintenance cost, 8,5-11,3€/kW-year; are also expected to be decreased at the same ratio by 2030.

Cogeneration, which has already been applied to large industrial sites, is being studied for its application in micro-sizes that will enable its integration in SMEs [47]. The cost of a Combined Heat and Power (CHP) equipment is very competitive, being its LCOE 0,018-0,066€/kWeh [48]. However, its initial investment for small sizes is considerably large, between 3.400€/kWe and 6.700€/kWe depending on the technology [49] and with operation and maintenance costs of approximately 35€/kWe-year [50]. CHP can be supplied by coal, natural gas or a gas mix including hydrogen. Still today, hydrogen technology is not ready in the market for its implementation [51]. Despite this, in this paper, a generic methodology is presented that will enable the incorporation of hydrogen in the future.

Responding to the growing electrification trend in the market, which will enable the supply of green energy from renewables and avoid the combustion of fossil-fuel energy, the incorporation of energy equipment to transform electrical power to thermal is required. Despite the vast variety of equipment available, heat pumps are gaining attention due to their high energy efficiency [52]. Their initial investment is approximately 700€/kWth with an operation and maintenance cost of 7€/kWth-year [53], having an already very competitive LCOE of 0,076€/kWh [54].

With the inclusion of energy transformer equipment that links the electrical side of the factory with the thermal side, it may be necessary to include thermal ESS for better synchronization between both sides of the factory. For the application in industrial sites, the most interesting types of thermal ESS are sensible heat storages, with stability under thermal cycling, chemical compatibility with different environments and low cost [55]. Sensible heat storages are already under application for large industrial sites in the form of solid storages such as packed-beds [56] or hot water tanks [57]. Its low initial investment, of 0,1-10€/kWh [58], with maintenance and operation costs of 11€/kW-year and an LCOE of 0,027-0,07€/kWh [59], make it an interesting option to be considered for its installation in SMEs [60]. Of course, other systems using phase chase materials (PCM) or thermochemical energy storage materials (TCMs) could be considered for thermal energy storage, although further research is needed to improve reliability and efficiency over a large number of thermal cycles and to reduce investment costs before considering its industrial use.

As one of the aims of this paper is to provide a solid base for investment in energy equipment with an expected lifetime of at least 15 years, electricity, gas and emission costs are also considered together with their evolution trend during the upcoming years.

In the case of electricity, its current cost is forecasted to increase at least 30% by 2030 due to the intense

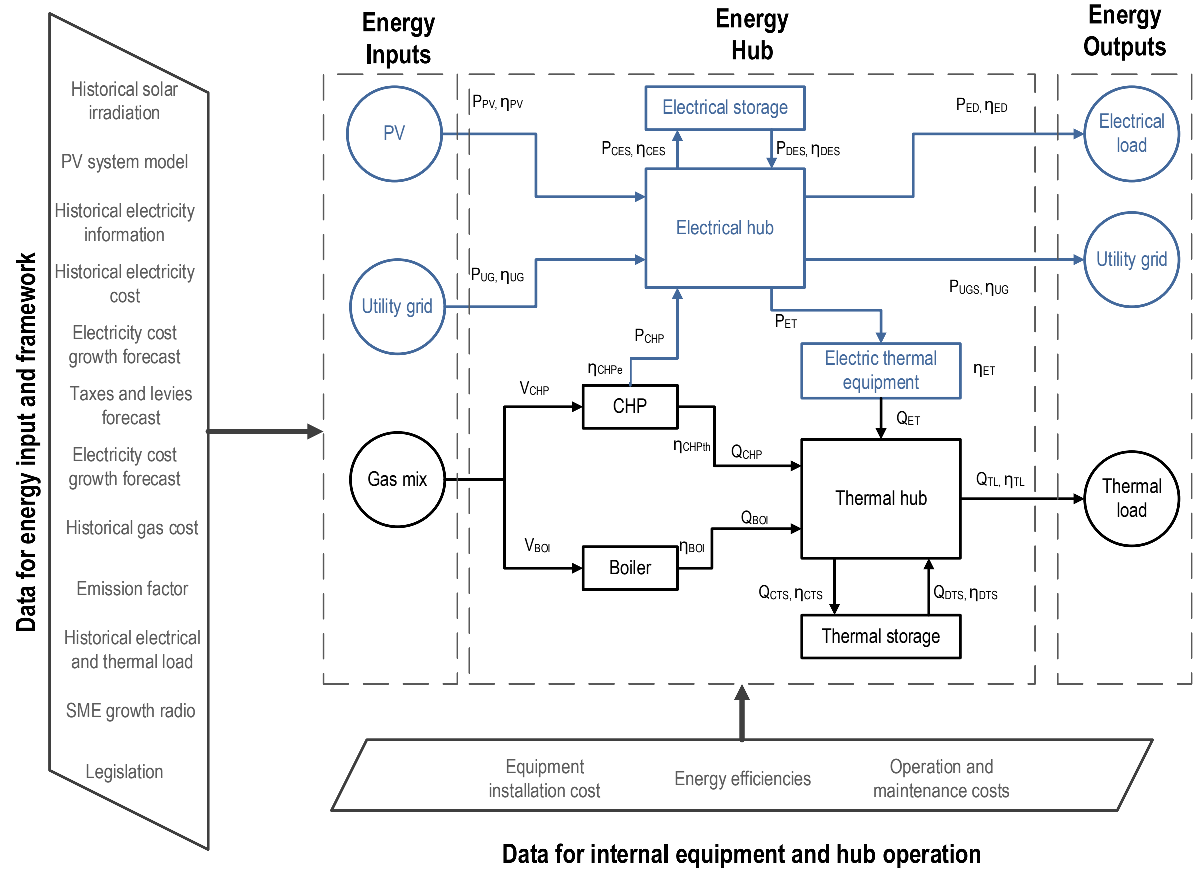

Figure 1: Potential upgraded plant: Data required for the optimisation and possible energy flows within the plant.

electrification of the energy system [61]. For final consumer electricity cost, it is required to account for taxes and levies. In 2019, these taxes represented the 40,7% [62] of energy cost in Europe, although they are lowered for prosumers up to 50% depending on specific country legislation [63]. The price at which the electricity is sold is specified according to legislation and varies depending on the considered country [42].

The cost of gas is also expected to increase by 11 to 25% by 2030 [64]. In this case, taxes and levies account for a lower fraction of the final energy cost, being the cost of the energy up to 80% of the total [65].

To enhance the electrification of the system and the support to the energy transition, the cost of emissions is also considered. Although the required emission costs to accomplish the Paris Agreement by 2020 should lay between 40€/tCO_2 and 80€/tCO_2, in 2019 most countries with implemented emission trading schemes dealt with costs below 25€/tCO_2 [66]. This cost is forecasted to increase until 30-70€/tCO_2 by 2035 [44]. These values do not depend only on market conditions but also on governmental decisions and thus are likely to increment to reinforce the implementation of measures for GHG emissions reductions.

3. Problem definition

To perform the analytical study, a standard SME reference plant is considered, with direct purchase of electricity to satisfy electrical demand and a boiler to transform chemical energy in the gas mix to thermal energy. The incorporation of a RES system, PV in this case; electrochemical ESS, thermal ESS, cogeneration and electric to thermal equipment is considered. The infrastructure of the potential upgraded industrial plant is exposed in Figure 1, and the nomenclature employed is described in Table 1. The contents of this figure reflect the equipment to install, the data needed and the energy flows, which are explained in this section. The objective of the optimisation is to obtain the optimal sizes of energy equipment while also evaluating their optimal dispatch along the expected infrastructure lifetime. In this paper, a two-stage optimisation approach is presented to solve this problem.

In the first stage, the “here-and-now” variables, which are the energy equipment sizes, are computed. The constraints that apply can be related to the maximum investment specified by the SME and the maximum available space for the installation of RES and other energy equipment. For energy equipment selection, and considering that the current interest of industrial enterprises lays in economic parameters, the

Table 1: Nomenclature employed in Figure 1.

Symbol	Description
P_{PV}	Power generated by the PV system
P_{CES}	Power at which the electrochemical storage is charged
P_{DES}	Power at which the electrochemical storage is discharged
P_{ED}	Electric power used by the electric to thermal equipment
P_{UG}	Power purchased from the utility grid
P_{UGS}	Power inserted to the utility grid
P_{CHP}	Electric power from the cogeneration system
P_{ET}	Electrical power used by the electrical to thermal equipment
V_{CHP}	Gas used by the cogeneration system
Q_{CHP}	Thermal power from the cogeneration system
Q_{ET}	Thermal power from the electric to thermal equipment
Q_{TL}	Thermal load
V_{BOI}	Gas used by the boiler system
Q_{BOI}	Output power from the boiler
Q_{CTS}	Power at which the thermal storage is charged
Q_{DTS}	Power at which the thermal storage is discharged
η_{PV}	Efficiency of the connexion with the PV system
η_{CES}	Charge efficiency of the electrochemical storage
η_{DS}	Discharge efficiency of the electrochemical storage
η_{ED}	Efficiency of the connexion with the electrical demand
η_{UG}	Efficiency of the connexion with the utility grid
η_{CHPe}	Cogeneration electrical efficiency
η_{CHPth}	Cogeneration thermal efficiency
η_{ET}	Efficiency of the electrical to thermal equipment
η_{BOI}	Efficiency of the boiler
η_{CTS}	Charge efficiency of the thermal storage
η_{DTS}	Discharge efficiency of the thermal storage
η_{TL}	Efficiency of the connexion with the thermal load

objective function should be related to the economic performance of the investment. cost of energy (COE) and net present cost (NPC) are often employed when optimally sizing energy equipment [67]. These parameters serve to analyse the present and annual cost of energy generated considering the repeatability of the analysed performance of the energy resources during its lifetime. However, the objective in this paper is to assess the optimal sizing considering the variation in the optimal operation according to external and internal changes that occur along the lifetime of the equipment. For this reason, the net present value (NPV) is a suitable parameter for projects and investments, as it considers the different cash inflows and outflows for every year analysed and transforms them into current value; evaluating the profitability of energy investments for their expected lifetime [68]. A positive NPV announces that the obtained benefits are higher than the costs, resulting in a good investment option. For computing the NPV, it is required to obtain the benefits and costs for the inclusion of the energy equipment along its expected lifetime, which is done with the information obtained from the second stage of the optimisation process.

In the second stage, the optimal operation of the prosumer plant for the sizes under study is obtained and compared with that of the reference plant so the costs and benefits of the modifications can be evaluated. This optimal operation is computed for a variation cycle of energy prices, which can be captured in a one-week time horizon. In this stage, a mathematical model of the plant is built based on the equipment sizes obtained from the first stage. The plant is modelled and its operation optimised along the lifetime of the energy equipment. The energy hub (EH) is the basis for the development of an energy management system (EMS), which will be in charge of managing the energy flow in the real plant once the sizing problem is solved and the equipment is installed. The EMS will consider the available energy from the RES and the utility grid to attend the demand aiming at benefit maximisation. In this paper, as the objective is the sizing problem, the EMS is out of the scope and the focus lays in the EH model and operation optimisation while assuring the performance of the global system.

The EH is formed by a set of connections, converters and storage devices that form an integrated structure which consumes various forms of energy at the input ports and provide different energy services at the output ports [69]. The plant considered in this paper is a multiple input and multiple output (MIMO) EH, where the energy inputs can be split among the different converters and managed to achieve a certain performance in the output of the system. The energy flows in the EH are optimised having as an objective the minimisation of the operation costs of the plant, including the costs related to the purchase of energy and the benefits obtained from the feed-in tariffs. The EH framework together with the information required to perform the optimisation can be seen in Figure 1. The external boxes represent the information required to obtain the optimal operation of the EH. Specifically, the “Data for internal equipment and hub operation” box represents the data related to the equipment itself while the “Data for energy input and framework" box refers to scenario information, which includes current and future data affecting the performance of the EH. The inputs of the system are formed by the energy generated by the on-site RES and the electricity and gas purchased to the grids. Inside the EH, the energy transformer equipment and the connexion hubs are depicted. It can be seen that there are two main hubs, one electrical and one thermal, each of them with a storage system. These two hubs are connected through two transformer equipment, enabling the exchange of energy between them. The outputs of the system are the energy delivered to internal demand, both electrical and thermal, and the electricity that is sold to the utility grid.

The following sections describe the mathematical formulation of the objective function and the problem's constraints.

3.1. Mathematical formulation

The aim of the sizing optimisation problem is the maximisation of the NPV over a time period T. This can be expressed mathematically following the indications provided in [70], where the different cash flows are considered together with the applicable discount rate. In the present case, for the sake of readability, the initial investment is kept out of the summation of cash flows arising from equipment's operation. The NPV is then expressed as:

$$\mathrm{NPV} = -C_0 + \sum_{i=1}^{T} \frac{C_i}{(1-r)^i} \tag{1}$$

Where C_0 is the investment performed, C_i is the cash flow, or benefits minus cost, for the period i, and r is the hurdle rate. The initial investment is computed as:

$$\begin{aligned} C_0 = A_{PV} C_{0,PV} + Cap_{ES} C_{0,ES} \\ + Cap_{TS} C_{0,TS} \\ + P_{CHP,max} C_{0,CHP} \\ + Q_{ET,max} C_{0,ET} \end{aligned} \tag{2}$$

Where A_{PV} is the area of the PV system, Cap_{ES} and Cap_{TS} are the capacity of the electrochemical and thermal storage, $P_{CHP,max}$ the power capacity of the CHP system and $Q_{ET,max}$ the power capacity of the electrical to thermal equipment. $C_{0,PV}$, $C_{0,ES}$, $C_{0,TS}$, $C_{0,CHP}$ and $C_{0,ET}$ are the initial costs of the PV system, electrochemical storage, thermal storage, cogeneration and electrical to thermal equipment, respectively.

The cash flow is computed for each time period. The variable cash flow is adjusted seasonally by considering four representative weeks along the year and extrapolating these results to the whole year. To this value, the fix operation and maintenance costs of the energy equipment are added:

$$\begin{aligned} C_i = \frac{52}{4}\big(C_{spring,i} + C_{summer,i} + C_{autumn,i} \\ + C_{winter,i}\big) \\ - \big(C_{O\&M,CHP} P_{CHP,max} \\ + C_{O\&M,ET} Q_{ET,max} \\ + C_{O\&M,ES} Cap_{ES} \\ + C_{O\&M,TS} Cap_{TS} \\ + C_{O\&M,PV} A_{PV} P_{nom}\big) \end{aligned} \tag{3}$$

Where $C_{spring,i}$, $C_{summer,i}$, $C_{autumn,i}$ and $C_{winter,i}$ are the variable cash flow of the four representative weeks for the year i and $C_{O\&M,CHP}$, $C_{O\&M,ET}$, $C_{O\&M,ES}$, $C_{O\&M,TS}$ and $C_{O\&M,PV}$ are the yearly operation and maintenance costs per unit capacity of CHP, electrical to thermal equipment, electrochemical storage, thermal storage and PV system, respectively.

For a given season, the cash flow is:

$$\begin{aligned} C_{season,i=} \sum_{j=1}^{N} P_{UGS,j} \eta_{UG,j} C_{UGS,i,j} \\ + \big(P_{UG,ref,j} - P_{UG,j}\big) C_{UG,i} \\ + \big(V_{BOI,ref,j} - V_{CHP,j} \\ - V_{BOI,j}\big)\big(C_{G,i} \\ + F_{gGHG} C_{GHG,i}\big) \end{aligned} \tag{4}$$

Where j represents the hour of the week considered, F_{gGHG} is the emission factor of the gas and C_{UGS}, C_{UG}, C_G and C_{GHG} are the benefit of selling energy to the utility grid, the costs of purchasing electricity, gas and the cost of emissions, respectively. The variables $P_{UG,ref}$ and $V_{BOI,ref}$ are the electrical energy purchased and the gas consumed by the boiler in a reference plant, which is used to evaluate the benefits of renovating the energy equipment and infrastructure.

The behaviour of the reference and the upgraded plants is optimised aiming for minimising the costs, considering the LCOE of the energy equipment and the costs of energy and emissions for the corresponding point in time. The objective function of the optimisation problem is formulated as follows:

$$f_{weekly} = \sum_{j=1}^{N} P_{PV,j}C_{PV} + P_{UG,j}C_{UG,i} + C_{ES}(P_{CES,j} + P_{DES,j}) + P_{CHP,j}C_{CHP} + P_{ET,j}C_{ET} + Q_{BOI,j}C_{BOI} + (V_{CHP,j} + V_{BOI,j})(C_{G,i} + F_{gGHG}C_{GHG,i}) + C_{TS}(Q_{CTS,j} + Q_{DTS,j}) - P_{UGS,j}C_{UGS,i} \quad (5)$$

Where C_{PV}, C_{ES}, C_{CHP}, C_{ET}, C_{BOI} and C_{TS} are the LCOE of the PV system, the electrochemical storage, the CHP, the electric to thermal equipment, the boiler and the thermal storage system. In the optimisation case of the reference plant, which does not include the new equipment under evaluation, the size of equipment that is not present is set to zero.

The sizing problem is subject to restrictions related to maximum allowable space for the installation of RES, maximum space for the installation of internal energy equipment and maximum investment limit. These are expressed as:

$$A_{PV} \leq A_{PV,max} \quad (6)$$

$$\frac{Cap_{ES}}{\rho_{ES}} + \frac{Cap_{TS}}{\rho_{TS}} + \frac{P_{CHP,max}}{\rho_{CHP}} + \frac{Q_{ET,max}}{\rho_{ET}} \leq A_{int,max} \quad (7)$$

$$C_0 \leq C_{0,max} \quad (8)$$

Where $A_{PV,max}$ is the maximum area for the installation of PV; ρ_{ES}, ρ_{TS}, ρ_{CHP} and ρ_{ET} are the energy and power densities of the electrochemical storage, the thermal storage, the CHP and the electric to thermal equipment. $A_{int,max}$ is the maximum area available for the installation of internal energy equipment and $C_{0,max}$ the maximum investment limit.

The optimal behaviour of the plant for all the cases is also restricted. To model the energy infrastructure of the plant, the EH concept is used, according to which energy equilibrium in the electrical and thermal hubs have to be achieved, and equipment operation thresholds should be accomplished. These equilibriums assure the fulfilment of the demand at all times. As the optimisation is performed considering the time evolution of parameters, the demand is susceptible to change together with the production of the industrial plant. For this reason, a robust strategy is adopted at which a yearly growth rate of 1,5% [71]along the optimisation horizon is considered, increasing the demand of the system and assuring the capacity of supply against possible realization scenarios [72]. Also, to better reflect the energy situation of industrial SMEs, the degradation of equipment is considered. Specifically, for the case of the PV system, a continuous performance loss of 0,8 % per year accumulated is implemented [73].

With this in mind the equilibrium for the electrical hub is stated as:

$$P_{PV}\eta_{PV} + P_{UG}\eta_{UG} + P_{CHP} + P_{DES}\eta_{DES} = \frac{P_{ED}}{\eta_{ED}} + P_{UGS} + \frac{P_{CES}}{\eta_{CES}} + P_{ET} \quad (9)$$

For the thermal hub, the equilibrium is stated as:

$$Q_{CHP} + Q_{BOI} + Q_{DTS}\eta_{DTS} + Q_{ET} = \frac{Q_{TL}}{\eta_{TL}} + \frac{Q_{CTS}}{\eta_{CTS}} \quad (10)$$

The thermal power from the cogeneration and from the energy to thermal equipment are related to the parameters in the electrical hub as follows:

$$Q_{CHP} = P_{CHP}\frac{\eta_{CHPth}}{\eta_{CHPe}} \quad (11)$$

$$Q_{ET} = P_{ET}\eta_{ET} \quad (12)$$

The restrictions related to power exchange with external grids are formulated as:

$$0 \leq P_{UG} \leq E_{max} \quad (13)$$

$$0 \leq P_{UGS} \leq E_{max} \quad (14)$$

$$0 \leq V_{CHP} + V_{BOI} \leq V_{gmax} \quad (15)$$

Where E_{max} is the maximum exchange of power with the electrical grid and V_{gmax} the maximum for the gas grid.

The restrictions related to the power exchange with the energy equipment are:

$$0 \leq P_{CES} \leq R_{CE}Cap_{ES} \quad (16)$$

$$0 \leq P_{DES} \leq R_{DE}Cap_{ES} \quad (17)$$

$$0 \leq P_{CTS} \leq R_{CT}Cap_{TS} \quad (18)$$

$$0 \leq P_{DTS} \leq R_{DT}Cap_{TS} \quad (19)$$

$$0 \leq Q_{BOI} \leq Q_{BOI,max} \quad (20)$$

$$0 \le P_{CHP} \le P_{CHP,max} \quad (21)$$

$$0 \le Q_{ET} \le Q_{ET,max} \quad (22)$$

Where R_{CE} and R_{DE} are the charging and discharging ratio of the electrochemical storage and R_{CT} and R_{DT} describe the ratios for the thermal storage.

Last of all, the maximum and minimum energy stored in the electrochemical and thermal storage systems have to be between specified thresholds, described as:

$$E_{ES}^{t} = E_{ES}^{t-1} + \Delta t(P_{CES} - P_{DES}) \quad (23)$$

$$Cap_{ESmin} \le E_{ES}^{t} \le Cap_{ES} \quad (24)$$

$$E_{TS}^{t} = E_{TS}^{t-1} + \Delta t(Q_{CTS} - Q_{DTS}) - SD_{TS}E_{TS}^{t-1} \quad (25)$$

$$Cap_{TSmin} \le E_{TS}^{t} \le Cap_{TS} \quad (26)$$

Where E^{t} is the stored energy at the evaluated instant, E^{t-1} describes the energy stored in the previous instant while Δt is the time step. The subscripts ES and TS refer to the electrochemical and thermal storage, respectively and Cap_{ESmin} and Cap_{TSmin} the minimum capacity of these storages. SD_{TS} is the self-discharge ratio, which is only applied to the thermal storage. Electrochemical energy storage systems, as PV systems, suffer an important degradation over time. In this case, however, the degradation appears in the form of loss of capacity instead of loss of efficiency. In this paper, continuous degradation of 6% per year accumulated has been applied to obtain a realistic result on the energy performance of the plant [74].

3.2. Optimisation methodology

An overview of the optimisation procedure is shown in Figure 2. First of all, data is extracted from databases, which include meteorological information, market costs, internal demands and equipment parameters. With this information, data for the 4 representative weeks per year along the lifetime of the energy equipment, which is considered to be 15 years, is obtained. Then, the operation of the reference plant is optimised, with the energy equipment already owned by the enterprise. This optimisation serves as a baseline to compute the performance improvement if new energy equipment is included in the energy infrastructure of the factory. Once this step is performed, the algorithm continues to the two-stage optimisation.

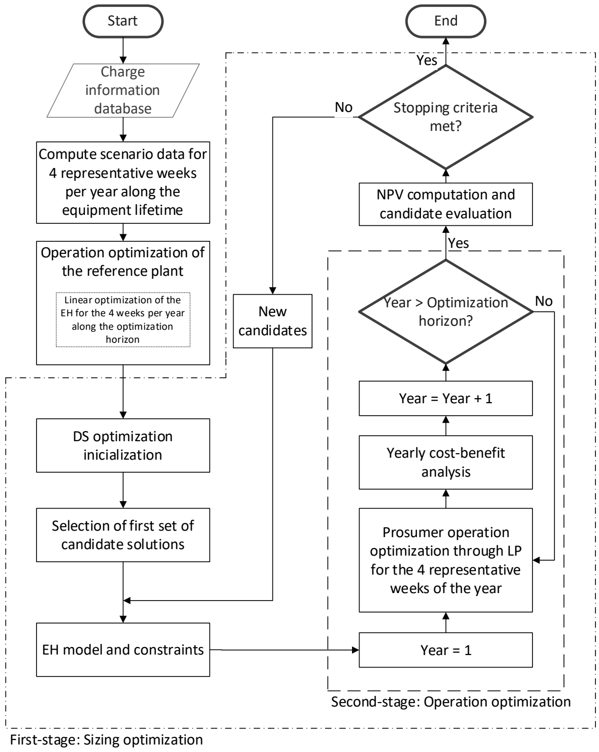

Figure 2: Flowchart of the two-stage optimisation resolution.

The optimisation algorithm is initialized for the first stage. The optimisation problem formulated presents unconnected complex feasible areas, so gradient-based and local optimisation algorithms are not suitable for its resolution as they tend to reach local maximums close to the starting point. For this reason, the use of global optimisation algorithms is preferred in this case, as they have a better chance of finding the global optimal and do not require information from the derivative of the objective function [75]. For the specific situation considered, the optimisation problem is solved using DS, a derivative-free global optimisation algorithm based on branching techniques that performs successfully in front of practical problems with complex search areas [76] and that provides global convergence as proven in [77]. Once the global optimiser is initialized, the first candidates are obtained. These candidates are the equipment sizes to be evaluated in the second stage of the optimisation, which starts with the construction of the model of the upgraded plant. This plant is optimised through LP for one-week time horizon to obtain the dispatch set-points and energy transactions. The obtained behaviour is compared to that of the reference plant to obtain the benefits of including the energy equipment for the corresponding weeks and the results are extrapolated for the year under study. The process is repeated for the expected lifetime of the energy equipment.

When the evaluation of the operation along the optimisation horizon is completed, the NPV is computed, which enables to evaluate the candidates' performance. At this point, the global optimiser checks whether the near-maximum global has been obtained or not through its stopping criteria, which deal with the result tolerance, number of iterations without improvement, time constraints, etc. If a near-maximum global has been reached, the algorithm finalizes its operation. Otherwise, new potential solutions are created and the process is repeated.

Robustness and near-maximum global are achieved through the proposed methodology, as it contemplates the main parameters that influence the design problem and consider their variation along the lifetime of the energy infrastructure. Moreover, the two different stages allow for a proper selection of equipment considering their optimal scheduling and operation, reaching the degree of precision suitable for the problem under study.

4. Case study

In this section, a case study based on a real manufacturing plant of the automotive sector, located in Catalonia, at the south-west of Europe, is exposed. Most industrial SMEs, have higher thermal consumption than electrical consumption [78] and are characterised by a diversity of processes and equipment that enable the incorporation of energy assets to interconnect the different sides of the industry, increasing the robustness of the energy system [79]. Especially, in the automotive industry, electricity consumption accounts for approximately 22% of total primary energy used [80], and the determinant resource depends highly on the type of process performed, being natural gas the primary energy source for the industrial entity considered in this article.

The demand that industrial plants fulfil is directly related with the production system adopted by the enterprise, existing a direct relationship between power consumption and productivity [80]. Generally, the load pattern in the industrial sector drastically differs from that of the tertiary sector, being the latter susceptible to working hours and human behaviour while the former presents a more constant evolution [18]. This is especially true in the case of the automotive sector, whose production is based on a just-in-time system without stocks where the manufacturing load is maintained constant to supply materials and components to other enterprises contributing in vehicle manufacturing [81].

The plant studied in this paper is aligned with the general trends of industrial automotive entities, and has a strong thermal side, being its annual thermal and electrical consumptions of 974,250 MWh and 485,580 MWh, respectively. The energy equipment

Table 2: Costs and parameters considered in the evaluated scenarios.

Cost	**Scenario 1**	**Scenario 2**	**Scenario 3**
C_{PV} (€/kWh)	0,07	0,0425	0,02
$C_{0,PV}$ (€/kW)	950	582	350
$C_{O\&M,PV}$ (€/kW-y)	9,5	6,65	4,75
C_{ES} (€/kWh)	0,12	0,045	0,02
$C_{0,ES}$(€/kWh)	430	342	152
$C_{O\&M,ES}$ (€/kW-y)	9,9	7,65	7,65
C_{CHP} (€/kWeh)	0,042	0,042	0,066
$C_{0,CHP}$(€/kWe)	3.400	3.400	3.400
$C_{O\&M,CHP}$(€/kWe-y)	35	35	35
C_{HP}(€/kWh)	0,076	0,076	0,076€
$C_{0,HP}$ (€/kW)	700	700	700
$C_{O\&M,HP}$(€/kW-y)	7	7	7
C_{TS} (€/kWh)	0,0485	0,0485	0,027
$C_{0,TS}$(€/kWh)	5	5	0,1
$C_{O\&M,TS}$(€/kW-y)	11	11	11
Emission cost the starting year (€/tCO_2)	15	50	70
Tax on electricity (% of total cost)	25%	20%	15%
Electricity sell price	90% market cost	90% market cost	100% market cost
Electricity price increase	30%	30%	30%
Gas cost increase	15%	25%	30%
Gas cost tax (% of total cost)	30%	35%	40%

already owned by the industry is a boiler, which is used to supply power to thermal demand, while electric demand is directly fed from the utility grid. The maximum investment that the SME can perform is of 800.000€ and the maximum area to install the RES, in this case a PV system, is of 6.000 m^2.

To evaluate the optimal energy equipment to install for prosumer purposes, four representative weeks have been extracted for each of the differentiated seasons along the year, which can be seen in Figure 3. It is possible to appreciate that the thermal demand rises in extreme seasons, especially in winter, where it is used for space heating. In this season, the demand is higher during the first day of the week as the heating is off during the weekend, while for the rest of days the thermal inertia persists and the heating demand is lower. In contrast, the electrical demand does not present the same strong variations as the thermal one along the seasons. The electrical side of the factory also provides power to cooling demand, as it can be observed in the demand profile for the summer season, although the most driving factor for electric demand is the production of the plant, which is kept approximately constant during working days.

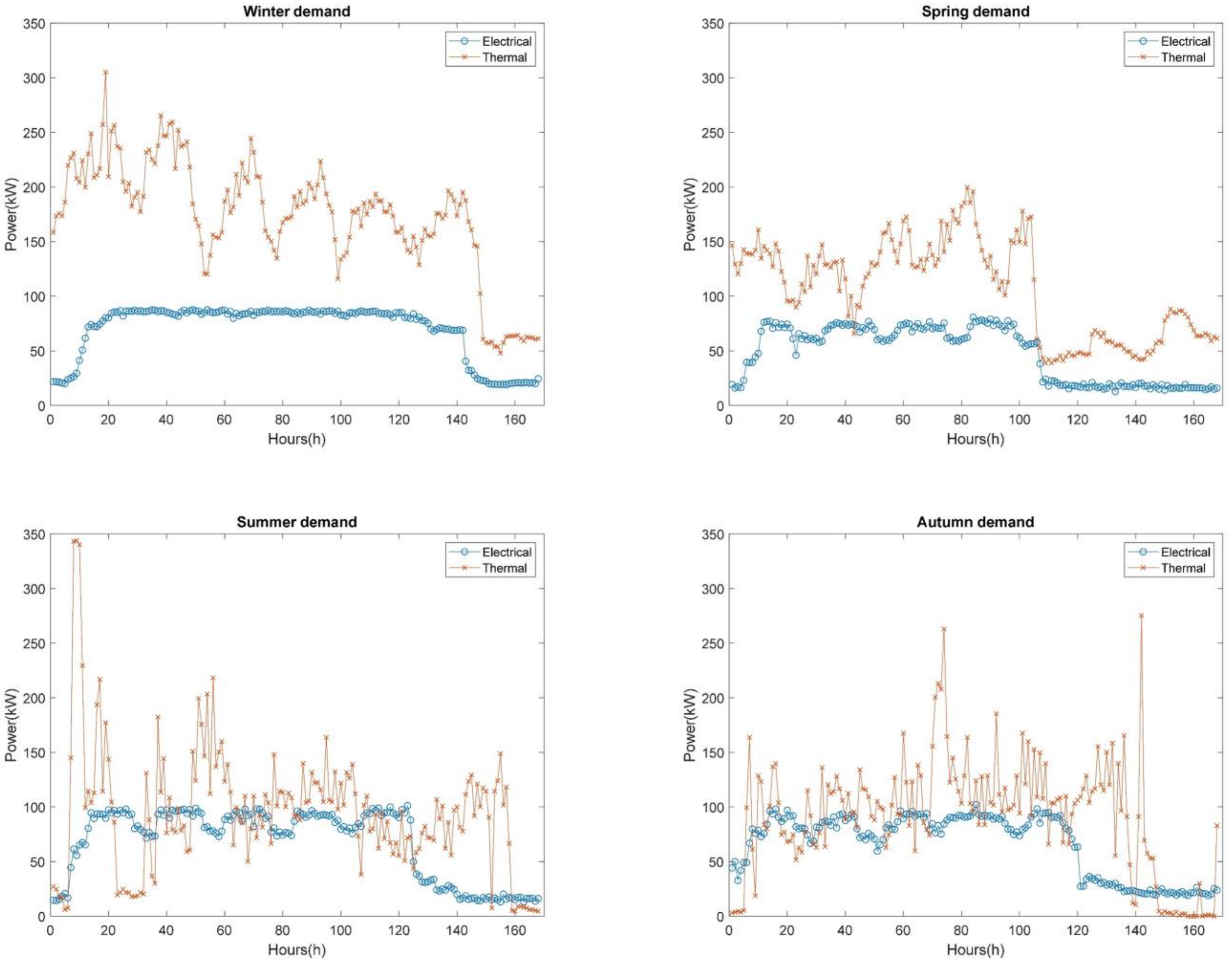

Figure 3: Electrical and thermal demands of the case study plant for the first evaluated year.

The possibility to invest in energy equipment in the close-future is assessed, having 2020 as starting year for the optimisation. This situation is reflected in scenario 1. According to what has been shown in section 2, the costs of energy and equipment are likely to change significantly in upcoming years, increasing the profit margin for consumers who are willing to adopt a more active behaviour. To reflect the impact of these changes, the investment in energy equipment in 2035, once the lifetime of the previously installed equipment is over, is also studied. As the prices are uncertain, two possibilities are considered. The first one, represented in scenario 2, supposes a moderate evolution of prices of the energy and equipment costs that does not benefit the use of RES to trade energy. The other possibility, represented in scenario 3, shows a favourable situation, with costs that facilitate the inclusion of RES, ESS and the electrification of the system. An overview of the costs and parameters for these three scenarios is available in Table 2.

5. Results and discussion

In this section, the results for the use case are presented. First of all, individual outcomes from the optimisation of the three scenarios are shown and then a comparison between them is exposed and discussed. All the figures in this section show the behaviour of the plant for a characteristic summer week.

5.1. Scenario 1

The first scenario is the one corresponding to an investment performed in 2020, with current energy costs, taxes and energy equipment parameters. The optimal energy equipment resultant from the optimisation procedure is shown in Table 3. The selection of this infrastructure supposes an initial investment of 640.650 € and an NPV of 6.111.000€.

Table 3: Energy equipment sizes obtained as results for Scenario 1 optimisation: 2020 energy framework.

Equipment	Size
PV	6000m^2
Thermal storage	0kWh
Electric storage	0kWh
Cogeneration	156kWe
Heat pump	0kWe

The behaviour of the plant, acting as a prosumer with the energy infrastructure of Table 3 is presented in Figure 4 and Figure 5. Due to the high-peak-power provided by the boiler, and for representation purposes, the output from this equipment corresponds to the right Y-axis. For this scenario, the optimisation procedure concludes that the PV system is installed in all the available area and a cogeneration system is employed to fulfil thermal demand and also to supply power to the electrical load. The boiler, which was already present in the factory as the main thermal energy provider, is now used as a back-up system to provide power during demand peaks. Regarding the electricity exchange with the utility grid, energy is being bought at intervals of relatively low cost and the system tries to sell the PV surplus at times of high cost, using this energy together with the one coming from the cogeneration to fulfil the internal electrical demand.

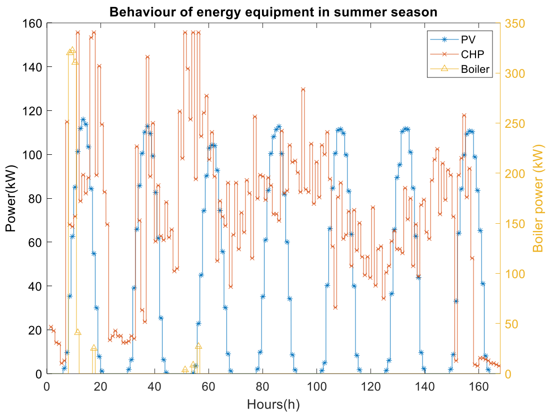

Figure 4: Energy equipment behaviour for Scenario 1: 2020 energy framework.

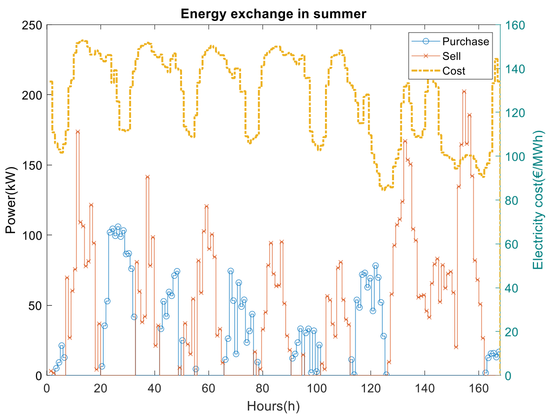

Figure 5: Electricity exchange with the utility grid for Scenario 1: 2020 energy framework.

5.2. Scenario 2

With the insight of the evolution of the forecasted energy and equipment prices exposed in section 2, in this scenario, the investment to be performed in 2035 is assessed considering a moderate evolution of prices of the energy and costs of the GHG emissions. The optimal energy equipment is shown in Table 4.

The selection of this infrastructure supposes an initial investment of 577.640 € and an NPV of 9.126.800€.

Table 4: Energy equipment sizes obtained as results for Scenario 2 optimisation: moderate evolution 2035 energy framework.

Equipment	**Size**
PV	6000m²
Thermal storage	16kWh
Electric storage	0kWh
Cogeneration	148kWe
Heat pump	7kWe

The RES-PV is also sized to cover all the available area for its installation. However, due to the increase in the cost of carbon emissions and also the increment of the revenue for the exchange of energy with the electrical utility grid, in this scenario, the resulting optimal plant has a cogeneration system smaller than in the previous one, while including thermal storage and heat pump. The behaviour of the equipment and the exchange of energy can be seen in Figure 6 and Figure 7. The cogeneration system follows the same working principles as in the case of Scenario 1, providing power to thermal demand and also covering part of the electrical demand, especially at times where electricity is not being purchased from the utility grid due to high energy prices. The increase in the cost of energy in the market, both electrical and gas, justify the installation of the heat pump and the thermal storage system. The heat pump is used most of the time at its nominal power to supply energy to the thermal demand or the thermal storage, while the energy storage is used at strategic times permitting more flexibility in the use of the cogeneration system; to be able to respond more favourably in front of variations in electricity prices. In regards to the energy exchange with the utility grid, the bid amounts have been significantly increased compared to the previous scenario due to the rise of prices in the energy market. However, as the years go by, less energy is being traded with the utility grid due to the degradation of the PV system.

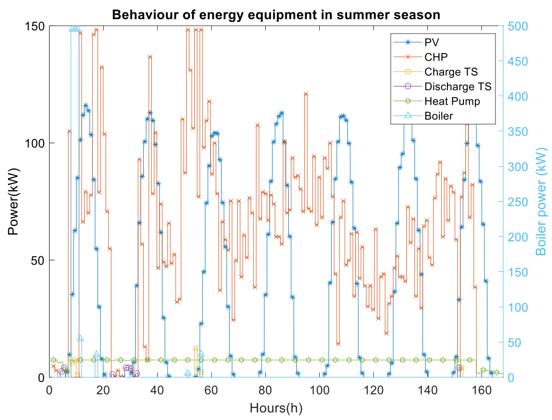

Figure 6: Energy equipment behaviour for Scenario 2: moderate evolution 2035 energy framework.

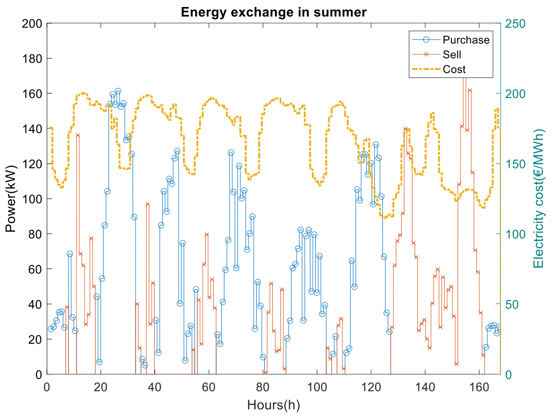

Figure 7: Electricity exchange with the utility grid for Scenario 2: moderate evolution 2035 energy framework.

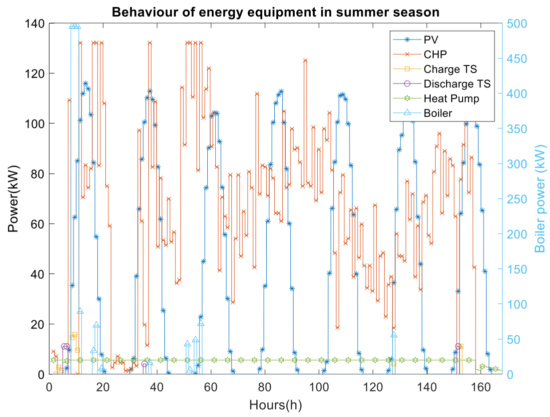

Figure 8: Energy equipment behaviour for Scenario 3: favourable evolution 2035 energy framework.

5.3. Scenario 3

This scenario also considers the investment to take place in 2035, although in this case a favourable costs evolution for the electrification of the system and the reduction of emissions is considered. The optimal energy equipment is shown in Table 5. The initial investment and the NPV for this case are of 494.240€ and 7.494.000€.

Table 5: Energy equipment sizes obtained as results for Scenario 3 optimisation: favourable evolution 2035 energy framework.

Equipment	Size
PV	6000m^2
Thermal storage	45kWh
Electric storage	0kWh
Cogeneration	132kWe
Heat pump	6kWe

On the one hand, the increase in the cost of emissions, gas and of cogeneration systems has caused the cogeneration equipment to be smaller. For this reason, and to maintain the possibility to supply power to thermal and electrical demand through this system and increase the cogeneration flexibility, the size of the thermal storage is significantly increased. On the other hand, as the electrical energy has a cost much higher than gas, for this demand profile the size of the heat pump remains the same. The behaviour of the equipment and the energy exchange with the utility grid can be seen in Figure 8 and Figure 9, respectively. Despite the lower investment in energy equipment, the energy exchange follows the same pattern and the performed bids are comparable to those of scenario 2 due to the inclusion of higher storage capacity.

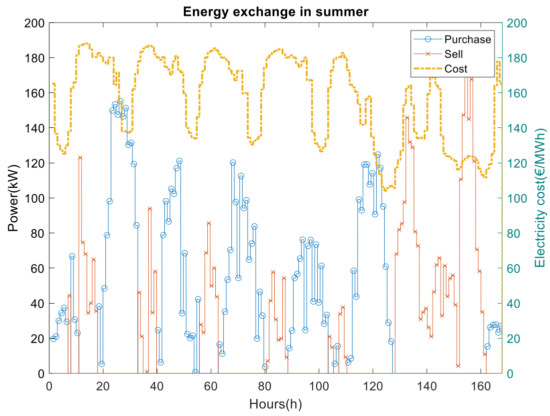

Figure 9: Electricity exchange with the utility grid for Scenario 3: favourable evolution 2035 energy framework.

5.4. Comparison and discussion

The results exposed in the previous section show the economic and technical viability of installing energy equipment to perform prosumer smart energy management considering market status in industrial SMEs. It is also possible to visualize that, in all the cases, the week-time is suitable as operation optimisation horizon to capture the dynamics of the internal demand and the external market. For scenario 1, which considers current energy costs and legislation, the results indicate the suitability of employing PV and cogeneration systems. The PV is used to generate electricity and sell it when possible if the electrical demand can be fulfilled by other means. The cogeneration is employed to optimise the overall efficiency of the energy infrastructure of the factory, coupling thermal and electrical sides and profiting from the characteristics of the demand profile present in this specific case study. Even though a boiler system is already installed in the factory and can be used to fulfil the thermal demand, it results advantageous to implement other energy equipment to improve the plant performance. This solution is aligned with current inversion trends in the industry, which is looking forward the installation of RES, especially PV, for covering daily baseload; and cogeneration systems, which are being offered by the market in various typologies and sizes to fit different consumptions patterns.

With the forecasted evolution of energy prices and cost of emissions and equipment, either moderate or favourable to electrification as described in scenarios 2 and 3, new energy equipment is likely to be included in the energy infrastructure of industrial SMEs. The implementation of these new equipment is already being studied nowadays, principally for energy-intensive industries, and it will also be favourable for SMEs to increase their flexibility in front of costs variations from external markets. It is worth mentioning that despite the increase in the cost of emissions, the use of gas for the cogeneration system in processes with high thermal load is a determinant factor. As this is not likely to change in upcoming years, in front of a possible increase in the cost of carbon emissions from the administration to meet the Paris Agreement, the use of natural gas mixtures will be key for the transition to the new energy paradigm.

Economically, the expense to be performed for the optimisation of the energy infrastructure of the factory does not reach the maximum threshold specified as a constraint. Figure 10 presents the NPV of the investment along the lifetime of the energy equipment for the three studied scenarios. The first scenario, with current energy parameters, presents the higher investment and payback time, resulting in a lower final benefit. Scenarios 2 and 3 improve the performance of scenario 1. However, for the specific case study considered in which the thermal side is dominant, the costs that favour the electrification of the system applied in scenario 3 reduce the economic benefits of the industry for the inclusion of new energy equipment. Despite this fact, the investment in systems for the energy optimisation of the industrial plant results advantageous even for the first scenario. Indeed, the earnings surpass those of several available financial products.

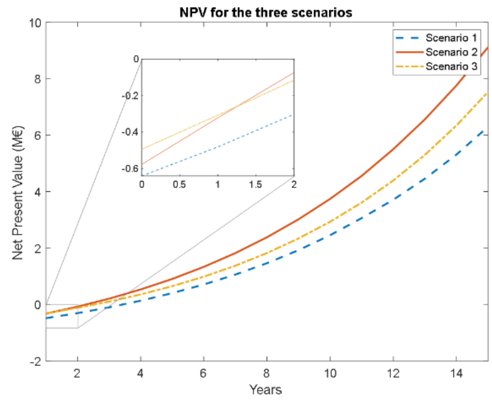

Figure 10: NPV of the three scenarios studied.

During the elaboration of this study, it was possible to appreciate that the results exposed and which are discussed here are highly dependent on the demand type of the industry and the constraints that apply to specific cases. To visualize it, the optimisation of the energy equipment for an SME with plastic processing facilities, which has lower demand load and consume mainly electrical energy is here considered. To perform the study, the electrical demand is half of the previous one considered and the thermal demand is lowered to minimums. For this case, the simulation results are exposed in Table 6:

Table 6: Energy equipment sizes obtained as results for the optimisation of an electricity-based SME.

Equipment	Size
PV	6000m^2
Thermal storage	0kWh
Electric storage	0kWh
Cogeneration	1kWe
Heat pump	0kWe

For this new scenario, the initial investment is 41.364€ and the NPV 415.360€, and, equally to the cases that were already studied, the RES system covers all the available area. However, the heat pump and the thermal storage system are kept out of the infrastructure. The equipment behaviour and the energy exchange with the utility grid can be seen in Figure 11 and Figure 12. In this case, the right Y-axis corresponds to the energy generated by the PV system which is in charge of meeting electrical demand while the boiler and the cogeneration are in charge of fulfilling the thermal demand. It is worth mentioning that despite storage systems do not appear as part of the solution, this does not necessarily mean that their incorporation is not beneficial. In this paper, following SMEs investment characteristics and expectations, the NPV of the energy infrastructure is optimised to obtain the best economic performance. However, if other parameters are included in the objective function such as energy autonomy from the utility grid, the storage system could appear as part of the solution to gain this independence while creating a profit, although of course this would be lower than in the case studied in this paper.

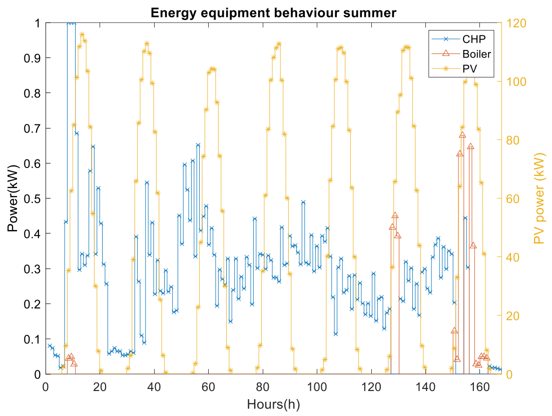

Figure 11: Energy equipment behaviour for an electricity-based SME.

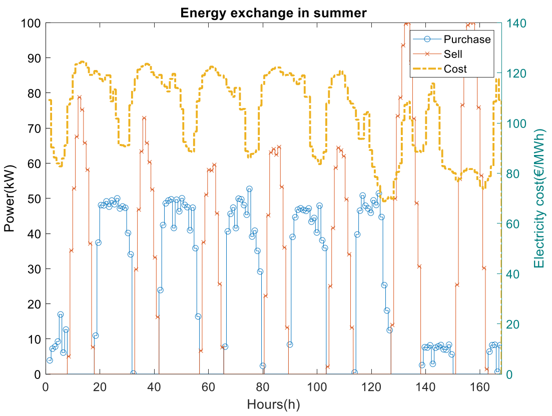

Figure 12: Electricity exchange with the utility grid for an electricity-based SME.

Despite the differences of this solution with the ones obtained in the case study, the inclusion of energy equipment to increase the flexibility of the system in front of the electrical market is always advantageous. This flexibility is employed to shift energy purchase from high-cost time frames to low-cost time frames and to sell energy at high-cost time frames. As the energy cost in the market is directly related with the emissions associated with its generation, the prosumer behaviour of industrial SMEs does not only create an economic benefit for them but also an environmental benefit for the energy market.

6. Conclusions

This paper has assessed the benefits of converting industrial small and medium enterprises (SME) into active stakeholders in the energy market through the optimal sizing and operation of their energy equipment. The current energy framework and background have been presented, together with the projected evolution trends for the coming years, with the aim of helping consumers to switch from a passive to an active role as prosumers. To verify the suitability of industrial SMEs to be part of this change, a characteristic SME energy infrastructure has been modelled mathematically and a sizing and operation optimisation has been performed. The optimisation problem has been solved through a two-stage global approach employing the Direct Search and Linear Programming algorithms, which is an adapted strategy given the characteristics of the studied problem. The energy equipment has been optimised by analysing its operation in weekly cycles along its whole lifetime, making it possible to consider the characteristic patterns of production energy load and energy markets as well as the time evolution of costs. Using this methodology, it is possible to obtain a realistic net present value of the investment as well as the expected payback. A case study has been developed to evaluate the benefits of integrating renewable energy sources, energy storage systems and other equipment that link the electrical and the thermal sides of industrial energy infrastructure. Although the specific technological solutions are highly dependent on the plant demand type and the evolution of external parameters, an upgrade of energy infrastructure improves the energy performance of the factory and permits trading with the external utility grid as a prosumer while boosting the profitability of the investment and contributing to the decarbonisation of the energy sector. The proposed framework for energy investment decision-making together with the obtained results are highly useful to the industrial sector and specifically to SMEs, enabling them to better analyse the energy and economic perspectives of the investment to perform. According to the analysis, industrial SMEs are likely to become important actors in the energy market, turning their energy systems into economic assets and integrating smart energy management into their business models while assuring the integration of renewable sources into their energy models.

Acknowledgements

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5.4. Uncertainty analysis for industries investing in energy equipment and renewable energy sources

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Publication framework:

This article analyses the uncertainty in the performance of the investment done by industrial entities to upgrade their energy infrastructure. It exposes the deterministic two-stage optimization and combines it with the characterization of inputs' uncertainties to carry out a UA.

Main contributions:

- Design and operation optimization of the energy equipment to be installed in an industrial enterprise with prosumer behaviour considering deterministic parameters along the expected lifetime of the equipment.
- Uncertainty characterization of the relevant input parameters.
- UA of the energy investment NPV to quantify the risk related to the investment decision.

Key words:

Industry, Uncertainty Analysis, Renewable Energy, Prosumer, Net Present Value.

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Uncertainty analysis for industries investing in energy equipment and renewable energy sources

E. M. Urbano[1], A.D. Gonzalez-Abreu[2], K. Kampouropoulos[1] and L. Romeral[1]

[1] MCIA Research Center, Department of Electronic Engineering
Universitat Politècnica de Catalunya
Rambla de Sant Nebridi 22 08222 Terrassa (Spain)
e-mail: eva.maria.urbano@upc.edu, konstantinos.kampouropoulos@upc.edu, luis.romeral@upc.edu

[2] HSPdigital CA-Mecatronica Engineering Faculty
Autonomous University of Queretaro
San Juan del Rio 76807 Queretaro (Mexico)
e-mail: agonzalez63@alumnos.uaq.mx

Abstract. This paper studies the optimal design and operation of new energy equipment including renewable energy sources for prosumer industries. In order to augment the interest of industries in performing energy actions, the economic parameters of the investment are analysed and the risk related to it considering the uncertainty in energy markets is evaluated. A two-stage optimization approach is proposed considering the whole lifetime of the energy equipment and an uncertainty analysis performed through the evaluation of the deterministic model under Latin Hypercube Samples of uncertain parameters. A case study based on a real industry is presented, whose results expose the robustness of the optimization methodology and the acceptable risk of investing in renewable energy sources and energy equipment for prosumer purposes.

Keywords. Industry, Uncertainty Analysis, Renewable Energy, Prosumer, Net Present Value.

1. Introduction

The 4th industrial revolution that is taking place is positioning this sector as key for the achievement of a sustainable energy market through the adoption of smart energy management strategies. However, the energy use in industrial enterprises is under-researched [1], and the existing studies focus primarily on energy efficiency measures [2], not studying the possibility to adopt a prosumer behaviour. In order to support industrial entities in the inclusion of renewable energy sources to behave as prosumers, the required energy investment and equipment operation problem for them should be addressed. The energy equipment design and operation optimization problems analysed in the literature until now focus on microgrids, buildings or energy hubs to supply energy to the tertiary demand. Those studies do not reflect the investment reality in the industrial sector due to two main reasons: uncertainty is not considered or time evolution is omitted.

Most of the research done up to date do not consider the uncertainty in the input parameters [3]. This approach leads to solutions that, translated into the real world with uncertain and non-deterministic parameters, may present an outcome different from the one obtained theoretically. This output uncertainty represents a risk for investors which has to be analysed. There is, in fact, a stream of research that evaluates the uncertainty in energy-related problems. In [4], the effect of the uncertainty in inputs parameter on the cost of energy is analysed for a hybrid renewable energy system. Similarly, in [5], the system behaviour uncertainty is studied, and in [6], the impact in the design parameters on the energy performance of a building is analysed. However, none of these works considers the evolution of parameters over time, and they do not evaluate the economic suitability of the energy infrastructures designed. In order to enhance industrial actors to take energy investment decisions, it is essential to study the whole expected lifetime of the energy infrastructure and analyse the uncertainty in its economic performance.

Based on the above explanation, in this paper, the uncertainty is studied for an industrial enterprise aiming to invest in energy equipment including renewable energy sources to act as a prosumer. To do so, the following analysis, as exposed in Fig. 1, is performed:

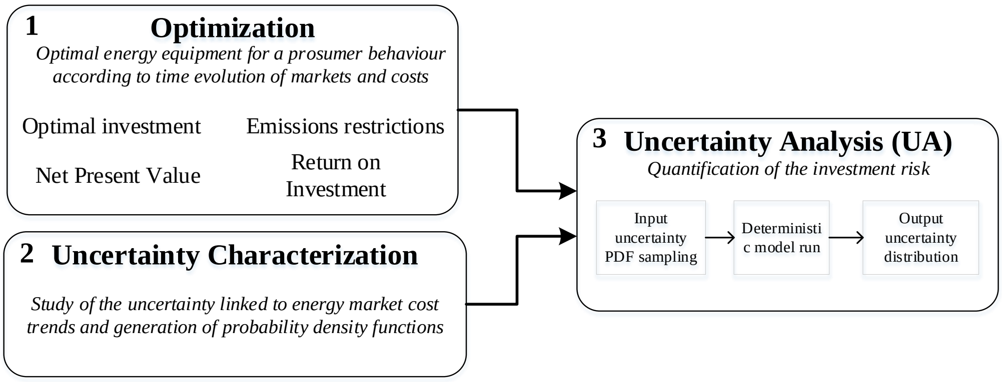

Fig. 1: Proposed methodology to assess the uncertainty in energy investment decisions

1) Design and operation optimization of the energy equipment to be installed in an industrial enterprise with prosumer behaviour considering deterministic parameters along the expected lifetime of the equipment.
2) Uncertainty characterization of the relevant input parameters.
3) Uncertainty Analysis (UA) of the energy investment Net Present Value (NPV) to quantify the risk related to the investment decision.

This paper is structured as follows. Firstly, the methodology applied to perform the optimization of the investment is presented in section 2 together with the uncertain inputs' characterization and the UA strategy. Then, in section 3, this methodology is applied to a case study reflecting the real industrial situation. The results of this case study and their discussion are exposed in section 4 and, lastly, the conclusions of the study are presented in section 5.

2. Methodology

In this section, the methodology proposed to properly optimize the energy equipment and its operation considering the whole lifetime framework and assess the relevant uncertainties linked to its performance is exposed. The general workflow for the approach presented is shown in Fig. 1. First of all, the optimization of the energy infrastructure is performed considering the input parameters as deterministic along the expected lifetime of the equipment, which is taken to be 15 years. Then, the uncertain inputs are identified and their probability distributions characterized to be able to evaluate their influence on the output. Finally, the uncertainty in the economic performance of the decision is studied through a UA.

A. Optimization of the energy equipment

Considering industrial enterprises interest, the optimization of the energy equipment aims to maximize the final economic value of the energy infrastructure to install. In order to do so, a two-stage optimization approach is presented to maximize the NPV of the investment. The two-stage optimization strategy enables to obtain the design parameters in the first stage, formed by the equipment to install and their sizes while considering their operation in the second-stage. The flowchart of the approach can be seen in Fig. 2.

First of all, information is gathered and the data required to perform the optimization along the lifetime of the equipment is computed. To capture the yearly behaviour of the plant along its lifetime with a feasible computational expense, a set of typical days are employed. According to [7,8], these days have to be distributed per season to correctly represent the different types of demands that occur along the year, being suitable the use of one day per season or one day per month. However, the industrial sector and the electricity market also present significative energy differences between week-days and weekend-days, requiring their consideration for the selection of typical days. Thus, for the problem under study, each of the years is analysed through 12 characteristic days, three per season, being two of them week-days and the other a weekend-day.

In order to obtain the NPV of the investment, it is required to obtain its benefits compared to a baseline scenario. For this reason, a linear optimization of the baseline of the enterprise, with the current existent energy infrastructure, is performed. Then, the first stage of the optimization is initialized. For the problem under study here, the Direct Search (DS) optimizer is employed due to its capability to globally search the optimal value in an efficient manner for a limited set of variables with clearly defined boundaries. DS selects a set of candidates, which are evaluated in the second stage and their NPV computed. In the second stage, the operation of the energy infrastructure selected as candidates is evaluated for the whole lifetime through a Linear Programming (LP) approach, assuring the achievement of minimal costs. The restrictions regarding emissions and payback are verified and, if accomplished, the NPV of the investment is computed comparing the operation of the upgraded plant with that of the baseline. This procedure is repeated until the first-stage optimizer reaches an optimal value.

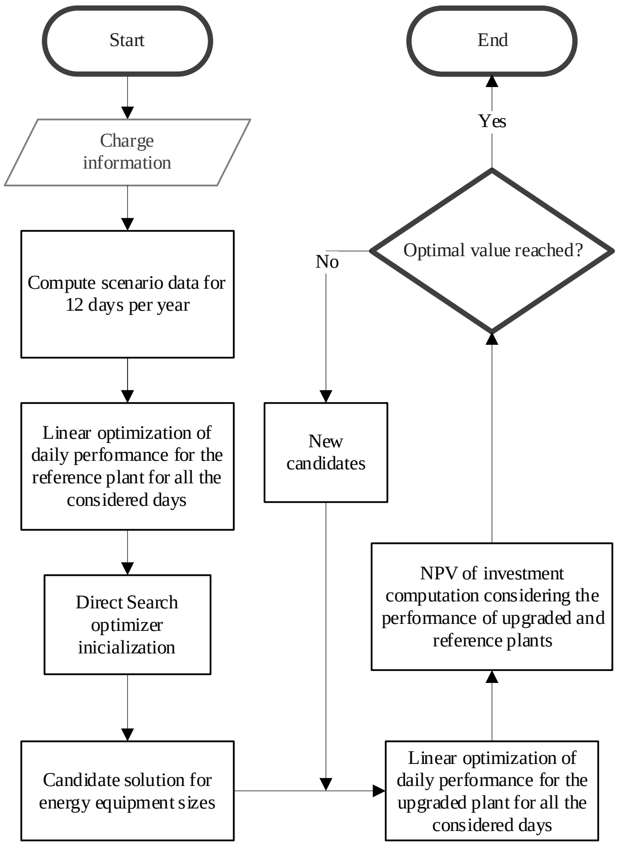

Fig. 2: Flowchart for the energy design optimization

B. Uncertainty characterization

The energy infrastructure of the industry as a prosumer has a performance linked to the costs of the energy carriers. As the energy transition will affect the energy markets and the cost of energy is forecasted to grow continuously in upcoming years, although at different rates depending on the forecasting approach adopted [9], it is essential to study how this evolution and its uncertainty affect the result of the investment performed by the industry.

These uncertain parameters are considered by assigning a Probability Distribution Function (PDF) to each of them, which enables the application of methods that consider the probability of the occurrence of scenarios and provides robust results [10]. According to [9,11,12], the cost of electricity is forecasted to increase between 25% and 110% by 2035; while the cost of gas is forecasted to increase between 11% and 33% [9,13]. These yearly percentage values are transformed into PDF fitting possible distribution functions and selecting the most suitable ones as evaluated by the likelihood function. The resultant distributions functions are exposed in Table I.

Table I: PDF of the studied uncertain inputs

Uncertain parameter	PDF
Electricity price yearly percentage increase	Nakagami (μ=0.885; ω=10.14)
Gas price yearly percentage increase	Weibull (λ=1.44; *k*=3,11)

C. Uncertainty Analysis

Once the optimal design and operation of the plant is obtained and the uncertainty in the inputs is characterized, it is possible to perform a UA to evaluate the uncertainty in the output of the system which, in this case, is the NPV of the investment.

A UA method that considers the PDFs of inputs to obtain the distribution in the output through sampling and repeatedly evaluating the deterministic model is a suitable strategy that provides robust results [14]. In this case, and given the complexity of the system, a quasi-random sampling strategy is selected. This type of strategy improves the performance of commonly used techniques such as Monte Carlo [15], which requires a high computational effort. In this paper, the Latin Hypercube Sampling (LHS) technique is used [16]. LHS is a probabilistic technique that obtains samples by dividing the PDF into N intervals with equal probability and choosing randomly one sample per interval. Combining randomly the different samples, N scenarios are generated which are used to run N times the deterministic model, enabling to capture the uncertainty in the output.

3. Case study

A case study is developed based on a real manufacturing industrial plant with total electrical and thermal consumptions of 679,240 MWh and 1,127,600 MWh, respectively. The initial infrastructure of the plant consists of a boiler to transform natural gas into thermal energy, while the electrical demand is directly met with energy purchased at the utility grid. The enterprise is considering the possibility to install a PV system as well as cogeneration and energy storages. To account for the deterioration of the PV system along its expected lifetime, an efficiency loss of 0.8% per year has been considered [17]. The capital cost and the levelized cost of energy (LCOE) including operation and maintenance costs employed in the optimization process for each of the evaluated technologies can be seen in Table II.

Table II: Cost of energy equipment

Equipment	Capital cost	LCOE
PV system	950 €/kW	0.07 €/kWh
CHP	3,400 €/kW$_e$	0.042 €/kWh
Electrochemical energy storage	430 €/kWh	0.06 €/kWh

The constraints considered by the studied enterprise regarding the investment and its performance are exposed in Table III.

Table III: Applicable constraints for the case study

Constraint	Value for the case study
Maximum investment	1,000,000€
Maximum area for the installation of PV	12,000m^2

4. Results and discussion

A. *Deterministic optimization*

The optimal energy infrastructure to install is exposed in Table IV. The PV system is chosen to cover all the available space and the cogeneration is sized to optimally fulfil demand and interact with the utility grid obtaining the maximum profit. It can be seen that although there was the possibility to include energy storage, this has not been selected due to its high cost compared with the possible revenue obtained by trading its energy with the utility grid. The decision to upgrade the energy infrastructure with this equipment supposes an investment of 913,630€ with a payback period of 5 years and an NPV at the end of the lifetime of the equipment of 6,788,400 €.

Table IV: Optimal energy equipment to install in the industrial case study

Energy equipment selected	Size
PA Area	12,000m^2
Cogeneration	200We

The prosumer behaviour of the plant for a typical autumn week-day and a typical autumn weekend-day can be seen in Fig. 3 and Fig. 4, where the energy exchange with the utility grid is exposed in front of the energy cost at the wholesale market and the internal electrical demand. It is possible to see that, due to the existence of a renewable energy source, surplus energy can be injected into the utility grid when the cost is high while still fulfilling internal demand. Also, and due to the difference in costs between the electrical and gas energy carriers, the inclusion of a cogeneration system is favourable to support fulfilling electrical demand and thus not purchasing it directly from the electrical grid at high costs.

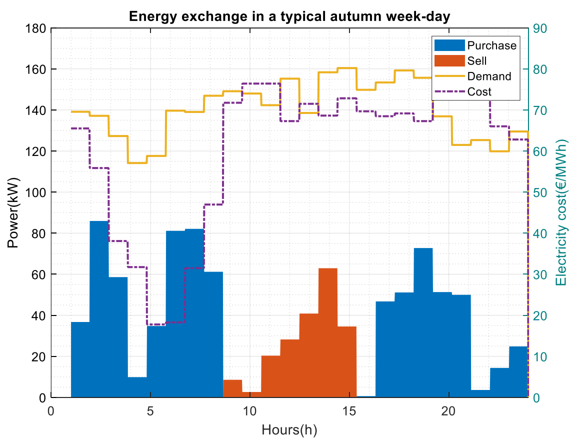

Fig. 3: Prosumer energy exchange for an autumn weekday

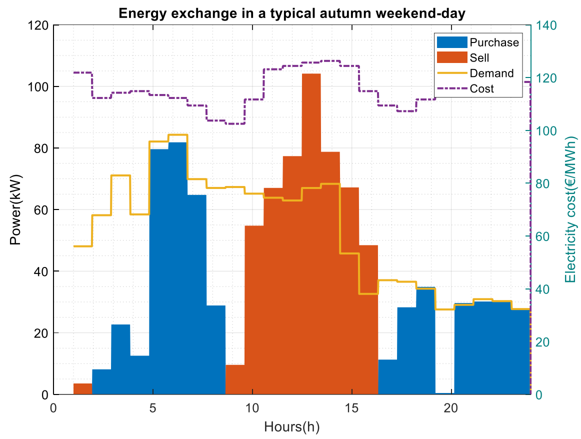

Fig. 4: Prosumer energy exchange for an autumn weekend

B. *Uncertainty Analysis*

Once the deterministic behaviour is obtained, in this section the results for the UA are exposed to evaluate the risk of performing the energy investment and the optimal operation selected in the previous stage. To perform the UA, the PDFs of the electricity and gas costs are sampled for each of the years to obtain realistic time evolution scenarios. A total number of 1000 is generated, which is a suitable value to obtain an accurate and representative result [6]. These samples are then randomly combined between them, creating the scenarios analysed, which are employed to repeatedly run the deterministic plant model, obtaining the final NPV distribution, which is exposed in Fig. 5.

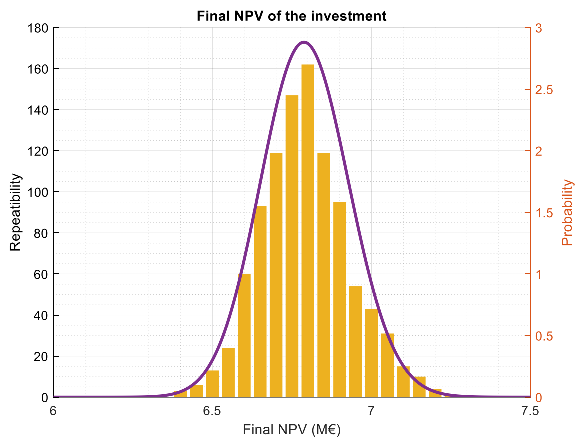

Fig. 5: Probability distribution of the NPV according to inputs' uncertainties

In this figure, it is possible to appreciate the repeatability of the obtained NPV as well as the PDF that best fits the data, which in this case is an Inverse Gaussian with parameters (μ=6.792; λ=16,324). The standard deviation of the NPV is 138,500 €, which means that it is probable to have a final NPV 138,500 € lower or higher than the obtained in a deterministic manner due to the uncertainties in the energy markets. Although the standard deviation is by itself a considerable amount, the final deterministic NPV is 6,788,400 €, meaning that this value can vary due to the uncertainty present in the energy markets a 2%.

These results clarify the impact of energy market uncertainties in energy investment. With the obtained values in this case study, it is shown that despite the expected variations in the cost of energy carriers, the economic value for energy infrastructures adopting a prosumer behaviour is robust and the risk can be acceptable by enterprises.

5. Conclusions

The economic benefits of including renewable energy sources and new transformer equipment to adopt prosumer behaviour have been analysed in this paper. A workflow to study the energy investment characteristics and their uncertainties has been presented, including the optimal design and operation, the characterization of uncertainties of energy carrier prices, and the Uncertainty Analysis, performed through repeatedly evaluating the model under the uncertain scenarios obtained through Latin Hypercube Sampling. This methodology has been applied to a case study that represents a typical industry with electrical and thermal demand and the capability to install a PV system and transformer and storage equipment. For this case study, it is optimal to install the PV system in all the available space and incorporate a cogeneration system to link the electrical and thermal sides of the industry. The Net Present Value (NPV) of the investment multiplies by more than 7 the initial investment required and the payback period is of 5 years, making energy infrastructure upgrading an interesting option for industrial enterprises. This energy investment decision has been analysed under the uncertainty present in the energy markets, represented by the increase in the cost of energy carriers. With current uncertain values, the expectable NPV of the investment varies 2 % concerning its deterministic value, showing the robustness of the optimization procedure. These results are of high utility for the industrial sector, enhancing them to perform energy actions and providing a framework for industrial enterprises to evaluate their energy investment decisions.

Acknowledgement

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5.5. Risk assessment of energy investment in the industrial framework – Uncertainty and Sensitivity analysis for energy design and operation optimisation

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Publication framework:

This article exposes the complete risk assessment methodology to evaluate the risk in energy investments and its sources. Uncertainty characterization is carried out, evaluating the uncertainty in the current values of parameters as well as their evolution. UA is done employing the LHS method on inputs' PDF and a two-stage SA based on the Morris and Sobol methods is applied to identify the most influencing inputs.

Main contributions:

- Optimization of energy investments considering equipment operation over its lifetime which evaluates the production and energy market weekly cost cycles, hourly operation, and economic, environmental and social implications.
- Continuous probabilistic uncertainty characterization of optimization's inputs over the expected lifetime of energy equipment.
- Energy system investment uncertainty quantification for risk acknowledgement of the upgraded infrastructure over time.
- Identification of the main inputs that influence the output uncertainty in the energy investment decisions through a complete sensitivity analysis.

Key words:

Energy investment, Optimal design, Prosumer, Uncertainty Analysis, Sensitivity Analysis.

Risk assessment of energy investment in the industrial framework – Uncertainty and Sensitivity analysis for energy design and operation optimisation

Eva M. Urbano*[a], Victor Martinez-Viol[a], Konstantinos Kampouropoulos[a] and Luis Romeral[a]

[a] MCIA Research Center, Department of Electronic Engineering

Universitat Politècnica de Catalunya

Rambla de Sant Nebridi 22, 08222 Terrassa (Spain)

*Corresponding author. E-mail address: eva.maria.urbano@upc.edu

Abstract

The industry is a crucial actor towards the energy transition with the possibility to adopt new energy strategies including a prosumer model. However, industries are struggling to adopt smart energy approaches, and initiatives supporting them should be improved. To enhance industrial participation in energy transition, it is required to assess the optimal energy infrastructure considering its economic advantages and associated risks. Up to date, the literature dealing with energy sizing optimisation does not consider the time evolution of parameters or the uncertainty linked to the energy framework. The objective of this paper is to fill this literature gap by proposing a novel complete methodology to optimise the design and operation of the energy infrastructure for its lifetime while assessing its uncertainty and risk through an uncertainty analysis, as well as to identify the inputs causing it by a two-stage sensitivity analysis. This framework is applied to a case study based on a real industrial manufacturing SME. The results indicate that the proposed methodology produces robust results in front of the present uncertainties, being energy price the one that causes most of it and thus the one more attention should be paid to when evaluating energy investment decisions.

Keywords

Energy investment, Optimal design, Prosumer, Uncertainty Analysis, Sensitivity Analysis

1. Introduction

1.1. Motivation

The industry is gaining an increasingly important role in the energy sector due to its possibility to adopt smart energy management strategies that can improve their productivity while creating flexibility in the energy market. The energy consumption, energy infrastructure, and the current Industry 4.0 revolution opportunities [1] place industrial entities as new actors in the energy market fundamental for market decarbonization [2]. Among industrial enterprises, SMEs represent more than 13% of total global energy consumption and account for more than half of the energy used in the industrial and commercial sectors, although they are under-researched in terms of their energy use [3]. Some scientific publications deal with energy efficiency improvements in the SME sector such as [4], where a study is done on energy efficiency drivers for industrial SMEs, or [5], where an information platform is presented to promote the usage of energy efficiency technologies. However, these studies deal only with efficiency improvement and, following the energy transition changes. Therefore, it is required to adjust the latest trends and practices to SMEs framework [6], being the adoption of a prosumer model a key activity to incorporate in the sector.

SMEs could face the problem of having to invest in energy infrastructure due to equipment obsolesce or the existence of governmental, social and market pressures. For an industrial entity, this investment gives added value to the enterprises, supporting the achievement of their primary goal, which is its productivity. Industrial SMEs tend to select

Nomenclature

Abbreviation	Full description
General Abbreviations	
CHP	Combined Heat and Power
EE	Elementary Effect
ESS	Energy Storage System
HP	Heat Pump
JC	Job Creation
LHS	Latin Hypercube Sampling
NPV	Net Present Value
O&M	Operation and Maintenance
OAT	One-At-a-Time
PDF	Probability Density Functions
PPA	Power Purchase Agreement
PV	Photovoltaic
RES	Renewable Energy Source
ROI	Return On Investment
RTP	Real-Time Pricing
SA	Sensitivity Analysis
SME	Small-and-Medium Enterprise
UA	Uncertainty Analysis
Energy infrastructure sizing and operation parameters	
P_{PV}	Power generated by the PV system [kW]
P_{CES}	Power at which the electrochemical storage is charged [kW]
P_{DES}	Power at which the electrochemical storage is discharged [kW]
P_{ED}	Electric power used by the electric to thermal equipment [kW]
P_{UG}	Power purchased from the utility grid [kW]
P_{FI}	Power injected to the utility grid [kW]
P_{CHP}	Electric power from the cogeneration system [kW]
P_{HP}	Electrical power used by the heat pump equipment [kW]
V_{CHP}	Gas used by the cogeneration system [kW]
Q_{CHP}	Thermal power from the cogeneration system [kW]
Q_{HP}	Thermal power from the heat pump [kW]
Q_{TL}	Thermal load [kW]
V_{BOI}	Gas power used by the boiler system [kW]
Q_{BOI}	Output power from the boiler [kW]
Q_{CTS}	Power at which the thermal storage is charged [kW]
Q_{DTS}	Power at which the thermal storage is discharged [kW]
η_{PV}	Efficiency of the connexion with the PV system [%]
η_{CES}	Charge efficiency of the electrochemical storage [%]
η_{DS}	Discharge efficiency of the electrochemical storage [%]
η_{ED}	Efficiency of the connexion with the electrical demand [%]
η_{UG}	Efficiency of the connexion with the utility grid [%]
η_{CHPe}	Cogeneration electrical efficiency [%]
η_{CHPth}	Cogeneration thermal efficiency [%]
η_{HP}	Efficiency of the heat pump [%]
η_{BOI}	Efficiency of the boiler [%]
η_{CTS}	Charge efficiency of the thermal storage [%]
η_{DTS}	Discharge efficiency of the thermal storage [%]
η_{TL}	Efficiency of the connexion with the thermal load [%]
$C_{O\&M,PV}$	PV O&M costs [€/kW-year]
$C_{O\&M,ES}$	Electro-chemical ESS O&M costs [€/kW-year]
$C_{O\&M,CHP}$	CHP O&M costs [€/kW-year]
$C_{O\&M,TES}$	Thermal ESS O&M costs [€/kW-year]
$C_{O\&M,HP}$	Heat Pump O&M costs [€/kW-year]
C_{UG}	Electricity price [€/kWh]
C_G	Gas price [€/kWh]
C_{FI}	Feed-in tariff [€/kWh]
C_{GHG}	Emissions costs [€/tCO_2]
Uncertainty Analysis and Sensitivity Analysis parameters	
Δ	Morris step
E	Expected value
p	Number of levels at which the PDF is divided in the Morris method
r	Number of trajectories created for the Morris method
S_i	First-order Sobol index for parameter i
S_{Ti}	Second-order Sobol index for parameter i
μ_i^*	Morris index for parameter i
V	Variance

investments with short payback periods and favourable economic, environmental and social parameters and; once the investment has been made, the infrastructure is maintained in operation until another relevant event occurs that requires a new investment, thus exploiting the equipment for its whole lifetime [7]. When upgrading the energy infrastructure, it may be beneficial to evaluate the possibility of adopting smart energy management strategies such as a prosumer model. However, the intrinsic characteristics of industrial SMEs are not compatible with standard prosumer approaches, and specific investment selection strategies are required for them. Moreover, as exposed in the analysis performed in [8] considering investment trends in firms during the last years, entities tend to intuitively invest less if the uncertainty in the energy market increases. Therefore, as important expenses are to be performed, it is crucial to optimise not only the plant design and operation for the expected lifetime of the equipment but also to evaluate the risk of these actions according to the uncertain ranges and probabilities of the inputs. For this reason, the renovation of energy equipment has to consider the current and future feasibility of the decided energy solutions maximising the return of investment while evaluating the risk associated with the decision.

The optimisation of the energy design and sizing has been treated extensively in the literature. Many energy infrastructure and equipment sizing studies, such as [9], focus on islanded mode. Few studies consider a connection with the utility grid. This is the case of [10], where a hybrid energy system is proposed for an industrial area performing the optimisation separately for each month of the year and without analysing prosumer capabilities. Following the same line, in [11] a grid-connected photovoltaic system is sized parametrically, while in [12] an approach to select the sizes and locations of energy sources is performed with the objective to evaluate possible future energy expansions. In all the mentioned studies, the energy equipment sizing is optimised for a single year, omitting the time evolution of parameters and without calculating the value of the investment along its lifetime. Also, all input variables are treated as deterministic, not evaluating the uncertainty created by them. Overlooking the time evolution of parameters and the uncertainty can lead to a suboptimal and unexpected result, representing a risk for entities performing the investment activity. Recently, a study has been published where an optimisation model for long-term, multi-stage planning of a general decentralized multi-energy system is exposed without analysing uncertainties [13]. In this work, the optimal investment is addressed from a multi-stage point of view, distributing the investment over years and performing retrofitting. This strategy could be suitable for urban planning applicable to big governmental entities or districts where buildings are added in multiple phases but is not suitable for SMEs due to their investment characteristics. Also, despite multiple years are evaluated to perform the investment at different points in time, the considered parameters are discretized and considered constant during the year. This fact discerns from reality, as input parameters are subject to important seasonal and hourly variations [14]. This is especially true for the industrial sector, where the production is maintained constant during week-days and is diminished during weekends to perform minor activities such as adopting new plant configurations and maintenance [15], making it essential for industrial SMEs to consider continuous weekly operation to capture production and costs patterns and properly size their energy infrastructure.

To evaluate the real risk related to energy investments, it is essential to understand the value of the investment, the uncertainty in the design problem output and the inputs that cause this uncertainty or risk, which is the objective of this paper. When evaluating the optimal decision for an energy investment to be performed in an industrial SME, the complete lifetime of the energy infrastructure should be analysed considering continuous costs and production patterns. A complete Uncertainty Analysis (UA) has to be done to properly analyse the risk linked to the investment and its robustness, and Sensitivity Analysis (SA) is required to identify the parameters that cause this risk. This identification allows SMEs to decide if they put an effort on better defining the most critical factors, thus reducing the epistemic uncertainty and the investment risk; and also provides them with a framework to identify the points in time at which the investment perspectives are better due to a clearer evolution of these key parameters.

There are some studies in the literature that consider uncertainty inside the optimization problem through stochastic programming. This is the case of [16], where a two-stage stochastic recursive model is presented to design a distributed energy system under uncertainty. In this study, the first-stage decisions are computed considering discrete parameters and then all second-stage decisions possibilities are calculated and included in the optimization objective function to obtain its expected value. A different approach is exposed in [17], where an inexact optimization model for regional energy systems is developed. This methodology includes degrees of fulfilment for the uncertain constraints, which provides decision-makers with alternatives under different violation parameters. Despite the advantage of considering uncertainties in the energy optimisation problem, stochastic programming models grow very fast if there are a lot of scenarios and multiple stages to analyse, and represent a risk-neutral solution not providing risk measures [18]. Given the problem studied in this paper, where multiple years and continuously changing probability distribution functions are employed, an analysis is required previous to the application of a stochastic programming approach in order to characterize the uncertainty of the problem and the risk faced by the investor. Although it may be beneficial for the industrial SME to carry out a stochastic programming optimization if the risk is not acceptable or another objective is searched for, stochastic programming is out of the scope of this study, whose objective is to evaluate the risk of the energy investment problem and identifying the inputs that cause it.

Therefore, in this paper, a methodological framework is proposed to support SMEs in the optimisation of their energy infrastructure considering its whole lifetime together with weekly production and market operation cycles; as well as applying UA and SA.

Considering the existing structure and investment strategies of industrial SMEs as well as the current changing market structure, the proposed methodology is a novelty in the decision-making process performed by these entities.

1.2. Relevant literature discussion

Up to date, some studies have been presented where uncertainty is addressed for energy infrastructures design and operation. In most of them, the uncertainty is analysed employing uniquely a basic SA to evaluate the variation of the output of the system according to a set of selected inputs. This is the case of [19], where an energy system for rural electrification is optimised and a SA is done. In this study, the proposed SA methodology is not clear and the inputs' uncertainties studied are selected subjectively, not presenting their probability distributions. Similarly, in [20] a set of pre-defined system combinations are evaluated and their sensitivity in front of different parameters is performed, without providing details on the methodology. In [21], a hybrid system is optimized employing commercial software and a SA is done. In this case, it is mentioned that the SA is carried out changing only one parameter at a time once. This procedure is also followed in [22], where a trigeneration system is optimised considering the variation of load and energy carriers prices through analysing potential occurrence scenarios. The one-at-a-time (OAT) strategy employed in these studies, where each input parameter is modified in an isolated manner while the others remain the same, is common in the literature due to its ease of implementation and logic analysis of results. The OAT approach has also been used in [23], where the optimal design of a stand-alone hybrid energy system for a rural area is addressed. In this study, the configuration of the system is pre-stated and a SA based on scenarios is conducted to appreciate the influence of environmental policy on the total system cost. Similarly, in [24] a techno-economic analysis of a standalone hybrid energy system is carried out and a SA through OAT strategy is conducted to see the effects of costs of energy in the system economic performance, while in [25] four hybrid power system scenarios for a household application are tested and a SA is done employing three wind speeds and solar radiation possibilities. In [26], an optimisation sizing energy model considering yearly performance is presented and a SA is proposed. In contrast with other studies, in this work the SA is carried out considering 3 different scenarios combining subjectively distinct values of the uncertain inputs. In none of these works, however, the probabilities of the analysed uncertain inputs are considered. Moreover, the performed SA strategies do not provide the required insights to properly evaluate the output statistically, as they only consider a small number of scenarios and the interrelation of different energy inputs is most of the time overlooked. A slightly different approach is presented in [27], where an OAT methodology is carried out employing several samples performed on a uniform distribution, expanding the results of considering only few scenarios. However, the use of uniform distributions is a simplification of the reality, as it is common to have specific scenarios with higher probability of occurrence rather than intervals where the probability of all values is equal [28]. Therefore, the employment of uniform distributions limits the capacity of obtaining suitable insights for the investment problem faced by industrial SMEs.

Few studies with improved SA strategies have been published, such as [29], where a SA is applied for zero/low energy buildings aiming to obtain the design parameters that affect the performance. In this case, the SA is formed by a two-stage approach, using global and local methods as the first and second stage, respectively. However, in this analysis a UA is not performed and thus despite sensitivity is addressed to evaluate the inputs that most affect the performance, the output uncertainty is not known. In [30], UA and SA are both performed for the optimal design of a distributed energy system to supply energy to a tertiary demand. The objective is the minimisation of total system cost while meeting CO_2 emissions restrictions. The UA is performed using the Monte Carlo simulation while the SA consisted of a two-step global SA. Despite the existence of different market prognosis, the uncertainty linked to energy market costs is modelled as uniform, without considering the higher probability of some scenarios above others. Furthermore, in all the above studies the proposed optimisation models employ only one year as a representative time frame, simplifying the decision-making process and not evaluating the time evolution of parameters. According to [31], the fact of solving this optimisation problem using single "typical-year" approaches produces results that become suboptimal after a short time due to the changing framework where the energy systems are integrated. In the mentioned studies, the proposed inputs' probability distribution functions are static, i.e., they do not vary with time, which does not allow to evaluate the future costs probabilities and simplifies their consideration. This uncertainty handling is methodologically erroneous and does not enable to obtain a realistic framework for energy investment analysis.

Therefore, there is a gap in the literature regarding the optimisation and analysis of energy investments over time and the uncertainty linked to it which is filled in this paper to support industrial SMEs in energy investment decisions. In the following paragraphs, suitable techniques employed for uncertainty assessment in other research fields are reviewed to be able to propose the most correct methodological framework for its application in the prosumer energy investment problem of industrial SMEs.

The uncertain parameters that influence the investment decision can be characterized through different strategies, such as scenarios, numerical ranges or Probability Density Functions (PDF). The latter is more suitable for the problem presented here, as it enables the application of sophisticated methods that provide robust results [32]. To perform the UA, a method that generates samples according to these PDFs allows obtaining a reliable output for energy systems [33]. Although Monte Carlo is a commonly used statistical sampling method [34], its high computational cost suggests the employment of quasi-random sampling methods such as the Latin Hypercube Sampling (LHS), which provides results efficiently at a low computational cost [35] and has been proved to perform well in energy models [36].

Once the uncertainty in the output is known, the risk becomes more tangible for investors, although it is convenient to perform a SA to know the inputs that cause most of this uncertainty. Among other approaches, statistical global SA methods are the ones that provide the most model insights [32]. Due to the complexity of the optimisation problem and its high computational cost, a two-stage SA methodology is considered for the study here presented. The first stage aims at reducing problem dimensionality, identifying and discarding less influential inputs through a screening technique. Among the different screening techniques for energy models, the Morris method is the most suitable one as it does not require hypotheses regarding the nature of the model and thus can be applied to a wide range of problems [37]. The second stage of the SA methodology is selected to be formed by a statistical variance-based global SA method, applicable to non-monotonic and non-linear models [38]. Among the variance-based methods, the Sobol method presents robust results and allows for a suitable sample size to capture the behaviour of the problem [39]. The combination of Morris and Sobol has already been used in the literature to assess complex uncertain problems, such as in [40]; and has been proved to provide results efficiently while quantifying the sensitivity effectively.

1.3. Contributions

After analysing the literature and the most suitable tools for assessing the energy investment uncertainty, a design and operation optimisation methodology considering the lifetime of the equipment and performing a UA based on LHS and a two-stage SA formed by the Morris and Sobol methods is proposed in this paper, which is a novel framework proposed for the decision-making process of industrial SMEs. The outputs of the methodology, which is designed to suit the industrial SMEs requirements, have important implications, allowing smart energy investment decisions, providing risk awareness, and identifying hotspots related to the economic, environmental, and social activities of the enterprise. Given the current managerial system of industrial SMEs, the adoption of this methodology forms a suitable, robust and efficient framework and provides SMEs with a different point of view that enables better asset planning, resulting in a competitive advantage.

The main contributions of this work to the state of the art can be summarized as:

- Optimisation of energy investments considering equipment operation over its lifetime which evaluates the production and energy market weekly cost cycles, hourly operation, and economic, environmental and social implications. This evaluation is a novelty in the analysis of energy investments and is especially suited for industrial SMEs given their managerial, technical, and economic characteristics.
- Continuous probabilistic uncertainty characterization of optimisation's inputs over the expected lifetime of energy equipment. This uncertainty characterization improves uniform static probability distributions employed until now in the literature.
- Energy system investment uncertainty quantification for risk acknowledgement of the upgraded infrastructure over time, which supposes a novelty in the field of energy investment analysis.
- Identification of the main inputs that influence the output uncertainty in the energy investment decisions through a complete sensitivity analysis, which supposes a novelty in identifying risk sources in investment outcomes.

The paper is organized as follows. First of all, the studied problem is presented in section 2. This problem definition section includes the explanation of the methodology and techniques employed, as well as the characterization of the uncertainty in the inputs. Secondly, in section 3, the case study at which the exposed methodology is applied is shown, which is based on a real remanufacturing industrial SME.

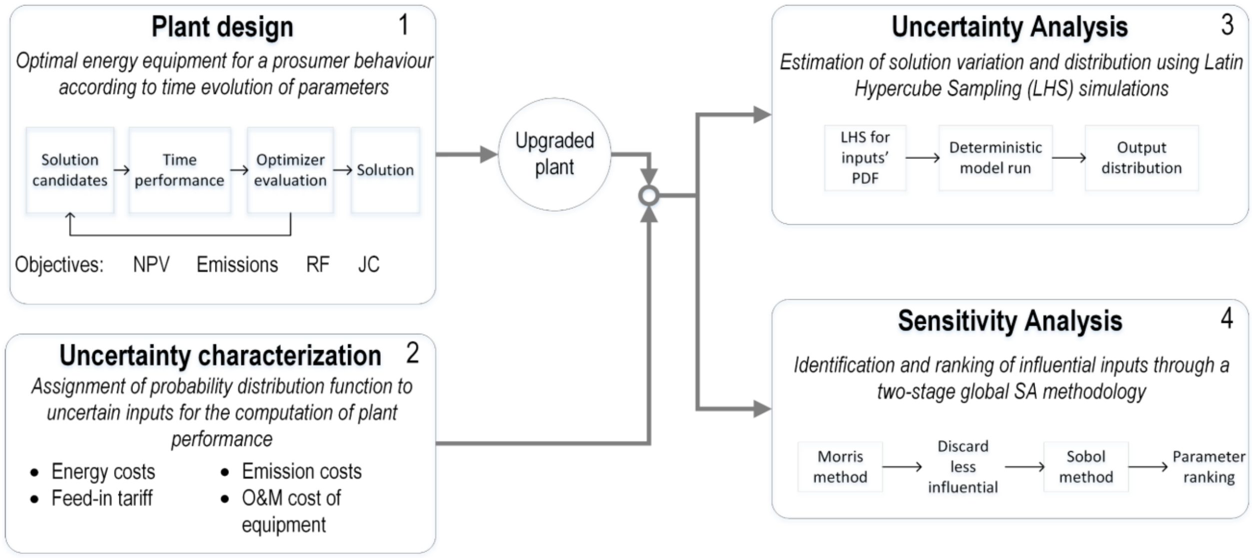

Figure 1: Workflow for investment optimisation and risk assessment

Then, the results of the optimisation, UA and SA are shown in section 4, where a discussion is also performed. Lastly, the conclusions of the study are presented in section 6.

2. Problem definition

The objectives of industrial SMEs willing to upgrade their energy infrastructure are the reduction of costs, the maximization of investment's return, the compliance with the legislation, the support to the green transition and the contribution to the progress of the local community. The methodology that is applied in this paper to properly evaluate the investment performed by SMEs in energy equipment is depicted in Figure 1, which considers the performance of the upgraded infrastructure acting as a prosumer along the lifetime of the equipment as well as the assessment of risks and the identification of key inputs causing uncertainty. The first stage of this methodology, labelled in Figure 1 as box number 1, is the deterministic optimisation of the investment to upgrade the energy infrastructure of the SME considering its benefits over time. In the literature, most studies addressing energy sizing optimisations including renewable energy sources (RES) have as unique objective economic profit maximisation or cost minimisation, such as [41], although some of them also consider environmental and social implications. From these, the most common approach is to combine economic objectives with environmental ones, including emissions either as a constraint or as an objective. This is the case of, for example, [42], where a small hybrid power system is sized minimising costs and the resultant emission factor from the generated energy. The incorporation of social criteria in these sizing studies is often overlooked due to the difficulty of their measurement [43] and the moderate implications that the resultant system has in the local community. However, the decisions taken by industrial SMEs have a great social impact since these entities are closer to the local community, both geographically and in a social proximity manner. For these reasons, it is beneficial in the long term for the SME to include social objectives in the energy investment optimisation problem.

Given the characteristics of the studied problem, economic, environmental and social criteria are included in the optimisation function to reach a solution that is not only suitable from an economic profit point of view but that also contributes to the long-term continuity of the SME and the acceptance of the solution by the society. The economic parameter is represented through the maximisation of the Net Present Value (NPV), which is a measure employed when assessing the profitability of projects in enterprises [43]. Emissions are included in the objective function for its minimisation, and the social field is considered through the incorporation of the Renewable Factor (RF) and Job Creation (JC). RF measures the amount of load covered by RES [44] and enables to evaluate local community content with the energy solution, as it is common that the community accepts energy infrastructures where renewable sources cover the load [45], whereas JC is understood as the employment generated per equipment for their installation and maintenance services [46]. Also, restrictions such as maximum Return on Investment (ROI) specified by the investor and maximum emissions allowable are considered.

This energy equipment sizing optimisation procedure performed in this first stage of the methodology provides the optimal energy equipment and capacities to install as well as their energy, economic and environmental performance. To evaluate the

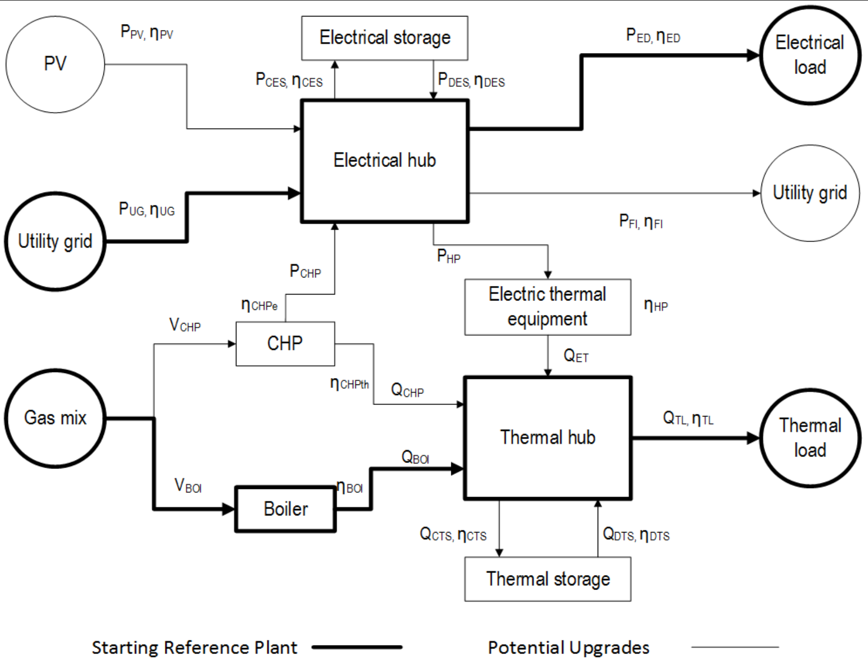

Figure 2: Energy infrastructure of a typical industrial SME and potential upgrade

risks associated with the investment and the most influential parameters, UA and SA are performed. For this, and as exposed in the second box of the methodology shown in Figure 1, the uncertainty in the input is characterized. The parameters considered as uncertain are those not under the control of the enterprise or that can change unexpectedly within some range. In this case, these are electrical energy costs, gas energy cost, selling price of electricity, emissions costs and operation and maintenance costs of equipment. With a PDF assigned to each of them and the upgraded plant model, it is possible to perform the UA and SA. The UA, which has to be carried out before the SA, uses LHS simulations to obtain input samples and repeatedly runs the deterministic plant model. Although in this methodological stage the selected energy equipment does not change, its hypothetical operation varies considering the different evolution of input parameters obtained through LHS. Thus, in the deterministic model run under the UA, the operation of the equipment is computed again for the considered inputs. With this process, the output distribution is obtained, making it possible to evaluate the robustness of the solution and the minimum expectable profit. Then, the SA is done through a two-stage global system, which enables to identify and rank the inputs that influence the most the uncertainty of the output obtained through the UA. This provides information about where efforts should be focused on when seeking additional framework data if the robustness of the solution wants to be improved.

The proposed methodological workflow is suitable for its application to industrial SMEs, with peak power ranging from dozens of kW to units of MW [47] and specific electricity and thermal consumption of 1.449 kJ/€ and 4.512kJ/€, respectively, concerning the value-added [48]. In Figure 2, the energy infrastructure of a typical SME is exposed. In bold lines, the original plant or "reference plant" existent before the investment is exposed, which purchases electricity to satisfy electrical demand and has a boiler to fulfil thermal demand. For the optimisation procedure to upgrade the energy infrastructure of the SME, the inclusion of equipment undergoing growing adoption and reducing its costs as well as equipment enabling the interconnection of the thermal and the electrical sides is considered. This equipment is formed by RES, in this case, photovoltaic (PV); electrochemical Energy Storage System (ESS), thermal ESS, Combined Heat and Power (CHP) units and electrical to thermal equipment, such as Heat Pumps (HP). In this paper, the considered lifetime of the energy upgrade is of 15 years.

In the following sections, details are provided regarding the optimisation procedure, the inputs' uncertainty characterization and the UA and SA techniques employed.

2.1. Energy sizing optimisation

The optimisation aims to select the investment to upgrade the energy infrastructure of the SME for improving its competitiveness, considering economic, environmental and social parameters as well as the adoption of a prosumer energy behaviour. A deterministic model of the plant is constructed and a two-stage procedure is applied to optimize both the energy equipment and their operation over their

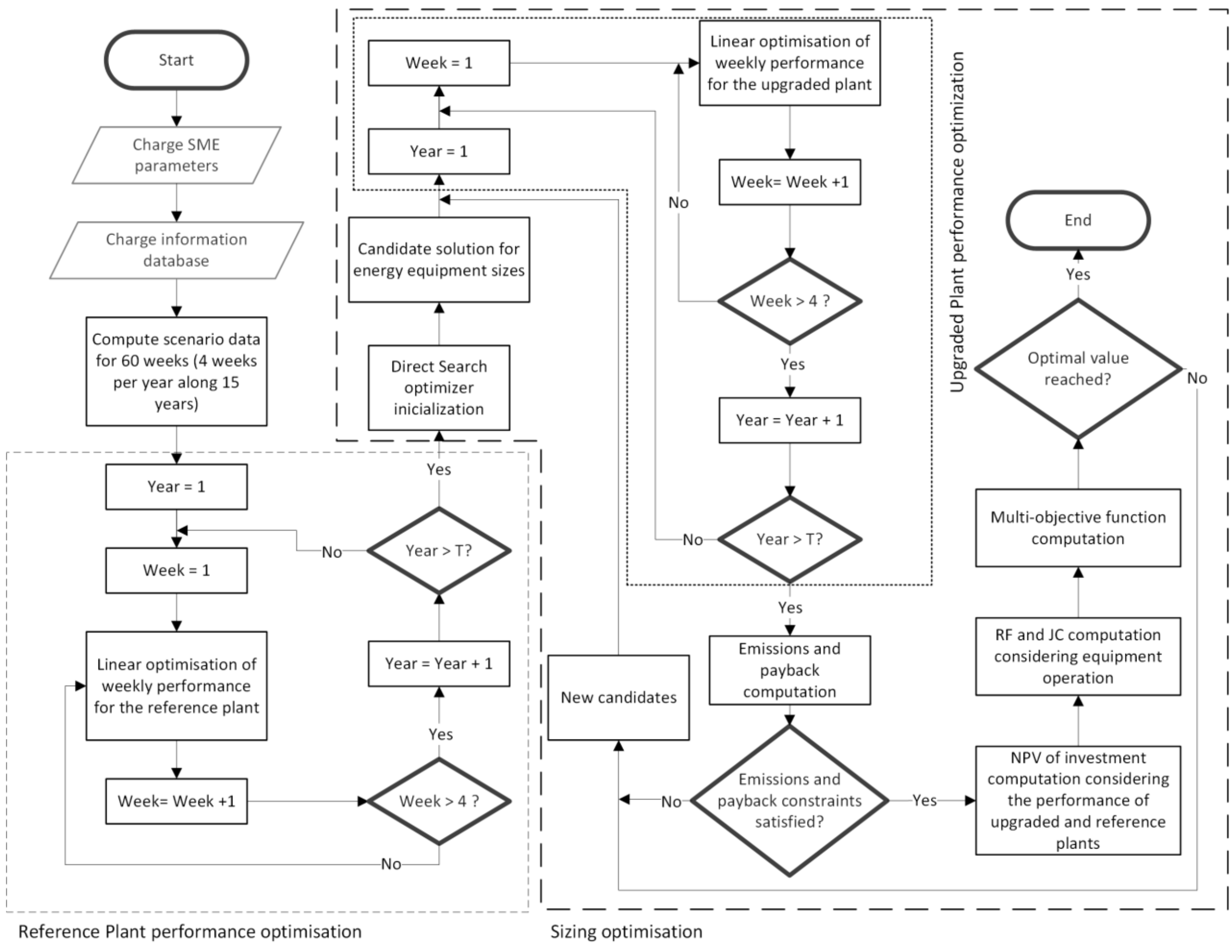

Figure 3: Flowchart of the energy sizing optimisation process

lifetime. This formulation requires the specification of two sets of constraints. On the one hand, constraints related to the design, which can include maximum equipment size, maximum emissions and maximum investment and time for ROI. On the other hand, operation constraints regarding the energy flow inside the resultant plant. These include electrical and thermal hub equilibriums, energy exchange constraints, storage constraints, and fulfilment of equipment power capacity thresholds.

The flowchart of the optimisation procedure can be seen in Figure 3. First of all, SME parameters, investment constraints, and information of RES generation, energy market and demand are obtained. Four seasonal representative weeks per year are selected along the considered time horizon, which are used to obtain the expected costs and benefits per year. Once all the information is loaded, the optimal operation of the reference or starting plant before the investment is obtained, computing the total operation cost along the optimisation horizon, i.e. 15 years. This optimisation is solved through linear programming in an hourly format minimising the weekly cost. The total operating costs along the optimisation horizon are used as the reference value for plant sizing optimisation, which is solved in the next block.

For the sizing optimisation, the operation of the energy infrastructure along time is also considered. This optimisation employs a Direct Search approach that works with a set of candidates and evaluates their suitability. The selected candidates, which are the equipment to install and their capacities, should fulfil the constraints regarding maximum investment and plant restrictions, such as maximum space available. If so, the energy flows are verified and the operation optimised. This operation optimisation is mathematically identical to that of the reference plant, although it is exposed separately in the diagram for the sake of readability. Once the operation optimisation is completed, ROI and emissions are computed and it is verified if their constraints are fulfilled. If so, the cost-benefit per year is obtained by comparing the performance of the upgraded plant with that of the reference plant and the NPV is computed. Then, bearing in mind the operation of the equipment, the RF is computed considering the total energy generated by the PV system and the load of the SME over the considered time horizon. JC is also

Uncertain parameter	Symbol	2020 PDF	2035 PDF
PV O&M costs	$C_{O\&M,PV}$	Nakagami (16,53; 43,69)	Nakagami (16,55; 21,39)
Electro-chemical ESS O&M costs	$C_{O\&M,ES}$	Weibull (9,07; 4,01)	Weibull (5,14; 3,25)
CHP O&M costs	$C_{O\&M,CHP}$	IG (36,6; 1.772)	IG (36,6; 1.772)
Thermal ESS O&M costs	$C_{O\&M,TES}$	Normal (0,26; $0{,}5^2$)	Normal (0,26; $0{,}5^2$)
Heat Pump O&M costs	$C_{O\&M,HP}$	IG (5,56; 12,36)	IG (5,56; 12,36)
Electricity price	C_{UG}	Nakagami (0,885; 10,14)	Nakagami (0,885; 10,14)
Gas price	C_G	Weibull (1,44; 3,11)	Weibull (1,44; 3,11)
Feed-in tariff	C_{FI}	U ($0{,}8C_{UG}$; $0{,}9C_{UG}$)	U ($0{,}8C_{UG}$; $0{,}9C_{UG}$)
Emissions costs	C_{GHG}	Nakagami (0,824; 20,03)	Nakagami (0,824; 20,03)

Table 1: Summary of PDFs for uncertain inputs

evaluated following the guidelines provided in [49], using the total energy generated by renewable sources and transformer equipment and the capacity of storage systems to compute the full-time jobs created over the expected lifetime of the new energy infrastructure. Once all the economic, environmental and social criteria values are obtained, they are normalised and included in a single weighted objective function. After its computation, a new set of solution candidates are created until the sizing optimizer reaches the optimal value.

This procedure enables to consider economic, energy, environmental, and social aspects in the investment and operation of the industrial plant and adjusts today's decision considering the forecasted changes in the external market over the lifetime of the equipment. For details on the mathematical formulation of the optimisation problem, please refer to Appendix A.

2.2. Uncertainty characterization

The inputs considered as deterministic in the optimisation stage are inherently uncertain. To evaluate the uncertainty of the computed NPV, it is indispensable to consider this uncertainty. In this section, these inputs are analysed and their uncertainty is evaluated and characterized. To do so, a literature search has been performed to gather the possible values for these parameters. These values are exposed in upcoming pages together with the source from which they have been obtained. Once data gathering is completed, several possible PDFs are tested on it and the one with better fit is employed to characterize its uncertainty. The goodness of the fit is evaluated through the loglikelihood function, which evaluates the joint probability distribution of the random vector resulting from the PDF to be the provided input data sample. The potential distributions considered in this paper for representing these input uncertainties are the BirnBaurn-Saunders, the exponential, the extreme value, the gamma, the generalized extreme value, the half-normal, the inverse Gaussian, the Kernel, the logistic, the log-logistic, the lognormal, the Nakagami, the normal, the Weibull, and the uniform distributions. A summary of the obtained PDFs for each of the parameters can be seen in Table 1.

2.2.1. Operation and maintenance of equipment

The distribution of the Operation and Maintenance (O&M) costs is studied for the PV system, the CHP, the electrochemical ESS, the thermal ESS and the HP system. For the same maintenance services, the O&M costs can vary due to the existence of additional services which do not affect the maintenance itself or due to external market causes. In this paper, this initial uncertainty is considered to improve the accuracy of the obtained results.

For the PV system, data collected from O&M contracts are obtained from [50]. The obtained data resembles a normal distribution with a positive skew, being the Nakagami distribution the one that shows better performance. In Figure 4, the histogram of the values and the Nakagami distribution are exposed. These values correspond to the year 2020 and are likely to decrease in upcoming years due to the growing practice and the economy of scale that the PV sector is experiencing. For this reason, PDFs are created for each year along the lifetime of the equipment, adjusting the initial distribution to the expected tendency exposed in studies [50–52], and decreasing the costs up to 30%.

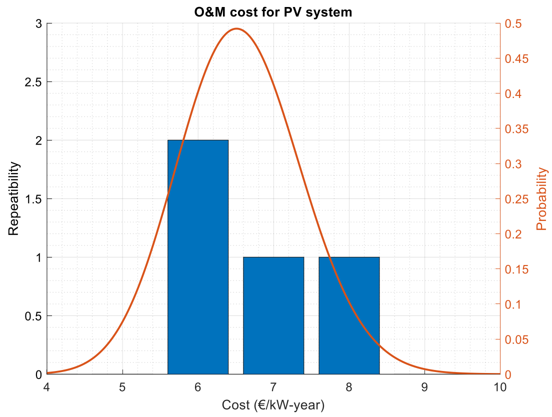

Figure 4: Histogram and PDF for the 2020 O&M cost of the PV system

Electrochemical ESSs are also undergoing technological developments that will decrease their economic costs. Despite that for power system stability and high energy capacity storage lead batteries are being used nowadays [53], there is a trend to implement more efficient technologies such as the Li-ion battery for smart energy management applications. The current O&M costs of Li-ion batteries lay around 8€/kW-year [54–56], which is forecasted to be reduced between 40% and 50% in the upcoming years [57,58]. In this case, the Weibull distribution is the most suitable, which is modified along the years according to the specified decrease range. In Figure 5, the values obtained for the O&M and the fitted PDF for 2020 is exposed.

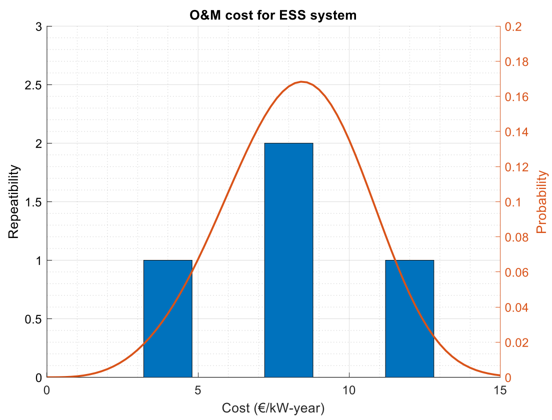

Figure 5: Histogram and PDF for the 2020 O&M cost of the electrochemical ESS

Regarding the rest of the systems, although they are still not widely included in smart grids, they have a considerable maturity level and their O&M costs are not likely to decrease in the near future [59]. Thus, their probability distribution will be kept constant along the considered time horizon. For CHP, O&M values are between 30€/kW-yr and 45€/kW-yr [60,61], and follow an Inverse Gaussian distribution, as exposed in Figure 6. In the case of the thermal ESS, sensible heat energy storage is considered due to its stability and its current use in industrial sites [62,63]. The O&M cost of these systems has a mean value of 0,26€ct/kW and a small variance [64]. This uncertainty is represented as a Normal PDF, as shown in Figure 7. HPs O&M costs range from 2,5€/kW-yr to 9€/kW-yr [14,65]. The Inverse Gaussian is the distribution function most suitable in this case. The histogram and the fitted PDF are shown in Figure 8.

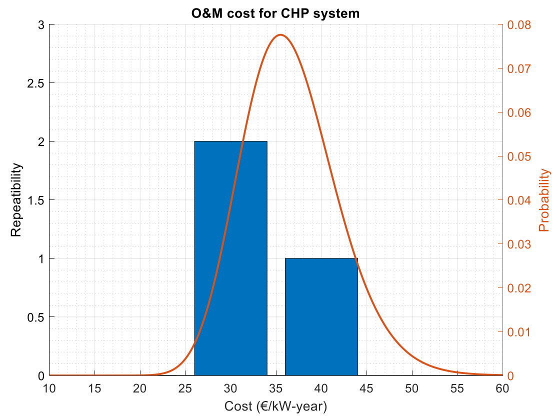

Figure 6: Histogram and PDF for the O&M cost of the CHP system

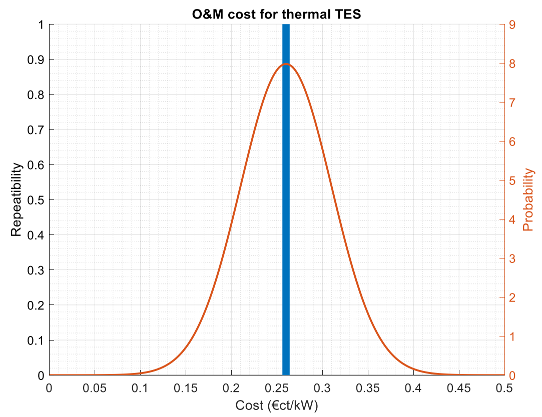

Figure 7: Histogram and PDF for the O&M cost of the thermal ESS

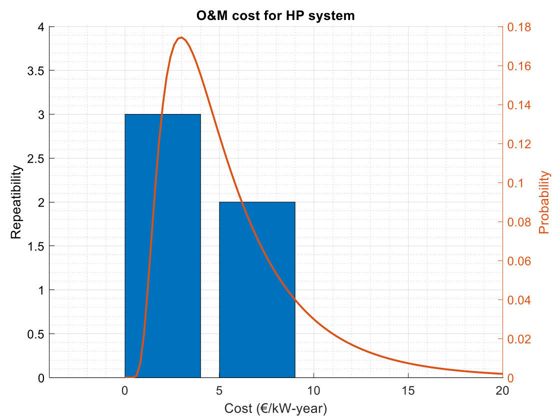

Figure 8: Histogram and PDF for the O&M costs of the HP system

2.2.2. Energy price

In this section, the uncertainty associated with the cost of electricity and gas during the lifetime of the energy equipment is evaluated.

In many countries, there are two main types of electrical tariffs: tariffs where the price is fixed and agreed with the supplier, and tariffs regulated by the energy market or governmental entities which include price variability. To enhance the employment of renewable energy sources, fixed price tariffs are increasingly reflected as power purchase agreements (PPAs) between energy consumers and renewable energy producers [66]. PPAs are performance-based contracts that aim to create a risk-controlled agreement for the purchase and sale of energy, and which typically last between 7 and 10 years. To enable the proliferation of PPAs, it is required to allocated RES at a considerable scale and therefore tendering schemes are being implemented. However, this strategy currently reduces the diversity of actors and presents a disadvantage for the participation of SMEs and private individuals in the renewable energy market [67], being big entities the ones primarily benefiting from these contracts.

In [68], it is argued that to promote a competitive inclusion of smart energy management strategies including RES, the most efficient pricing strategy would be for the electricity price to vary in real-time and reflect wholesale market dynamism market. This is also defended in [69], where electricity supply dynamic pricing is presented as a key strategy to enhance the flexibility of consumers. The energy transition is currently opening the path to the purchase of electricity following dynamic cost patterns reflecting wholesale market behaviour [70]. In fact, the European Directive 2019/944 [71] developed in the framework of the Clean Energy Package defines the "dynamic electricity price contract" as an electricity supply contract between a supplier and a final customer that reflects the price at the spot market or at the day-ahead market at intervals at least equal to the market settlement frequency. These flexible tariffs are already been implemented and have been studied in the literature, evaluating also its suitability for prosumer SMEs. In [72], an industrial SME with a PV system is analysed in which a variable price tariff of two bands per day changing in a monthly manner is applied. A dynamic price strategy is also employed in [73] to surpass the technical and economic barriers that exist for SMEs applying novel energy management strategies, and a case study based on a bakery industrial SME is developed to check its suitability. Similarly, the economic benefits of installing new energy equipment in a medium-scale facility are studied in [74]. In this case, a real-time pricing (RTP) scheme is chosen based on the energy prices at the wholesale market.

In this study, given the prosumer energy model that the industrial SME is transforming to and the ongoing green transition, as well as the impacts of the energy behaviour in the local community and environment, it is chosen to employ an RTP tariff, considering hourly changing electricity price according to the wholesale market while including the applicable taxes and levies as done in [74]. This electricity price is forecasted to increase yearly, on average, between 0,79% and 4,82% until 2035 [30,75,76]. In Figure 9, the forecasted scenarios are exposed considering an average starting price of 47,68€/MWh [14].

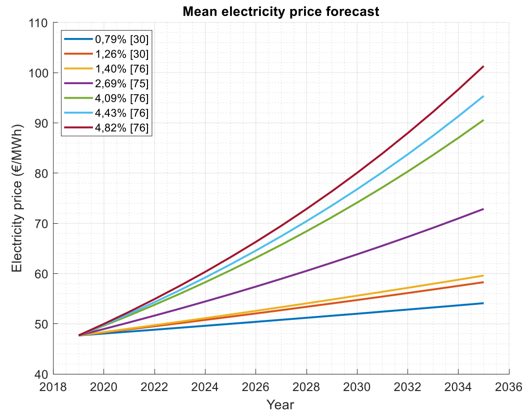

Figure 9: Electricity price forecast up to 2035

To capture the uncertainty of electricity price and obtain realistic time evolutions when sampling the PDFs, the energy price scenarios are translated into yearly percentage increases, allowing to obtain the electricity price based on previous year values. The most suitable distribution is the Nakagami one, which is exposed in Figure 10.

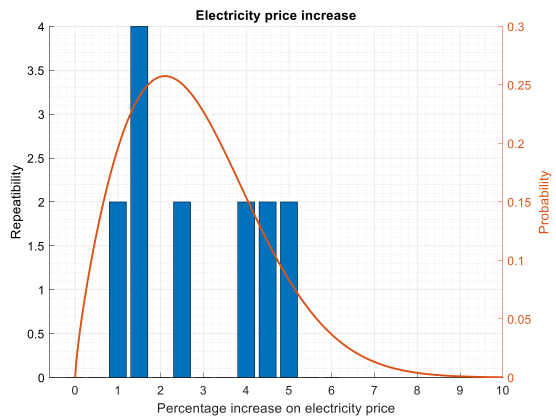

Figure 10: PDF of the electricity price increase

Regarding gas costs, tariffs do not differentiate the time of use and thus constant hourly prices are considered. The forecasting yearly increment of gas price lays between 0,65% and 1,81% until 2035 [76,77]. The forecasted scenarios, with a starting price in 2019 of 30,8€/MWh [78], are exposed in Figure 11. As with electricity, a PDF is generated based on the yearly percentage increase. The most suitable distribution is the Weibull, which is exposed in Figure 12.

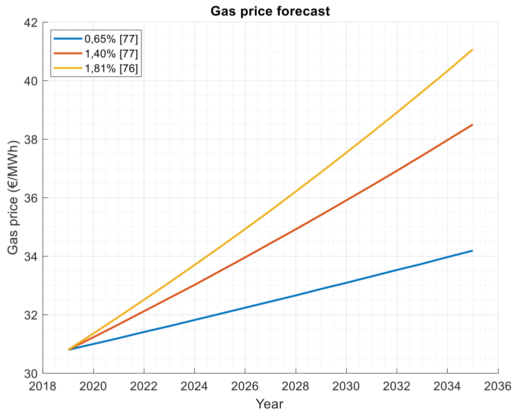

Figure 11: Gas price forecast up to 2035

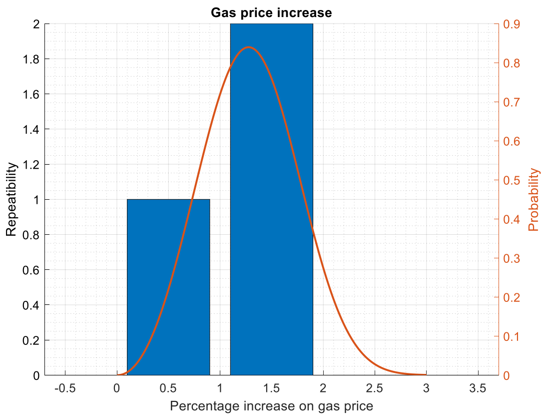

Figure 12: PDF of the gas price increase

The exposed energy costs and predictions do not consider the presence of taxes and levies. To obtain realistic final cost values, taxes of 40,7% and 20% are applied to electricity and gas price, respectively [79].

2.2.3. Feed-in tariff

When an SME faces the decision of upgrading its energy infrastructure, it may be beneficial to consider the incorporation of new business models involving an active role in the energy market. For this reason, it is crucial to consider a feed-in tariff that enables the delivery of energy to the utility grid at a specified cost. There are three types of feed-in tariffs [80]. The first type is the percentage-based, which establishes the price of the energy sold as a percentage of the energy cost at the same moment in the wholesale market. The second type are the fixed price tariffs, where the price is stated by the government and remains independent from the market, and the third type are the premium tariffs, which offer a price above the electricity price at the market at the same time. For the case studied in this paper, the most suitable approach is the employment of a feed-in tariff with dynamic prices, being these prices a percentage of the ones at the wholesale market [81]. This enhances the generation of energy at peak times and the purchase of energy at valley times, helping to decongest the electrical grid while creating a profit for the consumer. This percentage can vary due to political reasons. In this paper, the range of 80% to 90% of the wholesale market price is considered [82], modelled through a uniform distribution.

2.2.4. Emissions costs

Emissions are growing in importance due to their influence on global warming. In 2019, most countries with implemented emission trading schemes dealt with costs below 30€/ tCO_2 [83]. In this paper, the average European case is considered, with emission costs of 25€/ tCO_2 in 2019. This cost is forecasted to yearly increase as depicted in Figure 13, being the values obtained from [58,84]. This distribution is also captured by evaluating the yearly percentage increases. The Nakagami distribution is employed, which can be seen in Figure 14.

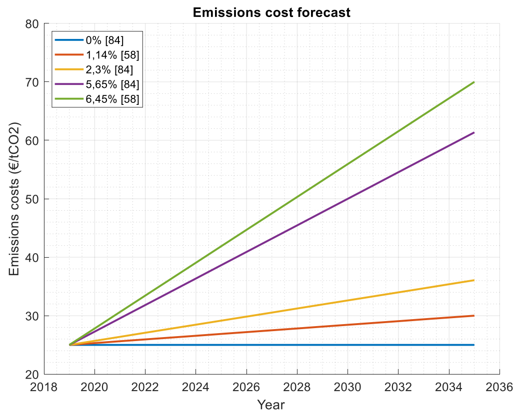

Figure 13: Emissions cost forecast up to 2035

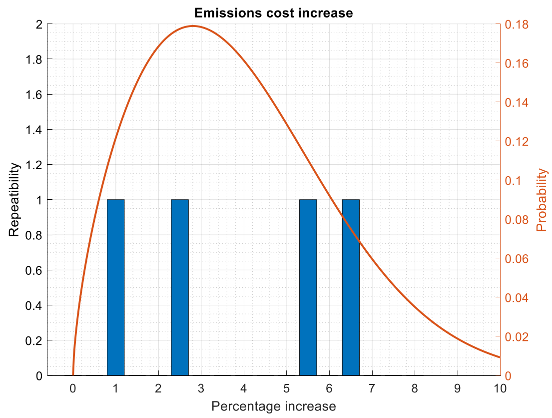

Figure 14: PDF of the emission cost at 2035

2.3. Uncertainty Analysis

In order to obtain the output distribution and the risk associated with the selected investment, a UA is performed. To do so, N samples are generated for each of the PDFs presented in the previous section using the LHS technique, a probabilistic procedure that divides the variable range into intervals with equal probability and selects one random sample within each interval. Combining randomly the samples generated, N scenarios are obtained [85]. These are introduced into the deterministic plant model, where the optimal operation of the equipment is computed considering the evaluated inputs. Then, the output is calculated for each of the scenarios, obtaining its uncertainty. In this paper, 9 uncertain inputs are evaluated. Considering their variation over the studied horizon, a total of 135 PDFs have to be sampled. For complex energy systems like this, 1000 samples per PDF is a suitable value to obtain an accurate and representative result that enables the study of the uncertainty in the output [29].

2.4. Sensitivity Analysis

With the output uncertainty obtained, it is possible to evaluate the risk of the investment decision. Once this uncertainty has been assessed, a SA is performed to identify the inputs of the system that cause most of it. A two-stage methodology is applied in this paper. In the first stage, the Morris method is used to reduce the dimensionality while, in the second stage, the Sobol method is applied to obtain the parameters ranking.

The Morris method is a global approach that can be considered as an extension of local OAT techniques which enables to discriminate the less influential inputs with a small sample size and low computational cost [86]. The uncertainty range of all the inputs is divided into p levels. Then, r base vectors are obtained from sampling one random level per uncertain input. These base vectors are recommended to be between 4 and 10 [87] and serve as the starting point for the creation of trajectories, which enable to analyse the influence of the inputs in the output. In this paper, each uncertain parameter is divided into $p = 11$ levels; and $r = 10$ trajectories are evaluated. In each trajectory, the inputs' values are increased or decreased a step Δ in a consecutive manner. The Elementary Effect (EE) of input x_i in the trajectory can be computed as:

$$EE_i = \frac{f(x_1, \ldots, x_i + \Delta, \ldots x_k) - f(x_1, \ldots, x_i, \ldots x_k)}{\Delta} \quad (1)$$

Where f represents the deterministic model. To ensure a desirable symmetric treatment of inputs [88], it is convenient to employ a value of p even and a step value of:

$$\Delta = \frac{p}{2(p-1)} \quad (2)$$

With the EE obtained, it is possible to rank parameters through the index μ_i^*:

$$\mu_i^* = \frac{1}{r}\sum_{j=1}^{r} |EE_i| \quad (3)$$

Following the procedure exposed, the total number of model evaluations is 380.

Once the less influential inputs are discarded, the Sobol method is applied, which aims to calculate two metrics per parameter named first-order Sobol index and total-order Sobol index. These metrics indicate the portion of the output variance that is explained by a parameter alone and the portion of the output variance that is explained by a parameter and its interactions with others [30].

On the one hand, the first-order index of the parameter x_i is defined as:

$$S_i = \frac{V_{x_i}\left(E_{X_{\sim i}}(Y|x_i)\right)}{V(Y)} \quad (4)$$

Where Y is the output of the system, $V(Y)$ is its total variance and $E_{X_{\sim i}}(Y|x_i)$ is the mean value of Y considering the variation of all model inputs except x_i, which remains fixed. This term is evaluated for all values of x_i, and its variance computed, which is expressed by the term V_{x_i}. On the other hand, the total-order index is defined as:

$$S_{Ti} = \frac{E_{X_{\sim i}}\left(V_{x_i}(Y|x_{\sim i})\right)}{V(Y)} \quad (5)$$

Where $V_{x_i}(Y|x_{\sim i})$ is the variance of the output over all the possible values of x_i when the rest of the inputs are fixed. This variance is computed for all the values of the inputs, which is represented by the $E_{X_{\sim i}}$ term. To compute the Sobol indices for complex energy problems considering the entire distribution of inputs, repeatedly running the model is required. To minimise the computational cost while maintaining the method robustness, the best practices exposed in [89] are employed, which are based on scenarios sampling and matrix combinations. In this paper, the number of primary scenarios created is 5.000, requiring a total number of model evaluations of 30.000. An overview of this computation strategy can be consulted in Appendix B.

3. Case study

A case study based on a real SME of the automotive sector is presented. The data to develop this case study has been obtained from a real automotive industry located in Spain. The plant considered has an annual electrical and thermal demand of 386MWh and 779MWh, respectively. The sizing study is based on four seasonal representative weeks which are exposed in Figure 15. The total operation cost of the energy infrastructure of the plant during the considered time horizon is 23.116.000€. The industrial SME is considering to perform an energy upgrade in which it would be possible to install a PV system, thermal ESS, electrochemical ESS, CHP and HP. For the energy sizing optimisation, the deterministic inputs shown in Table 2 are employed, which are the expected values of the uncertain parameters exposed section 2.2. Apart from these values, constraints imposed by the enterprise are also considered and exposed in Table 3. Moreover, information used as input can be consulted in Appendix C.

Input	2020 value	2035 value
$C_{O\&M,PV}$ (€/kW-yr)	6,56	4,70
$C_{O\&M,ES}$(€/kW-yr)	8,22	4,78
$C_{O\&M,CHP}$(€/kW-yr)	36,6	36,6
$C_{O\&M,TES}$(c€/kW-yr)	0,26	0,26
$C_{O\&M,HP}$(€/kW-yr)	5,56	5,56
C_{UG}(€/MWh)	47,68	70,0
C_G (€/MWh)	30,8	36,9
C_{FI} (€/MWh)	40,5	59,5
C_{GHG} (€/tCO_2)	25,0	42,5

Table 2: Deterministic inputs for the case study

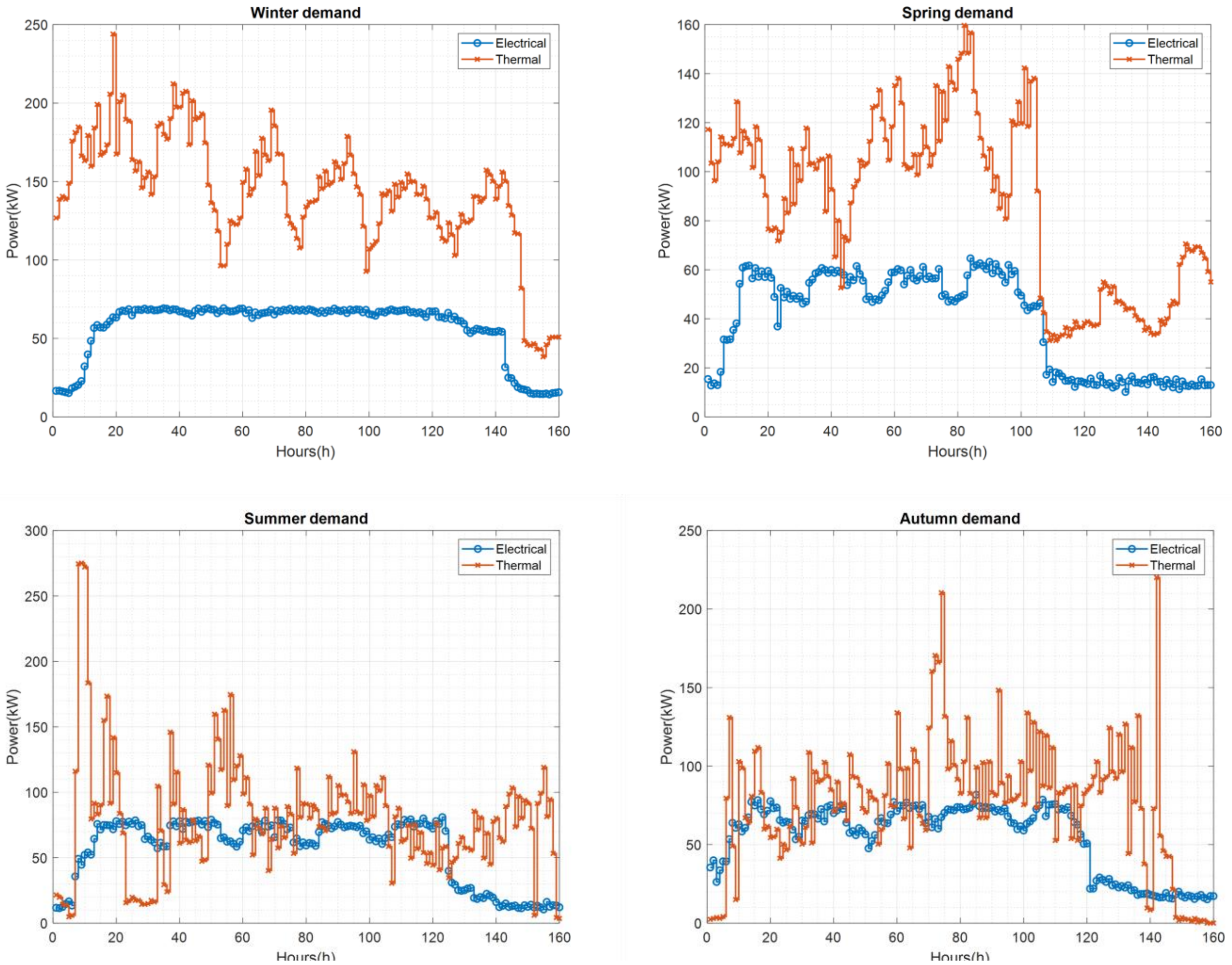

Figure 15: Electrical and thermal demands of the case study plant

Constraint	Value
Maximum investment	800.000€
Area to install PV	6.000m²
Maximum payback time	6 years
Maximum emissions at final year	300tCO_2

Table 3: Constraints specified by the enterprise

4. Results and discussion

4.1. Deterministic energy sizing

The results of the deterministic energy sizing problem can be seen in Table 4. Through the proposed strategy, the equipment to include in the upgraded energy infrastructure of the industrial SME are a PV system, a thermal ESS and a CHP system. Although electrochemical ESS and HP were also considered for installation, the characteristics of the industrial load together with the cost, social and environmental parameters of the equipment led to an optimal solution in which these are not included. In Table 4, it is possible to observe that the initial investment is quickly recovered and its value is multiplied almost by 10, reaching a final NPV of 5,078M€, which represents a 22% of the total operation cost of the initial plant, leading to a considerable energy saving and economic benefit. As the optimisation has been performed considering also environmental and social parameters, the resultant energy infrastructure represents a trade-off solution bearing in mind the different interests of the SME. Therefore, the energy investment does not only provide profit for the enterprise in economic terms but is also a good option considering the long-term strategy of the SME related to economic and social implications. It is worth mentioning that the optimal energy infrastructure found by the algorithm depends on the constraints specified by the enterprise. To exemplify this, the results of the optimisation for the same industrial plant but with a maximum investment of 400.000€ are exposed in Table 5. It can be seen that through forcing a smaller investment, the PV and the thermal storage are maintained, whereas the CHP size is reduced. This is due to the fact that PV positively affects all the criteria and the thermal storage has low costs, whereas CHP has a high capital cost and there already exist a boiler system in the industrial plant to fulfil thermal demand. Nonetheless, the installed capacity of the CHP and the thermal storage still enable an interconnection between the thermal and the electrical sides of the plant, enhancing a smart energy management strategy that improves the prosumer behaviour.

Bearing in mind the demand of the industrial plant exposed in Figure 15 and the energy infrastructure optimally obtained and shown in Table 4, the operation of the resultant energy infrastructure as a prosumer is here analysed. The operation of the selected energy equipment is exposed in Figure 16 for the summer week and in Figure 17 for the winter week, both corresponding to the final evaluation year. It can be seen that, in the summer season, as thermal demand is generally lower than in winter season, the boiler system is used only as back-up for peak-power moments and the thermal ESS is employed to store excess thermal energy from the CHP system. In contrast, in the winter season the boiler has a more active role and thermal storage is rarely used as almost all power is employed to cover demand.

Parameter	Value
Initial investment	400.000€
PV Area	6.000m²
Thermal Storage Size	480kWh
Cogeneration Size	64kWe
NPV	4.964.400 €
Payback time	4 years
Emissions at the final year	210tCO_2
RF on electrical load	0,29
Job Creation	4,43 full-time jobs

Table 4: Optimisation results considering different economic constraints

Parameter	Value
Initial investment	530.920€
PV Area	6.000m²
Thermal Storage Size	465kWh
Cogeneration Size	123kWe
NPV	5.078.900 €
Payback time	4 years
Emissions at the final year	210tCO_2
RF on electrical load	0,43
Job Creation	5,34 full-time jobs

Table 5: Results of the deterministic optimisation

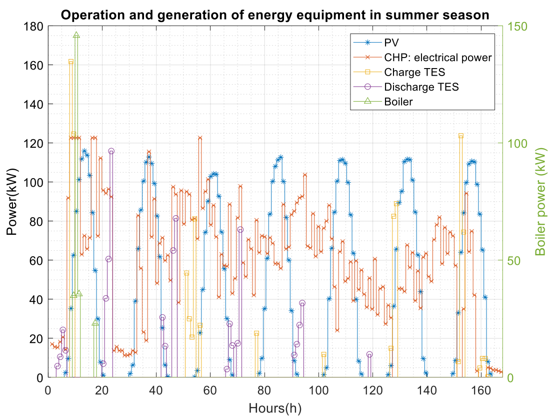

Figure 16: Power operation and generation of the energy equipment selected for the summer week.

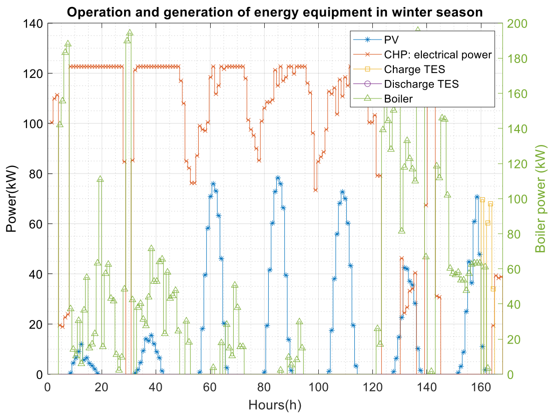

Figure 17: Power operation and generation of the energy equipment selected for the winter week.

With this operation, the total energy generated and consumed in the electrical and thermal sides for summer and winter weeks are exposed in Figure 18, Figure 19, Figure 22 and Figure 23. In these figures it appears that the electrical demand is covered through a combination of the CHP and the PV system in both seasons, and that excess electrical energy is present in the system. For the thermal side, it is possible to appreciate that, in summer, almost all demand power is covered by the CHP system while in the winter, the CHP works most of the time at near maximum capacity and the boiler is employed to completely fulfil demand requirements.

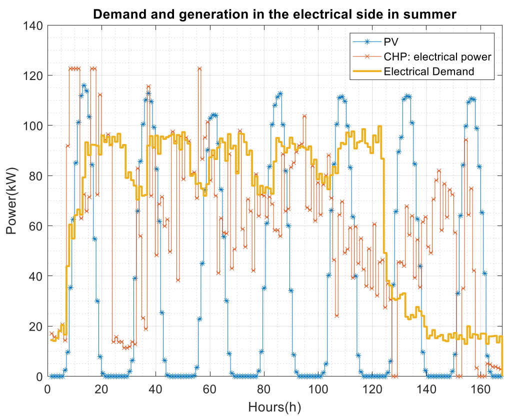

Figure 18: Electrical demand and generation for the summer week.

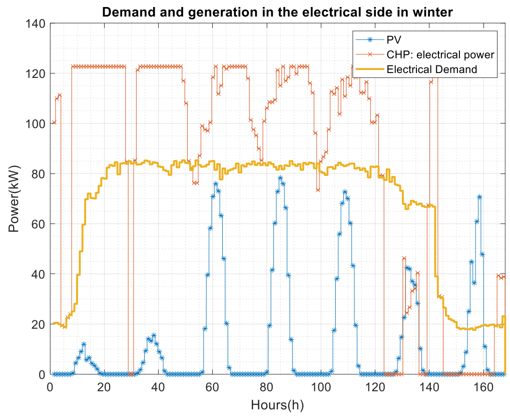

Figure 19: Electrical demand and generation for the winter week

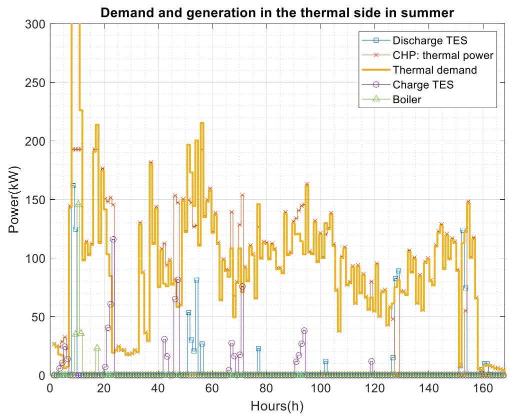

Figure 20: Thermal demand and generation for the summer week

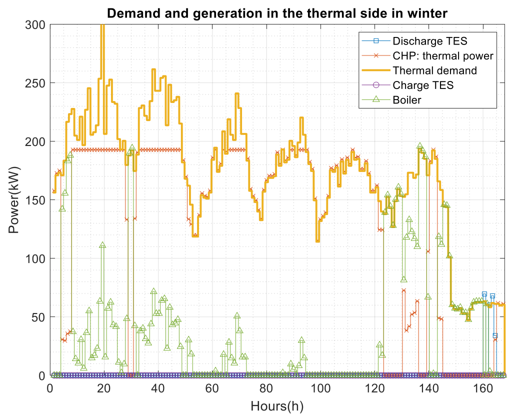

Figure 21: Thermal demand and generation for the winter week

The exposed energy equipment behaviour has been computed considering a prosumer model. The obtained energy exchange is shown for the two analysed seasons in Figure 22 and Figure 23. For the summer case, a combination of CHP, PV and electricity bought at low prices is employed to fulfil electrical demand. When the electricity price for feed-in is high, electrical energy coming from both the PV and the CHP is injected into the utility grid. This happens for example at hour 10. The decision of employing CHP electrical power to fulfil electrical demand and also to sell it to the utility grid is a consequence of the difference between energy carriers costs. Most of the time, the added cost of gas and emissions is lower than the cost of electricity making it profitable to burn gas and employ the electrical energy coming from the CHP to fulfil electrical demand and to sell it to the utility grid. As the thermal demand is considerably higher than the electrical demand, the CHP thermal power, linked to the CHP electrical power, is directly used to cover internal thermal load. If the desired CHP electrical operation and corresponding CHP thermal production exceed the required thermal power, thermal storage enters into action and absorbs the surpluses of thermal power to provide it at later times where thermal demand is higher. An example of this performance can be seen at hour 45, when the electricity price is high, electrical demand is also high, but PV generation is low. To reduce the electricity purchased from the utility grid, electrical demand from the CHP system is used. However, thermal demand is relatively low and thus more thermal power is generated than used. For this reason, the thermal ESS stores this surplus and delivers it later, in hour 55, where there is a small peak of thermal power. Where important thermal power peak occurs in this season, the boiler is also employed.

In the winter season, the thermal demand is higher than in summer and the electrical demand is more stable and lower. For this reason, the CHP operates most working hours at maximum capacity. In this case, the boiler takes a more active role, as it is employed to support the CHP in meeting thermal demand. Regarding the electrical demand, it is fulfilled by the energy generated from the CHP and the PV system, minimising the energy purchase and selling the surpluses. In case of electricity costs being remarkably low, as happens on weekend days, the operation regime of the CHP is lowered down and electricity is purchased and employed to fulfil electrical demand, using the boilers to meet the thermal demand at that moment.

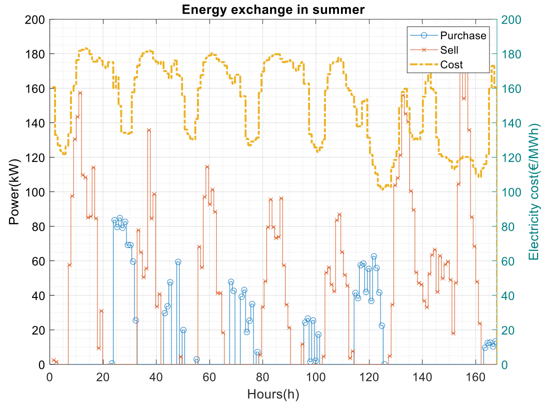

Figure 22: Exchange of energy with the utility grid for the summer week.

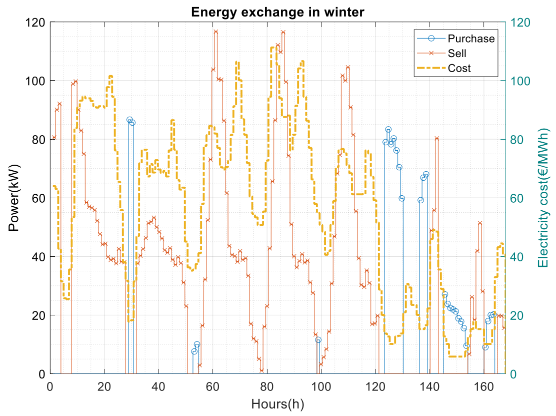

Figure 23: Exchange of energy with the utility grid for the winter week.

4.2. Uncertainty Analysis

The results of the UA showing the evolution of the uncertainty of the NPV are exposed in Figure 24 while the final NPV uncertainty is shown in Figure 25 together with the fitted PDF, which in this case is an inverse Gaussian with parameters (5,08; 8.869). The mean final value is 5.082.200€, slightly higher than the obtained in the deterministic case due to the change in equipment operation. It can be seen that the uncertainty on the value of the investment increases with time following the same pattern as the exposed by the uncertainty in prices related to energy and emissions. For its final value, the NPV presents a standard deviation of 121.700€, which means that there is a 68% chance that the final realized value lays around 2,4% of the mean value and a 95% of probabilities that the final realized value lays around 4,8% of the mean value. These results expose that, despite the uncertainty existent in the input parameters, the proposed optimisation methodology provides robust results which creates a benefit for the industrial enterprise with an acceptable risk level.

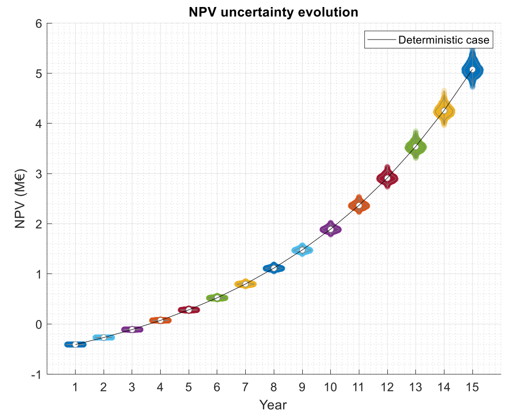

Figure 24: Uncertainty evolution of NPV along the lifetime of the energy equipment.

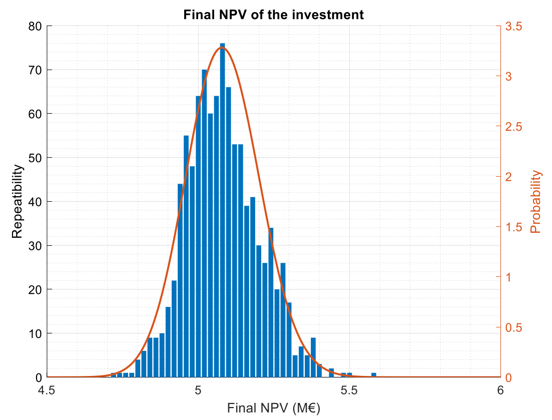

Figure 25: Final NPV uncertainty and fitted PDF.

4.3. Sensitivity Analysis

4.3.1. First stage: Morris method

As the objective of this first stage is to discard the less influential inputs, all the inputs exposed in section 2.2 are considered. The results of the Morris SA are exposed in Figure 26.

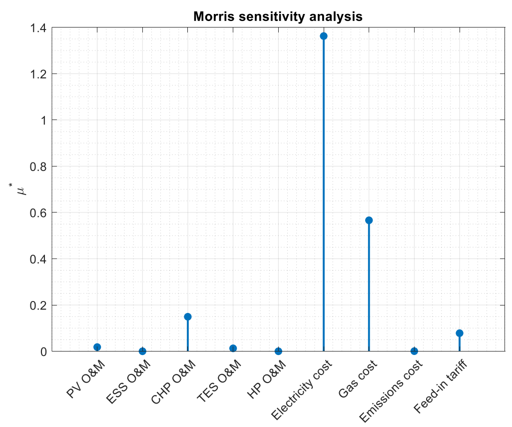

Figure 26: Morris SA results.

It can be seen that five parameters have almost no influence on the output uncertainty, which endorse the methodology employed to perform this evaluation as they can be clearly identified and erased from further analysis. The O&M cost of the PV, ESS, TES and HP systems can be considered as deterministic as they are inconsequential in terms of output variance. The results also expose that emissions costs have a negligible influence. By eliminating the mentioned O&M costs and the cost of emissions at this point of the evaluation, the computational effort in the second stage of the SA is reduced 54% while maintaining the uncertain information intact.

4.3.2. Second stage: Sobol method

The results of the Sobol analysis are exposed in Figure 27, in which the y-axis is presented on a logarithmic scale.

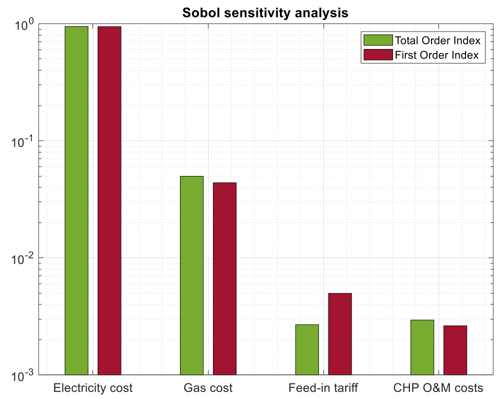

Figure 27: Sobol SA parameter ranking results.

It can be observed that the input that has the main influence in the final NPV uncertainty is the cost of electrical energy, being the influence of the cost of gas more than 10 times lower, and the influence of the feed-in tariff and the O&M costs negligible.

The dependence of the performance of energy equipment on energy prices was also exposed in [30], where the sensitivity of the single-year economic performance of an energy system was studied and gas price was presented as primary uncertainty factor. Being the cost of energy carriers the inputs that cause most of the uncertainty, it is here shown that the demand profile together with the framework and boundary conditions applied determine which of them has a predominant role. Apart from claiming the importance of the energy price in the investment uncertainty, the results obtained here also justify mathematically the firms' investment tendencies found in [8], in which it was appreciated through a statistical analysis based on historical information, that enterprises tend to invest less if the uncertainty in the energy market increases.

5. Conclusions

This paper presents a novel methodology to optimise the investment in energy equipment for prosumer industrial SMEs. It considers SMEs' operation along time and assesses the risk this action supposes together with the inputs that influence it the most to support SMEs in taking energy investment actions. The proposed methodology includes a design and operation optimisation evaluating the expected lifetime of the investment, as well as production and market weekly cost cycles. The optimisation procedure enables to compute the net present value of the investment as well as the environmental and social implications that the upgraded energy infrastructure has, providing industrial SMEs with the solution that best suits their interests. The risk linked to this energy investment is also evaluated to enrich the investment procedure typically followed by SMEs due to their managerial and financial characteristics. Considering the time characteristics of the investment and the existent market prognosis, continuous probability density functions of input parameters are employed to characterize the uncertain framework at which the industrial SME operates. To compute the investment risk, the upgraded energy infrastructure is analysed under uncertain scenarios through an Uncertainty Analysis (UA). This UA enables to obtain the statistical final expected value of the investment as well as its deviation, exposing the probability of the outcome to be within a certain range and thus the risk that the enterprise is facing. A Sensitivity Analysis (SA) is also performed to provide industrial SMEs with information regarding the inputs that influence the most the risks of the investment, being possible for them to better define these inputs and thus reduce the risk. A case study has been developed in which it is possible to appreciate the economic, social and environmental benefits of enterprises upgrading their energy infrastructure and adopting a prosumer model. The proposed methodology provides robust results and a risk analysis that allows a more informed investment by industrial SMEs. The results exposed in this paper are of high utility for industrial entities when upgrading their energy infrastructure, exposing their suitability to adopt a prosumer behaviour and providing a framework to further support their energy investment decision making process.

Acknowledgements

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Appendix A. Energy optimisation problem formulation

A.I Reference Plant performance optimisation

- Constraints:
  - Electrical hub equilibrium:

$$P_{UG,ref}\eta_{UG} = \frac{P_{EL}}{\eta_{EL}} \quad (6)$$

Where $P_{UG,ref}$ is the energy purchased by the reference plant, P_{EL} the power required by the electrical demand and η_{UG} and η_{EL} the efficiencies of connexion with the utility grid and the demand.

  - Thermal hub equilibrium

$$V_{BOI,ref}\eta_{BOI} = Q_{BOI,ref} = \frac{Q_{TL}}{\eta_{TL}} \quad (7)$$

Where $V_{BOI,ref}$ is the gas consumption by the boiler at the reference plant, $Q_{BOI,ref}$ the heat produced by the boiler, Q_{TL} the thermal demand, η_{BOI} the boiler efficiency and η_{TL} the connexion efficiency with the thermal demand.

  - Energy exchange:

$$0 \leq P_{UG,ref} \leq E_{max} \quad (8)$$

$$0 \leq V_{BOI,ref} \leq V_{gmax} \quad (9)$$

$$0 \leq Q_{BOI,ref} \leq Q_{BOI,max} \quad (10)$$

Where E_{max}, V_{gmax} and $Q_{BOI,max}$ are the maximum power thresholds in the utility grid, gas grid and also in the boiler.

- Objective function:

$$f_{weekly,ref} = \sum_{j=1}^{N} P_{UG,ref,j}C_{UG,i,j} + Q_{BOI,ref,j}C_{BOI} + V_{BOI,ref,j}(C_{G,i} + F_{gGHG}C_{GHG,i}) \tag{11}$$

Where j represents the hour considered and i the year under evaluation. This computation is performed for the different weeks along the yeas of the optimisation horizon. C_{UG} is the cost to purchase energy from the utility grid, C_{BOI} is the cost for using the boiler, C_G is the cost to purchase gas, F_{gGHG} is the emission factor of the purchased gas and C_{GHG} the cost of emissions.

A.II Upgraded Plant performance optimisation

- Constraints:
  - Electrical hub equilibrium:

$$P_{PV}\eta_{PV} + P_{UG}\eta_{UG} + P_{CHP} + P_{DES}\eta_{DES} = \frac{P_{ED}}{\eta_{ED}} + P_{FI} + \frac{P_{CES}}{\eta_{CES}} + P_{HP} \tag{12}$$

Where P_{PV}, P_{UG}, P_{CHP}, P_{DES}, P_{FI}, P_{CES} and P_{HP} are the power from the PV system, from the utility grid, from the CHP, from the electrochemical ESS, to the utility grid, to the electrochemical ESS and the HP. η_{PV}, η_{UG}, η_{DES}, η_{ED}, η_{UG} and η_{CES} are the efficiencies of the connection with the PV system, the utility grid, the efficiency for discharging the ESS, the efficiency of the connexion with the demand, the utility grid and the efficiency of charging the ESS, respectively.

  - Thermal hub equilibrium:

$$Q_{CHP} + Q_{BOI} + Q_{DTS}\eta_{DTS} + P_{HP}\eta_{HP} = \frac{Q_{TL}}{\eta_{TL}} + \frac{Q_{CTS}}{\eta_{CTS}} \tag{13}$$

Where Q_{CHP}, Q_{BOI}, Q_{DTS} and Q_{CTS} are the thermal power from the CHP, the boiler, the thermal ESS and the power to the thermal ESS. $\eta_{TL}$is the efficiency of the connexion with the thermal load and η_{DTS} and η_{CTS} are the efficiencies of discharging and charging the thermal storage.

  - Energy exchange

$$0 \le P_{UG} \le E_{max} \tag{14}$$

$$0 \le P_{UGS} \le E_{max} \tag{15}$$

$$0 \le V_{CHP} + V_{BOI} \le V_{gmax} \tag{16}$$

Where E_{max} is the maximum exchange of power with the electrical grid and V_{gmax} the maximum for the gas grid.

  - Energy storage.

The formulation is exposed for general energy storage, which is applied to both electrochemical and thermal storages.

$$0 \le P_C \le R_C \times Cap \tag{17}$$

$$0 \le P_D \le R_D \times Cap \tag{18}$$

$$E^t = E^{t-1} + \Delta t(Q_C - Q_D) - SDE^t \tag{19}$$

$$Cap_{min} \le E^t \le Cap \tag{20}$$

Where Cap is the capacity of the storage and R_C and R_D its charge and discharge ratios. E^t is the stored energy at the evaluated instant, E^{t-1} describes the energy stored in the previous instant while Δt is the time step. SD is the self-discharge ratio.

  - Power capacity of energy equipment

$$0 \le Q_{BOI} \le Q_{BOI,max} \tag{21}$$

$$0 \leq P_{CHP} \leq P_{CHP,max} \tag{22}$$

$$0 \leq Q_{HP} \leq Q_{HP,max} \tag{23}$$

Where $Q_{BOI,max}$, $P_{CHP,max}$ and $Q_{HP,max}$ are the maximum power thresholds for the boiler, the CHP and the HP.

- Objective function:

$$\begin{aligned} f_{weekly} = \sum_{j=1}^{N} & P_{PV,j}C_{PV} + P_{UG,j}C_{UG,i} + C_{ES}\left(P_{CES,j} + P_{DES,j}\right) + P_{CHP,j}C_{CHP} + P_{HP,j}C_{HP} \\ & + Q_{BOI,j}C_{BOI} + \left(V_{CHP,j} + V_{BOI,j}\right)\left(C_{G,i} + F_{gGHG}C_{GHG,i}\right) \\ & + C_{TS}\left(Q_{CTS,j} + Q_{DTS,j}\right) - P_{FI,j}C_{FI,i} \end{aligned} \tag{24}$$

Where C_{PV}, C_{ES}, C_{CHP}, C_{HP}, C_{BOI} and C_{TS} are the LCOE of the PV system, the electrochemical storage, the CHP, the HP, the boiler and the thermal storage system.

A.III Optimisation of energy equipment to install

- Constraints:
    - Equipment size:

$$A_{PV} \leq A_{PV,max} \tag{25}$$

$$\frac{C_{ES}}{\rho_{ES}} + \frac{C_{TS}}{\rho_{TS}} + \frac{P_{CHP,max}}{\rho_{CHP}} + \frac{Q_{HP,max}}{\rho_{HP}} \leq A_{int,max} \tag{26}$$

Where $A_{PV,max}$ is the maximum area for the installation of PV; ρ_{ES}, ρ_{TS}, ρ_{CHP} and ρ_{HP} are the energy and power densities of the electrochemical storage, the thermal storage, the CHP and the HP. $A_{int,max}$ is the maximum area available for the installation of internal energy equipment.

- Initial investment

$$C_0 = A_{PV}C_{0,PV} + C_{ES}C_{0,ES} + C_{TS}C_{0,TS} + P_{CHP,max}C_{0,CHP} + Q_{HP,max}C_{0,HP} \leq C_{0,max} \tag{27}$$

Where C_0 is the initial investment and $C_{0,PV}$, $C_{0,ES}$, $C_{0,TS}$, $C_{0,CHP}$ and $C_{0,HP}$ are the initial costs of the PV system, electrochemical storage, thermal storage, cogeneration and HP, respectively. $C_{0,max}$ the maximum investment limit.

- Emissions:

$$\begin{aligned} GHG_T = \frac{52}{4}\left(\sum_{k=1}^{4} GHG_{T,k}\right) = \frac{52}{4}\left(\sum_{k=1}^{4}\sum_{j=1}^{N} F_{gGHG}C_{GHG,T}\left(V_{CHPT,k,j} + V_{BOIT,k,j}\right)\right) \\ < GHG_{max,T} \end{aligned} \tag{28}$$

Where GHG_T are the total yearly greenhouse gas emissions for and $GHG_{max,T}$ the maximum emissions limit. The factor k represents the week of a year considered.

- Payback

$$PB_t \equiv \left\{ i_{PB} \middle| \left(-C_0 + \sum_{i=1}^{i_{PB}} C(i) = 0\right) \right\} \tag{29}$$

Where PB_t is the payback time and i represents the years evaluated.

- Objective: The objective function is composed by economic, environmental and social parameters included in a weighted and normalised manner.
    - Economic objective

      The economic objective is the maximisation of the Net Present Value, which is computed as:

$$NPV = -C_0 + \sum_{i=1}^{T} \frac{C_i}{(1-r)^i} \tag{30}$$

Where C_i is the cash flow, or benefits minus cost, for the period i, and r is the hurdle rate.

To obtain the NPV, the computation of costs and benefits per year is required.

- Seasonal benefit minus cost (obtained through its representative week):

$$C_{season,i=}\sum_{j=1}^{N} P_{FI,j}C_{FI,i} + \left(P_{UG,ref,j} - P_{UG,j}\right)C_{UG,i} + \left(V_{BOI,ref,j} - V_{CHP,j} - V_{BOI,j}\right)\left(C_{G,i} + F_{gGHG}C_{GHG,i}\right) \quad (31)$$

- Benefits minus cost for the year *i:*

$$C_i = \frac{52}{4}\left(C_{spring,i} + C_{summer,i} + C_{autunm,i} + C_{winter,i}\right) - \left(C_{O\&M,CHP}P_{CHP,max} + C_{O\&M,HP}Q_{HP,max} + C_{O\&M,ES}Cap_{ES} + C_{O\&M,TS}Cap_{TS} + C_{O\&M,PV}A_{PV}P_{nom}\right) \quad (32)$$

Where $C_{spring,i}$, $C_{summer,i}$, $C_{autumn,i}$ and $C_{winter,i}$ are the variable cash flow of the four representative weeks for the year i and $C_{O\&M,CHP}$, $C_{O\&M,HP}$, $C_{O\&M,ES}$, $C_{O\&M,TS}$ and $C_{O\&M,PV}$ are the yearly operation and maintenance costs per unit capacity of CHP, HP, electrochemical storage, thermal storage and PV system, respectively.

- Environmental objective
  Total emissions over the lifetime of the energy infrastructure.

$$GHG = \sum_{i=1}^{T}\frac{52}{4}\left(\sum_{k=1}^{4}\sum_{j=1}^{N} F_{gGHG}C_{GHG,i}\left(V_{CHPi,k,j} + V_{BOIi,k,j}\right)\right) \quad (33)$$

- Social objective
  The social objectives are represented by the RF and JC.
  - Renewable factor
    Ratio between the energy generated by the PV system and the total demand of the SME.

$$RF = \frac{\sum_{i=1}^{T}\sum_{k=1}^{4}\sum_{j=1}^{N} P_{PVi,k,j}}{\sum_{i=1}^{T}\sum_{k=1}^{4}\sum_{j=1}^{N}\left(P_{EDi,j,k} + Q_{TLi,j,k}\right)} \quad (34)$$

  - Job Creation
    Full-time jobs created through the upgrade of the energy infrastructure over its lifetime.

$$JC = PV_{JC}\sum_{i=1}^{T}\frac{52}{4}\sum_{k=1}^{4}\sum_{j=1}^{N} P_{PVi,k,j} + CHP_{JC}\sum_{i=1}^{T}\frac{52}{4}\sum_{k=1}^{4}\sum_{j=1}^{N} P_{CHPi,k,j} + HP_{JC}\sum_{i=1}^{T}\frac{52}{4}\sum_{k=1}^{4}\sum_{j=1}^{N} P_{HPi,k,j} + ES_{JC}C_{ES}T + TS_{JC}C_{TS}T \quad (35)$$

    Where PV_{JC}, CHP_{JC}, HP_{JC}, ES_{JC}, and TS_{JC} are the job creation for the PV, CHP, HP, ES, and TS equipment, each represented in the units exposed in Table C.1.

- Multi-objective function
  The economic, environmental and social criteria are included in a single objective function:

$$f = w_{ec}NPV^{trans} + w_{en}GHG_{trans} + w_s\left(w_{s1}RF^{trans} + w_{s2}JC^{trans}\right) \quad (36)$$

Where w_{ec}, w_{en}, and w_s are the economic, environmental and social weights respectively, and w_{s1} and w_{s2} are the weights of the renewable factor and job creation inside the social dimension. As the criteria in the optimisation function present different units, their value is normalised to remove dimensions and balance magnitude differences [90]:

$$p^{trans} = \frac{p - p^0}{p_{max} - p^0} \quad (37)$$

Where p^{trans} is the normalised parameter which lays between 0 and 1, p is the measured value and p^0 and p_{max} are the minimum and maximum value achievable, respectively.

Appendix B. Sobol indices computation strategy

Starting from two different sampling matrices ***A*** and ***B*** with rows equal to the number of simulations and columns equal to the number of considered uncertain inputs, the matrix $\boldsymbol{A}_{\boldsymbol{B}}^{(i)}$ is constructed for all factors with all the columns from ***A*** expect the *i*-th column, which is obtained from ***B.*** Then, the numerical estimators of the sensitivity indices are computed as:

$$V_{x_i}\left(E_{X_{\sim i}}(Y|x_i)\right) = \frac{1}{N}\sum_{j=1}^{N} f(\boldsymbol{B})_j\left(f\left(\boldsymbol{A}_{\boldsymbol{B}}^{(i)}\right)_j - f(\boldsymbol{A})_j\right) \tag{38}$$

$$E_{X_{\sim i}}\left(V_{x_i}(Y|x_{\sim i})\right) = \frac{1}{2N}\sum_{j=1}^{N}\left(f(\boldsymbol{A})_j - f\left(\boldsymbol{A}_{\boldsymbol{B}}^{(i)}\right)_j\right)^2 \tag{39}$$

Appendix C. Parameters employed for the optimisation

The data exposed in this section has been obtained from [49,91–98].

Parameter	Value
PV	
Initial cost	950 €/kW
LCOE	0.07 €/kWh
PV connexion efficiency	99%
Job creation	0.87 jobs/GWh
Electrochemical storage	
Initial cost	430 €/kWh
LCOE	0.06 €/kWh
Charge efficiency	94%
Discharge efficiency	94%
Charge ratio	0.5C
Discharge ratio	5C
Job creation	0.01 jobs/MWh- capacity
CHP	
Initial cost	3400 €/kWe
LCOE	0.042 €/kWeh
G2E efficiency	35%
G2T efficiency	55%
Job creation	0.31 jobs/GWh
HP	
Initial cost	700 €/kW
LCOE	0.076 €/kWh
COP	4.5
0.25	jobs/GWh
Thermal storage	
Initial cost	5 €/kWh
LCOE	0.0243 €/kWh
Charge efficiency	92%
Discharge efficiency	92%
Self-discharge	1%
Charge ratio	5C
Discharge ratio	0.25C
Job creation	0.01 jobs/MWh- capacity

Boiler	
LCOE	0.053 €/kWh
Efficiency	90%
Connexion efficiencies	99%
Objective function weights	
w_{ec}	0.65
w_{en}	0.20
w_s	0.15
ws_1	0.75
ws_2	0.25

Table C.1: Input values employed

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5.6. Energy-Investment Decision-Making for Industry: Quantitative and Qualitative Risks Integrated Analysis

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Publication framework:

This article exposes the methodology for the incorporation of quantitative and qualitative parameters and risks in the energy investment optimization problem of industrial SMEs. Quantitative parameters are addressed numerically through scenarios whereas qualitative parameters are evaluated through fuzzy logic to include in their value the vagueness existent in their subjective measurement. These parameters are incorporated in the two-stage optimization methodology, obtaining a resultant energy infrastructure that evaluates quantitative and qualitative criteria and minimizes risks.

Main contributions:

- Methodology to support industrial SMEs in the energy investment optimization problem considering relevant factors and criteria to improve their competitiveness and accounting for related risks that could affect their performance.
- Optimization of the energy investment problem including equipment options and their prosumer operation through a continuous time-optimization strategy.
- Transformation of subjective criteria represented as qualitative risks into fuzzy sets to account for judgmental vagueness.
- Evaluation of both qualitative and quantitative risks for energy investment optimization in a unique function that considers uncertainty in the value of input parameters and vagueness in the measurement of subjective criteria.

Key words:

Decision-making, Risk assessment, Uncertainty, Optimal energy design, prosumer.

Article

Energy-investment decision-making for industry: Quantitative and qualitative risks integrated analysis

Eva M Urbano [1]*, Victor Martinez-Viol[1], Konstantinos Kampouropoulos[1], Luis Romeral[1]

[1] MCIA Research Center, Department of Electronic Engineering, Universitat Politècnica de Catalunya, Rambla de Sant Nebridi 22, 08222 Terrassa (Spain); eva.maria.urbano@upc.edu; victor.martinez.viol@upc.edu; konstantinos.kampouropoulos@upc.edu; luis.romeral@upc.edu
* Correspondence: eva.maria.urbano@upc.edu

Abstract: Industrial SMEs may take the decision to invest in energy efficient equipment to reduce energy costs by replacing or upgrading their obsolete equipment or due to external socio-political and legislative pressures. When upgrading their energy equipment, it may be beneficial to consider the adoption of new energy strategies rising from the ongoing energy transition to support green transformation and decarbonisation. To face this energy-investment decision-making problem, a set of different criteria such as economic and environmental have to be evaluated together with their associated risks. Although energy-investment problems have been treated in the literature, the incorporation of both quantitative and qualitative risks for decision-making in SMEs has not been studied yet. In this paper, this research gap is addressed, creating a framework that considers non-risk criteria and quantitative and qualitative risks into energy-investment decision-making problems. Both types of risks are evaluated according to their probability and impact on the company's objectives and, additionally for qualitative risks, a fuzzy inference system is employed to account for judgmental subjectivity. All the criteria are incorporated into a single cost-benefit analysis function, which is optimised along the energy assets' lifetime to reach the best long-term energy investment decisions. The proposed methodology is applied to a specific industrial SME as a case study, showing the benefits of considering these risks in the decision-making problem. Nonetheless, the methodology is expandable with minor changes to other entities facing the challenge to invest in energy equipment or, as well, other tangible assets.

Keywords: decision-making; risk assessment; uncertainty; optimal energy design; prosumer

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1. Introduction

The selection and management of assets are crucial for the achievement of enterprises' objectives in the industrial sector. Among the company's tangible assets, those related to energy generation and management have special interest due to their impact on production costs and thermal comfort. Currently, small-and-medium enterprises (SMEs), and particularly those in the manufacturing sector, have a high environmental footprint and literature estimates that they contribute 60-70% of industrial pollution in Europe [1]. Therefore, equipment investment and operation of the SMEs are critical for the green transformation and can increase their growth performance [2]. However, the inclusion of new energy assets such as Renewable Energy Sources (RES) and other supporting equipment to improve the competitiveness of enterprises and reduce the environmental footprint has not been studied adequately [3], and industries, especially SMEs, are facing difficulties in incorporating them in their energy infrastructure [4]. Besides, the energy transition that is already taking place presents an opportunity for the industrial sector to adopt an active role in transforming the energy market, for example becoming a prosumer. This active role implies the establishment of a smart energy management strategy that would make use of the industrial energy assets to meet internal demand while adapting their operation to external market conditions, generating a profit from this interaction and opening new business models in the industrial entity. To be able to incorporate these strategies, it could be necessary, among other solutions, to perform an investment for upgrading the energy equipment and infrastructure of the industry through its re-design and sizing to use it as a productive asset. Due to their limited financial capacity and managerial system, industrial SMEs investments occur in discrete points in time, not prolonging the investment in multiple phases as performed by other entities such as governmental organizations or large companies, which can modify the project according to the evolution of industrial, legal or social boundary conditions [5]. Instead, SMEs' decisions are taken based on immediate investment return and maximization of profit along the lifetime of the equipment [6]. Therefore, industrial SMEs face the investment decision-making problem only with the current information and accepting the uncertainty related to the real situation evolution at which the upgraded infrastructure would operate. Moreover, some of the factors that are commonly employed as criteria in the decision-making process are hard to measure and its mere definition presents levels of venture and hazard, as, for example, social acceptance and legislation alignment. Thus, the required investment for industrial SMEs to upgrade their energy infrastructure is inherently linked to risks arising from both the uncertainty in the future situation, which can be represented as a quantitative risk, and the measurement or subjectivity of some of the possible decision criteria, reflected as a qualitative risk. To support industrial SMEs in performing these investments, the research objective of this paper is to create a framework that addresses risk-informed decision-making (RIDM) for their energy investment problem. The specific research questions that have to be answered and that are addressed here are:

- Which risks and factors have to be treated for the energy investment RIDM problem in industrial SMEs and how can they be processed?
- Which methodology is suitable to address this RIDM problem?
- Which techniques and tools are convenient and how should be used for optimising the energy investment RIDM problem in industrial SMEs considering the previously addressed risks and factors?

To created framework to answer these questions, in the following paragraphs a review of the state-of-the-art on methodologies and techniques applied to RIDM processes and energy investment decisions is exposed.

Up to date, some RIDM approaches for general industrial applications have been presented in the literature. In [7], a methodology for decision-making considering quantitative and qualitative risk factors is presented with a focus on enterprises with serious health and environmental risk aspects such as mining, nuclear and aerospace industries. In this work, a set of alternatives exist and the decision is taken by deliberation. In [8], a Multi-Criteria Decision Analysis (MCDA) is presented for planning the energy generation network of a country, selecting the best option among the alternatives employing an Analytical Hierarchy Process (AHP). Although a Cost-Benefit Analysis (CBA) would have been suitable for this case, it is argued that qualitative attributes are difficult to transform and incorporate in the final functions.

In CBA, advantages and disadvantages accounting for different criteria over the lifetime of investment alternatives are both assessed and incorporated in a single function [9], which can be optimised to reach either the best value of the investment or the best benefit to cost ratio. In [10], both quantitative and qualitative parameters are included in the CBA, although qualitative attributes are set as crisp numerical values without considering the vagueness of qualitative judgements. Also, the weight selection methodology is not clear, stating that the application of weights to compare qualitative and quantitative data is difficult and presents a barrier to the development of CBAs. This weighting issue is solved in [11], where an AHP is employed to weight the criteria and ease the selection of the best alternative through an MCDA. AHP enables to structure the decision-making problem according to a hierarchy of preferences from which each of the weight of the criteria, which can be of various natures and have different units, is obtained through the analysis performed by decision-makers [12]. All these RIDM problems presented until now deal with a discrete number of alternatives, and qualitative and quantitative risks considered are transformed to crisp and precise values. However, qualitative measurements are subject to judgmental vagueness and thus their consideration as crisp numbers cause loss of information. In the past, an alternative to deal with qualitative values' vagueness for decision-making was presented based on a fuzzy approach, which transformed the linguistic risk appreciations into continuous numerical functions [13]. In this work, however, only qualitative fuzzy parameters were employed to assess the risk of construction projects, omitting quantitative information, which is by its own nature much more precise. Although the exposed RIDM approaches have addressed the investment problem for some industrial applications, a suitable framework for industrial SMEs' RIDM energy investment and optimisation problem has not been developed yet.

In the general field of energy investment including industrial, services and residential sectors, research has been performed focusing on energy design and planning without analysing the associated risks [14,15]. Although in some cases the uncertainty of the output is studied after performing the decision, RIDM is not carried out. This is the case of [16], where the performance of a hybrid energy system is analysed under uncertain events; and of [17], where the response of an energy system is studied according to fluctuations in system inputs', such as the cost of energy. The literature on energy investments considering risks inside the decision-making problem is scarce, although risk analysis is a common tool for companies. In [18], a life cycle cost (LCC) analysis is performed for a building energy system considering the risk related to economic parameters through Monte Carlo simulation. In [19], the design is done evaluating through the same technique the risk related to quantitative costs and technological aspects, and in [20], energy carriers price and investment costs uncertainties are considered. In all of these works, the risk is expressed employing a quantitative probability approach, focusing on economic parameters. However, real-world industries decision-making problems include a mixture of criteria that are not easily quantifiable and have to deal with insufficient information, such as the contribution of the investment into social benefit or the future continuity of the enterprise, which makes it not possible to employ probabilistic methods [21]. This fact enhances the application of both quantitative and qualitative risk assessment techniques which have not been employed in the energy investment literature until now. Due to the investment characteristics and the inclusive growth role the SMEs play in society, as well as the requirements of energy assets to fulfil internal enterprise requirements over time and the possible adoption of an active energy role to open a new business models, it is required to create a methodology in which risks are correctly considered.

In this paper, a methodology to properly address the RIDM energy equipment investment problem considering the mixture of criteria that exist for industrial SMEs is proposed with the aim of improving their competitiveness and allow them to play an active role in the energy market. In this new methodology, both quantitative and qualitative risk must be assessed accounting for the judgemental vagueness of decision-maker, while addressing the optimisation problem continuously over operation the time and space of possible combined solutions of the equipment so use rather than analysing only a few subjectively chosen alternatives. As a basis for solving this problem, a CBA approach is employed, which is suitable for the application in enterprises assets management problems [22]. In order to deal with real-world situations where a mixture of criteria exists, the proposed CBA approach incorporates both quantitative and qualitative data, being the latter assessed through a fuzzy approach to account for judgemental vagueness. These risks, together with the non-risk criteria to make the decision, are unified into a single objective function employing an AHP weighting technique that represents a balanced trade-off of the different factors considered in the RIDM energy investment problem. The objective function is evaluated and optimised continuously over time and also over the continuous space of solutions, analysing all the alternatives and not relying on a pre-specification of them. This procedure enables to reach an optimal decision considering the specifications and constraints provided by the industrial SME.

Bearing in mind the state-of-the-art in RIDM and its application to the problem of energy investment for industrial SMEs, this paper presents the following main novelties and improvements:

- Creation of a methodology to support industrial SMEs in the energy investment decision-making process considering relevant factors and criteria to improve their competitiveness and accounting for related risks that could affect their performance.
- Optimisation of the RIDM energy investment problem including equipment options and its operation to attend internal demand and produce a profit from exchanges with the energy market. To do this, the continuous-time operation of the SME and all possible combinations and sizes of energy equipment are evaluated.
- Evaluation of both qualitative and quantitative risks for energy-investment decision-making in a unique function to account for uncertain deployment scenario and face the difficulty in the measurement of subjective criteria.

These novelties imply the adoption and usage of strategies, techniques and tools which have not been employed until now in RIDM for energy investment. These are considered as collateral paper contributions consequence of the previously stated ones, and are:

- Transformation of subjective criteria represented as qualitative risks into fuzzy sets to account for judgmental vagueness of industrial SMEs' decision-makers.
- Incorporation of qualitative and quantitative measurements into a single function expressed as CBA through AHP weighting, properly reflecting the preferences of decision-makers.

This paper is structured as follows. First of all, in section 2, the proposed methodology for energy-investment decision-making is further explained. Secondly, in section 3, a case study based on a real manufacturing industrial plant at which this methodology is applied is exposed. The results of this case study and their discussion are shown in section 4, and, lastly, conclusions are drawn in section 5.

2. Energy-investment decision-making methodology

In this section, the methodology to assess the RIDM for industrial SMEs aiming to invest in energy assets to upgrade their energy infrastructure and improve their competitiveness is presented. Industrial SMEs are characterised by performing investments in discrete points in time to maintain or increase the productivity of their plant. For the case of investment in energy assets, their selection influences the long-term continuity of the enterprise as it affects the efficiency at which the production load is met as well as its impact on local social welfare and corporate image. However, the information which industrial SMEs manage to perform these decisions present uncertainty both in the forecast of the future situation and in the measurement of qualitative decision-making criteria. These facts, together with decision-making difficulties involving access to financial sources, are challenges faced by SMEs worldwide [23]. Therefore, the proposed methodology to address and support SMEs' RIDM in energy investment, which can be seen in Figure 1, has been defined to be expandable to SMEs around the globe.

To implement this methodology, information regarding specific industrial SME framework and the variables and constraints that apply are required. On the one hand, the specific SME internal and context information include:

- production and energy consumption profiles,
- local energy and emissions costs and applicable legislation,
- available energy solutions and technological maturity of the company for using them, and
- Opinion and views of the local community on innovative energy infrastructures and equipment for renewable energy, who may have, for instance, different acceptance of photovoltaic and biomass due to their different landscaping and logistic impacts

On the other hand, the constraints that apply for energy-investment problem in industrial SMEs and that should be considered are:

- limited initial investment,
- required payback period,
- geographic constraints, and
- legislation constraints.

These parameters and variables must be locally analysed and stated to process them according to their uncertain nature. Then, they serve as input for the optimisation problem, where the potential energy infrastructures in which the SME can invest are analysed, evaluating the identified risks and criteria. This evaluation of possible energy infrastructures is performed through an iterative algorithm, which analyses the output for each of them and moves towards the solution most suited to the studied industrial SME, the priorities of which are specified by decision-makers and adequately incorporated in the optimisation problem to reach the best trade-off solution.

In the following sections, each of the stages of the proposed methodology is exposed together with the techniques employed and their background.

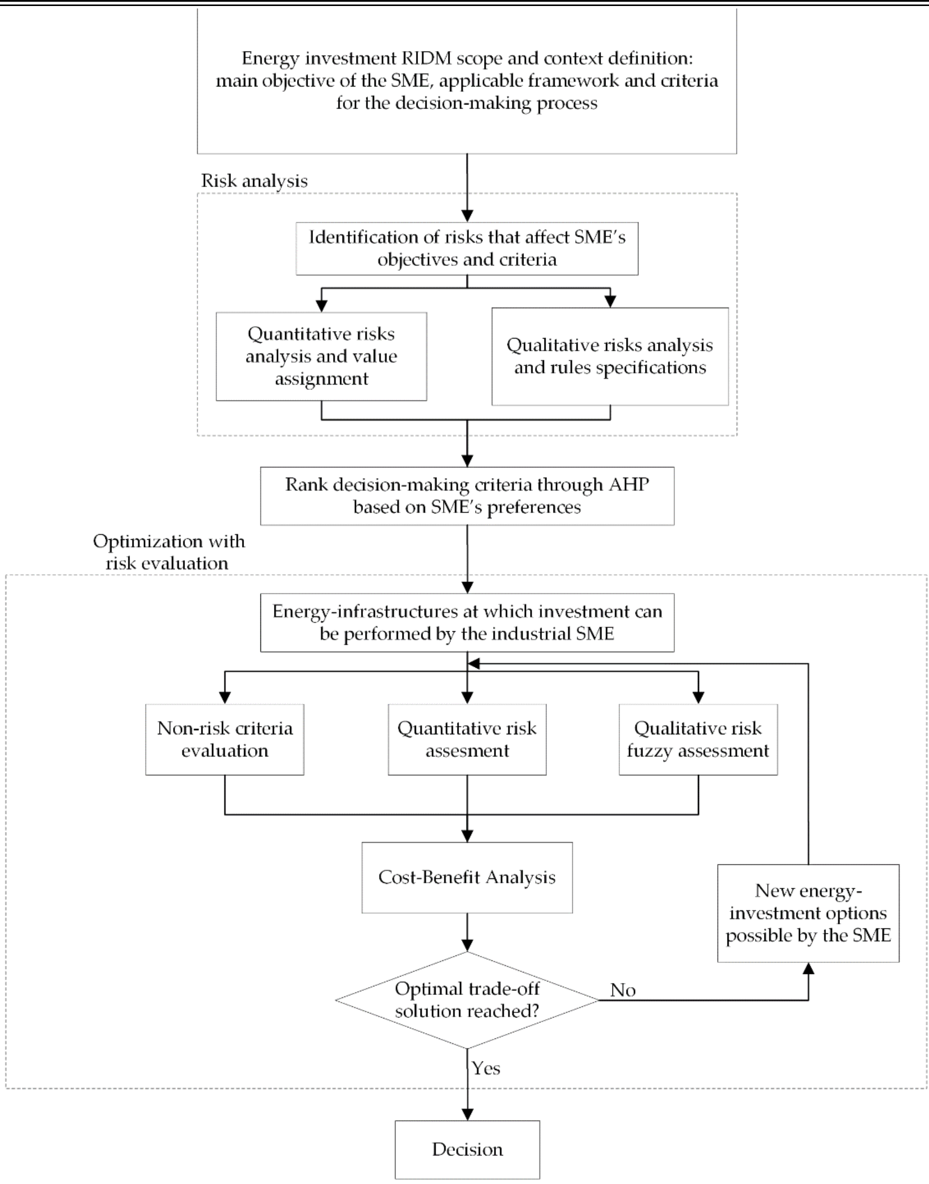

Figure 1. Energy-investment decision-making methodology.

2.1. Scope, context and criteria

Industrial SMEs face the problem of investing equipment to upgrade their energy infrastructure and include RES due to the required replacement of outdated energy assets or the existence of a socio-political framework that forces or encourages them to do so. The current economic, environmental and technical context is also opening the path and promoting the inclusion of distributed energy resources and active energy actors to achieve a cleaner and sustainable energy system [24]. For industries, it is possible to be part of this change by adopting a prosumer role, being one way to do so the upgrade of their energy infrastructure. However, the uncertain future market situation and the energy price volatility supposes a financial risk that inhibits industries to perform these investments [25]. For this reason, the methodology presented in this paper considers the relevant criteria to take into account for choosing the most suitable energy-investment solution, and the risks related to them.

The criteria represent the decision drivers to evaluate the potential energy-investment solutions. These criteria can be related to risks or not, being possible the following situations, or a combination of them:

- Non-risk criteria: Their value is computed objectively and it is not influenced by the uncertainty in the inputs of the system. In the RIDM energy investment optimisation problem, these non-risk criteria are selected according to the scope of the problem and can be, for example, the total emissions of the system if the emission factor is considered constant, which is a common approach in energy-investment optimisation problems [26].
- Criteria affected by inputs' uncertainty: The value of the criteria depends on uncertain inputs. These uncertainties have to be identified as quantitative risks, and the variation of the affected criteria according to them have to be computed. This variation is then included in the decision-making problem as an additional criterion aiming for its reduction, minimizing the risk at which the enterprise is exposed. For the case of energy investment problems in industrial SME, a common decision-making criterion is the net present value (NPV). The value of the NPV in the proposed energy infrastructure is influenced, among others, by the cost of energy carriers. As there is uncertainty in future energy costs that can be quantifiable, the variation of the NPV should be computed according to them and introduced in the optimisation problem.
- Subjective criteria: These criteria are difficult to assess mathematically as they lay on subjective opinions and, consequently, their evaluation represents a risk by itself. To include them in the decision-making process, they are treated as qualitative risks employing a fuzzy methodology to account for judgemental vagueness. This is the case of criteria such as social acceptance, whose value relies on the knowledge about the local community where the SME is placed and the opinion based on the experience of decision-makers.

In this paper, and to properly address the mixture of criteria and risks present in the energy investment RIDM problem of industrial SMEs, the combination of criteria with both quantitative and qualitative risks is considered. For this problem, the non-risk criteria are related to factors arising from the operation of the upgraded energy infrastructure and its economic and environmental impact, such as the obtained profit and emissions. To compute these parameters, the industrial plant is modelled mathematically and its operation optimised. Also, quantitative and qualitative risks related to the upgraded energy plant are evaluated following the indications of relevant research performed in the literature up to date, including the fuzzy treatment of qualitative measurements.

The criteria and risks to decide the best trade-off energy-investment solution are selected according to specific enterprise interests and should include economic, environmental, technical and social aspects. A review of the criteria for energy investment evaluations commonly employed in the literature is available at [27], which can be modified and adapted to the specific problem treated. The scope of the energy-investment decision problem has also to be settled by the company, specifying the equipment considered for installation, the available space for installation and other limitations, the required risk detail, and any restriction that apply, such as maximum initial investment, payback time, etc.

2.2. Risks analysis

Once the SME decides the criteria which are relevant for consideration in the energy-investment problem, the risks that affect them have to be identified. In this section, the methodology to classify and treat these risks is assessed.

2.2.1. Identification

The first stage in the risk analysis process is the identification of the risks present in the energy investment decision-making problem. Industrial SMEs are characterised by a management system where the owner of the enterprise acts, most of the time, as manager of the company, and there is a lack of a management body with suitable specialised knowledge for decision-making [6]. To successfully implement an energy-investment decision-making process, it is required to establish a decision-board either internally in the enterprise or resorting to external advisors. Once decision-makers have been established, the risk detection process has to be performed aiming to identify as many risks as possible according to the scope of the problem. The possibility of not identifying a risk due to a lack of knowledge or awareness is not assessed in this paper.

As mentioned in the previous section, risks can be embedded in the criteria or can be the effect of quantitative inputs uncertainty in the criteria. To properly deal with them, their probability and impact on the enterprise's objectives and criteria have to be addressed, reaching a risk evaluation measure [28]. The probability of a risk is the measure of how possible it is for an uncertain event to happen and the impact refers to the effect that this event would cause on the performance of the energy infrastructure and the SME's objectives. In the following subsections, the definition strategy for both types of risks is exposed.

2.2.1. Quantitative risks definition

The steps to treat these risks in the decision-making process are exposed in Figure 2.

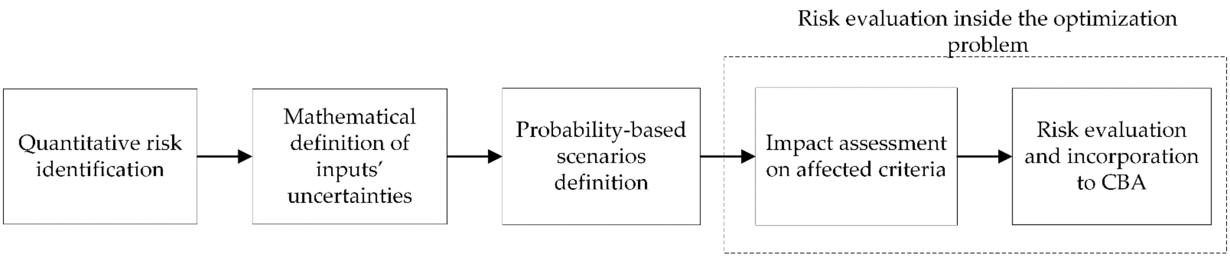

Figure 2. Quantitative risks treatment.

In the energy-investment decision-making problem for industrial SMEs, quantitative risks deal with the uncertainty related to the future energy situation, and include, among others, future energy carrier and emissions costs. Once the decision-board identifies all the applicable risks for the specific problem considered, the inputs' uncertainties have to be expressed mathematically. The possible values that the uncertain inputs can take can be denoted as a set of discrete values with their corresponding probabilities[16], such as in the case of existent forecasting scenarios of future energy costs, or as continuous probability distribution functions [19] if a more detailed analysis is available. The type of expression depends on the nature of the risk and the information gathered. If a continuous probability distribution function is employed, this has to be transformed into a set of probability-based scenarios to be able to evaluate their impact on the criteria. This is done through the Monte Carlo sampling strategy, which is widely used and accepted in RIDM processes [29]. In the case that discrete values with probabilities are used, the scenarios to compute the impact are all the possible values with their associated probability.

With these scenarios, it is possible to compute the impact of the risk on the affected criteria. Then, the risk is evaluated as the variation present in the criteria due to the different inputs' uncertainties. This variation is the parameter that is incorporated into the CBA function as a cost.

2.2.2. Qualitative risks definition

The steps to consider qualitative risks in the decision-making process are exposed in Figure 3.

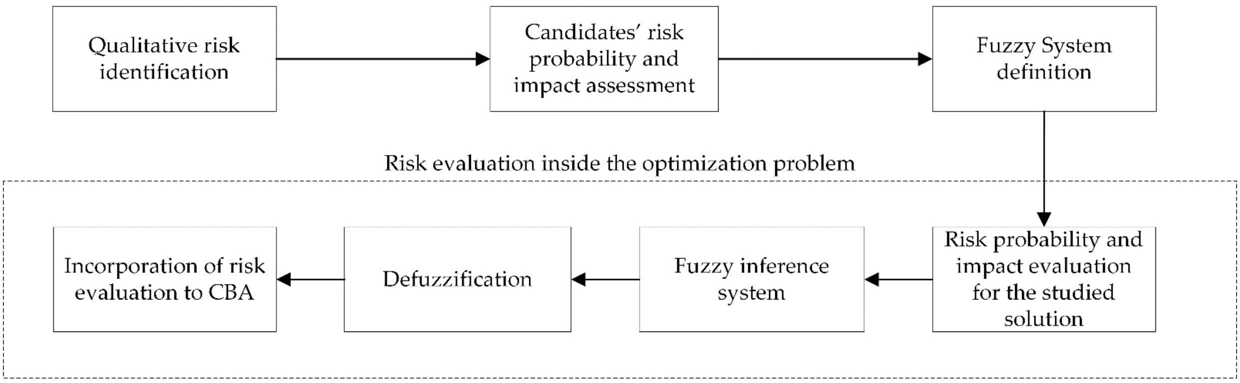

Figure 3. Qualitative risks treatment.

As commented previously, qualitative risks deal mainly with criteria that cannot be easily defined mathematically and that are approximated subjectively by decision-makers. This is the case of some social and environmental aspects which do not have clear measurement strategies, such as social welfare and local community perceptions. Once these risks are identified, it is required to evaluate and assign a numerical value to both their probability of occurrence and their impact on SME's objectives if they occur. Although there are other manners to define qualitative risks, the employment of probability and impact values, which is also suitable for quantitative risks, is the most appropriate one to deal with qualitative ones in decision-making problems in the industrial sector [28]. The assessment of probability and impact of qualitative parameters is done considering the decision-board experience in the sector, knowledge on local society obtained through interviews, government surveys, etc.; and vary according to the equipment considered for installation and their size. In the proposed methodology, the optimisation of the energy investment RIDM problem is performed continuously evaluating all possible solutions, not existing a set of them pre-defined. Thus, it is required to implement a strategy for the specification of probability and impact of qualitative parameters based on decision-makers opinion for all possible solutions. This is done by the creation of a decision tree whose branches divide all the possible solutions in ranges of specific equipment and sizes at which the probability and impacts can be defined by decision-makers. This decision tree is resorted by the continuous optimisation algorithm to identify the applicable impact and probability values for the solution that are iteratively analysed.

Although these probability and impact values can be defined as crisp values, they are unavoidably subject to judgemental vagueness. To avoid losing experts and decision-makers valuable opinions, these parameters should not be considered as crisp but as part of a continuous function. To do so, a set of fuzzy membership functions are defined, which serve as input for the Fuzzy Inference System (FIS) that computes the risk evaluation. Two FIS are widely accepted and employed in the literature; the Mamdani and the Takagi-Sugeno [30]. In this paper, the Mamdani method and the max-min inference are selected as they perform better in extracting expert's opinion on risk factors and thus it is more suitable for RIDM problems [31]. In the Mamdani method, *if-then* rules and the implication method are used to obtain a fuzzy output which has to be defuzzified in a later stage for its treatment in further mathematical equations. The *if-then* rules are designed to follow the logic of an expert risk assessor through a qualitative risk matrix [32], and the defuzzification is performed employing the centroid strategy, which provides solutions that naturally and smoothly respond to the created rules [33].

2.3. Criteria ranking

In this stage, the criteria selected and the risks identified are ranked to reflect the preferences of industrial SME in the energy investment RIDM problem. To capture these preferences, an AHP is employed, which is a tool to methodologically determine the weights based on subjective preferences and which is suitable to incorporate various criteria of different nature [34], including non-risk, quantitative risks and qualitative risks. The AHP method decomposes the problem into a hierarchy, having the goal on top and structuring the criteria and risks into levels, as can be seen in Figure 4. In classic AHP applications, the set of studied alternative solutions are included in the hierarchy, and they are analysed in a bottom-up perspective, from sub-criteria to criteria preceding them in the hierarchy until reaching the overall goal. In this paper, as the evaluation of solutions is performed through a continuous optimisation problem, the AHP is employed to select the weights which are later incorporated in the CBA function.

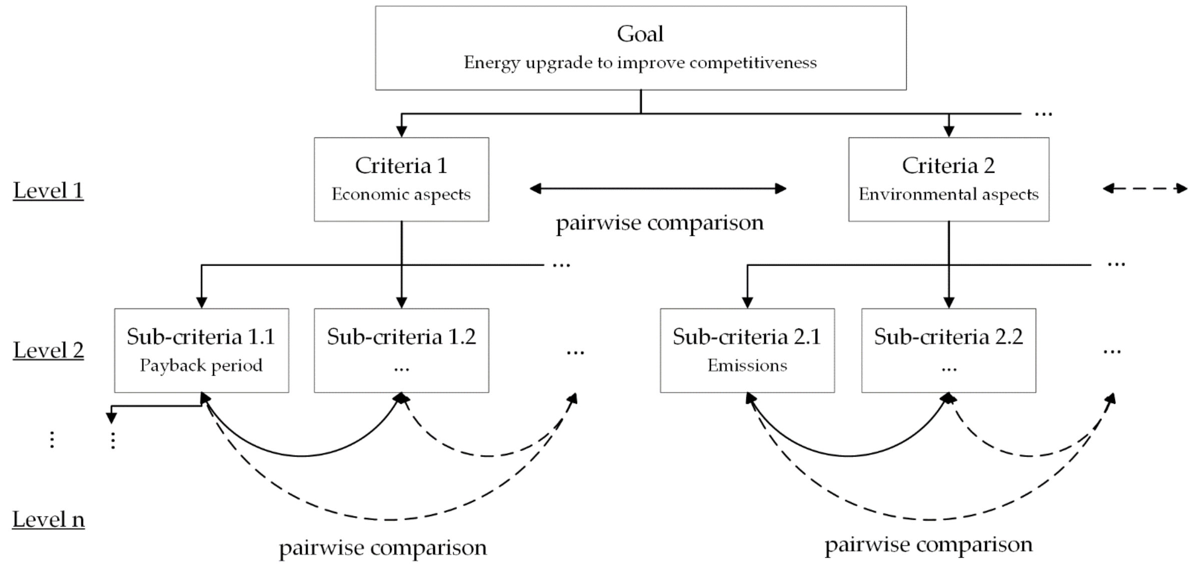

Figure 4. AHP hierarchy structure and pairwise comparison strategy.

The goal of the problem, located at the top of the hierarchy, is in this case the energy upgrade to become a prosumer and improve the competitiveness of the enterprise. Immediately below the goal, a set of criteria appears which designate the main aspects considered by the enterprise to reach the decision, such as economic and environmental aspects. Then, the next level details the criteria linked to these aspects and the relevant risks that apply. In this case, the sublevel below the economic criteria can be formed by the NPV, the payback period, and their variation according to uncertain inputs, whereas the environmental field can include CO_2 emissions or soil depletion. After generating the hierarchy, each of the items in a level is compared to the rest in the same level and under the same hierarchy branch in a pairwise manner [35]. This process is reflected in a paired comparison matrix, in which the element a_{ij} denotes the importance of parameter *i* in front of parameter *j* following the Saaty scale definition [36], exposed in Table 1. This matrix definition process is done for the upper or lower diagonal part, being the parameter in the opposite part, a_{ji}, equal to $1/a_{ij}$. Thus, the resultant matrix has the following structure:

$$\begin{bmatrix} 1 & 1/a_{12} & 1/a_{13} \\ a_{12} & 1 & 1/a_{23} \\ a_{13} & a_{23} & 1 \end{bmatrix} \quad (1)$$

Based on this matrix, the weights can be computed using the geometric mean and multiplying the results of the matrix from the lower levels of the hierarchy until reaching the goal [37].

Table 1. Saaty fundamental AHP scale.

Intensity of importance	Definition
1	i and j are equally important
3	i is moderately more important than j
5	i is strongly more important than j
7	i is very strongly more important than j
9	i is extremely more important than j
2,4,6,8	Intermediate values between two adjacent judgements employed when compromise is needed

2.4. Optimisation

Once the criteria and risks have been identified and ranked, establishing the framework for selecting the best trade-off energy investment to upgrade the energy infrastructure of the plant, it is possible to enter the optimisation stage. In this stage, the possible energy infrastructures are evaluated iteratively to reach the optimal energy investment decision. This is done by incorporating all the criteria and risks into a CBA, which forms the optimisation's objective function. In the CBA, the parameters that are beneficial and want to be maximised are included as benefits, such as the NPV of the investment and the social acceptance of the solution. In contrast, the parameters that represent a disadvantage or hazard are introduced as costs. This is the case, for example, of emissions and NPV variability. As these factors present different units, their value is normalised for its inclusion in a single function. This normalisation process is performed both to remove the dimensions and also to balance possible magnitude differences that exist between different criteria [38]. The transforming approach employed here, which is considered one of the most robust regardless of the original range of parameters [39], is:

$$p^{trans} = \frac{p - p^0}{p^{max} - p^0} \tag{2}$$

Where p^{trans} is the normalised parameter which lays between 0 and 1, p is the measured value and p^0 and p^{max} are the minimum and maximum value achievable, respectively. Once the parameters are normalised, they are included in the CBA function with the weights obtained in the AHP.

Some of the parameters included in the CBA function are related to the performance of the energy infrastructure over time, and for this reason, it is required to compute the operation of the upgraded plant for the expected lifetime of the energy investment. This is performed modelling the plant employing the Energy Hub (EH) concept [40], which can be expressed mathematically as:

$$L = \eta P \tag{3}$$

Where L represents the demand of the plant or power output, P the generation or power input, and η the connectivity matrix, which includes the dispatch factors and the efficiency of the equipment. This model represents the power balance which has to be fulfilled at all times which, together with other restrictions such as power exchange thresholds with external grids and equipment operation bounds, serve as the basis to evaluate the operation of the plant and obtain relevant parameters which should be included in the CBA such as the NPV and payback period.

The CBA obtained from the different criteria is optimised aiming to reach as many benefits as possible with the least costs. To do so, a stochastic global algorithm is employed, which assures the surveillance of the entire search space and has better chances to find the global optimum compared to other optimisation methodologies [41]. In this paper, the Direct Search (DS) global optimizer is employed due to its capabilities to reach the global solution efficiently. Through this method, the search space surveillance is performed through the selection of a set of possible solutions or candidates, which are evaluated for the problem under study. The first set of candidates is computed based on an initial point provided by the decision-maker, which can be any point in the search space. The algorithm adds the unitary pattern vectors to the initial point, creating the first mesh. All the points in the mesh are possible energy-investment solutions, whose CBA is evaluated. The results of these energy-investment possibilities enable the algorithm to move in the search space, creating new meshes having as starting points those in the previous mesh that provided favourable results, approaching the global optimum efficiently. The calculations required to compute the CBA and optimize it depend on the specific case study considered and the criteria and risks identified.

2.5. Methodology generalisation

The exposed methodology has been designed for RIDM energy investment problems in industrial SMEs, addressing the challenges globally faced by these entities and creating a solid framework for the assessment of new energy equipment and management solutions. As can be inferred from previous paragraphs, this methodology can be divided into three different strata:

1. Input information from enterprise characteristics and the framework at which it operates.
2. Risks, factors and limitations applicable to the energy-investment problem.
3. Mathematical strategies, techniques and tools for the proper incorporation of factors different in nature in an optimisable function.

All these three points are directly applicable to worldwide SMEs that face the energy-investment decision-making problem. However, and although the proposed methodology has been especially designed for these entities in the energy-investment context, it is expandable to other decision-making problems.

For instance, the current energy-investment problem faced nowadays by managers of buildings, communities or districts can also be assessed through the proposed methodology. In such case, the methodology should be modified to incorporate as input information the specific data and characteristics of tertiary and residential sectors, such as:

- space occupation and energy consumption demand at different conditions,
- consumers' flexibility and load shifting behaviour,
- compatibility of energy equipment with building/community/district purposes, and
- integration with Smart City initiatives, etc.

The constraints that apply to the energy investment itself may also differ, focusing more on operational benefits and allowing larger payback periods. Moreover, as in these entities the human factor is much stronger than in the industry, issues related to social welfare, environment and safety should be considered as determinant criteria, having economic criteria either in the same level or moved to the background. Despite these differences with the industrial SMEs' problem treated in this paper, energy-investment problems deal with a similar mixture of criteria which have to be evaluated along the lifetime of the infrastructure. For this reason, the mathematical strategies, techniques and tools exposed for suitably address the energy-investment RIDM problem are applicable not only to industrial SMEs' problems but also to other entities facing the challenge to perform an energy investment with minimum risks.

Furthermore, if the energy investment is not performed by SMEs or individuals but by governmental entities or big corporations, the proposed methodology can be adapted to incorporate the possibility to carry out multiple-phase investments and project expansions. In this case, the inputs of the system should incorporate the time frames at which investments are desired and the growing energy requirements to be fulfilled.

Apart from its application to energy-investment problems from a wide point of view, the proposed methodology can also expand to suit other RIDM problems not directly related to energy issues but with other tangible assets, such as the placement and investment of distribution centres. For this case, the inputs should incorporate the expected products' traffic, location of stakeholders and clients, earth-moving constraints, etc. Also, for distribution and logistics centres, the investment problem is not only economic, and constraints are closely related to the acceptance of the local community since it can strongly affect the structure of the environment and the communications infrastructure of the district and area in which it is placed, due to important visual impact for the community. Therefore, and in a similar way to the case of energy-investment in non-industrial entities, it is possible to use the proposed methodology, strategies and tools to evaluate the selected criteria and the qualitative and quantitative risks that should be considered to make the decision.

Thus, it can be concluded that the proposed methodology can be applied to a vast number of decision-making problems in which quantitative and qualitative risks have to be evaluated. For these new applications, the general methodology and tools can be maintained while the inputs of the system should be modified to suit the specific problem to addressed as well as the application constraints. In this way, it is possible to employ the proposed strategies and tools to reach the balanced trade-off solution that best reflects the interests of the entity taking the decision.

3. Case Study

In this section, a case study for an industrial SME of the automotive sector is presented in which the methodology exposed in the previous section is applied. Industrial SMEs, in contrast with other entities in the tertiary and residential sector, have higher thermal consumption than electrical consumption [42–44] and are characterized by a diversity of processes and equipment that enable the incorporation of different energy assets to interconnect the different energy carriers present in the industry, increasing the robustness of the energy system [45]. Also, the load pattern of industrial SMEs is much more predictable than in other sectors as it is strongly affected by production and vary only slightly with daily human behaviour [46]. This is especially true for the case of industrial SMEs of the automotive sector, as they do not have stocks and produce in a just-in-time manner to supply materials and components to other enterprises for continuous vehicle manufacturing [47,48], thus presenting a much more stable load curve.

The case study exposed in this section is based on a real industrial SME of the automotive sector and reflects the main characteristics exposed of overall industries and especially of those related to the automotive sector. The annual electrical and thermal demands of the industrial plant are 679,240 MWh and 1,127,600 MWh, respectively; and an example of the demand pattern followed in one day can be seen in Figure 5.

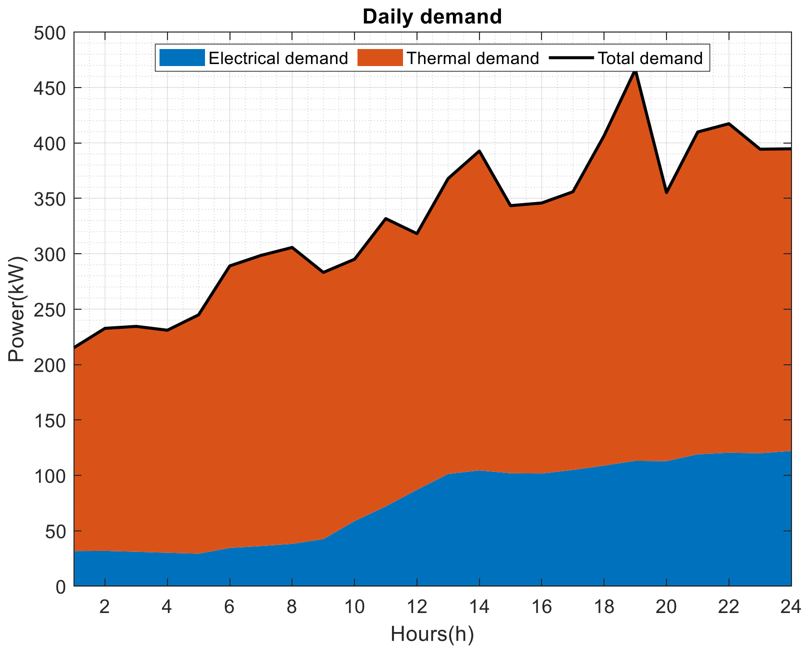

Figure 5. Daily load demand for the case study industrial SME.

In the following subsections, each of the stages of the proposed methodology are developed with the objective to achieve the best energy-investment decision in accordance with the objectives and characteristics of industrial SMEs.

3.1. Scope, context and criteria

The considered industrial manufacturing plant wants to upgrade its energy infrastructure to improve its competitiveness. This can be done by incorporating RES and other equipment to enhance its efficiency and reduce its carbon footprint, and to explore the capacity of exchanging electricity with the utility grid by adopting an active prosumer model.

Currently, the plant fulfils its electrical and thermal demands through the direct purchase of electricity and the combustion of natural gas in a boiler. The boiler equipment is foreseen to continue in operation for the next 15 years and thus its substitution is not evaluated. The enterprise has 12,000m^2 of available space for the installation of a PV system, and it is also considering the inclusion of a Combined Heat and Power (CHP) unit, a Heat Pump (HP), Thermal Storage System (TSS) and an Electrochemical Storage System (ESS). However, the maximum investment is limited to 1,000,000€ and the payback period has to be lower than 6 years. With this context and scope, the combination of criteria proposed in this article to evaluate the best energy-investment decision is exposed in Table 2.

Table 2. Criteria for the energy-investment decision-making problem case study.

Criteria	Sub-criteria	Description
Economy	NPV	Value of the investment at the end of its expected lifetime
	Business continuity	Investment influence on supporting business continuity in the future
Technology	Innovation	Competitive advantage through innovation

	Maturity	Feasibility of the technological solutions to be integrated into the SME
	Safety	Safety of the solution for workers and local community
Social	Social benefits	Contribution to the advancement of society
	Social acceptance	Attitudes of users on the energy infrastructure upgrade
	Administration alignment	Alignment of the solution with administrative and legislative energy trends
Environment	Pollutant emissions	Emissions of greenhouse gases to the atmosphere
	Ecology influence	Direct and indirect influences on ecosystem

3.2. Risk identification and analysis

Keeping in mind the criteria selected, the identified quantitative and qualitative risks that affect them for this case study are exposed in Table 3. In the following pages, each of these risks is characterized for its inclusion in the optimisation problem.

Table 3. Risks identified for the energy-investment decision-making problem case study.

Risk ID	Risk description	Criteria affected	Risk type[1]
1	Electricity cost market uncertainty	NPV	QT
2	Gas cost market uncertainty	NPV	QT
3	Feed-in tariff uncertainty	NPV	QT
4	Emissions cost market uncertainty	NPV	QT
5	PV O&M[2] costs uncertainty	NPV	QT
6	Electrochemical storage O&M costs uncertainty	NPV	QT
7	Business continuity subjectivity	Business continuity	QL
8	Innovation subjectivity	Innovation	QL
9	Maturity subjectivity	Maturity	QL
10	Safety subjectivity	Safety	QL
11	Ecology influence subjectivity	Ecology influence	QL
12	Social benefit subjectivity	Social benefit	QL
13	Social acceptance subjectivity	Social acceptance	QL
14	Administrative alignment subjectivity	Administrative alignment	QL

[1] QT = Quantitative; QL = Qualitative. [2] O&M= Operation & Maintenance.

3.2.1. Quantitative risk analysis

Here, the quantitative risks are analysed and a numerical description assigned to them.

- Risks 1-4

These risks correspond to the uncertainty in the forecast of future market costs, including the price of electricity, gas and emissions as well as the feed-in tariff at which electricity is sold. The uncertainty of the increment ratio of energy and emissions costs creates different operation and financial scenarios for which the studied solutions provide distinct results on the criteria. These uncertainties and criteria variation have to be evaluated as a risk in the decision-making process. To do so, the future scenarios represented as price increments possibilities obtained from the literature are analysed. These scenarios, which present an equal probability of occurrence, are exposed in Table 4.

Table 4. Risks 1-4 numerical description.

Risk ID	Factor description	Scenarios	Source
1	Electricity cost yearly percentage increase	[1.40;4.06;4.82]	[49]
2	Gas cost yearly percentage increase	[0.65;1.40]	[50]
3	Percentage of the electricity cost at which electricity is sold	[0.80;0.9]	[51]
4	Emissions cost yearly percentage increase	[1.14;6.45]	[52]

- Risks 5-6

These risks relate to the fact that PV and electrochemical energy storage systems are growing in adoption, decreasing their operation and maintenance (O&M) costs as a consequence of the economy of scale that the sectors are experiencing, although the cost evolution is not clear yet. To capture this uncertainty, the cost decrease expectation is extracted from the literature and the possible scenarios, also with equal probabilities and exposed in Table 5, are analysed under the point of view of its impact on the criteria for RIDM.

Table 5. Risks 5-6 numerical description.

Risk ID	Factor description	Scenarios	Source
5	PV O&M costs yearly percentage decrease	[0.5;0.95;1.7]	[53]
6	Electrochemical storage O&M costs yearly percentage decrease	[3.3;3.7;4.5]	[52,54]

All these quantitative risks affect the NPV criteria. To evaluate this risk, the impact in the NPV is computed for all the risk scenarios combinations, obtaining, as a result, the variation of the NPV. This NPV variation is included in the CBA function aiming at its reduction for risk minimisation.

3.2.2. Qualitative risk analysis

Risks 7-14 are qualitative and thus they are defined based on the opinion of decision-makers and experts. To capture their knowledge, decision-makers perform an analysis of the probability of risks to happen and the impact these would have on the enterprise's objectives depending on the energy infrastructures evaluated. As the energy investment RIDM is optimised continuously, all possible energy infrastructure that could be a solution have to be assessed. To do this analysis, decision-makers rely on their experience and knowledge of the local community, legislation trends and company environmental and social commitment, as well as initial enterprise's constraints such as maximum investment. The probability and impact evaluations are reflected into decision trees allowing the optimisation algorithm to obtain these risks' values for the evaluated energy-investment solutions. As probability and impact are not necessarily distributed in the same ranges of equipment, for each studied risk one decision tree is required for probability and another for impact. Therefore, in the case study presented here, a total of 16 decision trees are constructed. The resultant decision trees for the decision-making problem are subjective as they derive from the opinion of experts considering previous experience surveys performed to users and local social agents. An example of a decision tree is exposed in Figure 6. This decision tree serves to specify the impact of the solution on business continuity according to the equipment selected. A higher value means that the studied solution has a higher impact than other solutions, being a high impact desirable. In this case, the decision-makers specify that business continuity shouldn't have a big CHP installation, whereas it is positive to include a PV system, although in a moderate manner. Of course, this assessment can change depending on the location of the company, the production sector, local trends and opinions about the industries, etc.

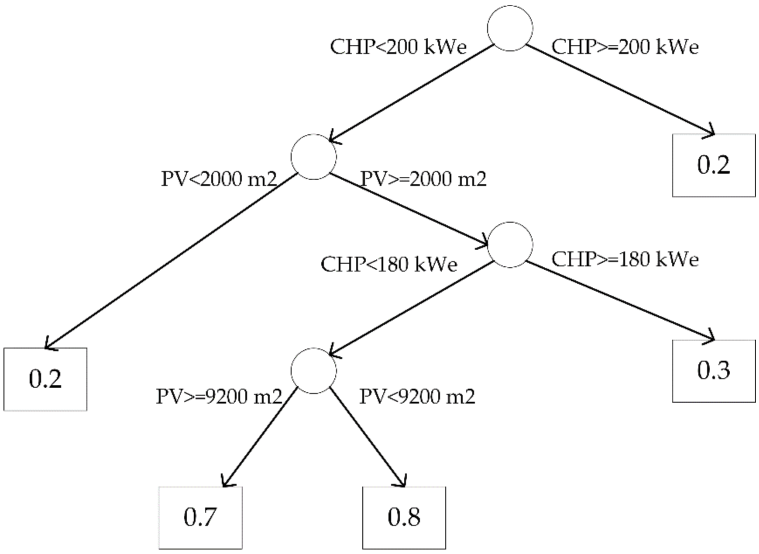

Figure 6. Decision tree for Risk 7 impact, business continuity.

The probability and impact values specified by decision-makers are influenced by vagueness, as one person can understand 0.7 to be a moderate impact whereas another one can understand it to be high. To avoid losing information regarding the true meaning behind the value specified by the decision-maker, a fuzzy strategy is employed in which probability and impact can correspond to one or more fuzzy membership functions that serve to compute the risk evaluation through the FIS. In Table 6, the membership functions employed for probability, impact, and risk evaluation are exposed. In this case study, the employed membership functions specified in the last column of Table 6 are trapezoidal. Their definition is performed in the (a_1, a_2, a_3, a_4) form, which correspond to the specific function's shape such that:

$$f(x;\ a_1, a_2, a_3, a_4) = \begin{cases} 0, (x < a_1)\ or\ (x > a_4) \\ \dfrac{x - a_1}{a_2 - a_1}, a_1 \le x \le a_2 \\ 1, \quad a_2 < x < a_3 \\ \dfrac{a_4 - x}{a_4 - a_3}, a_3 \le x \le a_4 \end{cases} \tag{4}$$

Table 6. Fuzzy membership functions and linguistic description of risk impact, probability and evaluation.

Risk aspect	Linguistic definition	Fuzzy number
	High	(0.6, 0.9, 1, 1)
Probability	Medium	(0.2, 0.4, 0.6, 0.8)
	Low	(0, 0, 0.1, 0.4)

Impact	Large	(0.7, 0.9, 1, 1)
	Considerable	(0.5, 0.7, 0.8, 0.9)
	Moderate	(0.2, 0.4, 0.6, 0.8)
	Minor	(0.1, 0.2, 0.3, 0.4)
	Negligible	(0, 0, 0.1, 0.2)
Evaluation	High	(0.6, 0.9, 1, 1)
	Medium	(0.2, 0.4, 0.6, 0.8)
	Low	(0, 0, 0.1, 0.4)

The membership functions for risk impact, probability and evaluation can be seen graphically in Figure 7.

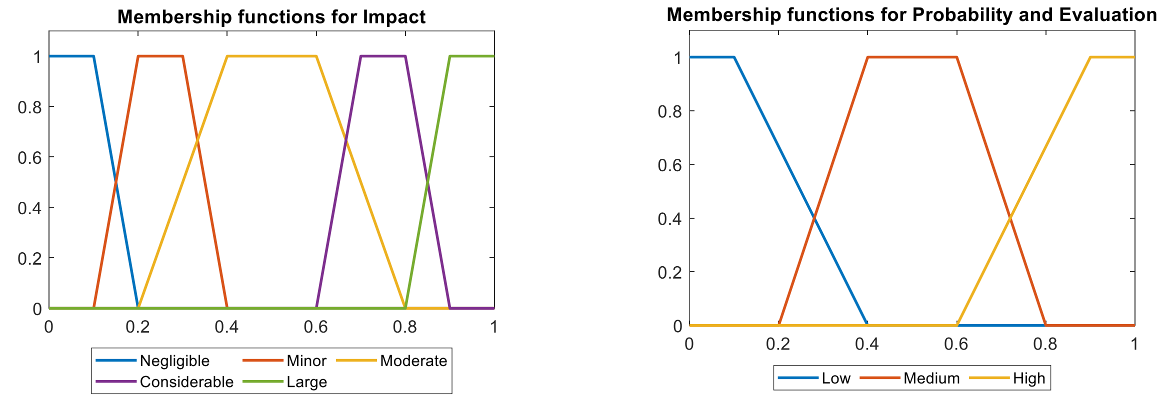

Figure 7. Risk impact, probability and evaluation membership functions.

Once the linguistic terms, fuzzy sets and decision trees for impact and probability assessment of candidate solutions are defined, the 15 required *if-then* rules for the Mamdani FIS are designed, which enable to compute the risk evaluation that has to be included in the CBA function. To support their creation, the qualitative risk matrix shown in Table 7 is generated, where the risk evaluation fuzzy set is identified based on the risk probability and impact specified by the decision-maker.

Table 7. Qualitative risk matrix for the case study.

		Impact				
		Large	**Considerable**	**Moderate**	**Minor**	**Negligible**
Probability	**High**	High	High	High	Medium	Medium
	Medium	High	High	Medium	Low	Low
	Low	Medium	Medium	Low	Low	Low

From this matrix, the rules for the Mamdani FIS are generated. As an example, five of them are shown here:

If (Probability is High) and (Impact is High), then risk is High

If (Probability is High) and (Impact is Moderate), then risk is Moderate

If (Probability is Medium) and (Impact is Considerable), then risk is High

If (Probability is Medium) and (Impact is Moderate), then risk is Moderate

If (Probability is Low) and (Impact is Minor), then risk is Minor

Here, an example of the working behaviour of the developed FIS is exposed to assess the business continuity when analysing the possibility of installing 6,000 m^2 of PV, a CHP system of 180 kW_e and an HP of 150 kW. According to the decision tree exposed previously, the impact of this solution on business continuity is 0.3. For the case of the probability of contributing to business continuity, the resultant value is 0.5, which has also been established following decision-makers judgments. With this information, the risk can be evaluated through the FIS as exposed in Figure 8. According to the fuzzy membership functions used, the probability parameter belongs only to one membership function. In contrast, the impact value belongs to two membership functions as it can express either a minor impact or a moderate impact. Thus, it is necessary to analyse two rules: one for medium probability and moderate impact and another for medium probability and minor impact. These two rules lead to two possible risk evaluations, which are combined to consider judgemental vagueness.

In the first activated rule, the obtained risk is medium. As the value of the impact is 0.3, it belongs to the moderate impact membership function although it does not completely fulfil it. For this reason, the implication is performed through max-min composition to reduce the influence of this rule in the output according to the degree of fulfilment of input membership functions [55]. In the second activated rule, the obtained risk is low and the *min* operator is not activated as both membership functions are completely fulfilled. These two outputs are aggregated, obtaining the fuzzy risk evaluation, which is defuzzified through the centroid method. The centroid returns the centre of gravity in the x-axis of the area under the membership function and is a consistent method suitable for one-dimensional output problems where no real-time implementation occurs, such as the one presented here [56]. In the example here shown, the defuzzification returns a final value of 0.3188, which is the measure of risk evaluation included in the CBA function.

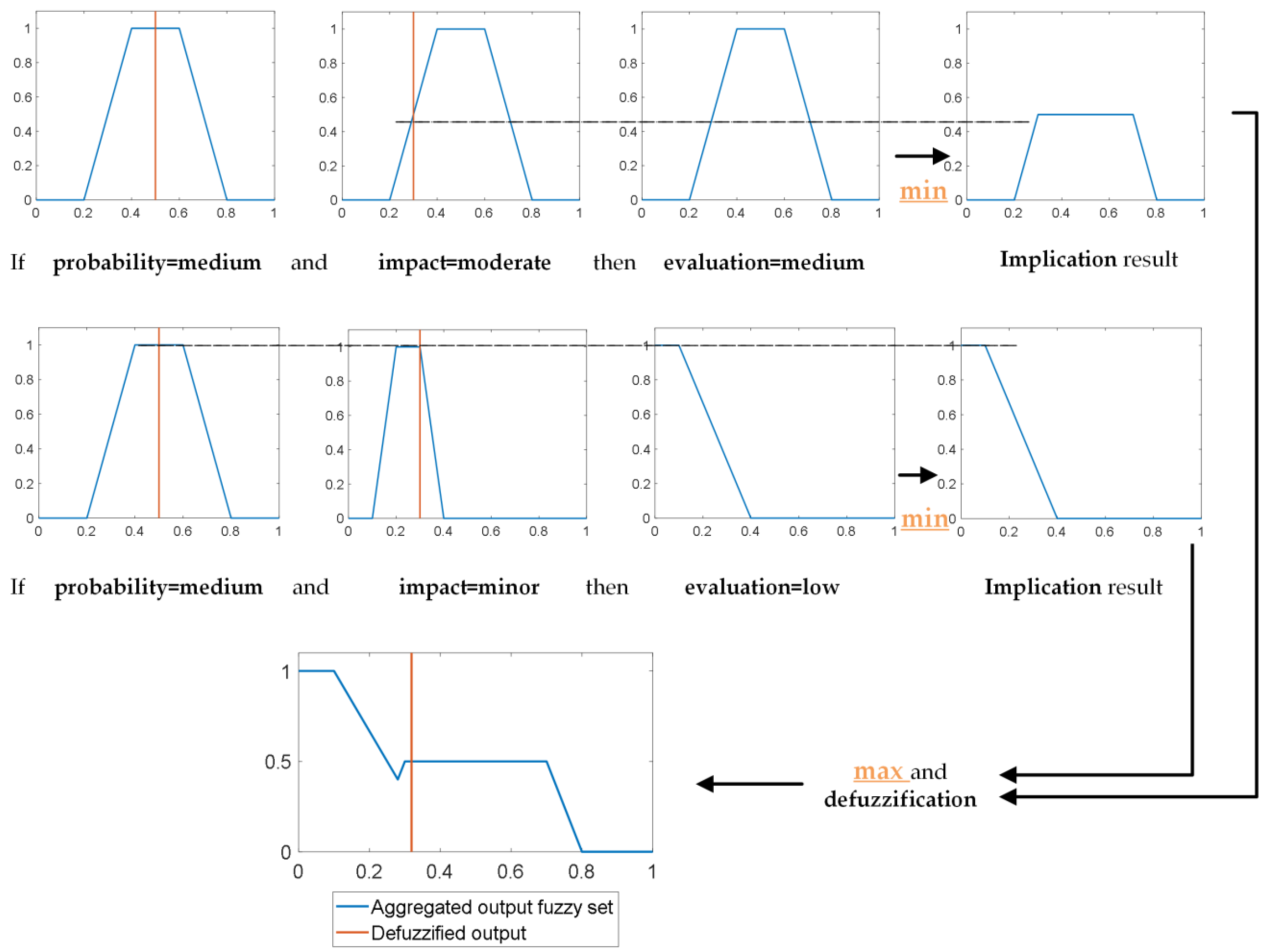

Figure 8. FIS procedure for evaluating the business continuity of a candidate solution for the case study developed.

3.3. AHP ranking

Being the main goal of the energy upgrade of the company to improve the competitiveness, a hierarchy with all the criteria and risks identified is constructed, which can be seen in Figure 9. The first level is formed by the main decision criteria, which are economy, technology-based, social, and environmental criteria. Then, each of these criteria is sub-divided into several items that are those already exposed in previous sections, specifically in Table 2. To these items, the NPV variation is included as a sub-criterion arising from the consideration of quantitative risks.

Once the structure is created, the criteria in the same level are compared in a pairwise manner using the Saaty fundamental scale, and the weights for this level are obtained. This process is performed by decision-makers considering the interests of the enterprise and the importance of each of the elements in terms of its predecessor in the hierarchy. These preferences are independent of the value that the criteria and risks take when evaluating possible energy infrastructure upgrades. Therefore, they are maintained constant, reflecting the preferences of the enterprise, and appear in the CBA function multiplying the value of criteria and risks, which change for every solution analysed, to assure a balanced trade-off suitable for the industrial SME.

As an example of the application of the Saaty fundamental scale, the comparison matrix and resultant weights for the first hierarchy level, where the main criteria are placed, are exposed in Table 8. The weights, as specified in Section 2.3, are obtained through the geometric mean, expressed as:

$$W_i = \left(\prod_{j=1}^{n} W_{ij}\right)^{\frac{1}{n}} \tag{5}$$

Where W_i is the obtained weight, W_{ij} represent the comparison performed between parameters in row i and column j, and n is the total number of parameters in the same layer for comparison. Given that the Saaty scale and the geometric mean can produce weights greater than one, once all the weights in the same layer are obtained, these have to be normalised:

$$W_{i,norm} = \frac{W_i}{\sum_{i=1}^{n} W_i} \tag{6}$$

Table 8. Pairwise comparison matrix for the second hierarchy level.

	Economic	Technology	Social	Environment	Weights
Economic	1	5	6	6	0.6324
Technology	1/5	1	3	3	0.2
Social	1/6	1/3	1	1	0.0838
Environment	1/6	1/3	1	1	0.0838

This process is repeated for all the sub-criteria, obtaining the weight hierarchy structure shown in Figure 9.

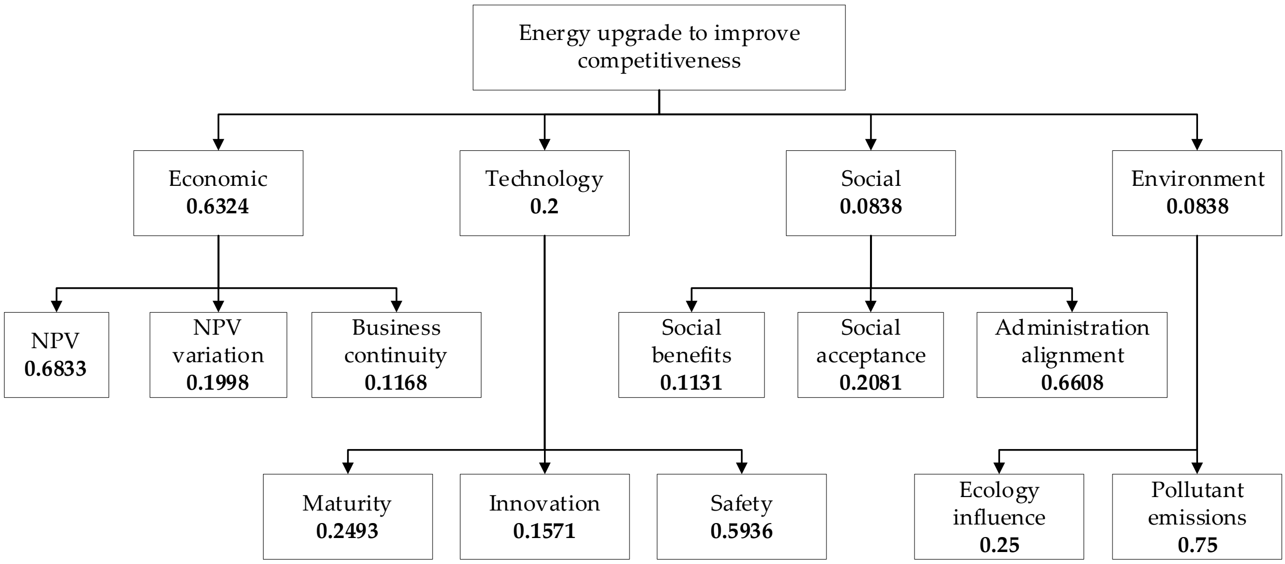

Figure 9. Criteria hierarchy with their corresponding level weights for the case study.

With this information, the global weights of the sub-criteria for their incorporation in the CBA function are computed through the multiplication of the resultant weights in a bottom-up perspective:

$$W_{i,global} = W_{i,normL2} \times W_{predecessor,norm} \tag{7}$$

Where $W_{i,global}$ represents the global weight of a parameter, $W_{i,normL2}$ the normalised weight obtained for the parameter in the second layer of the diagram through pairwise comparison, and $W_{predecessor,norm}$ the normalised weight of its predecessor in the hierarchy.

The global weights for all the considered criteria and risks are exposed in Table 9, together with the symbols employed to express them in upcoming mathematical equations.

Table 9. Global weights for the sub-criteria in the analysed case study.

Sub-Criteria	Symbol	Weight
NPV	NPV	0.4321
NPV variation	NPV_V	0.1264
Business continuity	BC	0.0739
Maturity	M	0.0499
Innovation	IN	0.0314
Safety	SF	0.1187
Social benefits	SB	0.0110
Social acceptance	SA	0.0174
Administration alignment	AA	0.0554
Ecology influence	EI	0.0629
Pollutant emissions	PE	0.0210

3.4. Optimal energy-investment selection process: continuous CBA

Once the criteria are selected and ranked, it is possible to proceed to the optimisation of the energy-investment RIDM for the industrial SME. The variables to optimise are the equipment to install and their sizes, whereas the constraints include the maximum investment that can be performed by the enterprise and the maximum allowable payback period. The objective function of the optimisation problem is the CBA function, where all the criteria and risks are considered either as a benefit or as a cost, including the quantitative and qualitative risks. This CBA function is maximised, aiming for an energy infrastructure that creates as many benefits as possible with low costs. The benefit criteria are those attributes included as positive terms and which wish to be maximised, while the cost criteria are those included as negative terms and that want to be kept as low as possible. For the present case study, bearing in mind the weights obtained through AHP, the resultant CBA function is:

$$\begin{aligned} f = 0.4321NPV - 0.1265NPV_V + 0.0739BC + 0.0499M + 0.0314IN \\ + 0.1187SF + 0.011SB + 0.174SA + 0.0554AA \\ - 0.0629EI - 0.0210PE \end{aligned} \tag{8}$$

It can be seen that almost all criteria are incorporated with a positive value, being the NPV variation, ecology influence and pollutant emissions the negative criteria which represent a cost that have to be kept low This CBA function has to be evaluated for all possible energy-investment solutions to upgrade the energy infrastructure of the plant, examined through the DS optimisation algorithm. The value of some of the criteria can be obtained directly from the selection of the energy infrastructure, the decision trees and the FIS exposed in previous sections. However, the NPV, NPV variation and pollutant emissions criteria require the computation of the infrastructure operation along the lifetime of the equipment and, in the case of the NPV, a comparison with the hypothetical situation of not performing any investment. For this reason, an analysis of the plant performance for the lifetime of the new equipment, which is considered to last for 15 years, is included inside the optimisation process. This analysis is carried out employing the EH concept. For the studied industrial plant, the EH equilibriums for the electrical and thermal sides are stated as:

$$P_{PV}\eta_{PV} + P_{UG}\eta_{UG} + P_{CHP} + P_{DES}\eta_{DES} = \frac{P_{ED}}{\eta_{ED}} + P_{UGS} + \frac{P_{CES}}{\eta_{CES}} + P_{ET} \tag{9}$$

$$Q_{CHP} + Q_{BOI} + Q_{DTS}\eta_{DTS} + Q_{ET} = \frac{Q_{TL}}{\eta_{TL}} + \frac{Q_{CTS}}{\eta_{CTS}} \tag{10}$$

Where P_{PV}, P_{UG}, P_{CHP} and P_{DES} are the electrical power coming from the PV system, the utility grid, the CHP system and the energy storage, respectively; P_{ED}, P_{UGS}, P_{CES} and P_{ET} are the electrical power to the internal demand, the one injected back to the utility grid, the employed to charge the energy storage and the sent to the HP system, respectively; and η_{PV}, η_{UG}, η_{ED}, η_{DES}, and η_{CES} are the connectivity efficiencies with the PV system, the utility grid, the electrical demand and also de discharge and charge efficiencies of the energy storage. On the thermal side, Q_{CHP}, Q_{BOI}, Q_{DTS} and Q_{ET} are the thermal power generated by the CHP and the boiler and coming from the thermal storage and the HP; Q_{TL} and Q_{CTS} are the thermal power for thermal load and the one injected in the thermal storage; and η_{TL}, η_{DTS} and η_{CTS} are the connectivity efficiencies with the load and the discharge and charge efficiencies of the thermal storage.

These equilibrium equations are accompanied by restrictions that allow the EH to operate following the physical constraints existent in the real plant. These restrictions include equipment connectivity, power equipment operation bounds and external grid requirements. This mathematical model can be employed for the different energy infrastructures analysed and also for studying the operation of the current industrial plant, as it is possible to set equipment to any size including zero, maintaining the operationality of the infrastructure. With this model, the operation of the upgraded plant can be obtained through optimising its behaviour aiming at minimising costs, which serves for the computation of parameters that have to be included in the CBA function for assessing the suitability of the analysed energy infrastructure.

Considering these aspects and the methodology exposed in Figure 1, the energy-investment RIDM optimisation flowchart is detailed for this specific case study in Figure 10. First of all, the industrial plant, market information, uncertainty scenarios and decision-makers judgements data are obtained. This information is employed, in part, to compute the scenarios at which the performance and operation of the industrial plant are analysed for the non-risk criteria and quantitative risk criteria. After obtaining the scenarios data, the operation of the reference plant is computed, which reflects the situation if no energy investment is performed and the currently existing energy infrastructure continues in operation for the next 15 years. This reference plant computation serves as a base for comparison and calculation of the NPV for the analysed energy investments.

Once this first part of the process is performed, the optimisation starts, aiming to find the energy investment that provides the best trade-off solution considering the risks related to its selection. Employing the DS algorithm, the first mesh is created through the addition of pattern vectors to the initial point provided by the decision-maker. Each of the points in the mesh represents a candidate energy investment solution with a linked upgraded energy infrastructure, which is analysed for the non-risk criteria, quantitative risks, and qualitative risks. For the non-risk criteria, which are the NPV and pollutant emissions, the operation of the plant is computed for the whole expected lifetime. In the case of the quantitative risk, which is the variation of the NPV, the operation of the plant analysis process is repeated for all the considered uncertain scenarios. Then, for qualitative risks, the impact and probability are obtained through the decision trees and the risk evaluation is computed employing the designed FIS. The evaluation of all the criteria is included inside the CBA function, obtaining the expected benefits and costs and the suitability of the analysed solution. At this stage, the DS optimisation checks its finalisation constraints, which include, among others, the change tolerance in the CBA function and the achievement of a minimum step variation. If the algorithm has reached an optimal value, the process ends, obtaining the best energy investment for the enterprise and the upgraded energy infrastructure. If not, a new set of candidate solutions is generated by re-meshing the search space, considering the results of the last set of candidate solutions to approach the global optimal.

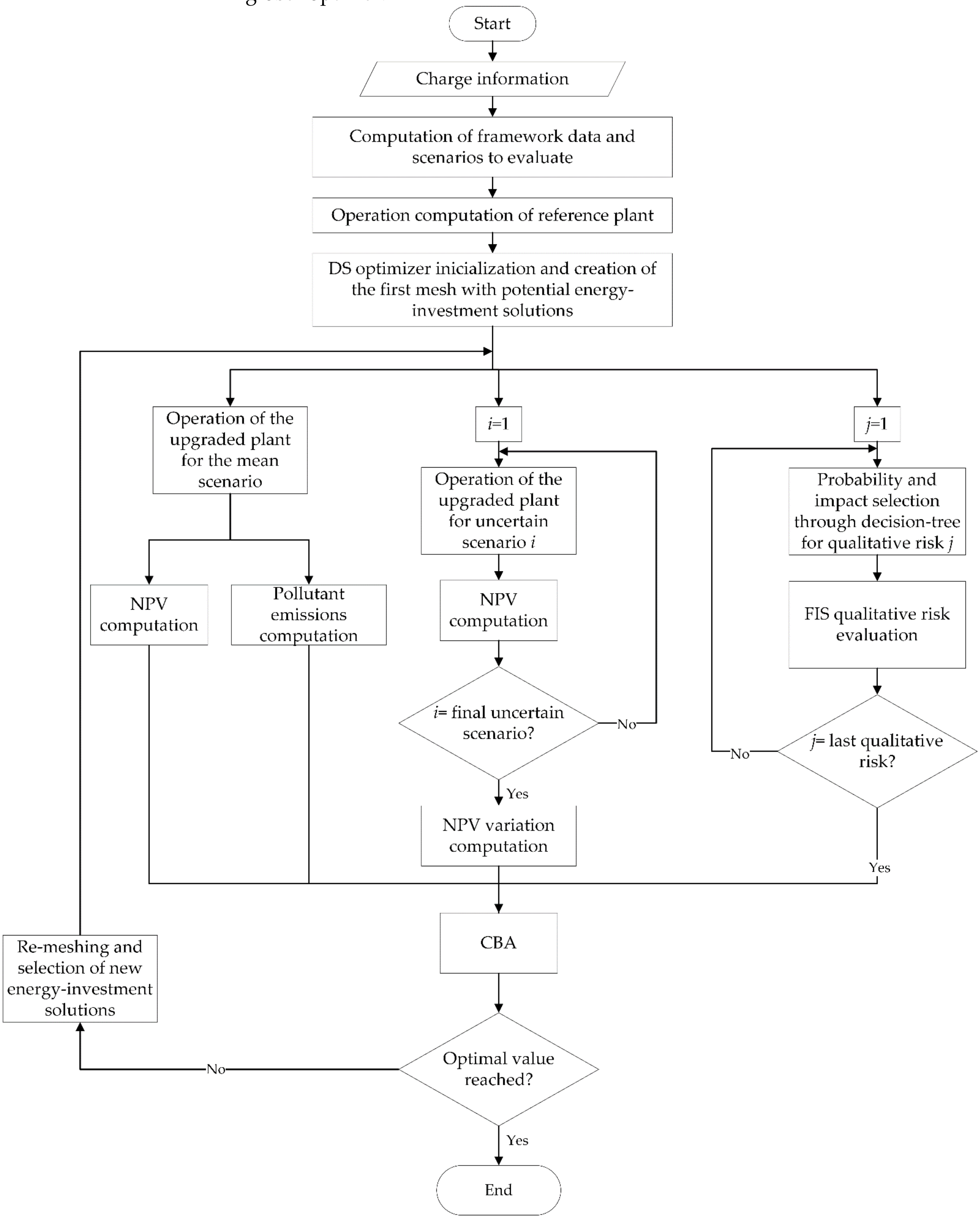

Figure 10. Optimisation flow chart for the case study.

4. Results and discussion.

The results of performing the energy investment RIDM optimisation in the studied SME to upgrade its energy infrastructure are presented in this section. In order to evaluate the benefits of incorporating the risks into the decision-making problem, an optimisation considering only the non-risk criteria, which are the NPV and the emissions, has also been carried out. In Table 10, the initial investment and payback periods for both solutions, with and without risks, are exposed. Figure 11 depicts their NPV during the first 6 years, showing graphically the evolution of the investment and its return along time until the payback is achieved. The equipment selected by the optimiser for each of the alternatives is exposed in Table 11. As one of the investment solutions has been obtained through a without risks analysis whereas the other is the result of an optimisation accounting also with quantitative and qualitative risk factors, the energy infrastructure resulting from the different optimisation problems present also different consequences in terms of risk implications, which can vary the real outcome for the enterprise. To appreciate these implications, Table 12 has been created in which it is possible to see the value of all the criteria including risks for both optimisations. It is worth noting that for the without risks optimisation, risks have not been considered during the optimisation, but are computed at the end of the process for the sake of comparability.

Table 10. Energy investment main characteristics.

	With risks	Without risks
Initial investment	689,600 €	909,960 €
Payback period	3.4 years	4.1 years

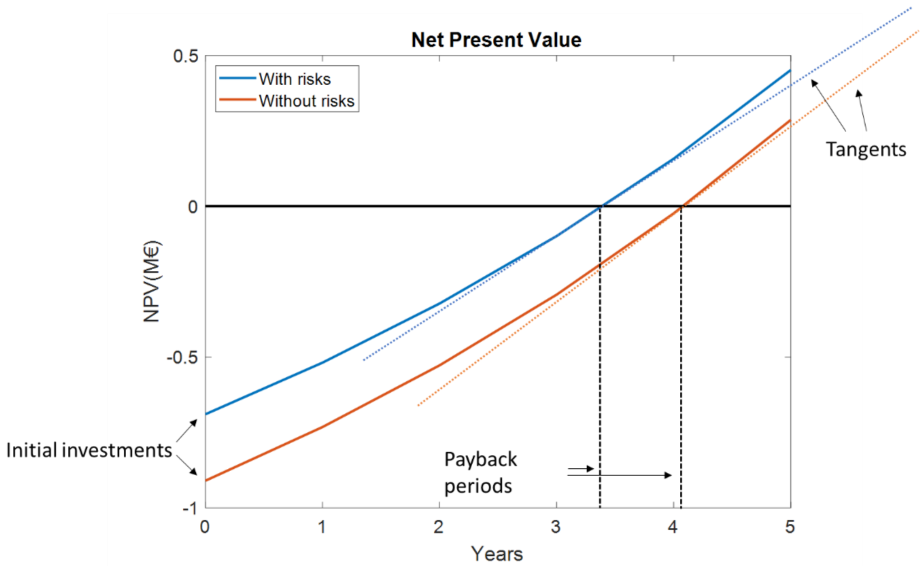

Figure 11. NPV evolution during the first 6 years after investment.

Table 11. Energy equipment selected and their sizes.

Equipment	Size	
	Optimisation with risks	Optimisation without risks
PV energy source	12,000 m²	12,000 m²
Thermal storage	140 kWh	135 kWh
CHP system	140 kWe	200 kWe

Table 12. Criteria evaluation for the two obtained solution.

Criteria evaluation	Value	
	Risks included in the optimisation problem	Risks not included in the optimisation problem

Non-risk criteria		
NPV	7,162,700 €	7,470,000 €
Pollutant emissions (last year)	306.136 tCO_{2eq}	307.4459 tCO_{2eq}
Quantitative risk criteria		
NPV range	6,356,650 – 7,968,750 €	6,616,350 – 8,323,650 €
Qualitative risk criteria		
Business continuity	0.8470	0.3188
Maturity	0.4071	0.5000
Innovation	0.8470	0.5902
Safety	0.5929	0.4071
Social benefits	0.1372	0.1372
Social acceptance	0.8470	0.8470
Administration alignment	0.8470	0.5000
Ecology influence	0.6263	0.6263

First of all, it is possible to see that, for the without risks case, the required energy investment is higher and the payback period is larger. It should be pointed out that these parameters are considered as constraints in the optimisation problem, specified as maximum allowable values chosen by the enterprise, but are not optimised. Instead, the objective for the without risks case is mainly the NPV maximisation while, for the case with risk, the objective is the trade-off between NPV, emissions and quantitative and qualitative risks. Therefore, the NPV for the without risk case analysis results higher than for the with risk one as almost no other parameter is optimised. In Figure 11 appears that despite both initial investment and payback period are higher for the without risks case, its NPV line ascents at a higher grade, as exposed by the tangents of the graphs, obtaining more benefits per year and eventually surpassing the NPV for the case with risks. Although the final economic value is more favourable for the without risks case, this solution does not consider any risk and creates an illusion of the investment's real profitability. Also, the NPV range, as exposed in Table 12, is higher for the without risks case, which reflects a less robust result where the final economic value is more uncertain and spans in a wider range which does, indeed, cover the NPV obtained for the with risks case.

Regarding the equipment selected, in both alternatives it is chosen to cover completely all the available area for the installation of the PV system together with thermal storage and a CHP system. The PV system is always chosen at its maximum capacity due to its low costs and, when considering risks, its positive influence in most of the evaluated qualitative criteria. In contrast, electrochemical storage and heat pump, which were also considered during the optimisation, do not appear as part of the new energy infrastructure. This is a consequence of the relationship between the economic benefits obtained from the equipment and their costs for the resultant energy infrastructure, which is not high enough to justify their incorporation. Also, when evaluating the risks, the influence of these equipment on the favourable risk criteria is not enough to include them regardless of their economic disadvantage. Despite these similarities between both solutions, when optimising the energy investment without considering risks, the size of the CHP system is significantly higher, which is the cause of the higher initial investment and larger payback period discussed previously.

Although the financial considerations exposed regarding the differences between the cases with and without risks are of importance for the SME, they only reflect a part of the global situation. In general, taking a decision considering only the non-risk criteria can lead to a situation with high exposure to strictly non-economic risks with great impacts on the enterprise. In this specific case study, not considering the risks leads to a solution that also compromises the qualitative risk criteria, having lower business continuity, safety and administration alignment, among others, as exposed in Table 12. For example, the solution obtained considering risks inside the optimisation decision-making problem evaluates that the contribution of the energy infrastructure to business continuity is 84.70%. In contrast, if this factor is not considered as criteria as happens in the without risks optimisation, the contribution of the resultant infrastructure to business continuity is only 31.88%, reflecting the possibility of not supporting the company in future challenges. This variation in some of the qualitative criteria in the evaluated case study is a consequence of the danger related to CHP operation and the fact that these systems have been lately a focus of interest by governments, reducing the maximum installed capacity to reach a sustainable energy system and thus inhibiting further investments on them [57].

Thus, incorporating risk analysis in the energy-investment RIDM process enables the achievement of a solution that represents a trade-off between the considered criteria, allowing a smarter initial investment.

The energy investment obtained from considering all the risk and non-risk criteria enable the SME to upgrade its energy infrastructure and start acting as prosumer and, through the risk analysis performed, the operation of this energy infrastructure presents high reliability and robustness that supports the achievement of enterprise's objectives. For the case study analysed in this paper, the operation of the energy equipment and the exchange of energy with the utility grid are exposed in Figure 12, Figure 13, and Figure 14. In Figure 12, it is possible to appreciate that electricity is being purchased when energy from the PV is not available, although at a smaller quantity than required by the internal demand. This is because part of this demand is fulfilled by electricity generated in the CHP system, which is employed both by the electrical side shown in Figure 12 and by the thermal one, shown in Figure 13. The energy exchange behaviour with the utility grid can be seen in Figure 14, where the electricity exchange with the utility grid is exposed together with the price of electricity in the wholesale market. It is possible to appreciate that, when the PV system is generating energy, this is employed for internal demand or to sell to the utility grid if the feed-in price is high enough and economic profit can be obtained. At the moments where electricity is sold, internal electrical demand is fulfilled by both the energy from the PV not injected into the utility grid and the electricity coming from the CHP system. To adopt this optimal working behaviour, it is required to have a great synchronization between the electrical and thermal sides of the industrial plant. For this reason, it is beneficial to include thermal storage to support the mismatches between electrical and thermal demand and allow an optimal operation energy flow.

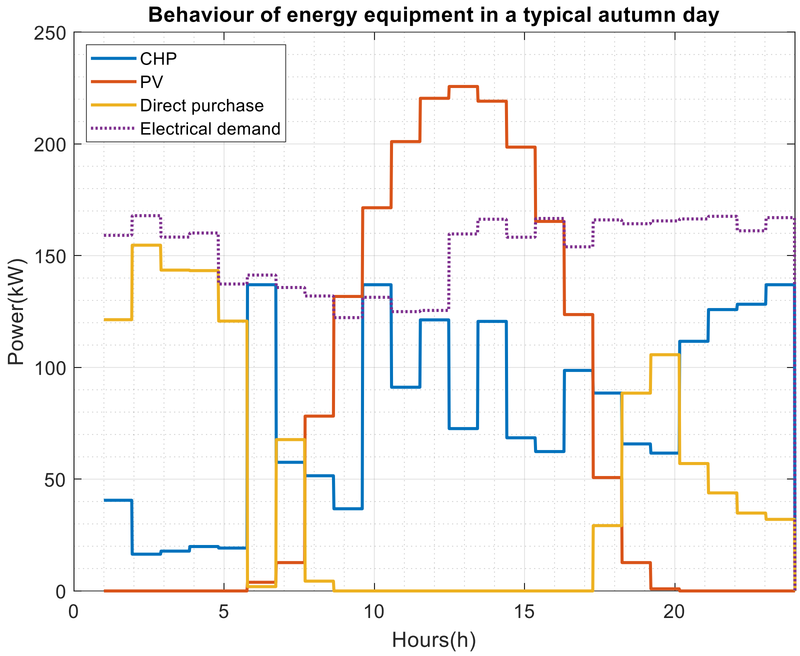

Figure 12. Electrical side energy equipment behaviour for the optimal energy investment.

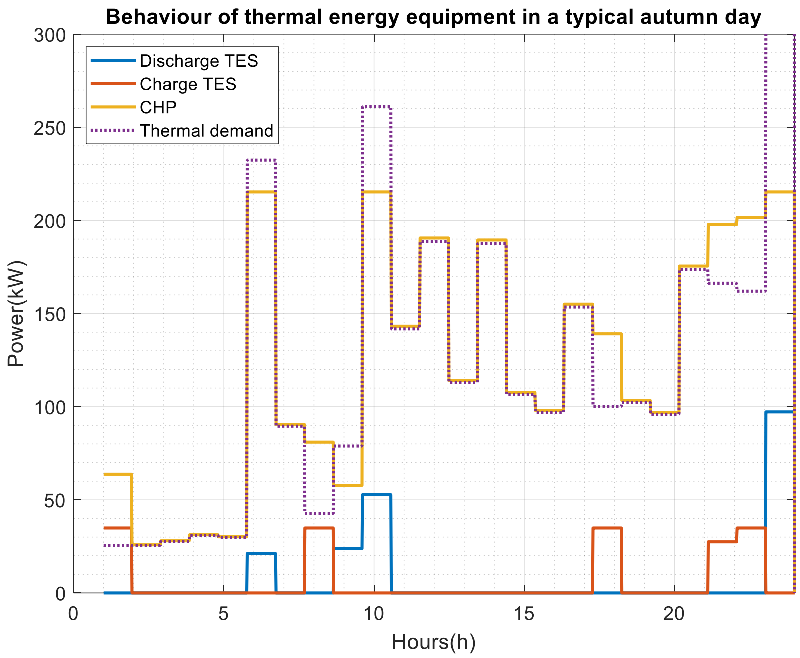

Figure 13. Thermal side energy equipment behaviour for the optimal energy investment.

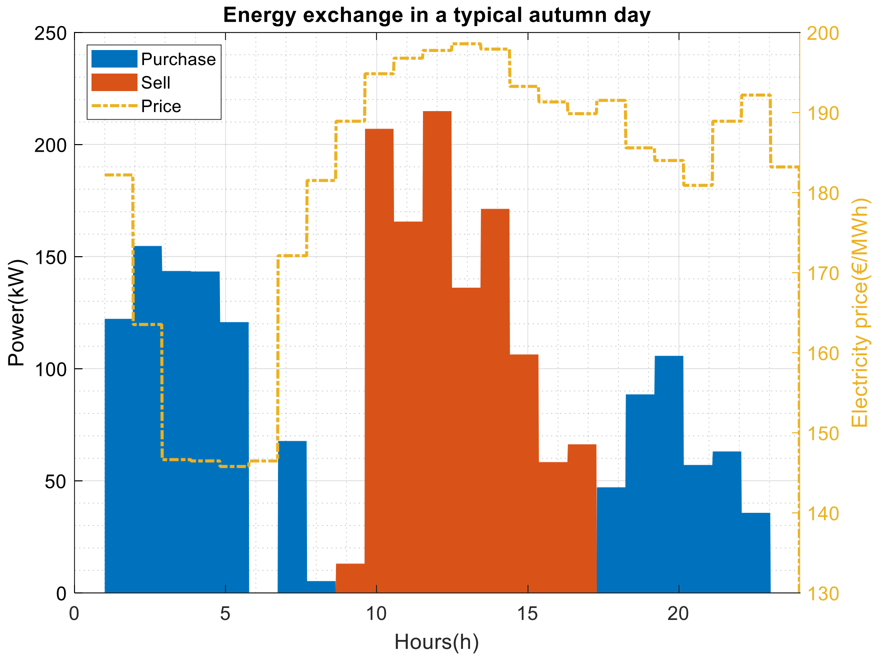

Figure 14. Energy exchange with the utility grid for the optimal energy investment.

5. Conclusions

This paper addresses the energy-investment optimisation problem to upgrade the energy infrastructure of an industrial SME to improve its competitiveness and support the green transformation by adopting an active role in the energy market. This energy investment optimisation problem is discussed considering all the relevant risks associated with the investment decision. A new methodology is proposed which incorporates the specification of the relevant criteria that apply for the industrial SME and the identification and characterization of quantitative and qualitative risks related to them. All these parameters are included in a single function through fuzzy logic and AHP weighting, performed with the support of experts and decision-makers. To reach the best-balanced trade-off solution for the SME, this function is optimized through Direct Search, a global optimisation algorithm that enables the surveillance of the continuous solution's search space. The created methodology, although especially designed to fulfil the requirements of industrial SMEs in upgrading their energy infrastructure, is expandable to other energy investment RIDM problems and also to problems related to the investment in other tangible assets. In these problems, decisions should also be taken considering a mixture of criteria including quantitative and qualitative measures of economic, technical, social, and environmental parameters along the expected lifetime of the investment. The weights granted to the different criteria in the decision-making process depend on the specific problem and its influences in the surroundings, which have to be specified by decision-makers. For this reason, it is required for decision-makers to have a deep knowledge on the interests of the entity taking the decision as well as on social, technical, political, and environmental local framework.

As a demonstration case, in this paper, the developed framework is applied to optimise the energy investment of an industrial SME based in a real manufacturing plant with the possibility to include a PV system, electric and thermal storage systems, a CHP system and an HP. Results show that employing a RIDM approach affects the optimal investment solution, reaching an energy infrastructure that represents a trade-off between the evaluated non-risk and risk criteria. Also, it is demonstrated that without incorporating the risk in the problem, industries would have to face the decision with incomplete information, reaching solutions that could be less beneficial and affect the future of the enterprise and trigger consequences on the surrounding community and environment. This conclusion can be transposed to other entities performing investment decisions, as the omission of risks in the decision-making problem leads to solutions that do not consider possible impacts on the future, such as environmental effects or social welfare.

Thus, the methodology exposed in this paper presents a large practical value for both industrial SMEs and other entities where decision-making problems have to be addressed evaluating both quantitative and qualitative risks, as it can be modified and tailored to suit the specific problem addressed and its application constraints. This methodology can be adopted by decision-boards to analyse energy-investment problems and investment decisions on other tangible assets, enhancing the incorporation of criteria characterized by different nature in a single optimisation function and adjusting the input parameters to decision-makers requirements.

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5.7. Quantitative and qualitative risk-informed energy investment for industrial companies

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This article further defines the methodology for the incorporation of quantitative and qualitative parameters and risks in the energy investment optimization problem of industrial SMEs. Quantitative parameters are addressed statistically and qualitative parameters are evaluated through fuzzy logic to include in their value the vagueness existent in their subjective measurement. These parameters are incorporated in the extended two-stage optimization methodology, which evaluates them both at the moment of taking the decision and over the investment lifetime considering a risk-averse strategy.

Main contributions:

- Handling of qualitative parameters and related uncertainty through a fuzzy logic approach, enabling their measurement considering uncertainty and improving crispy strategies.
- Inclusion of risk-averse factors for energy infrastructure optimisation, which improves risk-neutral strategies.
- Investment optimisation considering combined quantitative and qualitative parameters, contributing to the inclusion of qualitative parameters in the energy problem and improving quantitative only approaches.
- Energy infrastructure operation optimisation considering dynamic quantitative and qualitative parameters over time, improving static approaches in which parameters and related uncertainty do not evolve over time.

Key words:

Energy investment, Risk-informed decision-making, qualitative criteria, fuzzy risk assessment.

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Research paper

Quantitative and qualitative risk-informed energy investment for industrial companies

Eva M. Urbano *, Victor Martinez-Viol, Konstantinos Kampouropoulos, Luis Romeral

MCIA Research Center, Department of Electronic Engineering, Universitat Politècnica de Catalunya, Rambla de Sant Nebridi 22, 08222 Terrassa, Spain

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ABSTRACT

In the ongoing energy transition, small and medium-sized industrial companies are making energy equipment investments due to the obsolescence of their current equipment as well as social, political and market pressures. These firms typically choose investments with low risk exposure based on a combination of criteria that are not always quantifiable. However, published studies on energy investment to date have not been suitable for industrial SMEs because they do not assess the value of the investment over time, ignore the qualitative aspects of decision-making, and do not consider uncertainties. To fill this gap in the literature, this paper proposes a methodology that considers both quantitative and qualitative parameters and risks over time through an extended two-stage risk-informed approach. The proposed methodology includes fuzzy and statistical techniques for evaluating both qualitative and quantitative parameters, as well as their uncertainties, at the time of decision-making and over the investment lifetime. Fuzzy logic is used in the first stage of the optimisation process to measure qualitative parameters and their uncertainty, while quantitative parameters are expressed using probability density functions to account for their uncertainty and measure the quantitative risk assumed by the investor. This methodology is applied to a case study involving a real industrial SME, and the results show that considering both quantitative and qualitative parameters and uncertainties in the optimisation process leads to a more balanced consideration of economic, environmental and social criteria and reduces the variability of the outcome compared to economic-only approaches that do not account for risks. Specifically, the case study shows that considering these parameters and uncertainties resulted in a 15.7% reduction in the size of the cogeneration system due to its environmental and social impacts, and 4.2% reduction in the variability of the economic result.

1. Introduction

The energy sector is undergoing a change of paradigm aiming to achieve a system in which energy supply is guaranteed without negatively affecting its sustainability. The transition requires the reduction of greenhouse gas (GHG) emissions through, among others, the incorporation of Renewable Energy Sources (RES), an increased penetration of distributed energy resources, and an active participation of actors in the energy market. Among these actors, consumers are foreseen to take on a key role switching their behaviour from passive to active flexible prosumers. In the current landscape, industrial consumers account for 37% of global energy use and produce 24% of total emissions (IEA, 2020). Industrial small-and-medium enterprises (SMEs) are especially interesting energetically as they consume more than half of the energy used in industrial and commercial sectors (Fawcett and Hampton, 2020), being critical for the green transformation (Özbuğday et al., 2020). Despite this, they are generally under-researched and find more difficulties than larger entities in adopting new energy strategies (Kakran and Chanana, 2018). SMEs may face the need or duty to upgrade their energy infrastructure by incorporating RES and flexibility because of the obsolescence of previous equipment and also as a result of the current Industry 5.0 revolution, which tries to renew industries and transform them into more future-proof, resilient, sustainable and human-centred entities (Cotta et al., 2021). SMEs naturally tend to select investments with short payback periods, favourable economic, environmental and social parameters, low risks exposure and such that the infrastructure is maintained in operation for this whole lifetime once it is upgraded (Gveroski and Risteska, 2017). However, energy investments are inherently linked to risks arising from uncertainty in quantitative parameters, whose exact value along time is unknown; and in qualitative parameters, which reflect subjective preferences and opinions. Given the current changing situation, where public perception is increasingly important and the energy market is becoming more volatile, the existent risks inhibit investments and firms′ innovation activity (Alaali, 2020). To enhance these actions in industrial

* Corresponding author.
E-mail address: eva.maria.urbano@upc.edu (E.M. Urbano).

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Nomenclature

Abbreviation	**Full description**
General Abbreviations	
AHP	Analytical Hierarchy Process
CHP	Combined Heat and Power
CVaR	Conditional-Value-at-Risk
DS	Direct Search
EES	Electrochemical Energy Storage
FIS	Fuzzy Inference System
HP	Heat Pump
JC	Job Creation
LHS	Latin Hypercube Sampling
MF	Membership Function
NPV	Net Present Value
O&M	Operation and Maintenance
PDF	Probability Density Functions
PV	Photovoltaic
RES	Renewable Energy Source
RF	Renewable Factor
SA	Sensitivity Analysis
SME	Small-and-Medium Enterprise
TES	Thermal Energy Storage
UA	Uncertainty Analysis
VaR	Value at Risk
Energy infrastructure sizing and operation parameters	
P	Electrical power
Q	Thermal power
η	Efficiency
C	Economic cost
QC	Qualitative cost
Cap	Capacity of energy storage
RC	Charge ratio of energy storage
RD	Discharge ratio of energy storage
SD	Self-discharge ratio of energy storage
E	Energy stored in energy storage system
I	Cash flow
r	Hurdle rate
W	Weeks per year analysed
W_Y	Total weeks per year
A	Area
w	Weight assigned to a decision parameter
VAR_{level}	Probability level for computing the VaR

Subscripts and superscripts

max	Maximum capacity of equipment
min	Minimum capacity of equipment
j	Time instant considered for operatio optimisation
i	Optimisation year
0	Instant when decision is taken
T	Expected lifetime of energy infrastructu
PV	PV system
ES	Electrochemical energy storage
CES	Charge EES
DES	Discharge EES
ED	Electrical demand
UG	Utility Grid
FI	Feed-in
CHP	Cogeneration system
CHP_e	Electrical side of the CHP system
CHP_{th}	Thermal side of the CHP system
TL	Thermal Load
BOI	Boiler
TS	Thermal energy storage
CTS	Charge TES
DTS	Discharge TES
g	Gas from the grid
GHG	Greenhouse gases
$O\&M$	Operation & Maintenance
ref	Hypothetic case without investment
JC	Job Creation
nom	Nominal power
ec	Economic parameter
ql	Qualitative parameter

SMEs, in this paper their energy investment problem is addressed considering quantitative and qualitative parameters and uncertainties along the expected lifetime of the upgraded infrastructure.

In most of the current studies dealing with energy investment, optimisation is presented without considering uncertainties. Some papers analysed energy investment′s uncertainty only after obtaining the solution, without optimising it with respect to uncertainties. In (Mavromatidis et al., 2018), Uncertainty Analysis (UA) and Sensitivity Analysis (SA) are carried out to evaluate the effect of uncertain input values on the year cost performance of a multi-carrier energy system. Similarly, in (Solangi et al., 2019), several strategies for sustainable energy planning are addressed and a SA is done to evaluate the robustness of the obtained solution, and in (Qiao et al., 2022) the risks of renewable energy projects investment are analysed but the investment itself is not optimised These approaches enable the investor to know the risk assumed when making the investment, although they do not propose an adaptation strategy for unacceptable risk levels nor incorporate the uncertainty analysis inside the optimisation problem.

The literature on energy investment optimisation that considers risks within the decision-making problem is scarce. In (Chen et al., 2016), an optimisation model for regional energy systems is developed. This methodology includes degrees of fulfilment for the uncertain constraints, which provides decision-makers with alternatives under different violation parameters. In (Afzali et al., 2020), an optimal energy system is addressed by minimizing total annual cost while limiting the average worst-case emissions. Both of the aforementioned studies do not consider risk as an optimisation objective, but rather as a limitation, creating a strategy that is robust in front of uncertainties. Although robust optimisations provide a simple framework for dealing with uncertainty, they are conservative and trade off the performance of the system for its robustness (Lekvan et al., 2021). Another strategy commonly employed in the literature for optimisation under uncertainty is two-stage stochastic optimisation, in which the decision parameters are selected in the first stage and all possible scenario realisations are considered in the second stage, optimising the mean resultant value. This is used in (Pickering and Choudhary, 2019) where two-stage stochastic model is applied to a district energy system optimisation under uncertainty on the demand side, and in (Tian et al., 2021) where two-stage stochastic search is employed for the optimal sizing and placement of energy storage. Even though two-stage stochastic methods incorporate uncertainty in the optimisation problem, they do so in a risk-neutral perspective not providing a clear measure of the risk taken by the investor (Noyan, 2012). (Li et al., 2020) presents an improved method including a risk-aversion strategy. In this study, the planning of an integrated energy system is done incorporating Conditional-Value-at-Risk (CVaR) as part of the objective function. Following the same approach, (Xie et al., 2021) proposed a sizing methodology assessing risk through the computation of the mean-variance. In all the above works, the risk is expressed employing quantitative only approaches, focusing mainly on economic parameters. Few of the aforementioned studies consider other objectives such as environmental or social ones and, when these are considered, quantifiable parameters are chosen as criteria. (Zhang et al., 2022) creates an index covering techno-economic, financial and social environmental benefits although only measurable criteria are used, and in (Gao, 2022) social utility is included in the optimisation problem computed as a combination of the value of price and quantity of energy delivered by the sized system. Quantitative only models, however, are insufficient for the energy sizing problem as there are uncertainty dimensions that can only be addressed through qualitative approaches which can equal or dominate quantitative ones (Pye et al., 2018). Therefore, it is essential to incorporate qualitative considerations in energy investment decision-making (Bhardwaj et al., 2019), which will improve the evaluation of uncertainty and will also improve the competitiveness of the enterprise creating significant positive outcomes (Cornejo-Cañamares et al., 2021).

Up to date, qualitative parameters inside the decision-making process have been considered in the literature for non-energy optimisation problems. In (Boudreau et al., 2019), a generic methodology for assets management decision-making considering quantitative and qualitative factors is presented where qualitative factors are crisply measured. In (Solangi et al., 2019), country energy planning strategies are proposed where qualitative criteria are employed, although they are not optimised. (Harter et al., 2020) considers both quantitative and qualitative parameters for uncertainty assessment in the design of a building although qualitative attributes are set as crisp numerical values without considering judgemental vagueness. Even though these studies incorporate qualitative parameters, they do not account for the uncertainty linked to them given their subjective nature. In (Kaya et al., 2019), decision-making methodologies for energy policy making are assessed and fuzzy set theory is presented as a tool to express uncertainties inherently associated to human opinions. Fuzzy set theory can be successfully used together with multi-criteria optimisation problems to get a more sensitive, concrete and realistic result. Although the approaches mentioned in this paragraph include qualitative parameters, they leave quantitative information in a background position, not creating a suitable framework for energy infrastructure optimisation.

In addition to the lack of a methodology incorporating both quantitative and qualitative parameters and their uncertainties for energy investment decisions, most studies dealing with this problem do not consider the lifetime value of the investment, but only its cost or profit for a shorter period. In the energy-sizing studies described above, a time frame is specified as in (Guo and Xiang, 2022), where a set of typical days of a year is simulated to reveal the performance of the energy system. Thus, the suitability of the investment is evaluated based on a static time frame, simplifying parameters' evolution and considering them to be constant during several years. This optimisation procedure does not reflect the current changing context and leads to suboptimal solutions which over-estimate the performance of the selected energy infrastructure (Pecenak et al., 2019). Few of the most recently published papers incorporate a continuous-time framework for energy sizing problems. It is the case of (Mavromatidis and Petkov, 2021), where a model for multi-year, multi-location of energy sources is presented without considering uncertainties. In (Urbano et al., 2021), the design of multi-carrier energy infrastructure is performed considering the time evolution of parameters. UA and SA are carried out to acknowledge the risk and identify the most relevant parameters, but uncertainty is not incorporated into the optimisation problem. In (Bohlayer et al., 2021), energy carriers price and investment costs uncertainties are considered within the optimisation problem through a two-stage stochastic strategy. However, this two-stage stochastic strategy is risk-neutral as it optimises the expected value of the solution, not directly analysing the risk related to it.

In a nutshell, although some methodologies for energy investment decision-making proposed up to date include time variations, they are neither complete nor suitable for the energy investment problem of industrial SMEs since quantitative uncertainty is either neglected, analysed outside of the optimisation problem or included in the optimisation through a risk neutral strategy, omitting the qualitative spectrum. In light of this, the objective of this paper is to present a novel optimisation methodology which considers quantitative and qualitative parameters and their uncertainties both at the moment of taking the decision and along the lifetime of the energy infrastructure to fill the gaps encountered in the literature. This methodology is presented as an extended two-stage risk-informed optimisation. In the first stage, the equipment is selected and qualitative criteria is measured considering the uncertainty linked to them through a fuzzy approach. In the second stage, the performance of the energy infrastructure is computed by optimising its operation along

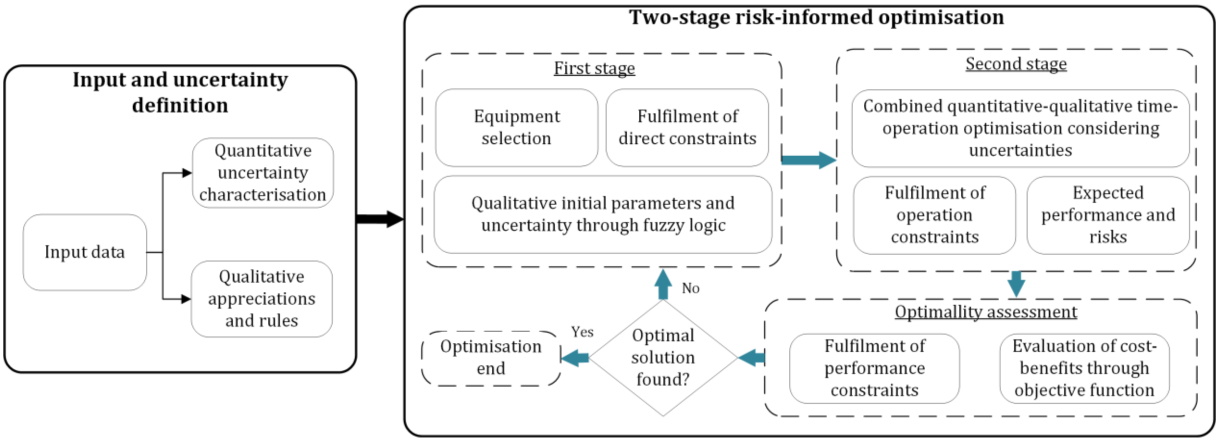

Fig. 1: Risk-informed energy-investment optimisation procedure.

lifetime evaluating both quantitative and qualitative parameters together with their uncertainty through a risk-averse strategy. In this way, it is possible to optimise the energy investment by taking into account its global performance in terms of quantitative and qualitative parameters as well as its risks. A practical case study based on a real manufacturing industrial SME is described to appreciate the effects of including quantitative criteria, qualitative criteria and risks in enterprises' decision-making process. The specific novelties and contributions of this paper to the state-of-the art can be summarised as follows:

- Extended two-stage risk-informed optimisation considering combined quantitative and qualitative parameters and uncertainties.
- Qualitative parameters and related uncertainty handled through a fuzzy logic approach for their inclusion in the optimisation problem.
- Energy infrastructure operation optimisation considering dynamic quantitative and qualitative parameters along time.
- Inclusion of risk-averse factors for energy infrastructure optimisation considering quantitative and qualitative uncertainties.

The rest of the paper is organised as follows. Section 2 describes the methodology for energy investment optimisation considering quantitative and qualitative parameters and risks. Section 3 presents a case study to which the proposed methodology is applied and whose results are reported and discussed in Section 4. Finally, Section 5 presents the conclusions of the study.

2. Methodology

Fig. 1 illustrates the methodology proposed in this paper to address the energy investment optimisation problem. The first step is to identify the input parameters and their uncertainty. Once defined, it is possible to proceed to the two-stage risk-informed optimisation. In the first stage, the equipment is selected through an optimiser and direct constraints, e.g., allowable investment and space availability for installations, are checked. Then, qualitative parameters such as ecological danger and administration alignment are evaluated. Given their subjective nature, the uncertainty linked to these parameters is considered through a fuzzy logic approach. Next, the operation of the selected energy infrastructure is optimised for its lifetime considering quantitative and qualitative costs and the uncertainty linked to them. Operation constraints are verified and the expected performance of the energy infrastructure and its risks are computed. With this information, the costs and benefits of the upgraded energy infrastructure are evaluated through the selected criteria. In this stage, the fulfilment of constraints imposed by the enterprise such as maximum payback or minimum return is verified. If the optimiser meets its stopping criteria, the process finalizes here. Otherwise, another possible energy equipment solution is analysed.

2.1. Input data, uncertainty characterisation and base case

The input data required to address the energy investment problem depends on the characteristics of the potential energy infrastructure as well as on the criteria that the enterprise wants to consider for taking the decision. These data can be divided into two types: quantitative and qualitative.

2.1.1. Qualitative data

Qualitative data are those required to take the decision but which are not measurable in a quantitative manner. Their value is assigned by an expert or decision-maker based on their knowledge about, for example, the community where the industry is placed and the governmental framework (Peng et al., 2019). The dependence of qualitative parameters on judgmental vagueness generates uncertainty and their consideration as crisp numbers causes loss of information. A suitable strategy to include vagueness and uncertainty in the energy investment optimisation problem is the employment of Fuzzy logic (Antucheviciene et al., 2015) evaluating the *probability* and *impact* of the energy infrastructure on the qualitative perceptions of interest (Brocal et al., 2019). In the studied problem, *impact* is a measure of the potential effect that the qualitative perception can have on the performance of the energy infrastructure while *probability* is a measure of how likely is the impact to happen (Nieto-Morote and Ruz-Vila, 2011). *Impact* and *probability* depend on the mix of technologies considered for upgrading the energy infrastructure as well as on their social, environmental and technical influences. To consider all these parameters and obtain a measure of the qualitative perception including uncertainty, the fuzzy system illustrated in Fig. 2 is proposed. First of all, the capacities of the technologies selected to upgrade the infrastructure are fuzzified and membership functions (MFs) are assigned to them. *Probability* and *impact* are computed considering the rules specified by decision-makers.

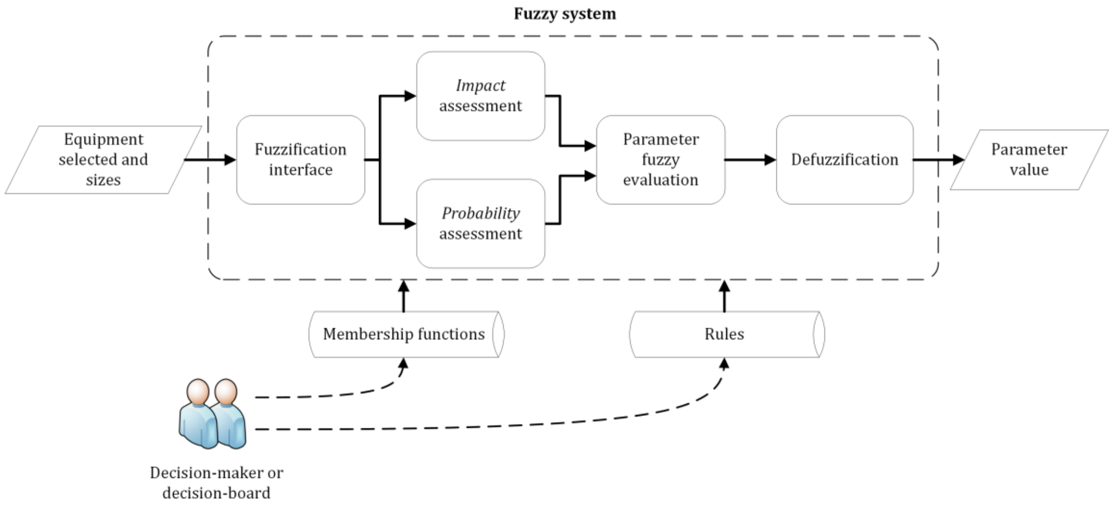

Fig. 2: Process flow for the assessment of qualitative criteria through a fuzzy approach.

Impact and *probability* functions are then aggregated to obtain the qualitative perception fuzzy set, which is later defuzzified, improving the consideration of qualitative parameters as crisp.

This analysis supports a non-only quantitative process that adjust the solution to enterprise's interests by including qualitative parameters in the first-stage of the optimisation. Nonetheless, the socio-political framework is susceptible to changes and therefore these parameters have also to be included in the second-stage of the problem. To do so, decision-makers should analyse the potential socio-political changes and the eventual positive or negative influence that the employed technologies would have on investments' performance, considering the new context. This analysis reflects the alignment of the chosen technologies on enterprise's interest over time and can be translated to dynamic qualitative cost for its inclusion in the operation optimisation, creating a qualitative-aware operation strategy. As these dynamic costs are also subject to vagueness, fuzzy logic is employed. For it, technologies are evaluated in an isolated manner to compute the cost for employing them and therefore *probability* and *impact* can be directly assigned to them. Once *probability* and *impact* are obtained, the qualitative dynamic cost is computed through the same fuzzy methodology that is used for the initial qualitative perceptions.

2.1.2. Quantitative data

Quantitative data is required to perform a technical and economic analysis of the solution. Since the computation of the value of the investment requires an evaluation of its performance along time, it is indispensable to account for the uncertainty of input parameters within the decision-making problem. Quantitative data can also be characterised through *probability* and *impact*. On the one hand, *probability* refers to the values that the input parameters can take and how likely they are. This probability can be contemplated by employing a discrete range of values or by assigning Probability Distribution Functions (PDF) (Borgonovo and Plischke, 2016). On the other hand, *impact* refers to the influence that the values of the inputs have on the result or on the criteria selected by the enterprise. To compute it, the enterprise's criteria should be evaluated for the possible inputs value and thus it is required to sample the PDFs and solve the energy infrastructure performance optimisation problem for the obtained samples. With a PDF assigned to uncertain quantitative parameters, a method that generates samples according to these probability distributions allows obtaining a reliable output capturing its distribution in the variation range (Tran and Smith, 2018). In the present study, the Latin Hypercube Sampling (LHS) is selected as it presents results efficiently allowing a broad coverage of the entire PDF at a relatively low computational cost (Kristensen and Petersen, 2016). Once uncertainty samples are generated, the *impact* is computed through the second stage of the optimisation problem.

2.2. Two-stage risk-informed optimisation

This section provides details on the two-stage risk informed optimisation considering a standard industrial SME plant. This industrial plant purchases electricity directly from the utility grid to satisfy electrical demand and owns a boiler to transform chemical energy to thermal one. The candidate equipment to be included are: PV system, thermal energy storage (TES), electrochemical energy storage (EES), cogeneration (CHP), and heat pump (HP).

2.2.1. First-stage

In the first stage of the optimisation, a set of candidate solutions formed by equipment's capacities that could be installed in the enterprise is obtained from a global optimiser. An optimiser capable to deal with unconnected complex feasible areas is required. In this case, Direct Search (DS) is selected, as it is a derivative-free global optimisation algorithm that performs successfully in front of practical problems (Lewis et al., 2000). Once DS selects the potential solutions, their compliance with enterprise's constraints is verified. If so, initial qualitative parameters are computed by introducing the equipment to the employed fuzzy system.

2.2.2. Second-stage

The selected equipment proceed to the second stage where the operation of the infrastructure is optimised considering quantitative and qualitative costs. Fig. 3 illustrates the process. First of all, data is obtained from previous stages, and the first scenario is selected from the samples of quantitative uncertain inputs. Then, the operation is optimised for the lifetime of the infrastructure. This optimisation is carried out based on 7-days weeks selected through the years which enables to consider the existent weekly energy patterns both in industrial demand and energy markets. Inputs are considered to vary with time in a representative time frame. Electricity cost, for example, varies in an hourly manner and presents an evolution between different weeks and years. To obtain realistic dispatchment strategies over time, equipment degradation is also included in the optimisation problem. A prosumer behaviour is evaluated in this stage to consider the adoption of new roles arising in the energy market. To carry out the operation optimisation, a mathematical model of the plant is required. The model is formulated considering all possible equipment to be installed, whose capacity is set to zero when they are not included in the analysed solution. For a standard industrial SME, the energy equilibrium for the electrical side is:

$$P_{PV}\eta_{PV} + P_{UG}\eta_{UG} + Q_{CHP}\frac{\eta_{CHPe}}{\eta_{CHPth}} + P_{DES}\eta_{DES} = \frac{P_{ED}}{\eta_{ED}} + P_{FI} + \frac{P_{CES}}{\eta_{CES}} + P_{HP} \quad (1)$$

For thermal side, the equilibrium is:

$$Q_{CHP} + Q_{BOI} + Q_{DTS}\eta_{DTS} + P_{HP}\eta_{HP} = \frac{Q_{TL}}{\eta_{TL}} + \frac{Q_{CTS}}{\eta_{CTS}} \quad (2)$$

These equilibriums are subject to restrictions related to power exchange with external grids and to maximum capacity of equipment:

$$0 \le P_{UG} \le P_{UG,max} \quad (3)$$

$$0 \le P_{FI} \le P_{UG,max} \quad (4)$$

$$0 \le \frac{Q_{CHP}}{\eta_{CHPth}} + \frac{Q_{BOI}}{\eta_{BOI}} \le Q_{g,max} \quad (5)$$

$$0 \le Q_{BOI} \le Q_{BOI,max} \quad (6)$$

$$0 \le Q_{CHP} \le Q_{CHP,max} \quad (7)$$

$$0 \le P_{HP} \le P_{HP,max} \quad (8)$$

For the energy storage, restrictions include not only their capacity ratios but also the energy stored. The formulation for the TES and EES is similar, and is described below:

$$0 \le Q_{CTS} \le RC_{TS} \times Cap_{TS} \quad (9)$$

$$0 \le Q_{DTS} \le RD_{TS} \times Cap_{TS} \quad (10)$$

$$E_{TS}^{j} = E_{TS}^{j-1} + \Delta t(Q_{CTS} - Q_{DTS}) - SD_{TS}E_{TS}^{j} \quad (11)$$

$$Cap_{TS,min} \le E_{TS}^{j} \le Cap_{TS} \quad (12)$$

With this mathematical model, it is possible to carry out the equipment's operation optimisation. As the proposed optimisation considers both quantitative and qualitative costs, the objective function of the operation optimisation is:

$$\begin{aligned} f_{op} = \sum_{j=1}^{N} w_{ec}\Big(&P_{PV,j}C_{PV} + P_{UG,j}C_{UG,j} \\ &+ C_{ES}(P_{CES,j} + P_{DES,j}) \\ &+ P_{CHP,j}C_{CHP} + P_{HP,j}C_{HP} \\ &+ Q_{BOI,j}C_{BOI} \\ &+ \left(\frac{Q_{CHP,j}}{\eta_{CHPth}} + \frac{Q_{BOI,j}}{\eta_{BOI}}\right)(C_{G,j} \\ &+ F_g C_{GHG,j}) \\ &+ C_{TS}(Q_{CTS,j} + Q_{DTS,j}) \\ &- P_{FI,j}C_{FI,j}\Big) \\ &+ w_{ql}\Big(P_{PV,j}QC_{PV} \\ &+ QC_{ES}(P_{CES,j} + P_{DES,j}) \\ &+ P_{CHP,j}QC_{CHP} + P_{HP,j}QC_{HP,j} \\ &+ Q_{BOI,j}QC_{BOI} \\ &+ QC_{TS}(Q_{CTS,j} + Q_{DTS,j})\Big) \end{aligned} \quad (13)$$

This optimisation can be solved through a linear programming approach, which assures the achievement of the global minimum efficiently (Liberti, 2008). Once the operation for one scenario has been obtained, quantitative parameters can be computed. One of the most suitable parameter to evaluate the performance of the energy infrastructure along time is the net present value (NPV), as it considers the different cash inflows and outflows for every year and transforms them into current value; evaluating the profitability of energy investments (Eriksson and Gray, 2017). For computing the NPV, the upgraded industrial plant is compared with its hypothetical operation if no investment is performed. The NPV is evaluated as:

$$NPV = -I_0 + \sum_{i=1}^{T}\frac{I_i}{(1-r)^i} \quad (14)$$

Cash flow are computed for the analysed weeks and extrapolated for years as:

$$\begin{aligned} I_i = \frac{W_Y}{W}\sum_{k=1}^{W}\Bigg(\sum_{j=1}^{N} &P_{FI,i,k,j}C_{FI,i,k,j} \\ &+ (P_{UG,ref,i,k,j} \\ &- P_{UG,i,k,j})C_{UG,i,k,j} \\ &+ \left(\frac{Q_{BOI,ref,i,k,j}}{\eta_{BOI}} - \frac{Q_{CHP,i,k,j}}{\eta_{CHPth}} \right. \\ &\left. - \frac{Q_{BOI,i,j,k}}{\eta_{BOI}}\right)(C_{G,i} \\ &+ F_g C_{GHG,i})\Bigg) \\ &- (C_{O\&M,CHP}Q_{CHP,nom} \\ &+ C_{O\&M,HP}Q_{HP,nom} \\ &+ C_{O\&M,ES}Cap_{ES} \\ &+ C_{O\&M,TS}Cap_{TS} \\ &+ C_{O\&M,PV}A_{PV}P_{PV,nom}) \end{aligned} \quad (15)$$

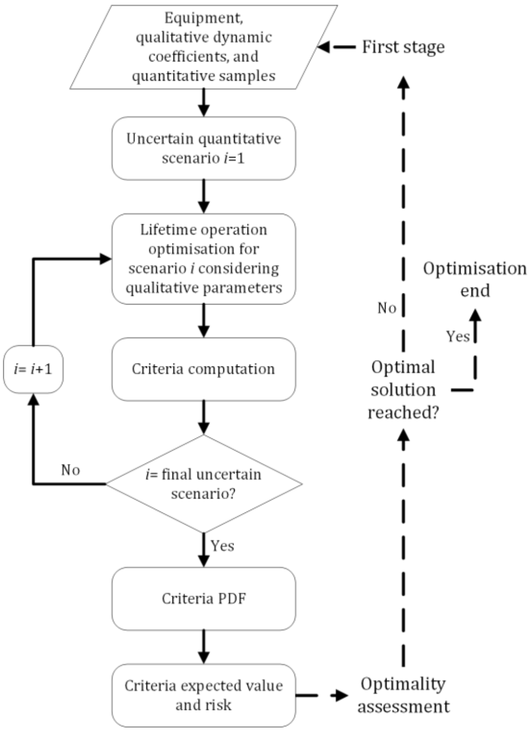

Fig. 3: Second-stage optimisation procedure.

Once the quantitative parameters are computed, another scenario including a different set of possible inputs is evaluated until all scenarios are covered. Then, the PDF of the quantitative parameters is obtained. This is used to compute their expected value and to evaluate the risk through CVaR, which enables to consider the complete outcome PDF avoiding undesirable profit distributions (Vahedipour-Dahraie et al., 2020). CVaR is computed as:

$$CVaR(x) = \frac{1}{1-VaR}\int_{-1}^{VaR_{level}} xp(x)dx \qquad (16)$$

Where $p(x)dx$ is the probability of the value x according to the PDF.

2.2.3. Optimality assessment

In this stage, it is decided whether the analysed equipment are the optimal one or if more iterations are required. This decision is reached based on the quantitative and qualitative criteria computed through the two stages of the optimisation process, which have to be included in a single function. The criteria's union can be performed through aggregation or multiplication. In this case, it is better to employ aggregation as it considers positive and negative criteria and deals better with outliers, limiting their influence in the final function value. Qualitative criteria measured in the first-stage of the optimisation include their uncertain definition and risk in their value. In contrast, for quantitative criteria, there are two differentiated measures: expected value and CVaR. In this paper, these values are unified in a single measure by employing the VaR level which defines CVaR as:

$$X_{measure\ with\ risk} = E(x) + VAR_{level}CVaR(x) \qquad (17)$$

Then, quantitative and qualitative criteria are structured under the main decision-making criteria employed for investment evaluation in enterprises: economic, social and environmental (Hoogmartens et al., 2014). Main criteria are computed as the arithmetic mean of the criteria under them. To avoid numerical illness, remove dimensions, and obtain a realistic measure of the criteria, all parameters are normalized previous to the balance. Main criteria are then incorporated in a single function reflecting the preferences of decision-makers. These preferences are obtained through Analytical Hierarchy Process (AHP) (Saaty, 1987), which allows to consider subjective preferences in a robust manner (Roszkowska, 2013). The objective function including all the criteria is computed and the global optimiser checks its stopping criteria, which can include result tolerance, number of iterations without improvement, optimisation time, etc. If the optimal solution has been reached, the optimiser finalizes its operation. Otherwise, the result is returned to the first-stage where new potential solutions are created and the process is repeated.

3. Case study

In this section, the methodology presented is applied to a manufacturing industrial SME from the automotive sector located in Spain.

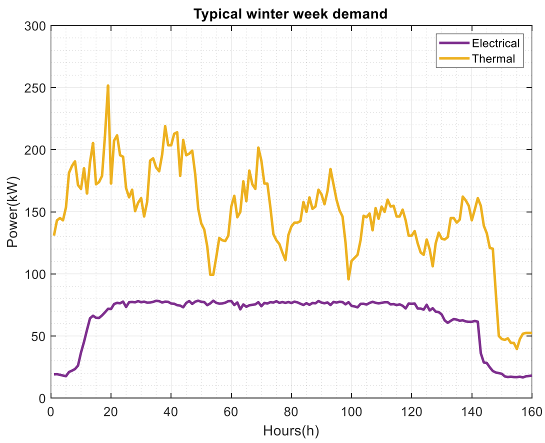

Fig. 4: Demand for a typical winter week.

3.1. SME industrial plant

The case study enterprise currently relies on a boiler to transform gas to thermal power and purchases electricity from the utility grid to meet electrical load. Fig. 4 illustrates as an example the demand pattern for a typical winter week. The enterprise is exploring the possibility to upgrade its energy infrastructure and transform into a prosumer by including increasingly adopted technologies. These technologies are: PV system, CHP system, a HP and storage, both electrical (EES) and thermal (TES). The new equipment are foreseen to be kept in operation for the next 15 years. Equipment degradation considering this horizon is mainly present in PV and EES systems. For the case of PVs, a continuous performance loss of 0.8% per year is implemented (Jordan et al., 2015). For the ESS, the degradation appears as loss of capacity instead of loss of efficiency. In this paper, continuous degradation of 6% per year accumulated is applied (Carnovale and Li, 2020). Table 1 exposes the criteria that the enterprise considers of importance for taking the decision. From these criteria, NPV and GHG emissions can be computed quantitatively. In contrast, business continuity, ecological impact, social acceptance, and administration alignment are considered qualitatively. The

Table 3
Qualitative risk matrix for continuous technologies' qualitative cost.

		Probability				
		Large	Considerable	Moderate	Minor	Negligible
Impact	Large	Large	Large	Considerable	Considerable	Moderate
	Considerable	Large	Considerable	Considerable	Moderate	Moderate
	Moderate	Considerable	Considerable	Moderate	Moderate	Minor
	Minor	Considerable	Moderate	Moderate	Minor	Negligible
	Negligible	Moderate	Moderate	Minor	Negligible	Negligible

energy investment should fulfil the set of constraints specified by the industrial SME that appear in Table 2.

Table 1
Criteria of importance for the case study industrial SME.

Main Criteria	Sub criteria
Economic	• NPV • Business continuity
Environmental	• GHG emissions • Ecological impact
Social	• Social acceptance • Administration alignment

Table 2
Energy investment constraints for the case study.

Constraint	Value
Maximum initial investment	1000000€
Maximum time for return of investment	6 years
Maximum emissions at year 15	300 tCO_2
Maximum area of the PV system	$12000m^2$

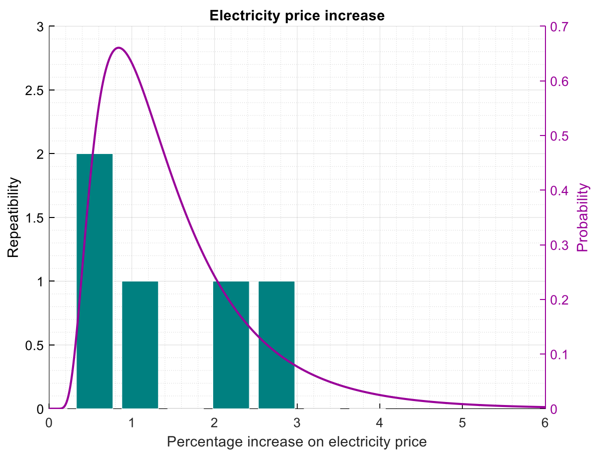

Fig. 5: Electricity price evolution uncertainty characterisation.

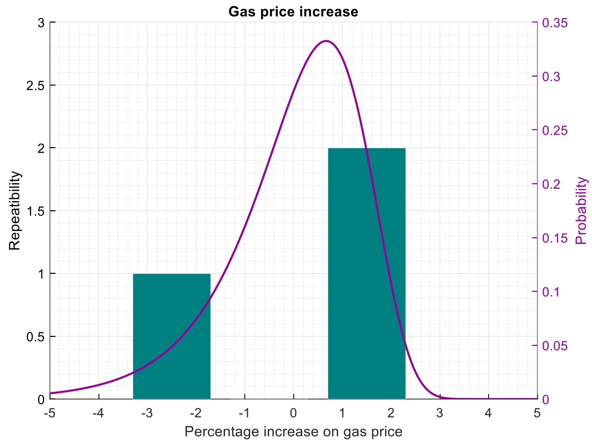

Fig. 6: Gas price evolution uncertainty characterisation.

3.2. Quantitative data

The quantitative data required to carry out the optimisation includes equipment parameters, operation and maintenance (O&M) costs, energy carriers' costs and connexion efficiencies. Although the evolution of all of these parameters is uncertain, only energy carriers' costs uncertainty affect significantly the performance of the energy infrastructure (Urbano et al., 2021). Therefore, this uncertainty is incorporated in the optimisation process whereas the rest of quantitative parameters are considered deterministic. The industrial SME under study employs two energy carriers: electricity and gas. For electricity, its price is forecasted to increase between 0.51% and 2.69% yearly (Afman et al., 2017; Comission, 2016; Zhou, 2021). Fig. 5 shows how these cost evolution scenarios can be fitted to a PDF. The PDF is selected according to the goodness of the fit measured through the loglikelihood function and is in this case an Inverse Gaussian distribution with parameters μ=1.48 λ=3.72. For the case of the gas, today's cost is forecasted to vary in upcoming years between -2.19% and 1.4% (Zhou et al., 2019; Zhou, 2021). Fig. 6 shows these values together with the fitted Extreme Value PDF with parameters μ=0.67 σ=1.10. Initial energy carrier's costs are obtained from wholesale markets in Spain, being of 90€/MWh (Omie, 2021) for electricity and of 48€/MWh for gas (MIBGAS, 2021). Other quantitative data employed in the optimisation can be consulted in Appendix A.

3.3. Qualitative data

3.3.1. Initial perception

In the first stage of the optimisation the qualitative criteria are computed according to the selected technologies. To do so, MFs and rules of the fuzzy system are defined. MFs represent imprecise information coming from human opinions and sentiments regarding energy equipment. To do so, the employment of Gaussian MFs is preferable as they describe the continuity of opinions better than other common types of MFs due to its smoothness and naturality (Abdar et al., 2020). MFs can be directly defined by decision-makers through their expertise in the field or obtained through opinion mining (Serrano-Guerrero et al., 2021). The process of opinion mining and definition of most suitable MFs is out of the scope of this study and thus, for the sake of exposition, the MFs shown in Fig. 7 and Fig. 8 are assumed to suitably represent society opinion for this case study.

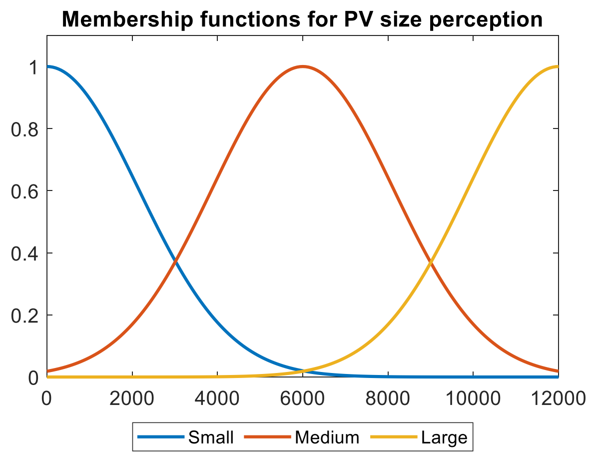

Fig. 7: PV system MFs.

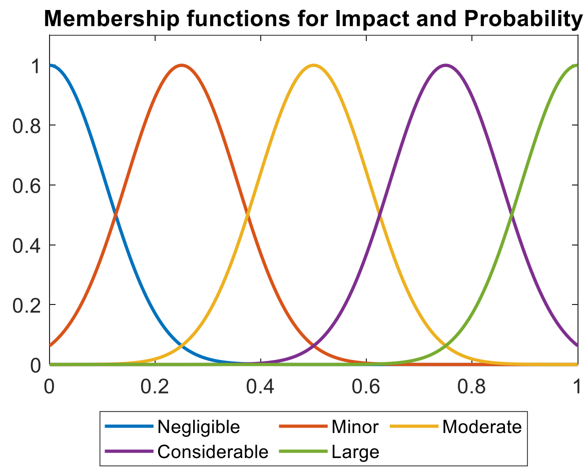

Fig. 8: MFs for *impact* and *probability*.

Decision-makers also establish the rules to compute *impact* and *probability* for business continuity, administration alignment, social acceptance, and ecological impact. The rules are written in *if-then* format and enable to obtain the output based on the set of provided inputs and the MFs. As an example, Fig. 9 shows the resultant surface exposing the *impact* in administration alignment of the solution according to different PV and CHP sizes. The fuzzy method to compute *impact* and *probability* employs max-min composition to consider all activated rules. Then, *probability* and *impact* resultant functions are aggregated through the max method and the resultant function defuzzifed employing the centroid method.

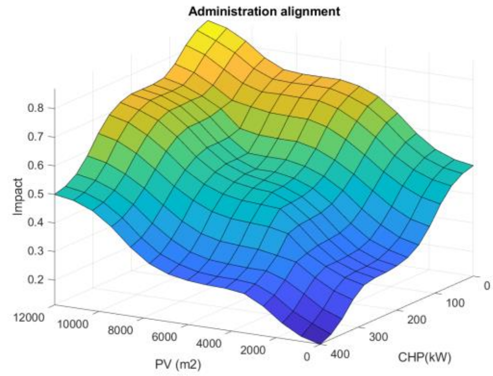

Fig. 9: Impact surface for administration alignment.

3.3.2. Continuous qualitative cost of technologies

Qualitative perceptions are included in the second stage of the optimisation as the qualitative costs of employing a technology. To obtain this cost, decision-makers evaluate for 15 years of the investment's lifetime the *impact* and *probability* of the technology to contribute negatively in the specified qualitative criteria. *Impact* and *probability* are then incorporated in a fuzzy system which computes the cost. The MFs for these inputs and for the output are the same as exposed in Fig. 8, with the difference that the output's range is [0,0.1] to have the same magnitude order as the economic costs. In this case, the rules generated by decision-makers, depend only on two inputs and therefore can be expressed in a qualitative risk matrix (Table 3).

3.4. Decision preferences

The sub criteria are structured under the main criteria as seen in Table 1. To obtain the criteria weights the Saaty method is followed. Table 4 shows the resultant comparison matrix with the computed weights.

Table 4
Saaty pairwise comparison matrix.

	Economic	Social	Environmental	Weight
Economic	1	5	5	**0.7089**
Social	1/5	1	2	**0.1786**
Environmental	1/5	1/2	1	**0.1125**

4. Results and discussion

Table 5 shows the optimal energy infrastructure for this case study. For the sake of comparison, a baseline optimisation is also performed considering deterministic parameters and NPV as single objective. Table 5 also shows the results for this baseline case. It can be seen that the PV system covers all available area as it contributes positively to all criteria. In contrast, the CHP size and its operation are moderated in the proposed optimisation whereas its size is larger for the baseline case. CHP is mainly employed to cover thermal demand, being the electrical contribution a complement for fulfilling electrical demand. In the proposed optimisation, the moderate use of CHP is a consequence of the emissions caused, the increasing qualitative cost of employing it (decreasing social acceptance and a high ecological impact), and the lack of alignment with the administration, as there are measures planned for reducing the installed capacity of CHP systems (Spanish Government, 2020). CHP size is considerably larger when qualitative criteria are not considered as it contributes positively to the economic

Table 7
Resultant qualitative costs. Values in €/kWh x10^{-3}.

Technology	Year 1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
PV	40.6	40.6	35.1	35.1	30.5	30.1	28.9	28.9	28.9	26.2	21.7	21.1	20.3	20.3	20.3
CHP	55.0	59.4	59.4	59.4	59.4	69.5	72.5	72.4	72.0	74.2	74.3	74.3	74.3	76.3	80.0
ESS	50.0	40.6	40.6	40.6	40.6	35.1	35.1	35.1	35.1	30.5	30.5	30.1	27.3	27.3	27.3
HP	40.6	40.6	40.6	35.1	35.1	35.1	30.5	30.1	27.3	27.3	24.4	24.4	21.1	20.3	20.3
TSS	40.6	40.6	35.1	38.4	35.1	35.1	32.1	30.4	28.9	27.3	24.9	24.4	20.5	21.1	21.1

performance of the enterprise and its size appears reduced when qualitative criteria and risks are considered as a consequence of its negative impacts on the environment, meaning that it is an overall riskier option given the current social perception of gas-burned facilities and the trends in the administration to move far away from them. Therefore, the benefits of incorporating quantitative and qualitative criteria and risks in the optimisation problem include a more complete perception of the CHP system. Thermal storage is used to better synchronise electrical and thermal demands and maximize the usefulness of CHP output. Regarding the HP system, it is not selected since the difference between electricity and gas costs make it not economically suitable despite the existence of some favourable qualitative parameters. For EES, their current costs and ecological impact lead exclude it from the optimal infrastructure. As an example of the operation of the optimal energy infrastructure, Fig.10 shows the plant operation for a typical autumn week.

Table 5
Results of the optimisation.

Equipment	Optimal size	Baseline size
PV	12000m^2	12000m^2
Thermal Storage	250kWh	250kWh
Cogeneration	118kW	140kW

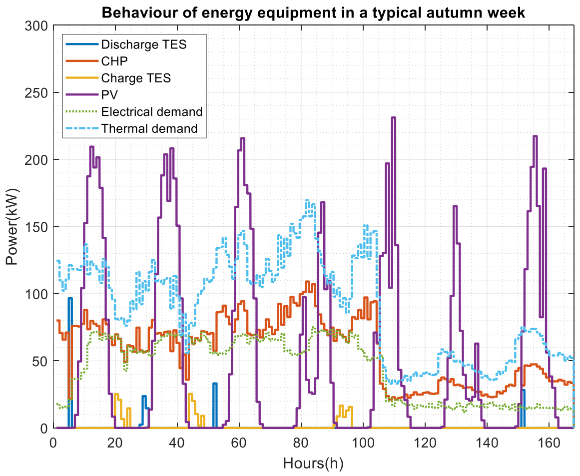

Fig. 10: Operation of the optimal energy infrastructure.

To reach the results with the proposed optimisation process, qualitative parameters are obtained through the initial fuzzy system, whose operation is exposed for ecological impact in Fig. 11. MFs for probability and impact are shown together with their aggregation and defuzzification. The followed process enables to obtain a final defuzzied value of the qualitative criteria which accounts for uncertainty and vagueness in judgements. Qualitative costs of employing technologies over time are also computed through fuzzy logic. Table 7 exposes the obtained values.

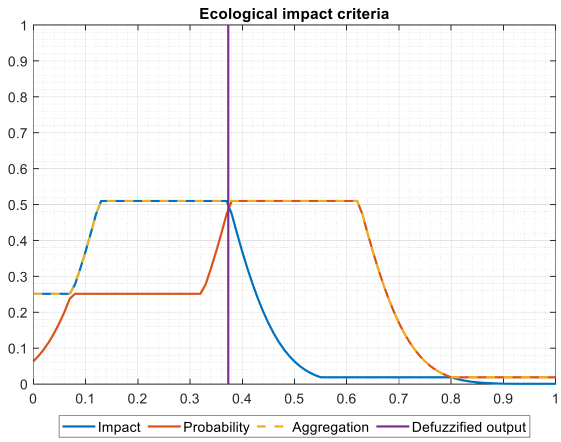

Fig. 11: Ecological impact criteria fuzzy computation.

Table 6 exposes NPV and GHG emissions' mean value, CVaR, and standard deviation both for the proposed optimisation and for the baseline case. For illustration purposes, Fig. 12 shows the results of the sampling process and risk analysis for the case of the NPV. It can be seen that in the optimal energy investment obtained through the proposed methodlogy has lower NPV compared to that of the baseline case. However, the proposed methodology trades off different criteria and thus the obtained GHG emissions are lower. Also, although there still exists variability in NPV and GHG, the proposed optimisation strategy reduces the CVaR and standard deviation of the quantitative parameters and thus the uncertainty in the investment outcome. Thus, through the proposed optimisation approach the variability and risks of quantitative outcomes is lower than in the baseline case, obtaining a more robust and resilient energy investment option.

Table 6
Quantitative parameters' value.

Parameter	Optimal value	Baseline value
NPV mean	9586600 €	9617900 €
NPV CVaR	9228400 €	9247800 €
NPV standard deviation	168970 €	176450 €
GHG mean	220630 $kgCO_2$	220776 $kgCO_2$
GHG CVaR	220426 $kgCO_2$	220579 $kgCO_2$
GHG standard deviation	103 $kgCO_2$	100 $kgCO_2$

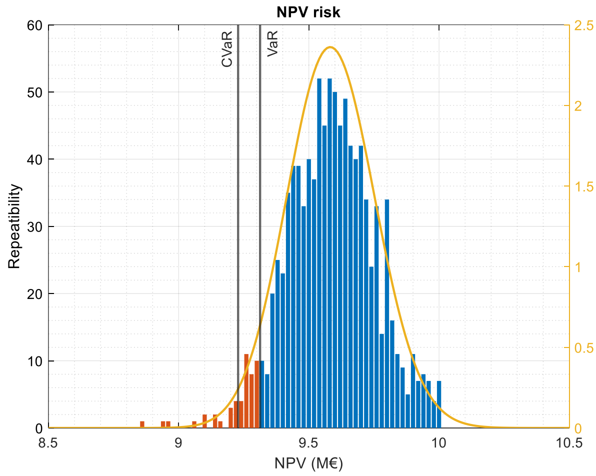

Fig. 12: NPV probability distribution function with obtained VaR and CVaR.

Fig. 13 shows the final values of the criteria employed in the optimisation. Economic criteria have been maximised followed by social and then environmental ones, reflecting decision makers' preferences. Even though the economic criteria predominate, their improvement has been conditioned by social and environmental criteria, reaching a trade-off solution where economic criteria are maximised while social and environmental criteria also reach acceptable values. As the criteria includes risks in qualitative and quantitaive parameters, the obtained optimal energy infrastructure represents a solution which minimises risk while obtaining a good performance in the different decision-criteria's spectrum.

Fig. 13: Resultant optimisation normalized criteria.

5. Conclusions

In this paper, an extended two-stage optimisation methodology for the sizing of energy infrastructures for industrial SMEs has been presented. This methodology evaluates quantitative and qualitative criteria and risks affecting the investment, both at the moment of taking the decision and during the operation of the energy infrastructure. This procedure fits industrial SMEs' requirements, as it considers diverse criteria different in nature and search for long-lasting low-risk investments. In the proposed methodology, qualitative parameters dealing with subjective perceptions are computed through a fuzzy system that evaluates the decision's impact and probability on the analysed qualitative perceptions. Fuzzy logic is also employed to calculate the dynamic qualitative cost of using the energy equipment over time. These approaches enable to obtain a measure for qualitative parameters that incorporates the uncertainty dimension. For quantitative parameters, their risks are handled through a probabilistic approach, obtaining over the optimisation their expected value and CVaR. During the first stage of the optimisation, the energy infrastructure to be analysed is selected and qualitative criteria directly linked to it are computed through the proposed fuzzy approach. In the second stage, the operation of the infrastructure is optimised considering both quantitative and qualitative costs and associated uncertainties to obtain the expected values and CVaR. The suitability of the analysed energy infrastructure is measured considering the preferences of decision makers and the different criteria and risks, enabling to obtain a solution which acknowledge the global performance of the investment over the different decision-making spectrums. A case study has been developed to observe the benefits of including quantitative and qualitative parameters and risks over time in the optimisation procedure. The energy infrastructure obtained through the proposed optimisation methodology is compared with a baseline optimal energy infrastructure resulting by considering only an economic objective. In the comparison, it has been possible to see that including quantitative, qualitative and risk parameters in the optimisation process does indeed affect the resultant energy infrastructure. When these criteria are not considered, equipment which are economically feasible but with possible strong negative social and environmental impacts are selected for installation. However, when qualitative criteria and risks are considered, the equipment is selected considering a trade-off between different criteria and reaching and overall less qualitative risky solution. Through the proposed optimisation approach the resultant quantitative risk is also less, obtaining a more robust and resilient energy investment option. Therefore, the methodology proposed in this paper opens the way to a new strategy for the energy investment decision-making process of industrial SMEs, enabling them to adapt their infrastructure to the changing energy situation and to improve their competitive position in the market and in the society.

CRediT authorship contribution statement

Eva M. Urbano: Conceptualization, Methodology, Software and models, Resources, Validation, Writing – original draft, Visualization, Funding acquisition. **Victor Martinez-Viol**: Software, Writing – review & editing, Visualization. **Konstantinos Kampouropoulos**: Conceptualization, Supervision, Writing – review & editing. **Luis Romeral**: Conceptualization, Supervision, Writing – review & editing, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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Appendix A Case study quantitative data

Parameter	Value
PV	
Initial cost	950 €/kW
LCOE	0.07 €/kWh
Initial O&M cost	6.56 €/kW-year
O&M cost variation	-2.3% per year
PV connexion efficiency	99%
Job creation	0.87 jobs/GWh
Electrochemical storage	
Initial cost	430 €/kWh
LCOE	0.06 €/kWh
Initial O&M cost	8.22 €/kW-year
O&M cost variation	-3.8% per year
Charge efficiency	94%
Discharge efficiency	94%
Charge ratio	0.5C
Discharge ratio	5C
Job creation	0.01 jobs/MWh- capacity
CHP	
Initial cost	3400 €/kWe
LCOE	0.042 €/kWeh
O&M cost	36 €/kWe-year
G2E efficiency	35%
G2T efficiency	55%
Job creation	0.31 jobs/GWh
HP	
Initial cost	700 €/kW

Parameter	Value
Thermal storage	
Initial cost	5 €/kWh
LCOE	0.0243 €/kWh
O&M cost	0.26 €ct/kW-year
Charge efficiency	92%
Discharge efficiency	92%
Self-discharge	1%
Charge ratio	5C
Discharge ratio	0.25C
Job creation	0.01 jobs/MWh- capacity
Boiler	
LCOE	0.053 €/kWh
O&M cost	70€/kW-year
Efficiency	90%
Connexion efficiencies	99%
Emissions	
Initial emissions cost	25 €/tCO_2
Increase ratio	3.9% per year
Feed-in tariff	0.85 of wholesale market price
Demand growth	1.5% per year

LCOE	0.076 €/kWh
O&M cost	5.56 €/kW-year
COP	4.5
0.25	jobs/GWh

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6. Other research activities: energy policy trends

The developments carried out in the thesis focus on the creation of a methodology for suitably optimizing energy equipment investment and operation considering prosumer behaviour to enhance energy transition and improve industrial competitiveness. The proposed methodology considers a market that, although uncertain, is relatively stable. This may change in the future, with the possibility of sharp fluctuations in economic and administrative trends that could alter the expected investment outcome.

At present, an energy crisis is shaking Europe which is changing immediate EU and Member States (MS) energy strategies. This chapter describes the activities that have been carried out in the thesis framework to analyse the impacts that this energy crisis could have, in this case on energy generation sources, and the possible alterations in the socio-economic landscape that might affect the investment decision of industrial SMEs. This analysis has been carried out on the basis of the knowledge gained during the stay at the Joint Research Centre, where the global European electricity market was analysed.

The chapter is organised as follows. First of all, section 6.1 introduces the European energy crisis and the EU policy reaction to have an overview of the current energy situation in Europe. Section 6.2 evaluates MS' electricity generation mixes and their position considering 2025 energy transition objectives, and section 6.3 addresses how these objectives and countries' energy strategies are being modified in light of recent geopolitical developments. Whereas these sections provide an overview of the research done, section 6.4 expose the publication in which the detailed analysis is presented, whose full version can be consulted in Annex A. Lastly, section 6.5 depicts the conclusions of these research activities.

6.1. European energy policy framework

The current energy crisis is forcing the EU to adopt new measures to accelerate the transition towards a more secure and sustainable energy system independent from adverse external circumstances. The EU has faced an unprecedented increase in electricity prices mainly due to the Ukraine war, which caused a sudden decrease in the availability of Russian supplies [146]. Before the war, 43% of total natural gas imports came directly from Russia [147], a figure which had been increasing as EU countries switched from coal to natural gas for decarbonisation purposes [148]. In fact, the EU's transition path did not foresee reducing natural gas in the system and understood it as a transition fuel [149]. However, the current situation is requiring the EU to move away from gas, thus gaining independence from Russia and bringing stability and security to energy markets.

Until now, the EU based its energy landscape and planning on four policy packages: "Energy Union Strategy" (2015), "Clean Energy for all Europeans" (2016), "European Green Deal" (2019) and "Fit for 55" (2021). These energy packages focus on the energy transition by encouraging the reduction of emissions through decreasing the use of fossil fuels, deploying renewable energies, and generating alternative green and bio fuels such as hydrogen and biogas. With the current energy crisis, a new policy package was announced in February 2022: the REPowerEU [7]. This package is a response to the disruption caused in the energy market by Russia's invasion of Ukraine. It aims to diversify the energy supply, moving away from Russian dependence and modifying the transition path depicted before the energy crisis enhancing also a stronger deployment of alternative energy sources [150]. The main energy proposals that appear in REPower EU are:

- Natural gas supply diversification

  Analyse the possibility to import more gas from other countries and evaluation of new gas alliances as well as coordinate with other gas buyers.

- Boosting renewable energies

  New proposal for increasing the renewable energies target from 40% to 45%. Special focus on solar PV to install new 320 GW by 2025, creating an EU Solar Strategy and a European Solar Rooftop Initiative. Also, the EC will study the declaration of 'go-to' areas for a fast permitting process for renewables deployment.

- Hydrogen promotion

  Proposal for a target production of 10 million tonnes of domestic renewable hydrogen by 2030 and the creation of a European Hydrogen Bank.

- Biomethane

  Initiative to boost sustainable biomethane production to 35 bcm by 2030.

- Increase to 13% the binding target in the Energy Efficiency Directive.

  Already ongoing a study for the incorporation of short-term measures that could achieve a 5% reduction in gas demand.

The application of this policy package will suppose an additional investment of €210 billion between 2022 and 2027 compared to that to be performed for Fit for 55 objectives [151]. Indeed, this latter policy package does not substitute previous ones but adds requirements and objectives to the decarbonisation and transition objectives stated before the energy crisis. The EC suggest that the MS integrate the REPowerEU policies into their existing recovery and resilience plans (RRPs) to accelerate energy transition [152]. Although the process for the modification of the RRPs has not been completed, MS are already taking measures and drafting a policy line focused on the mitigation of the impact of the energy crisis. However, as previously stated targets for decarbonisation are still valid there are currently appearing contradictory objectives in some situations which require the achievement of trade-off solutions.

6.2. Current situation and 2025 targets

For analysing and understanding MS' reactions arising from the energy crisis and the latest changes in European energy policy, it is required to first address their current situation in terms of energy generation and their position related to stated 2025 objectives. The focus of this thesis is on the electricity market and therefore the electricity mix is analysed. The current capacity mix is assessed considering information from the Transparency Platform (TP), a platform created by ENTSO-e to share all available data on European power systems [153]. The generation technologies under study, according to their energy source, are: coal, oil, nuclear, wind, solar and hydro. These technologies account for 97% of the total generation capacity in the EU and thus their analysis is illustrative enough to elaborate a discussion on the general circumstances. The current situation, as obtained from the TP, is compared with the objectives gathered by the Ten Year Network Development Plan (TYNDP) [154] for 2025 considering environmental EC goals and National Energy and Climate Plans (NECPs). TYNDP evaluates also the installed capacity of batteries, pumped storage and demand-side response. However, these are not considered here as they are not generation technologies per se, but flexibility sources.

6.3. Policy reaction to the energy crisis

European countries are modifying and adapting their energy strategy in order to mitigate the impact of the energy crisis. To evaluate where these modifications are pointing to and whether countries' new energy strategies are aligned with European energy packages, a per-country analysis is carried out. This is done by consulting the most recent legislation and policy drafts. Specifically, answers to the following questions are sought:

- Are countries promoting energy independence from Russia by diversifying their energy supply?
- Are countries' plans to shut-down fossil fuel-fired electricity generation facilities being modified?
- Are countries generating a framework for the creation of green gases – such as hydrogen – markets and investing in generation facilities and management infrastructure?
- Are plans related to the role of nuclear power in the country being altered?

- Are renewable energies – solar, wind, hydro – being increasingly incentivized to assure the achievement of more ambitious targets?

6.4. Publications

The analysis exposed in this chapter has been carried out and the results have been included in the paper below, which is currently under-review. A complete version of it can be consulted in Annex A.

- E. M. Urbano, K. Kampouropoulos, and L. Romeral, "Energy crisis in Europe: the union objectives and countries' policy trends: New transition paths?" Under review.

  This paper analyses the **electricity mix situation** of the six most significant EU countries in terms of generation capacity and their position with respect to **2025 energy transition targets**. **Legislative trends** for these countries are also analysed and a discussion is presented about their **alignment with EU objectives**.

6.5. Conclusions

The energy framework and policy trends have been analysed in the paper mentioned in the previous section for the six most significant EU countries from the point of view of generation capacity, which are: Germany, France, Spain, Italy, Netherlands, and Poland. Regarding their current situation and the comparison with 2025 energy transition objectives, it is possible to appreciate that despite efforts in progressing toward the achievement of secure and sustainable energy systems, their current energy mix is still considerably distant from EC and national plans' objectives drafted in the pre-crisis stage. With the new crisis and more exigent targets regarding decarbonisation and independence, preferences have changed significantly, and countries are acting to prioritise energy independence even though this choice negatively affects decarbonisation targets. The policy trends that have appeared during the last months show a significant deviation from the path depicted before the crisis to reach a sustainable and secure energy system. Specifically, the following general conclusions regarding changes in energy transition paths can be obtained from the analysis:

- The priority in EU countries is nowadays to gain independence from Russia's supplies, even though achieving this causes negative effects on other decarbonisation objectives.
- The prioritization of energy independence and security of supply is modifying the electricity mix foreseen before the energy crisis.
- The accomplishment of decarbonisation objectives depends on the technologies promoted.

    - The promotion of renewables together with nuclear power provides a suitable framework in which to reach a low-carbon economy in the short to medium term.
    - The promotion of renewables without nuclear power implies the current use of fossil fuel technologies since hydrogen, biogas and flexibility options are not implemented at a large-scale in the market. This makes it harder to achieve decarbonisation in the short-term.
    - Technological decisions based on day-to-day politics can affect how and when decarbonisation and energy independence goals are achieved.
- The path selected by each country depends on its historical background and supply origin.
    - Countries with ease for the obtention of gas from different sources are more likely to still rely on this energy carrier.
    - Countries with a strong nuclear background are likely to continue with a nuclear strategy.

This analysis provides an overview of the trends that are affecting European energy markets and that may alter their normal development through the sudden availability or unavailability of specific energy sources. Although the findings exposed are highly useful for industrial SMEs, it is important to follow the social and administrative developments to acquire a suitable overview of the situation and be able to incorporate these appreciations in the energy investment optimization problem.

7. Conclusions and future work

This chapter sets out the general conclusions of the thesis as well as the lines of future work and research arising from it.

7.1. General conclusions

The present thesis aims to advance the state of the art for the optimization of energy equipment investment and management considering the new prosumer framework for industrial SMEs. To make this progress, modelling and optimization techniques have been analysed and the inclusion of relevant parameters in the problem such as quantitative, qualitative, and risk factors and their interrelations have been evaluated, which is a novelty in this research field.

Firstly, the modelling of the industrial SME plant has been carried out using the EH concept, adapting it to represent a prosumer infrastructure, and the prediction of energy variables using ANFIS has also been addressed. Based on this model and these variables, the optimization of the operation of the industrial plant as a prosumer has been carried out. This operation considers the possibility of exchanging energy with the external electricity grid and also a weekly optimization horizon which enables to capture energy demand and electricity price patterns.

Once the industrial plant has been modelled and the methodology for optimizing its operation has been established, the optimization of the energy equipment to be installed to improve the energy infrastructure of the industrial SME has been addressed. This equipment sizing optimization considers the full lifetime of the investment to be made, analysing its time value. Since this value is influenced by uncertain external parameters, uncertainty and sensitivity analyses have been carried out to evaluate the risk faced by industrial SMEs when making an energy investment of this type.

Depending on the risk faced by these companies, it is beneficial not only to assess it but to include it as a further factor to be minimised in the optimization. Moreover, the latest social and administrative trends are driving the renewal of the industry by considering welfare and sustainability as a central axis, so it is essential to optimize not only quantitative values but also qualitative ones. In order to include quantitative and qualitative factors and related risks in the optimization, their values and uncertainties have to be modelled. Quantitative factors are tackled statistically, assigning PDFs to each of them to account for their uncertainty. In contrast, qualitative factors are measured using fuzzy logic, which evaluates their value as well as the uncertainty inherent in them due to their subjective definition. These values are included in a two-stage optimization, analysing quantitative and qualitative values and uncertainties both in the first stage, which sets the equipment in which to invest, and in the second stage, which optimizes the prosumer operation over time.

These developments have generated the following main contributions, directly linked to the hypothesis of this thesis:

- A methodological approach for the operation optimization of the industrial SME considering EH modelling and prosumer energy exchange with the utility grid has been developed. This operation optimization considers weekly energy cycles capturing demand and electricity price patterns. By applying this methodology to the different case studies, it has been possible to verify the benefit of transforming the industrial energy infrastructure from a consumer to a prosumer, reducing energy costs and emissions, and increasing social benefits according to the preferences of the industrial SME.
- The optimization of the equipment has been carried out considering their operation over their complete lifetime, which has improved the appreciation of the benefit by including the effect of variations of relevant parameters over time and has generated robust solutions, according to the results obtained in the case studies.
- A sizing and operation optimization methodology has been generated that incorporates not only quantitative but also qualitative factors. It has been found that the incorporation of both types of factors improves the possibility of obtaining a more complete assessment of the equipment to be installed.
- The optimization of the investment in energy equipment has been improved by also including uncertainties aiming to minimize the investment risk. By applying this comprehensive methodology to the case studies analysed, the results obtained are more robust in the face of increasing economic and administrative uncertainty, creating a suitable framework for investment decisions in industrial SMEs.

7.2. Future work

This section exposes future research lines that can be built based on the developments done in this thesis and that can complement it to create wider energy investment and management approaches to foster energy transition and industrial competitiveness.

- This thesis has addressed the energy equipment investment and operation optimization for industrial SMEs as individual prosumers. Nowadays, there are initiatives in the administration to promote not only the active participation of individual consumers in the energy market but also their aggregation into energy communities, which would foster even more renewable energy integration and energy system decentralization [155].

Therefore, to improve the benefits of acting as individual prosumers, the junction of several prosumers into an energy community could be evaluated. This junction can be performed through different strategies including peer-to-peer trading, the creation of an internal energy market, or the management of the community assets by an aggregator. This energy problem can be tackled by adapting the methodology proposed in this thesis, expanding it to include several prosumers and creating an exchange module, while still incorporating quantitative and qualitative parameters and uncertainties.

- The energy investment optimization methodology considers qualitative parameters and their uncertainties and assumes that decision-makers are capable to provide adequate values to them which are later introduced into the fuzzy system. Nonetheless, this field could be explored more in-depth to improve the initial measurement of qualitative parameters. Sentiment analysis strategies could be applied to mine the opinion of groups of people and improve the measurement of, for example, social-related qualitative criteria [156]. Also, the creation of decision boards could be addressed by profiling decision-makers and generating strategies for assembling different individual opinions.
- The effects that drastic changes in the market and the socio-administrative landscape have on the energy investment and energy operation performance could be analysed. This would test the robustness of the proposed methodology and point out ways of improvement. Such ways could include, for example, the incorporation of discrete and disruptive events in the optimization problem that alter the considered continuous uncertainty of external parameters.

8. References

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Annex A: Other publications

In this annex, other publications that serve to better understand the framework of the thesis and that have not been included in the compendium of publications, in the core document of the thesis, are exposed. These publications are:

- E. M. Urbano, V. Martínez-Viol, and L. Romeral, "Optimization of industrial plants for exploiting energy assets and energy trading," in *IEEE International Conference on Emerging Technologies and Factory Automation, ETFA*, 2019, vol. 2019-Septe.
- E. M. Urbano, K. Kampouropoulos, and L. Romeral, "Energy crisis in Europe: the union objectives and countries' policy trends: New transition paths?" Under review.

A.1. Optimization of industrial plants for exploiting energy assets and energy trading

Reference: © 2019 IEEE. Reprinted, with permission, from: E. M. Urbano, V. Martínez-Viol, and L. Romeral, "Optimization of industrial plants for exploiting energy assets and energy trading," in *IEEE International Conference on Emerging Technologies and Factory Automation, ETFA*, 2019, vol. 2019-Septe. Available on: https://doi.org/10.1109/ETFA.2019.8869176.

Publication framework:

Initial article exposing a first approach to the operation optimization of an industrial plant acting as a prosumer. It exposes the EH model of the industrial energy infrastructure, the forecast of energy parameters, and daily prosumer operation optimization.

Main contributions:

- EH modelling of an industrial prosumer energy infrastructure.
- Forecast of the energy vector employing ANFIS.
- Prosumer operation optimization of the industrial EH.

Keywords:

Virtual Power Plant, Energy Hub, Energy trading, Energy transition, Energy optimization.

Optimization of industrial plants for exploiting energy assets and energy trading

Eva M. Urbano, Víctor Martínez-Viol, Luis Romeral
MCIA Research Center, Dept. of Electronic Engineering
Technical University of Catalonia (UPC)
Terrassa 08222, Spain
{eva.maria.urbano,victor.martinez.viol,luis.romeral}@upc.edu

***Abstract*—The worldwide energy market is undergoing a transition that will lead to a greener and non-fossil fuel dependent situation in which demand side management and prosumers will play a key role. The digitalization of energetic industrial facilities to create a virtual power plant by forecasting future energy situation and modelling internal energy flow is performed for a specified case study. In this paper the proposal of creating a virtual power plant from an industrial plant is done to benefit from the opportunities raised by the energetic transition. A study of the market and exploitation approach is done. The feasibility of developing a virtual power plant considering future energy situation and internal energy assets is verified by optimizing its final cost in terms of performance against external markets. The results show that there are economic benefits for the owner of the facility while assuring the energy demand and the proper operation of the equipment.**

***Index Terms*—Virtual Power Plant, Energy Hub, Energy trading, Energy transition, Energy optimization**

I. Introduction

As can be observed from the industrial revolutions that have taken place along centuries and also in the current sociopolitical scenario of several countries in the world, there is a strong relationship between energy use, economic growth and industrial development [1]. The availability of reliable and affordable energy is crucial to create greater economic and social prosperity. In the current Industry 4.0, processes are analysed, modelled and monitored and the behaviour of the plant is optimized by real-time communication and cooperation between different systems. To reach optimal competitiveness positioning, the energy generation, transfer and consumption have also to be studied, modelled and monitored with the aim of forecasting the future energetic situation and take decisions regarding energy optimization, load scheduling, energy flow control inside the plant and even energy trading.
Until now, energy monitoring and management have focus on operational energy planning, energy audits, energy efficiency measures, energy accounting, measurements and development of reports [2]. However, with the rise of technologies related to Industry 4.0, energy management methods will change drastically. The growth of the virtual world with the development of the Internet of Things (IoT) facilitates the creation of an entity that resembles the real world. Whit this entity, which considers the energy consumption, energy generation and the situation of the external energy market and internal energy assets [3], it is possible to forecast future energetic situations and take decisions to optimize the performance of the industrial plant. The modelling and the prediction of the behaviour of the plant is possible due to artificial intelligence learning methods which adapt to the changing environment that represents the real industry [4].
As the industry is strongly related to energy use, its role will be affected by the energy market situation. Nowadays, a transition is taking place which aims to decrease harmful emissions, increase the share of renewable energies and improve overall energy efficiency [5]. By incorporating to the current energy management strategies the possibility to trade with the energy grids, the industry can support the transition and obtain benefits. In the industry, unlike in the residential and commercial sectors, the security of supply and the energy efficiency is decisive as it is strongly related to production and thus processes feasibility and benefits.
In this paper, an energy management and optimization method based on the creation of a digital twin of the real energy systems at an industrial plant will be studied. Nowadays, the energy assets inside a plant are modelled and optimized as an Energy Hub (EH) but external factors are not considered. Here the proposal is to create a Virtual Power Plant (VPP), which has the objective to optimize its internal energy use, trade with the external energy grid to exploit its energy assets and include the energy management into the business plan of the factory. By developing a VPP, the efficiency of the plant will increase, the emissions will decrease and the boost of renewable energies use will be supported while meeting the demand and trade with the market to exploit the capabilities of the plant. In this paper, it will be validated that it is possible to include the concept of VPP inside the business plan of the industry while meeting the internal demand. To create a VPP, design of suitable energy assets has to be done together with digitalisation and optimization by means of artificial intelligence methods.
This paper is structured as follows. In section II the analysis of the energy transition situation and the creation of a business strategy related to this transition is performed. In III the VPP mod l a d its possibilities will be further explained and,

following, th parameters that form it assessed: forecasting of energy framework is presented in IV and mathematical modelling in V. The optimization objective and process is presented in VI and the results for the case study of this paper are shown in VII. Last of all, conclusions are drawn in VIII.

II. Energy transition and business potential

The current situation and trends in worldwide energy markets are important when considering the development of a VPP as it can interact with several energy grids. For the case under study, the electrical market is the one considered. This is because it is where the energy transition is being focused and also the one who has an open possibility to establish a trading relationship between grid and consumer. In the following section, the role of the VPP inside the energy market and the benefits that its creation will provide are exposed.

A. *Demand Side Management*

In the electrical grid, a balance between supply and demand is needed to assure grid stability and feasibility. To ensure the security of supply there has to be capacity available to meet demand at all times. This is usually done via the primary, secondary and tertiary reserves. These reserves are costly to the grid as they need maintenance to be ready at all times to supply energy to peak-power demand. Energy storage could be another mean to effectuate the balance. This would be done by feeding the storage when the demand is low and the electricity prices are low too and releasing it when the demand exceeds the generation and the electricity prices are high. However, energy storages for providing this service would be very large and costly being an option not considered for the whole grid. An alternative approach to match generation and consumption is by using Demand Response (DR) or Demand Side Management (DSM). They suppose a temporal change in the consumer's energy demand due to a reaction to price or other types of signals [6]. The objective of DSM is to empower consumers to adjust their use of demand-side resources at strategic times. These demand-side resources may include consumption, use of distributed generation and/or storage capabilities [7]. DSM operates from the Energy Hub (EH), which is the addition of the different energy assets available in an industry, in order to re-schedule load and profit from energy storage and Renewable Energy Sources (RES) that may be directly connected to it. DSM is a cost-effective balancing resource for increasing the share of renewable energies generation, lower the need for non-flexible plants, lowering the cost of electricity and optimising the efficiency of the electric system and markets.

B. *Political trends*

To open the path to the energy transition the legislation should adapt to the needs of the coming energy markets. In [8] a review of EU policies regarding efficiency and DSM is done. It is shown that the Energy Services Directive requires Member States to develop plans for achieving targets for saving energy from end-users. In the articles of the Energy Efficiency Directive (EED), energy efficiency measures, demand response measure, grid stability and feasibility are assessed. From these directives, it is clear that the prosumer is likely to become a major actor in the future electricity market. The term prosumer was first introduced by Alvin Toffler [9] and was defined as a person or entity who consumes and produces a product. Translated into the electrical energy market, a prosumer is an entity that demands electricity and sells its surplus back to the grid. A VPP, from the point of view of the grid, is an active prosumer or a union of several prosumers that interact between them and that react to the status of the electricity market. The introduction of prosumers in the grid will lead to several benefits as, for example, support for energy balance, incorporation of small RES and decongestion of the transmission and distribution network. Although the maturity level of the technology needed to create the VPP parts already exists, barriers related to grid access, administrative procedures and techniques development are slowing down its progress and implementation. Nowadays the EU is in the process of updating its energy policy framework to facilitate a transition to clean energy. The Clean Energy Package is planned to be adopted during 2019 and its directive [10] stipulates the importance of:

- Granting demand side resources access to all markets at all timeframes.
- Empowering the consumer to participate in DR without the consent of the supplier and to switch aggregation service provider without penalty.
- Empowering independent aggregators by ensuring that they can enter the market without the consent of other actors and without compensating generator/supplier.

The trends lead to a future where DSM will be a powerful tool for small and large consumers that will be converted to prosumers and that the grid structure will be changed and adapted to include new actors such as aggregators and active prosumers, supported by distributed renewable energy sources and VPPs.

C. *Energy assets exploitation approach*

An existent industrial site has a specified amount of energy assets that are nowadays used for its exploitation inside the plant. Their main role is to provide energy efficiently to internal demand. However, the objective of a VPP is not only to guarantee the availability and efficiency of the energy equipment for meeting the local demand but also to determine an optimal operative strategy considering the external energy market. In [11] a collection of business concepts for the type of system studied is provided. They vary depending on the objective of the business and the most interested stakeholder in each case. For the implementation of a VPP, an energy broker is the most promising one. The business concept has been presented and approved by several European projects, as can be se n i [12] and [13].

The objectiv of this business concept is that an energy broker, who can be the energy supplier or a third party, trades energy on behalf of its customers on the wholesale market. The broker needs to manage his purchases and sales of energy including longer term markets, day-ahead and intraday markets. The service provided by the broker aims to minimise energy bills for consumers and maximise profit for producers or both for prosumers. Apart from the economic benefits that the prosumer will receive from an agreement with an energy broker, they do not need to take care of the energy retailing by themselves. The earnings of the broker can come from an agreed percentage of consumers energy savings and an agreed percentage of the energy sold on behalf of prosumers and producers. It has to be noted that for the suitable operation and optimization of the energy portfolio of the energy broker information about energy consumption, energy production, price of energy (produced and from the market) and costs of systems is needed. The broker can also deal with several customers at the same time, becoming an aggregator. This means that the flow of energy can be not only from the customer to the wholesale market but also from customer to customer without interaction with the external market by passing only through the aggregator. This will also lead to a reduction in costs as a consequence of the direct balance between two customers. In this case the revenue for the aggregator can come from an agreed percentage of the energy transferred between customers, as proposed in [14]. This type of exploitation approach is also interesting from the point of view of network operators. With smart energy trading, the active prosumer that represents the VPP will support the network by assuring the quality of the electricity transactions, minimizing unbalances and frequency mismatches.
This approach fits the trends in the European electricity market, its legislation and the needs of the different involved stakeholders.

III. Virtual Power Plan concept

A VPP is a network of decentralized power generating units as well as flexible power consumers and energy storage systems. A VPP can be implemented in an industrial site, composed by all the controllable energy assets and the renewable energy generation units in the factory. The VPP operates its energy assets efficiently taking into account the forecast of the future energetic situation, which includes internal and external factors intending to maximize or minimize a specified objective function. Internal factors can comprise Coefficient Of Performance (COP) and efficiencies of energy equipment, energy storage capacity, energy generation at a given moment, cost of the different subsystems and manageable loads. External factors may be constituted by electricity and natural gas prices. In Fig. 1, an example of a VPP is shown. It can be appreciated that the communication with the electrical grid is bidirectional, allowing to buy and sell electricity depending on the forecasted conditions. The working behaviour lays in an energetic, economic and/or environmental evaluation that takes into account the forecasted input energy price, the forecast of available energy inside the VPP and the forecasted demand.

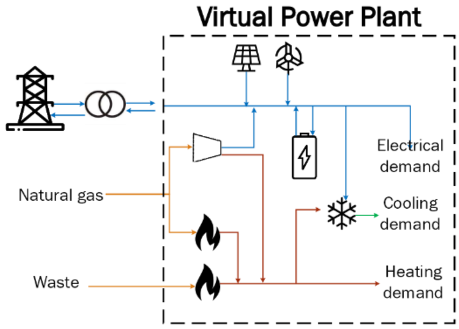

Fig. 1. Schematic of a VPP.

The energy conversion equipment inside the VPP forms the EH. With all the mentioned parameters the digital model of the VPP can be created and its mathematical optimization performed. In this paper, the concepts and methods introduced will be applied to a scenario that resembles a real industry in Spain. In the next sections, the methods to evaluate the future situation and also the process to create the digital entity and the optimization will be stated.

IV. Energetic situation forecasting

Quantitative forecasting methods, based on past data to estimate future states, are suitable for the prediction of the future energetic situation of a VPP. This type of approach extracts patterns of the available data and assume that these are expected to continue in the future. The variables to forecast are demand, generation from renewable energy sources and electricity price from the grid.

A. Renewable energy sources

For the case study industrial plant the RES available is a Photovoltaic (PV) installation. The prediction of its output power generated depend directly and mainly on the climatic conditions and the characteristics of the equipment and do not have a strong relationship with past data. The prediction of the sun irradiation can be obtained from the weather databases. The most important factor in estimating PV power performance is solar radiation. The uncertainty in this value is the largest source of error in the computation of the energy provided, as shown in [15]. A performance ratio which is influenced by shadows, dust, the reflectance of the module surface, etc. is also needed. This can be obtained statistically and the output power of the PV system can be computed as:

$$P = P_{nom}\frac{G}{1000}\eta \tag{1}$$

Where G is the received solar irradiance in watts per square-meter and P_{nom} the nominal power in kilo-watts.

B. Demand

Inside a VPP the demand can be divided into two types: manageabl a d non-manageable. Non-manageable loads are those who hav a pre-specified running cycle which can not be re-scheduled and thus are not controllable. Manageable loads refer to those that can change its consumption depending on the specifications of the owner or end-user. For the case of the industrial plant studied there are no manageable loads and thus the demand has to be forecasted. The industry is a sector where the demand can have irregular and infrequent behaviour depending on several conditions and it is constantly under improvement processes. For this reason, a method that enables periodically auto-adjustment and high accuracy results has been selected. Adaptive Neuro-Fuzzy Inference System (ANFIS) aims at mapping input to output for highly non-linear processes such as energy management field and is the chosen method. It must be noticed that ANFIS has been selected as pattern characterization technique in multiple energy forecasting studies in applications such as the ones shown in [16] and [17].

C. *Energy price from the grid*

Nowadays the energy price from the grid for the next 24h can be obtained by consulting the wholesale market. In a future situation, DSM will be broadly implemented and the prediction of the energy price will make a difference in the evaluation of the possibilities of the VPP for the coming days. Due to the integration of RES in the electricity market and the consequent changes in the pricing structure, the ANFIS is considered a critical technique to forecast electricity prices. In this case study, the estimation of the electricity price forecasting has been obtained from the wholesale market, which represents a reliable source of information.

V. Plant Modelling

To have a clear overview of the energy flow inside the plant, a block diagram of Fig. 2 shows a list of energy assets and their interconnection. The battery is placed both as an input and as an output because energy can come from the battery and it can also imply a demand as load if the optimal operation point states it. The same happens with electrical energy to and from the grid, it is present both as an input and as an output. To create a VPP the energy flow inside the plant has to be stated. The set of internal converters that connect the power input with the output defines the EH. The digitalisation of the plant will be performed by modelling the EH and its input and output ports. The mathematical model has the form:

$$L = \eta P \tag{2}$$

where L is the demand, P is the energy inputs and η is the connectivity matrix formed by the COPs and efficiencies of the conversion equipment. To evaluate the mathematical model of the EH the process shown in [18] has been considered in this study.

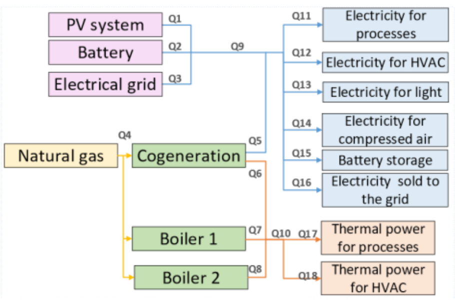

Fig. 2. Block diagram of the studied industry: energy systems and energy flow.

A. *Energy Hub simplification*

First of all, a simplification of the EH is done. Different electricity demands are connected to the same input ports and converters and can be grouped as a unique demand. For the case of electricity to charge the battery and electricity to sell to the grid they have to be kept separate as they form a variable to optimize. Another simplification is the creation of only one thermal demand. The boilers also work in a parallel manner so a boiler formed by the addition of both boilers can be used. Once this simplification is performed the situation of the EH can be visualized in Fig. 3.

B. *Energy flow within the hub*

Now that the EH has been simplified the energy transmission within can be studied. The parameters Q_x define the electric or thermal power at the point x as defined in Fig. 3.
The energy inputs are:

$$Q_1 = P_{PV} = P_{nom}\frac{G}{100}\eta_{PV} \tag{3}$$

$$Q_2 = P_{DB} = \eta_{DB} P_B \tag{4}$$

$$Q_3 = P_{BE} \tag{5}$$

$$Q_4 = P_G \tag{6}$$

where η_{DB} is the discharge efficiency and P_B the power extracted from the battery at the specified time. Natural gas can

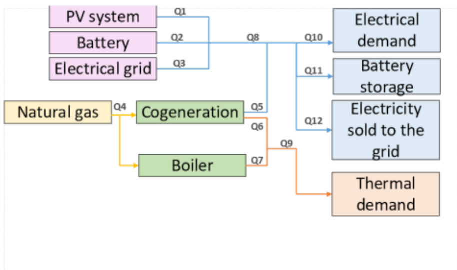

Fig. 3. EH block diagram simplified.

be converted to electricity using the cogeneration equipment. This can be computed as:

$$Q_5 = \eta_{CHP}^{g2e} Q_4 v_4 = \eta_{CHP}^{g2e} P_G v_4 \tag{7}$$

where η_{CHP}^{g2e} is the electrical efficiency of the cogeneration equipment and v_4 the dispatch factor of natural gas to the cogeneration equipment. The energy conversions are stated as:

$$Q_6 = \eta_{CHP}^{g2h} Q_4 v_4 = \eta_{CHP}^{g2h} P_G v_4 \tag{8}$$

$$Q_7 = \eta_{Boi} Q_4 v_5 = \eta_{Boi} P_G v_5 \tag{9}$$

where η_{CHP}^{g2h} is the thermal efficiency of the cogeneration equipment and η_{Boi} is the efficiency of the boiler. v_5 is the dispatch factor to the boiler. The demands in the system are Q_9 Q_{10}, Q_{11} and Q_{12}:

$$\begin{aligned} Q_9 &= P_{TD} \\ &= Q_6 + Q_7 \\ &= \eta_{CHP}^{g2h} Q_4 v_4 + \eta_{Boi} Q_4 v_5 \\ &= \eta_{CHP}^{g2h} P_G v_4 + \eta_{Boi} P_G v_5 \end{aligned} \tag{10}$$

$$\begin{aligned} Q_{10} &= P_{ED} \\ &= v_1(Q_1 + Q_2 + Q_3 + \eta_{CHP}^{g2e} Q_4 v_4) \\ &= v_1(P_{PV} + \eta_{DB} P_{DB} + P_{BE} + \eta_{CHP}^{g2e} P_G v_4) \end{aligned} \tag{11}$$

$$\begin{aligned} Q_{11} &= P_{SE} \\ &= v_2(Q_1 + Q_2 + Q_3 + \eta_{CHP}^{g2e} Q_4 v_4) \\ &= v_2(P_{PV} + \eta_{DB} P_{DB} + P_{BE} + \eta_{CHP}^{g2e} P_G v_4) \end{aligned} \tag{12}$$

$$\begin{aligned} Q_{12} &= P_{CB}/\eta_{CB} \\ &= v_3(Q_1 + Q_2 + Q_3 + \eta_{CHP}^{g2e} Q_4 v_4) \\ &= v_3(P_{PV} + \eta_{DB} P_{DB} + P_{BE} + \eta_{CHP}^{g2e} P_G v_4) \end{aligned} \tag{13}$$

where v_1, v_2 and v_3 are the dispatch factors of the electrical energy available in the EH to the different electric demands. The above equations can be re-written in order to obtain the mathematical model of the EH according (2):

$$L = \begin{bmatrix} Q_9 \\ Q_{10} \\ Q_{11} \\ Q_{12} \end{bmatrix} = \begin{bmatrix} P_{TD} \\ P_{ED} \\ P_{SE} \\ P_{CB} \end{bmatrix} \tag{14}$$

$$P = \begin{bmatrix} P_{BE} \\ P_{DB} \\ P_G v_4 \\ P_{PV} \\ P_G v_5 \end{bmatrix} \tag{15}$$

$$\eta = \begin{bmatrix} 0 & 0 & \eta_{CHP}^{g2h} & 0 & \eta_{Boi} \\ v_1 & v_1\eta_{DB} & v_1\eta_{CHP}^{g2e} & v_1 & 0 \\ v_2 & v_2\eta_{DB} & v_2\eta_{CHP}^{g2e} & v_2 & 0 \\ \eta_{CB}v_3 & \eta_{CB}v_3\eta_{DB} & \eta_{CB}v_3\eta_{CHP}^{g2e} & \eta_{CB}v_3 & 0 \end{bmatrix} \tag{16}$$

C. System restrictions

The system restrictions allow the digital twin of the plant to know the operational constraints of the real world. First, the amount of power entering the VPP from the electrical and the gas grid can not exceed the contracted power. In the same way, the electricity sold to the grid is also restricted due to connection constraints. Second, the power introduced and extracted from the battery can not surpass the nominal power. Third, regarding internal connection, the dispatch factors of natural gas and of the different electrical demands can not be more than 1. Finally, the possibility to trade energy with the grid and the battery adds two more constraints. These are related to the fact that energy can not be purchased and sold at the same time. The same happens with power introduced to the battery and released. All these constraints are expressed as:

$$0 \leq P_{BE} \leq P_{BE}^{max} \tag{17}$$

$$0 \leq P_G \leq P_G^{max} \tag{18}$$

$$0 \leq P_{SE} \leq P_{BE}^{max} \tag{19}$$

$$0 \leq P_{CB} \leq P_{CB}^{max} \tag{20}$$

$$0 \leq P_{DB} \leq P_{DB}^{max} \tag{21}$$

$$v_4 + v_5 = 1 \tag{22}$$

$$v_1 + v_2 + v_3 = 1 \tag{23}$$

$$P_{DB} \times P_{CB} = 0 \tag{24}$$

$$P_{BE} \times P_{SE} = 0 \tag{25}$$

For the case study and with the aim of validate the viability of implementing a VPP, these are the constraints applicable. However, others could be defined depending on the particular plant conditions.

D. Converter's bounds

The operation bounds are expressed as inequalities. The power obtained by an energy conversion unit can not be less than its minimum output power and can not be more than its maximum output power:

$$\begin{bmatrix} L_{CHP}^{min} \\ L_B^{min} \\ E_{Bat}^{min} \end{bmatrix} \leq \begin{bmatrix} \eta_{CHP}^{g2h} P_G v_4 \\ \eta_B P_G v_5 \\ E_{Bat} \end{bmatrix} \leq \begin{bmatrix} L_{CHP}^{max} \\ L_B^{max} \\ E_{Bat}^{max} \end{bmatrix} \tag{26}$$

The energy of the battery is a new variable that is computed by means of current and previous state, meaning that it is a time dependent variable:

$$E_{Bat}^t = E_{Bat}^{t-1} + \triangle t(P_{CB} - P_{DB}) \tag{27}$$

VI. Economical optimization

The objective of the optimization is to state the values of the parameters in order to obtain the best performance in economical terms. The forecast of the energy situation and the modelling of the EH have first been assessed. The variables that need to be defined according to the future situation and the EH model include: amount of primary energy purchased (electricity and gas), amount of energy stored into the battery, amount of energy used from battery, amount of energy sold to the electrical grid, dispatch factor between cogeneration and boiler and destination of the power generated by the PV system. This optimization needs to take into account present and future states as it should contemplate, for example, the possibility to store energy at a given moment to release it in the future, where the electricity price is higher and thus more benefit can be achieved. For the reason stated, the optimization should consider a period of time instead of being an instant optimization. The scheduling horizon of the VPP will be of 1 day, as this is the time interval at which the electricity price from the market is known. The time step will be 1 hour, which is the interval at which the energy cost remains constant.

In this paper the objective is to study the economical feasibility of creating a VPP. Thus, the objective function will be the minimization of the total running cost during the optimization period. This cost includes the purchasing cost of the primary energy and also the cost of the energy equipment, including the PV system and the battery. Of course, other optimization criteria could be defined, for instance including CO_2 emissions.

All the variables at all time intervals have to be specified during the optimization so the search space is very large. However, the constraints generated when modelling the plant defines the feasible regions of the solution and the search space is hence restricted. The constraints comprise the fulfilment of demand, the converter's operation bounds and others related to dispatch factors and state of the interaction with the battery and the electrical grid. The optimization problem of a VPP is then characterized by a high non-linear and a large constrained search space. Different solutions to the problem are not located in the same area and the decreasing of the objective function does not follow a specific direction. For this reason, Genetic Algorithm (GA) is the chosen optimization method to be used. GA is an evolutionary algorithm that operate on several candidates and does not try to find a decreasing direction of the fitness function for the available data, making possible to survey all feasible areas.

In Fig. 4, the flow chart of the optimization process is shown. First of all, the demand is predicted and modelled using ANFIS. Following, the GA first population is initialized. Once the population is obtained, it is verified that the individuals fulfil the constraints of the optimization problem. These constraints are the fulfilment of the demand, the equality constraints and the inequality constraints. Then, the fitness function is computed for the individuals that accomplish the previous equations. If the stop criteria is not met, a new population is generated and the constraints and fitness function are evaluated again. The new generation is created by selecting the best individuals, effectuating crossover and mutation. Due to the high-dimensionality of the search space and the location of the feasible areas the mutation ratio implemented is high to assure new generation diversity. If the stop criteria is met, the iteration finishes and the solution is obtained. These criteria is formed by maximum iteration time, maximum number of stall generations and fitness function tolerance.

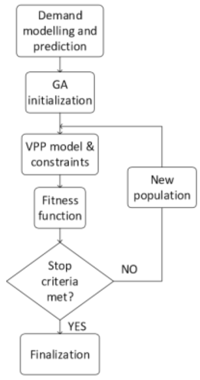

Fig. 4. Flow chart of the optimization process.

VII. Results

In this section, the results of the forecasting of the electrical and thermal demand using ANFIS methodology is shown. The optimization of the VPP has also be done and is exposed. The behaviour of the VPP is compared with the behaviour of a standard industrial plant that does not trade energy with the market.

A. *Demand forecasting*

The results can be seen in Fig. 5 and Fig. 6. For the case of the thermal demand prediction, the Mean Percentage Absolute Error (MAPE) is of 7.6% while for the electrical demand prediction the MAPE is of 5.1%. The energy drivers that have been used for the prediction are the day of the week, time of day, demand 1 day and 1 week before, scheduled production and external temperature. It is noticeable that with the same training parameters and training periods the error produced in the thermal demand is significantly larger than the one of the electrical demand. This could mean that important parameters for the thermal demand, such as occupancy and production type have not been included in the model due to unavailability of data. Another result that can be extracted is that the prediction fits real data when the demand is low and also in its transition to high demand. Nonetheless, the power consumed during peak-demand is not forecasted as good as other parts of the data set reaching an instantaneous error of up to 360kW.

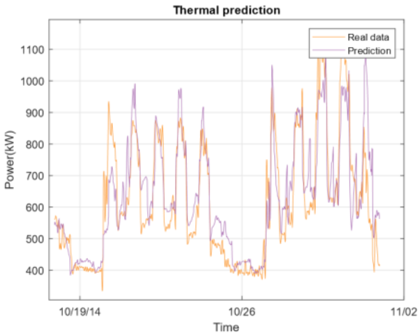

Fig. 5. Thermal demand prediction.

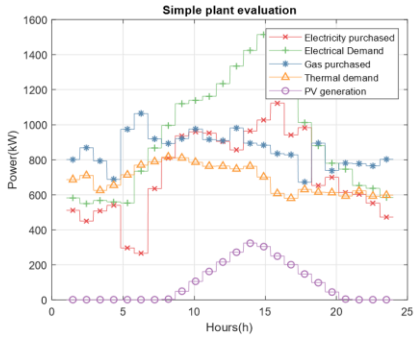

Fig. 7. Simple plant evaluation.

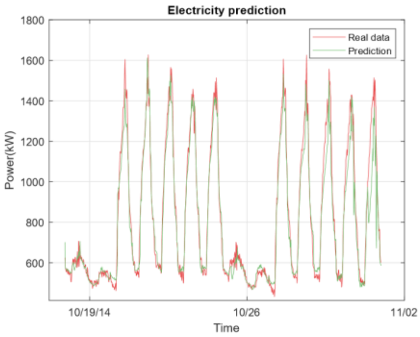

Fig. 6. Electrical demand prediction.

B. Virtual Power Plant optimization

In this section, the optimization of a standard industrial plant that does not trade with the electrical grid and the optimization of the VPP are exposed and compared. The time resolution is of 1 hour since it is the time step at which the electrical market state changes. The standard, simpler plant, is formed by a cogeneration system, a boiler and a PV system but it does not have an energy storage system or the possibility to trade with the electrical market. The optimization is carried out following the same process than for the case of the VPP. The result can be seen in Fig. 7. In this case, although electrical demand is higher than thermal one in all time instants, the most purchased primary energy is gas and not electricity, except in the point where electrical demand reaches its peak value. Gas can be used to fulfil electrical demand through the cogeneration system as long as the thermal power extracted from the cogeneration system is used to fulfil thermal demand and the extracted power does not exceed the maximum power of the cogeneration system. In the studied case, the cost of purchasing gas remains constant along time and is remarkably cheaper than the purchase of electricity. For this reason, even considering the costs of running the cogeneration system, the algorithm finds optimal to operate with more gas than electricity in its infrastructure.

Now the optimal operation of the VPP for the same day is exposed. The electricity price for the day under study is shown in Fig. 8. The optimal solution is given in Fig. 9 and the energy stored with time is shown in Fig. 10. First of all, the results show that the total cost of operating the plant for that day is 7.35% less than in the case of the simpler industrial plant. The same behaviour regarding the preference given to gas purchase is observed. Gas is being purchased at higher power than the needed for fulfilling the thermal demand because, in this case, it is being used to fulfil thermal demand and also to charge the battery. The power obtained from the PV system is not used in its totality for the electrical demand, it is sold directly to the grid as the time intervals where its production is high the electricity price is also high and thus revenue is obtained for that time intervals in the electrical side of the plant. Previous to the time intervals at which electricity is sold to the grid, the gas purchased is higher in order to allow the energy stored in the battery to fulfil the electrical demand in next time intervals, as it is not possible to buy electricity to fulfil these demand when power from PV is being sold to the grid. It is clear that the behaviour is complex due to the fact that there are a large number of possibilities to consider and the solution is highly dependent on the external energy price and the energy produced by the PV system.

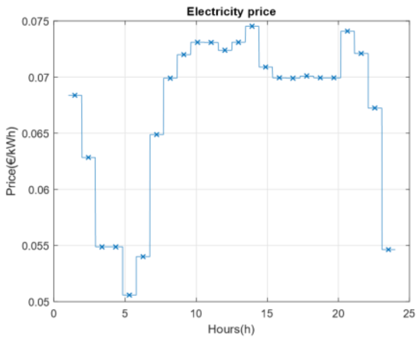

Fig. 8. Electricity price for the optimization period.

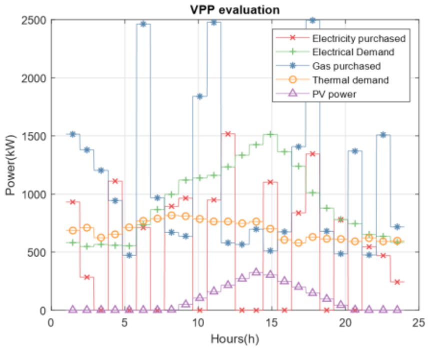

Fig. 9. VPP optimal solution.

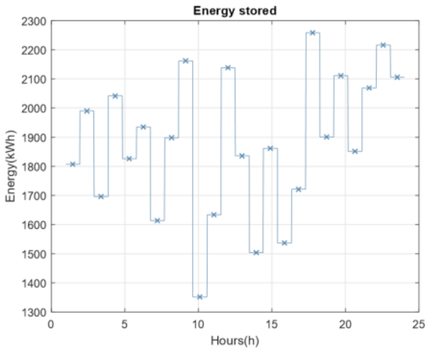

Fig. 10. Energy stored during the optimization period.

VIII. Conclusions

In this paper the needs for the creation of smart energy grids and the potential of industrial plants to become a key actor in future energy markets have been exposed. The shown political, economical and energetic trends present the requirement of incorporating DSM resources and prosumer entities to enable the transition to a green and non-fossil fuel dependent energy market. The concept of VPP has been defined as a digital model to allow a factory to become a prosumer. The forecasting and modelling of its parameters for a case study has been done. The results show that the creation of a VPP creates a benefit for the owner of the industrial facility allowing to incorporate the energy management inside the business concept of the factory. It is also verified that the VPP reacts to the state of the market, selling instead of purchasing electricity when the electricity cost is high and thus supporting grid stability. The modelling and the optimization of the energy inside an industrial plant can be incorporated into the digital twin sets for the Industry 4.0 such as logistics, processes, production planning, etc. In this way, the energy management can be satisfactorily included in the operation and business plan of the industry.

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A.2. Energy crisis in Europe: the union objectives and countries' policy trends: New transition paths?

Reference:

E. M. Urbano, V. Martínez-Viol, and L. Romeral, "Energy crisis in Europe: the union objectives and countries' policy trends," Under review.

Publication framework:

Given the changing energy and socio-political framework in Europe, this article aims to analyse the current electricity mix situation in the six most significant EU countries in terms of generation capacity and their position concerning the energy transition targets set for 2025. It also reviews the latest legislative trends and discusses the alignment of countries' actions with EU objectives. This analysis enables to obtain a wide knowledge of the energy situation and potential administrative incentives and disincentives that could, although maybe not directly, affect industrial SMEs on their path to becoming active actors in the energy market.

Main contributions:

- Analysis of the current electricity mix situation, comparison with objectives stated before the energy crisis, and evaluation of actions to perform to meet the objectives.
- Compilation and interpretation of the latest policies and initiatives rising from the energy crisis.
- Identification of strategic paths and associated technologies for the fulfilment of countries' objectives.
- Evaluation of the chances to meet global decarbonisation and energy independence targets considering the new initiatives aiming to guarantee the security of supply.

Keywords:

Energy independence, decarbonisation, policy trends, policy support.

Energy crisis in Europe: the union objectives and countries' policy trends. New transition paths?

Eva M. Urbano*[a], Konstantinos Kampouropoulos [a], Luis Romeral [a]

[a] MCIA Research Center, Universitat Politècnica de Catalunya, 08222 Terrassa, Spain

*Corresponding author. E-mail address: eva.maria.urbano@upc.edu

Abstract

In the context of the energy crisis that is shaking Europe, the EU has recently proposed a new legislative package that focuses on gaining gas independence from Russia, diversifying supplies, and increasing renewable energy deployment targets. In this situation, countries are acting swiftly to ensure energy security even at the cost of sacrificing or delaying some EU targets such as decarbonisation. This article analyses the electricity mix situation of the six most significant EU countries in terms of generation capacity and their position with respect to the energy transition targets set for 2025 before the crisis. Then, the latest legislative trends are analysed and a discussion is carried out about their alignment with the EU objectives. The paper concludes that EU members are currently prioritising maximising their gas independence from Russia by stepping back from decarbonisation and re-starting or extending the lifetime of coal-fired power plants. There is also an emerging trend towards the promotion of nuclear energy as a low-carbon source that can allow greater security of supply. All these changes are moving countries away from the energy transition path they had set out before the crisis and building new ones with different short and long-term perspectives.

Keywords

Energy independence, decarbonisation, policy trends, policy support.

1. Introduction

The current energy crisis in Europe is forcing the European Union (EU) to adopt new measures to accelerate the transition towards a more secure and sustainable energy system independent from adverse external circumstances. The EU has faced an unprecedented increase in electricity prices mainly due to the Ukraine war, which caused a sudden decrease in the availability of Russian supplies [1]. Before the war, 43% of total natural gas imports came directly from Russia [2], a figure which had been increasing as EU countries switched from coal to natural gas for decarbonisation purposes [3]. In fact, the EU's transition path did not foresee reducing natural gas in the system and understood it as a transition fuel [4]. However, the current situation is requiring the EU to move away from gas, thus gaining independence from Russia and bringing stability and security to energy markets.

The EU has added to its existing energy policy packages which foster energy transition and decarbonisation a new one, the REPowerEU [5]. REPowerEU came into force in mid-2022 and focuses on increasing energy independence, diversifying gas supply and enlarging renewable energy targets. Although EU Member States (MSs) have not officially adopted the package yet, the urgency of the situation is pushing them to take rapid actions and measures that may draw a new transition path towards more sustainable energy systems. Some of these measures are controversial and could cause a recession on the road to decarbonisation as foreseen in [6], where electricity markets are analysed from an economic point of view and the possibility of the return of coal is pointed out. The study presented in [7] also anticipates that the war and the resulting uncertainty around natural gas could lead to a change in the development of energy systems in Europe. Nonetheless, up to date, there is no study analysing specifically MS' initiatives to evaluate with evidence if current policy trends could jeopardise energy transition and decarbonisation goals. This article provides a detailed analysis of the current situation and MS' policy trends in the energy and particularly in the electricity sector in order to assess: (1) the path EU countries are taking; (2) its consequences on the framework objectives of the EU; (3) its effects on decarbonisation and energy independence goals.

To appreciate if decarbonisation and energy independence can be achieved, it is crucial to understand not only the direction that MSs are taking but also their starting point. To do so, the current electricity mix of countries is analysed and compared to the decarbonisation objectives stated before the energy crisis. For obtaining a convenient overview of the European situation with adequate detail in the analysis per country, this paper considers the situation and trends of the most important EU countries from the point of view of generation capacity. From the comparison between the current situation and targets, it is possible to outline the actions that are required to achieve pre-crisis decarbonisation and transition objectives. Then, a detailed analysis of the new initiatives and policy trends in the studied countries is done to evaluate their alignment with the EC framework. Therefore, the main contributions of this paper are:

- Analysis of the current electricity mix situation, comparison with objectives stated before the energy crisis, and evaluation of actions to perform to meet the objectives.
- Compilation and interpretation of the latest policies initiatives rising from the energy crisis.
- Identification of strategic paths and associated technologies for the fulfilment of countries' objectives.
- Evaluation of the chances to meet global decarbonisation and energy independence targets considering the new initiatives aiming to guarantee security of supply.

The rest of the paper is organised as follows. Section 2 exposes the methodology followed in the paper to evaluate current and future energy trends. Section 3 depicts nowadays' energy mix and decarbonisation targets, and section 4 presents an introduction to the energy crisis and its causes. Countries' policy trends, actions and initiatives consequence of the crisis are detailed in section 5, and in section 6 carries out a discussion on how the latest policy changes modify the energy framework and whether this modification is aligned with decarbonisation and independence objectives. Lastly, section 7 expose the conclusions of this work.

2. Methodology

This paper considers the EU framework which is constituted of 27 countries. From them, the ones that represent individually more than 5% of the total share of energy capacity in the EU are deeply analysed. Figure 1 illustrates this share of capacities. The ones with more than 5% are Germany (DE), France (FR), Spain (ES), Italy (IT), Netherlands (NL) and Poland (PL).

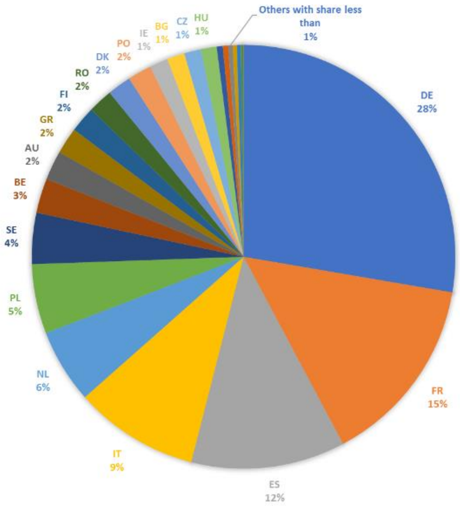

Figure 1: Share of generation capacity in the EU-27.

The current capacity mix situation for all these countries is assessed considering information from the Transparency Platform (TP), a platform created by ENTSO-e to share all available data on European power systems [8]. The generation technologies under study, according to their energy source, are: coal, oil, nuclear, wind, solar and hydro. These technologies account for 97% of total generation capacity in the EU and thus their analysis is illustrative enough to elaborate a discussion on the general circumstances. The current situation, as obtained from the TP, is compared with the objectives gathered by the Ten Year Network Development Plan (TYNDP) [9] for 2025 considering environmental EC goals and National Energy and Climate Plans (NECPs). TYNDP evaluates also the installed capacity of batteries, pumped storage and demand-side response. However, these are not considered here as they are not generation technologies per se, but flexibility sources. After the comparison between the current situation and the TYNDP objectives, the most recent legislation and policy initiatives are considered and analysed, and a discussion is carried out to appreciate whether these initiatives will modify the previously foreseen energy infrastructure and market and if they will enable to achieve both decarbonisation and energy-independence objectives.

3. Current situation and 2025 objectives

Current generation capacities for each country are gathered from TP and capacity objectives for 2025 are obtained from the TYNDP National Trends scenario [10]. Table 1 shows these capacities and the percentual difference between both of them. This section depicts the relative positions of the countries in comparison with 2025 targets.

For gas generation, all countries have currently more gas capacity than the stated objective for 2025. The amount of gas plants that need to be decommissioned is significant, reaching 46% of them in Poland. Regarding coal, the situation is slightly different. Germany and France still need to decommission an important part of their coal power plants. France decided to close all of them whereas Germany still has to reduce its capacity by 69%. In contrast, Spain and Poland have almost reached their objectives and the Netherlands has already less coal generation capacity than initially stated. This is due to the Dutch government's plan to phase out all coal power plants by 2030, which was decided by the end of 2021 [11]. The oil case is more similar to the gas one, as most countries have to still decommission an important part or even all of their oil-burning

Table 1: Generation capacities, current and TYNDP 2025 forecast.

		GERMANY	FRANCE	SPAIN	ITALY	NETHERLANDS	POLAND
GAS	TP (MW)	30649	11379	29926	41961	18530	3705
	TYNDP (MW)	22359	7435	24498	34577	10992	2016
	Difference (%)	-27	-35	-18	-18	-41	-46
COAL	TP (MW)	75396	1816	4641	8417	4492	26909
	TYNDP (MW)	23062	0	4317	6406	8002	25991
	Difference (%)	-69	-100	-7	-24	78	-3
OIL	TP (MW)	3966	2754	669	1490	0	392
	TYNDP (MW)	1059	152	0	946	0	0
	Difference (%)	-73	-94	-100	-37	0	-100
NUCLEAR	TP (MW)	4056	61370	7117	0	486	0
	TYNDP (MW)	0	61761	7126	0	486	0
	Difference (%)	-100	1	0	0	0	0
WIND	TP (MW)	63583	17191	27734	10658	11060	7886
	TYNDP (MW)	81315	29456	38956	12117	10900	7000
	Difference (%)	28	71	40	14	-1	-11
SOLAR	TP (MW)	56567	13861	14639	5137	16074	6035
	TYNDP (MW)	73549	23870	27584	26513	10900	3500
	Difference (%)	30	72	88	416	-32	-42
HYDRO	TP (MW)	5151	19815	20341	14948	38	790
	TYNDP (MW)	5375	22017	10394	12509	43	734
	Difference (%)	4	11	-49	-16	13	-7

facilities. For nuclear generation, almost no change is foreseen for 2025 in France, Italy, Netherlands, Poland, and Spain. However, Germany stated as an objective the decommissioning of all its nuclear power plants according to the amendment performed on its Atomic Energy Act on 30 June 2011 to phase out gradually nuclear power generation by the end of 2022 at the latest [12].

Regarding renewable energies, which include wind, solar and hydro generation, Germany and France need to increase significantly its generation capacity in all the technologies. Italy also requires installing more wind and solar power plants, increasing solar capacity by 416%. This figure depicts the deceleration in Italy's renewable energy plans. The policy implemented before 2014 placed it as the second EU country in the deployment of renewable capacity generation. However, there is currently a dismantling of the support scheme for renewable energies focused mainly on photovoltaics (PV) [13] which has caused the country to fall behind their objectives on solar energy. Italy's position is however different for hydropower. Hydro generation has been historically important in the country and covers approximately 15% of total demand [14]. Therefore, Italy has continued to invest in this technology, creating 172 new hydro implants between 2018 and 2020 [15], [16] and surpassing initial expectations. The Netherlands is more advanced in its renewable energy plans, with wind capacity already at the target level and more solar capacity than expected to balance the rapid phase-out of coal facilities. Indeed, the Netherlands' solar market is rapidly growing, having deployed almost 3 GW of PV systems only during 2020 as a consequence of schemes such as the SDE+ (Stimulering Duramen Energieproductie), which is the main driver for planned and contracted PV capacity in the country [17], [18]. Poland is also in a favourable position regarding renewables, having surpassed stated objectives for all technologies. Actually, renewable energy sources' capacity has increased by 31% only in 2021. The highest increase is in prosumer PV, which accounts for almost 80% of total PV installed capacity [19]. This increase is a consequence of strong regulatory support that includes subsidies, net metering, direct tax reduction and offset of personal income tax [20]. The case of Spain is more similar to the Italian one, with less generation capacity than foreseen in the wind and solar sectors and more in hydropower. Hydropower in Spain is also historically important given the country's terrain and a large number of existent dams [21] although in 2021 more than 100 dams were demolished as part of the national strategy for the recovery of rivers, which doesn't support the promotion of this type of installation in the country [22], [23]. Regarding solar and wind power generation, Spain was formerly a pioneer country in its adoption that has also carried out a dismantling of renewable energy policies, falling behind the objectives stated during the peak policy support period [24].

With this analysis it is possible to appreciate that although countries are doing an effort towards decarbonisation by dismantling fossil fuel-fired power plants and implementing renewable energy sources, most of them have still a long way to go, being necessary an increase in the pace of modifications to reach 2025 objectives, which were designed by countries to achieve, among others, Fit-for-55 targets [25].

4. Energy crisis and policy reaction in Europe

The beginning of the energy crisis in Europe can be placed in mid or late- 2021. By that time, global economies were recovering from the COVID-19 pandemic which caused a low demand, and therefore a drop in supply and energy prices. The fast economic recovery in countries created a rapid increase in energy demand that disrupted a supply side still not recovered from the pandemic. This crisis, which also generated supply chain disruptions and high volatility, affected mainly the oil and natural gas markets [26]. Simultaneously, France started to unexpectedly shut-down nuclear reactors due to security issues, which aggravated the energy crisis in Europe [27]. In late 2022, France still has 32 of its 56 nuclear reactors shut down due to corrosion, small cracks in cement works, or maintenance [28]. This situation already created stress in the electricity market in Europe, drastically increasing electricity prices and market uncertainty. The framework worsened at the beginning of 2022. In February 2022 Russia started to deploy troops toward the Ukraine border and several countries started negotiations to avoid a war situation. Nonetheless, negotiations did not solve the Russia-Ukraine crisis and the United States responded by imposing sanctions on the Nord Stream 2 gas pipeline, which connects directly Russia with Germany for natural gas supply [29]. On February 24, Putin announced the invasion of Ukraine and in March the United Nation Members voted to condemn Russia's offensive [30]. As a response to Russia's invasion of Ukraine, the EU adopted several packages of sanctions which included restrictions on economic relations, economic sanctions covering the finance, energy, transport and technology sectors, prohibition on transactions with the Russian Central Bank, prohibition on all transactions with state-owned enterprises, prohibition on new investments in the Russian energy sector, prohibition on import of coal, closure of ports to Russian vessels, etc. [31]. These sanctions affected directly the trading of natural gas between Russia and Europe. Before the sanctions, Russia supplied the EU with more than 40% of its total gas imports in 2021, and some countries, such as Slovakia, had a dependence of almost 80% on oil imports from Russia. For this reason, the sanctions were likely to increase the consequences of the existing energy crisis [32]. The described situation did indeed cause an important impact on the electricity market, with a 500% increase in wholesale electricity prices from 2021 until mid-2022 [33].

Until now, the EU based its energy landscape and planning on four policy packages: "Energy Union Strategy" (2015), "Clean Energy for all Europeans" (2016), "European Green Deal" (2019) and "Fit for 55" (2021). These energy packages focus on the energy transition by encouraging the reduction of emissions through decreasing the use of fossil fuels, deploying renewable energies, and generating alternative green and bio fuels such as hydrogen and biogas. With the current energy crisis, a new policy package was announced in February 2022: the REPowerEU [34]. This package is a response to the disruption caused in the energy market by Russia's invasion of Ukraine. It aims at diversify the energy supply, moving away from Russian dependence and modifying the transition path depicted before the energy crisis enhancing also a stronger deployment of alternative energy sources [35]. The main energy proposals that appear in REPower EU are:

- Natural gas supply diversification
  Analyse the possibility to import more gas from other countries and evaluation of new gas alliances as well as coordinate with other gas buyers.
- Boosting renewable energies
  New proposal for increasing the renewable energies target from 40% to 45%. Special focus on solar PV to install new 320 GW by 2025, creating an EU Solar Strategy and a European Solar Rooftop Initiative. Also, the EC will study the declaration of 'go-to' areas for a fast permitting process for renewables deployment.
- Hydrogen promotion
  Proposal for a target production of 10 million tonnes of domestic renewable hydrogen by 2030 and the creation of a European Hydrogen Bank.
- Biomethane
  Initiative to boost sustainable biomethane production to 35 bcm by 2030.
- Increase to 13% the binding target in the Energy Efficiency Directive.
  Already ongoing study for the incorporation of short-term measures that could achieve a 5% reduction in gas demand.

The application of this policy package will suppose an additional investment of €210 billion between 2022 and 2027 compared to that to be performed for Fit for 55 objectives [5]. Indeed, this latter policy package does not substitute previous ones, but adds requirements and objectives to the decarbonisation and transition objectives stated before the energy crisis. The EC suggest that the MS integrate the REPowerEU policies into their existing recovery and resilience plans (RRPs) to accelerate energy transition [36]. Although the process for the modification of the RRPs has not been completed, MS are already taking measures and drafting a policy line focused on the mitigation ofthe impact of the energy crisis. However, as previously stated targets for decarbonisation are still valid, there are currently appearing contradictory objectives in some situations which require the achievement of trade-off solutions.

5. Countries' policy trends

In this section, the current policy trends emerging in Germany, France, Spain, Italy, Netherlands, and Poland are analysed to evaluate whether these policies are likely to fulfil the new REPowerEU and previous decarbonisation objectives.

5.1. Germany

Germany has developed an important dependence on natural gas imports from Russia, which supplied 55% of total German natural gas imports in 2020 [37]. Germany has now settled the target to reduce natural gas imports from Russia to a maximum of 10% by 2024 [38]. To do so, the country has recently approved a package to reduce the consumption of gas. This package includes measures such as the diversification of gas supply and the reactivation of coal-fired power plants [39]. In fact, some hard coal-fired power stations have already restarted operations in August 2022 and the German government is preparing a regulation to restart also lignite-fired power plants which have been shut down [40]. German's energy policy is also considering the use of oil-fired power plants although it is currently not its main focus [41]. The debate is more intense in the field of nuclear power. As exposed in previous sections, Germany had the objective to decommission all nuclear power plants by the end of 2022. Nonetheless, the current energy crisis caused the government to announce at the beginning of September 2022 its plan to keep two of the three existing nuclear power plants online [42]. The lifetime extension of nuclear power plants is still uncertain, from April 2023 until the end of 2024 [42].

Regarding renewables, the government launched on April 2022 a comprehensive legislation package called the "Easter package" which revises the following acts aiming to accelerate the transition to renewables: the Renewable Energy Sources Act, the Offshore Wind Energy Act, the Industry Act, the Federal Requirements Plan Act, the Grid Expansion Acceleration Act, and further laws and ordinances in the field of energy legislation [43]. The "Easter package" sets as an objective the achievement of 80% renewable power in the mix by 2030 and 100% by 2035, with an onshore wind capacity of 115 GW and 215 GW of PV by 2030. The policies supporting the deployment of renewables include freeing up new land for green power production, speeding up permit procedures and grid connection, higher remuneration and subsidies for PV generation, new distance rules for onshore wind plants and reduction of financing needs for offshore wind [44]. The "Easter package" include also incentivisation measures for the production and use of biomethane in highly flexible plants although the use of biomass for power production will be superseded by its direct use in transport and industry. Although the policy regarding hydrogen and biogas enhancement has not been a special focus of interest in this last package, Germany is planning to import green gas from third countries such as Canada [4]. In addition, Germany has recently commissioned the biggest green hydrogen plant (8.75 MW) in the country[45].

Germany is doing an effort to phase-out gas although it is currently relying on other emitting energy sources such as coal with nuclear in the backstage. Policy support has been developed to deploy solar and wind generation which will probably grow in next years and alleviate the situation.

5.2. France

The French National Assembly has recently approved a package containing several measures focused on energy tariffs and energy security. The text proposes action in natural gas infrastructure investment by building new floating LNG import terminals to be commissioned in 2023 [46]. French government is also planning to re-activate abandoned pipelines to send natural gas to Germany and to strengthen the interconnection capabilities with other countries [47]. Also, regarding the operation of natural gas power plants, the state can order them to function under the orders of designated operators and is enhancing operators to fill gas storage and build security stocks [48]. For coal, the French government is planning to re-start a coal-fired power plant in north eastern France which was already closed. Nonetheless, the government claims that these modification in the decommissioning process of coal power plans will not affect the complete phase-out of coal-fired power plants expected by 2025 [49].

The energy crisis is also being tackled by a more intense use of the available nuclear power plants at the moment. In fact, the French Nuclear Safety Authority has granted a temporary waiver allowing five nuclear plants across the country to dispense more than authorized amounts of hot water into rivers, breaking the stablished environmental rules [50]. For the future, the government proposes to rapidly exit gas, coal and oil energy production by building new nuclear power plants. The latest proposal performed is the construction of six new nuclear reactors and the study for the possible development of another eight reactors [51]. The French Energy Ministry is also trying to persuade the EC to include nuclear among energy sources for the production of the so-called green hydrogen [52]. However, nowadays green hydrogen is defined as that derived from renewable sources other than biomass although it is also possible to label hydrogen as green if it is produced from electricity mixes containing more than 90% of renewables. Blue or low-carbon hydrogen is that derived from non-renewable sources such as nuclear power [53].

Concerning renewables, France is finding difficulties in their deployment, and investments are at risk due to inflation and higher commodity costs [54]. In [55] it is claimed that 13 GW of renewable energy projects may not go ahead because of the current economic environment. To address this issue, on August 2022 the French Energy Regulatory Commission published a modified version of all the specifications for two calls for tenders aiming to accelerate the commissioning of 6 GW of renewable production including wind, hydroelectric and self-consumption [56]. These modifications included the possibility for the new installations to sell electricity directly on the market for 18 months and that projects can increase their capacity by 40% before their completion. Nonetheless, these measures do not tackle general renewable deployment but only specific tenders and measures for the enhancement of renewables have not been announced during last months. The industrial network in France is also reacting with moderate enthusiasm to the proposal of defining 'go-to areas' from the EC, proclaiming that the idea is well-intentioned but drawing on a bad intuition and pointing out the difficulty of its implementation due to complex procedures related with the urban development law [57].

In summary, France is pushing hard towards the deployment of more nuclear power plants to reach decarbonisation while building a stronger gas infrastructure to exchange gas and future hydrogen with other countries, while the deployment of renewables is currently not a policy support focus.

5.3. Spain

Spain natural gas imports accounted in 2022 for 30% of total Europe liquified natural gas (LNG) imports, exporting 20% of what the country received directly to the EU [58]. This gas comes mainly from north Africa and the United States. The Iberian country also accounts with one third of the total storage and regassification capacity of Europe, although the interconnexion with the rest of the continent limits the usage of these resources [59]. For this reason, the Spanish government has settled up a plan to increase the export capacity with other EU countries [60]. This plans includes the restart of a regasification plant in January 2023, the increase of the compression capacity on current pipelines to France, boosting supply to Italy through small LNG vessels and new gas pipelines to France and Italy [61]. Given the relatively favourable gas situation of Spain, no change in the Spanish policy is foreseen regarding the closure of gas-fired power plants neither of oil-fired plants, which will continue with the plan foreseen before the REPowerEU package. For coal, the Spanish government is modifying the decommissioning plan of one of its most important coal-fired power plant due to the energy situation, closing only 2 of the planned 4 generation groups [62]. A coal-fired plant of 589MW, which was also on its way to the definitive decommission, was put into activity to avoid a higher increase in the electricity price during 2022 [63]. Regarding nuclear power, Spain has currently 7 nuclear reactors. All of them are planned to be decommissioned between 2027 and 2035 [64]. Although there are voices in the government requesting to study an extension of the lifetime of the plants [65], the government reaffirms that the hypothesis of prolonging the operation of nuclear power plants is not on the table [66].

In terms of renewable energies, Spain approved in May 2022 a new package of measures to boost green energies including solar, wind and hydrogen technologies [67]. This package includes a new regulatory framework for floating PV, regulations for the renewable gases' pipelines, the release of 10% of grid access capacity to absorb 7 GW for renewables under self-consumption regime, and an accelerated temporary process until the end of 2024 to determine environmental approval of new wind and solar parks. Spain is also planning to prepare the network for the connection and integration of renewables to achieve 70% in 2026 and also to multiply the production of renewable gases by 4. These measures, which address not only solar and wind generation but also hydrogen and green gases, reflect the interest of Spain to build a gas infrastructure and become a hydrogen hub in the future [68]. In June 2022 a new royal decree-law was published in which a promotion of self-consumption including storage capacity appeared and where subsidies were defined for different types of consumers, from big enterprises to individuals and public administrations [69].

Regarding hydro power, Spanish government is drafting a regulatory plan to guarantee the existence of investments in hydro power plants at the end of the license awarded to current management enterprises to assure their continuity [70]. The strategy to foster energy transition focuses on the development of pumped storage facilities. However, these storage plants have to undergo a process restricted by the national plan for the recovery and maintenance of rivers and projects which suppose new obstacles to the water flow are being rejected [71]. Indeed, the national plan for the recovery of rivers will probably cause a decrease in the installed capacity of hydro power given the current trend of demolishing damns, in which Spain is in the European lead position [72].

These policy trends outline the interest of Spain to become a green gas hub in Europe, being able to generate green hydrogen from renewable energy sources and exporting them to the rest of Europe. The Spanish government is also strongly supporting again the deployment of renewables with new incentives including storage and pumped storage, which will allow to create the needed flexibility in the system.

5.4. Italy

Italy is a strong gas-burning country whose 45% of total gas imports came from Russia before the Ukraine conflict [73]. As a consequence of the crisis and the increasing electricity prices, the Italian government approved on February 2022 a decree to maximise the production of thermoelectric power plants with a capacity higher than 300 MW [74]. This plan supposes a 25% increase in the production of six coal and one oil power plant. Also, the extension of the lifetime of coal-fired power plants is currently under discussion [75]. Nonetheless, Enel, the biggest energy company in the country, is considering the possibility to convert coal-fired power plants to gas [76] and a new combined cycle power plant is planned for completion by 2025 which will be able to be fired with up to 30% of hydrogen [77]. This increase in the gas capacity would be possible thanks to the gas supply diversification effort that the government has been doing during the last months. There is already an agreement to increase the gas supply from Algeria, which will become the most main exporter to Italy, and also an agreement with Egypt to provide LNG [78].

Regarding nuclear energy, the situation in Italy is complex due to the historical opposition of the population to nuclear power. There was a strong anti-nuclear movement in the country in the 80s as a consequence of worldwide accidents [79]. A referendum was carried out in 1987 which resulted in the decommissioning of the five nuclear power plants that Italy had. Despite the nuclear debate was re-opened between 2005 and 2008, a new referendum in 2011 rejected nuclear power with 94.9% of the votes [80]. Nonetheless, nuclear power is in the political plans of several parties [81] and, in fact, the coalition who recently won the elections has identified 14 possible sites for the commissioning of new nuclear power plants [82].

For renewables, Italian's RRP establishes as an objective the achievement of 70 GW of renewables for 2026 [83]. However, nowadays Italy's renewable capacity is of 33 GW and has been growing the last six years at a rate of 0.85 GW per year [84]. The 2022 budget for the country includes incentives for citizens for the energy re-qualification of buildings and also for the installation of renewable energies, being able to obtain a subsidy of up to 50% for rooftop PV [85]. The Italian government has also approved a renewable bonus for the installation of storage systems together with renewable energies, although the beneficiaries can only be individuals. Enterprises and energy communities can though benefit from a PV incentive promote the deployment of solar power generation [86]. The national strategy for hydrogen provides some guidelines for the deployment of this energy carrier, and exposes a 2030 generation capacity target of 5 GW [87]. To reach this objective, the Official Gazette published in January 2022 a bidding procedure for projects for the production and distribution of green hydrogen [88] and in February 2022 the Italian government announced that it will execute a program agreement with the National Agency for New Technologies, Energy and Sustainable Development covering research and development activities on hydrogen through the RRP funds.

According to these policy trends, Italy is currently employing other emitting energy sources to compensate the high price of gas, while it is approving measures for renewables, mainly focused on solar energy. Due to the recent change in the government, new measures can be expected which may include changes in the renewable energies' treatment and in the consideration of nuclear power.

5.5. Netherlands

Netherlands has activated the early warning phase of its Gas Protection and Recovery Plan and has extended to 2024 the production of gas from the Groningen field, which was foreseen to stop activities in 2023 [89]. Netherlands is also putting an effort on the diversification of supply through the deployment of a new LNG terminal with official opening date in September 2022 which will suppose doubling the importing capacity of the country [90]. Despite these efforts in obtaining gas at a lower price, the Netherlands is also currently opting to increase the operation of its coal-fired power plants. The government has recently removed the 35% production cap on these plants [91] and is extending the lifetime of some coal-fired power plants longer than planned [92]. Nonetheless, the government reaffirms that all coal-fired power plants will be shut down before 2030. For nuclear power, the Minister of Climate and Energy has recently announced plans for the construction of 2 new nuclear power stations [93] and for extending the lifetime of existing nuclear plants to 2033 [94]. These nuclear initiatives appear in the country's budget, were funds are being set aside for the construction of the new nuclear power plants [95].

Regarding renewables, the Dutch government accounts with aggressive renewable energies support strategies and is currently working towards having 21 GW of offshore wind energy operational by 2030 [96]. There are already project under construction off the coast which include 1.5 GW of wind, 1 MW of floating solar panels, and a platform to convert electricity to hydrogen [97]. Also, to promote individuals' self-consumption, the VAT rate on residential solar panels has been lowered down to 0%.

Hydrogen also appears as a strong energy vector in Dutch initiatives. The Netherland's current objective on hydrogen production capacity is of 500 MW by 2025 and 3-4 GW by 2030 and, to reach it, the government is launching initiatives for the regulation of the hydrogen market, market development and infrastructure [98]. Also, some of the offshore wind capacity is directly planned to be used for large-scale green hydrogen production [99]. The Netherlands is working not only to produce hydrogen but also to import it and supply it to other European countries. Indeed, the country has already signed a memorandum of understanding to establish a green hydrogen supply chain between Ireland and Europe through the Amsterdam Port [100].

Therefore, the Netherlands is employing coal-fired power plants for the moment waiting for the deployment of new sources including nuclear power and renewable energies together with a hydrogen market and infrastructure.

5.6. Poland

At the beginning of the year, Poland was planning to double capacity of gas-fired power plants to stop its dependence on coal and construct a transition path before switching completely to nuclear and renewables [101]. Several gas turbines are being under construction [102], some of them to be commissioned in 2025 [103]. To assure gas supply, Poland has been increasing imports of LNG from Qatar and the United States and will soon open the Baltic Pipe, connecting the country directly to Norway [104]. However, during 2022 coal-fired generation was cheaper than gas-fired generation, which resulted in an increase in the use of coal-fired capacity and the commission of a new unit of lignite-fired power plant [19].

Regarding nuclear power, Poland plans to build six nuclear energy reactors [105]. In order to accelerate the implementation of these nuclear power plants, the Council of Ministers has recently amended a law to ease nuclear energy investments [106].

For renewables, Poland has been Europe's fastest growing solar PV market during recent years [107]. Nonetheless, the government implemented new regulations in April 2022 which make home installations more complex and financially less attractive and which has caused a decrease in the demand for solar panels [108]. New legislation was also formulated which complicated the construction of wind farms. However, the government is planning to develop the first offshore wind farm of the country in the Baltic coast. Specifically, a 1.2 GW offshore project is under construction at 23 km north of the coastline which will be commissioned in 2026 [109]. Hydroelectric power has also been a focus of interest during the last months. The Polish government announced investments to make existent hydroelectric plants in pumped storage facilities [110] and works have been resumed on what will be the largest hydroelectric plant of the country, which will also be reversible [111].

Apart from its reputation as coal-fired country, Poland is also the 3rd country in Europe and 5th in the world in the production of hydrogen, although it is nowadays not green. The Council of Ministers has recently adopted the "Polish Hydrogen Strategy until 2030 with Outlook until 2040". As a consequence, plans and funds are set for the first hydrogen production plant [112]. The green hydrogen which could be produced in Poland is especially attractive since it can be one of the most competitive in Europe together with hydrogen from Sweden, Croatia, and Ireland [113]. The government is also introducing the hydrogen vector in the new gas-fired power plants of the country, being some of them planned to be able to run entirely on hydrogen in the future [104].

From these developments, it can be concluded that Poland has drawn a transition path which starts with gas-fired power plants and that will continue with nuclear and renewables, being the latter nowadays at a good deployment level in PV and progressing in wind and hydroelectric power.

6. Discussion

This section discusses the former described countries' actions and legislation trends considering decarbonisation and energy independence objectives. The objectives of the EC relative to electricity sector supply which appear in its energy policy packages can be very briefly summarized as:

- Reduction of emissions by decommissioning fossil fuel-fired power plants.
- Generation of green electricity through the deployment of renewable energies.
- Generation of green fuel such as hydrogen and biogas to support the decarbonisation of different sectors, including the electric one.

Table 3 expose a qualitative evaluation for each country and energy generation technology regarding whether policy trends on these technologies are aligned with EC energy packages or not. The last two rows of the table indicate the main objectives of the EC, decarbonisation and energy independence from Russia, and the evaluation on whether based on the trends for the rest of technologies these objectives are likely to be achieved or not. Table 2 details the legend meaning. The legend is a categorical classification, grouping tendencies and initiatives in three different states to appreciate the alignment of countries' paths with EC objectives.

Table 2: Legend for the qualification of actions and initiatives

	Actions and initiatives are being carried out for the achievement of decarbonisation and energy independence. There is high probability that the objectives stated by the different packages of the EC are fulfilled.
	The actions and initiatives considered do not clearly contribute to all objectives and therefore the achievement of them is not sure.
	Actions and initiatives affect directly the non-fulfilment of some of the objectives of the energy packages.

Also, and despite the EC does not defend a specific position regarding nuclear power, this technology has been included in the analysis adding a scale with the following meaning:

1. Nuclear power is not supported, there is no nuclear power plant or a clear decommissioning is planned. No new nuclear power plants are foreseen.

Table 3: Alignment evaluation of countries' policy trends and EC energy packages

	GERMANY	FRANCE	SPAIN	ITALY	NETHERLANDS	POLAND
GAS PHASE-OUT						
COAL PHASE-OUT						
OIL PHASE-OUT						
NUCLEAR POWER PROMOTION [1-5]	3	5	2	4	5	5
WIND GENERATION						
SOLAR ENERGY						
HYDRO POWER						
HYDROGEN AND GREEN GASES ENHANCEMENT						
DECARBONISATION						
RUSSIA GAS INDEPENDECE						

2. There is no clear support to the nuclear power and decommissioning plans are set although there are dissident opinions which may cause an extension in changing social and political circumstances.
3. Neutral opinion, maintenance or balance. Nuclear power is not supported but nuclear power plants life can be extended. No plans for the construction of new nuclear power plants.
4. Nuclear power is supported or there are strong opinions for their extension and/or implementation.
5. Nuclear power is supported and there are clear plans for the maintenance and/or commissioning of new nuclear power plants.

Due to the energy situation and to the fact that gas supply has become a main issue in the EU, a clear conclusion that can be drafted from the policy analysis is that most countries are prioritizing to avoid burning gas even though the actions undertaken cause more emissions than the gas alternative. This is true for all countries analysed except for Poland. Germany, France, Spain, Italy and Netherlands are opting for an extension of the lifetime and maximisation of the generation of coal and lignite-fired power plants or are even re-activating mothballed units to employ this cheaper energy source. Poland, however, is currently commissioning new gas-fired power plants to avoid the use of coal. The country plans to obtain this gas from Qatar and Norway. Countries are diversifying gas supply and strengthening gas connectivity with others. This is especially true for France, Spain and the Netherlands, which are creating new LNG terminals and have plans for new gas pipes. Although these measures contribute to the objective of gaining energy independence, they suppose a threaten for decarbonisation objectives as more emissions are being generated by the use of energy sources more pollutant than gas. Bearing in mind the fossil fuel power plant's decommissioning objectives collected in TYNDP, the current situation and nowadays policy initiatives; there is a considerable risk that the targets and specifically coal ones will not be fulfilled.

Nuclear power has also suffered a change due to the current energy crisis. The objective for 2025 exposed in TYNDP was the maintenance of current nuclear power plants or the decommissioning of all of them. However, France, Netherlands and Poland are clearly planning the commissioning of new nuclear power plants and Germany is extending the lifetime of those already active in the country. The situation in Italy and Spain is more complex, since there are diversified opinions and the continuity or the commissioning of new nuclear power plants depends on the specific political situation of the moment. Despite the commissioning of this type of power plants require time and may not be completed by 2025, it is highly probable that the nuclear generation capacity of some countries will increase considerable by 2050. The elongation of the operation of nuclear power plants or the commissioning of new reactors will definitely decrease emissions and foster decarbonisation as nuclear is a low-carbon technology. This technology is also useful to supply power for base load, being a good complement to intermittent-renewable energy sources. Nonetheless, energy security and waste disposal are still an issue and the countries still have to work to reach nuclear power independence, as the employed fuel comes from third countries. In fact, although Spain has its own uranium reserves, it is currently importing all of it mainly from Russia, Canada, Niger and Kazakhstan [114].

Regarding renewables, the approach followed by countries is more diversified. On the one hand, Netherlands and Germany have presented strong policy support during last years and will continue to do so in all renewable energy types. In fact, Netherlands has already achieved the 2025 target and with the current strategy is likely to keep the sector growing. Poland has also protagonized a strong increase in renewables and specially in solar PV. Nonetheless, the country has now decentivized solar PV investment and is trying to promote other type of renewables such as wind and hydroelectric generation. Spain, despite the deceleration of support policies wants to take action again and has proposed a wide package of measures to promote renewable energy deployment. In contrast, Italy which also suffered a deceleration in support policies, is carrying out some actions focused on solar energy although they migh not be enough to achieve the stated 2025 target. All these countries initiatives are aligned both with decarbonisation and energy dependency objectives and try to achieve the more exigent objectives of the REPowerEU package. However, it is still unclear whether the proposals performed will be more effective at accelerating decarbonisation compared to pre-existent plans and if the targets can be achieved through these measures [115]. On the other hand, despite France has implemented some measures to improve the situation of renewable investment, it has not presented a clear strategy on how to accelerate the implementation of renewables to achieve the targets and is in a situation where it might be difficult to do so.

In this framework, it is likely that all countries gain energy independence from Russia in a short period due to the diversification of supply and the activation of other power plants.

Nonetheless, decarbonisation objectives are more difficult to achieve and depend on the specific country strategy. Poland will probably reach decarbonisation later than stated by the EC due to its current movement towards gas as a bridge between its current coal situation and a future with renewables and nuclear. In contrast, France is basing its energy strategy on nuclear power which does not cause emissions and thus is closer to the achievement of decarbonisation. Germany and Spain are currently relying mainly on the deployment of renewables to achieve decarbonisation and are generating a strong policy support strategy to speed up their implementation. Nonetheless, they require the use of another energy source to maintain system stability. This can be achieved by the use of coal-fired power plants, nuclear power plants, by implementing more hydroelectric power, through producing and using of green hydrogen or by creating system flexibility. The last two alternatives are still at an early maturity stage and thus their participation in the market will be feasible only in the medium to long-term [116], [117]. For Italy the achievement of decarbonisation objectives is harder than for other countries as it is not strongly supporting renewables nor another type of low-carbon energy source. This may be due to the difficult political situation in which the country has been immersed during an important part of 2022. The new government's strategy towards decarbonisation is still to be drafted although it might include support to renewables, incorporation of nuclear power, and an important use of green hydrogen. Nonetheless, at the current pace, decarbonisation objectives for Italy may not be met. In contrast, the Netherlands is encouraging renewables with several incentives and is also planning the comissioning of nuclear power plants, and therefore may have a low-carbon economy soon enough to meet stated objectives.

From the analysis on energy policies and the evaluation performed, the following general conclusions can be obtained:

- The priority in EU countries is nowadays to gain independence from Russia's supplies, even though achieving this causes negative effects on other objectives.
- The priorization of energy independence and security of supply is modifying the electricity mix foreseen before the energy crisis.
- The accomplishment of decarbonisation objectives depend on the technologies promoted.
    - The promotion of renewables together with nuclear power provides a suitable framework in which to reach a low-carbon economy in a short to medium term.
    - The promotion of renewables without nuclear power imply currently the use of fossil fuel technologies since hydrogen, biogas and flexibility options are not implemented at a large-scale in the market. This makes it harder to achieve decarbonisation in the short-term.
    - Technological decisions based on day-to-day politics can affect how and when decarbonisation and energy independence goals are achieved.
- The path selected by each country depend on its historical background and supply procedences.
    - Countries with ease for the obtention of gas from different sources are more likely to still rely on this energy carrier.
    - Countries with a strong nuclear background are likely to continue with a nuclear strategy.

7. Conclusions

This paper has analysed Europe's situation regarding the energy crisis. In addition to previous energy policies, and in response to the current geopolitical situation, the EU has published a new energy package called REPowerEU which fosters energy independence from Russian gas and increases renewable energy targets for upcoming years. However, the achievement of both energy independence and decarbonisation objectives causes contradictory situations which each MS has to address. The current specific situation of the six most significant MSs in the EU from a generation capacity point of view has been analysed. The analysis shows that despite efforts in progressing toward the achievement of a secure and sustainable energy systems, their current energy mix is still considerably distant from EC and national plans' objectives drafted in the pre-crisis stage. With the new crisis and more exigent targets regarding decarbonisation and independence, preferences have changed significantly, and countries are acting to prioritise energy independence even though this choice negatively affects decarbonisation targets. The policy trends that have appeared during the last months show a significant deviation from the path depicted before the crisis to reach a sustainable and secure energy system. Coal-fired power plants are being brought back online and nuclear power is rising as an important asset favourable both to decarbonisation and autonomy which countries are including, now more than before, in their plans to reach a low-carbon economy. Although the duration of this situation is uncertain, an alternative to gas and coal has indeed to be found if decarbonisation targets want to be met. Hydrogen, biogas, and system flexibility can support the deployment of renewable energy sources, which are still being generally encouraged. However, their maturity does not allow them to support renewables nowadays but represents a medium to long-term solution. For this reason, it is crucial to discuss and define a realistic energy mix for the short-term, promoting the desirable alternatives by creating the required market, infrastructure and legislation for its rapid deployment.

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