# A Contribution to Multi-Criteria Decision Making in Sustainable Energy Management based on Fuzzy and Qualitative Reasoning

DOCTORAL THESIS

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تقدیم به مهربان مادر و پدرم
و صبور همسرم...
... که انرژیم بخشیدند

و بخشنده کشورم ایران
که انرژیش را به دنیا بخشید و اکنون آن را نو باید...

***Real knowledge, like everything else of value,***
***is not to be obtained easily. It must be***
***worked for, studied for, thought for,***
***and, more that all, must be prayed for.***

***-Thomas Arnold-***

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# Abstract

Energy problems are serious problems caused by limited resources and by human activity such as deforestation, water pollution and various other long-term practices that have environmental impact which produces global warming and climate change. These complex problems usually involve multiple conflicting criteria and multiple decision makers. They require the use of multi-criteria decision-making methods to evaluate different types of variables with respect to sustainability factors addressing conflicting economic, technological, social and environmental aspects. These factors, especially social ones, are not always precise, as imprecision and uncertainty are features of the real world. Therefore, in order to provide useful data from experts' assessments, in this thesis a new multi-criteria decision-making method, as a useful tool in energy planning, is presented. This method supports decision makers in all stages of the decision-making process with uncertain values.

An exhaustive literature review on multi-criteria decision analysis and energy planning has been conducted in this thesis. First, the in-depth study of criteria and indicators in the energy planning area is presented. Some well-known multi-criteria decision-making methods and their applications are introduced. These methods include various collections of mathematical techniques related to decision support systems in non-deterministic environments to support such applications as facility management, disaster management, urban planning and energy planning. In these problems, it is often difficult to obtain exact numerical values for some criteria and indicators. In order to overcome this short-

coming, qualitative reasoning techniques integrated with multi-criteria decision-making methods are capable of representing uncertainty, emulating skilled humans, and handling vague situations.

This study proposes a Qualitative TOPSIS (Q-TOPSIS) method, which is a new method for ranking multi-criteria alternatives in group decision making. This new method, in its first step, takes into account qualitative data provided by the decision makers' individual linguistic judgments on the performance of alternatives with respect to each criterion, without any previous aggregation or normalization. Then, in its second step, it incorporates the judgments of decision makers into the modified TOPSIS method to generate a complete ranking of alternatives.

Three applications of the proposed method in energy planning are presented. In the first case, the application of the Q-TOPSIS method in a case study of renewable energy alternatives selection is presented. These alternatives are ranked and the proposed method is compared with the modified fuzzy TOPSIS method. A simulation of thirty scenarios using different weights demonstrates that the simplicity and interpretability of Q-TOPSIS provides a general improvement over classic TOPSIS in the case of ordinal assessments. Second, a real case study in a social framework to find an appropriate place for wind farm location in Catalonia is presented. In this case different alternatives were proposed based on social actors' preferences for the location of the desired wind farms in a region between the counties of Urgell and Conca de Barberá. Ranking alternatives concludes that an alternative combining two different initial projects is the best option. Using the proposed method to handle a high degree of conflict in group decision making involving multi-dimensional concepts simplified the experts' measurements. Finally, an application to energy efficiency in buildings using the SEMANCO (Semantic tools for carbon reduction in urban planning) platform is presented in order to assess the energy performance and $CO_2$ emissions of projected urban plans at the city level in Manresa. In this case study, an application of Q-TOPSIS helps decision makers to rank different projects with respect to multi-granular quantitative and qualitative criteria and offers outputs which are very easy for decision makers to understand.

# Resumen

Los problemas de la energía son problemas graves causados por los recursos limitados y las actividades humanas como la deforestación, contaminación del agua y otras prácticas con efectos a largo plazo. Estas prácticas tienen un gran impacto ambiental y dan lugar al efecto invernadero, que ocasiona el calentamiento global y cambio climático. Los problemas complejos implican generalmente múltiples criterios contradictorios y múltiples decisores. Requieren el uso de métodos toma de decisiones multicriterio para evaluar diferentes tipos de variables con respecto a factores de sostenibilidad, incluyendo aspectos conflictivos económicos, tecnológicos, sociales y ambientales. Estos factores, especialmente los sociales, no siempre son precisos, dado que la imprecisión y la incertidumbre son características del mundo real. Por lo tanto, con el fin de proporcionar datos útiles a partir de evaluaciones de expertos, en esta tesis se presenta un nuevo método de toma de decisiones multicriterio, como una herramienta útil en la planificación de la energía. Este método permite a los decisores utilizar valores con imprecisión en todas las etapas de la toma de decisiones.

En esta tesis se ha realizado una revisión exhaustiva de la literatura sobre el análisis de la decisión multicriterio y la planificación de la energía. En primer lugar, se presenta el estudio a fondo de los criterios e indicadores en el área de planificación de la energía. Se introducen algunos de los métodos más conocidos de toma de decisiones multicriterio y sus aplicaciones. Estos métodos incluyen diversas técnicas matemáticas relacionadas con sistemas de soporte de decisiones en entornos no deter-

ministas para aplicaciones tales como gestión de instalaciones, gestión de desastres, planificación urbana y planificación de la energía. En estos problemas, a menudo es difícil obtener valores numéricos exactos para algunos criterios e indicadores. Para superar esta deficiencia, la integración de técnicas de razonamiento cualitativo en métodos de decisión multicriterio permite representar la incertidumbre, emular el trabajo de seres humanos cualificados y manejar situaciones vagas.

Esta tesis contribuye a la literatura de decisión multicriterio y especialmente a los modelos capaces de soportar incertidumbre en la toma de decisiones, desarrollando un nuevo método para apoyar a los decisores en áreas complejas como la de los problemas de la energía. Este estudio propone un método TOPSIS cualitativo (Q-TOPSIS), que es un nuevo método de ranking de alternativas para la toma de decisiones multicriterio en grupo. Este nuevo método, en el primer paso, toma en cuenta los datos cualitativos proporcionados por los juicios lingüísticos individuales de los decisores sobre el rendimiento de alternativas con respecto a cada criterio, sin necesidad de previa agregación o normalización. En el segundo paso, incorpora los juicios de los decisores en el método TOPSIS modificado para generar un ranking completo de las alternativas.

Se presentan tres aplicaciones del método propuesto en la planificación de la energía. En el primer caso, se presenta la aplicación del método Q-TOPSIS en un caso práctico de selección de alternativas de energías renovables. Se efectúa el ranking de las alternativas y se compara el método propuesto con un método TOPSIS fuzzy modificado. Una simulación de treinta escenarios utilizando diferentes pesos demuestra que la simplicidad y la interpretabilidad de Q-TOPSIS proporcionan una mejora general del TOPSIS clásico en el caso de evaluaciones ordinales. En segundo lugar, se presenta un estudio de un caso real para decidir el lugar apropiado para ubicación de parques eólicos en una zona de Cataluña. En este caso, las distintas alternativas fueron propuestas en base a las preferencias de los actores sociales sobre la ubicación de los parques eólicos deseados en una región entre los condados del Urgell y la Conca de Barberá. El ranking obtenido de las alternativas concluye que la mejor opción es una alternativa que combina dos proyectos iniciales diferentes. La utilización del método propuesto para la decisión en grupo permite manejar un alto grado de conflicto entre conceptos multidimensionales y simplifica las mediciones de los expertos.

Por último, se presenta una aplicación a la eficiencia de la energía en edificios mediante la plataforma SEMANCO (Herramientas semánticas para la reducción de carbono en la planificación urbana) para evaluar la eficiencia de la energía y las emisiones de $CO_2$ de planes urbanísticos proyectados en la ciudad de Manresa. En este caso estudio, la aplicación de Q-TOPSIS ayuda a los decisores a realizar el ranking de los diferentes proyectos con respecto a criterios cuantitativos y cualitativos multi-granulares y ofrece resultados fácilmente inteligibles para los decisores.

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# List of Acronyms

**AHP** Analytic Hierarchy Process . . . 31
**AI** Artificial Intelligence . . . 4
**AOM** Absolute Order-of-Magnitude . . . 4
**CC** Closeness Coefficient . . . 58
**CHP** Combined Heat and Power . . . 75
**CRSA** Classic Rough Set Approach . . . 42
**DM** Decision Maker . . . 25
**DRSA** Dominance-based Rough Set Approach . . . 42
**ELECTRE** ELimination Et Choix Traduisant la REalité . . . 37
**GDM** Group Decision Making . . . 3
**GHG** GreenHouse Gas . . . 77
**GP** Goal Programming . . . 32
**IDSS** Intelligent Decision Support Systems . . . 50
**MADM** Multi-Attribute Decision Making . . . 23
**MAUT** Multi-Attribute Utility Theory . . . 30
**MCDM** Multi-Criteria Decision Making . . . 3
**MCDA** Multi-Criteria Decision Analysis . . . 26
**MODM** Multi-Objective Decision Making . . . 23
**NIS** Negative Ideal Solutions . . . 58
**OR** Operations Research . . . 22

**PIS** Positive Ideal Solution ........ 58

**PROMETHEE** Preference Ranking Organization MeTHod for Enrichment Evaluations ........ 35

**PV** Photo Voltaic ........ 75

**QCC** Qualitative Closeness Coefficient ........ 64

**QNRL** Qualitative Negative Reference Label ........ 63

**QPRL** Qualitative Positive Reference Label ........ 63

**QR** Qualitative Reasoning ........ 4

**Q-TOPSIS** Qualitative TOPSIS ........ 61

**RE** Renewable Energy ........ 5

**ROM** Relative Order-of-Magnitude ........ 55

**SAW** Simple Additive Weighting ........ 29

**SEIF** Semantic Energy Information Framework ........ 105

**SEMANCO** Semantic tools for carbon reduction in urban planning .. 74

**SMART** Simple Multi-Attribute Rating Technique ........ 29

**SMCE** Social Multi-Criteria Evaluation ........ 90

**TOPSIS** Technique for Order Preference by Similarity to the Ideal Solution ........ 34

**UTA** Utility Theory Additive ........ 28

# Chapter 1

# Introduction

Human activities are gradually damaging the environment. Concentrations of greenhouse gases and global warming are increasing because of human activities such as burning fossil fuels and deforestation. Continued global warming may have far-reaching environmental consequences. Climate change is occurring even faster than previously expected, and it shows that the 50% reduction in $CO_2$ emissions by 2050 may be inadequate to prevent a dangerous climate change (IEA, 2012). Today the threat to the environment is high on the political agenda in many countries in the form of short-term or long-term strategies to improve environmental systems and make them more sustainable. In addition, due to economic and population growth coupled with overconsumption of our natural resources, sustainability has become increasingly important. One of the most important challenges in developed and developing countries is avoiding sustainable processes that waste resources, especially in the energy sector. Energy is crucial to modern economies for industry, transport, infrastructure, information technology, buildings heat and cooling, agriculture and household uses, among others. Nations need energy to grow their economies and improve living standards. To do so, they urgently need to take policy actions toward comprehensive sustainable energy models, new technologies and renewable energies.

Since the 1990s the importance of renewable energy has increased from both the institutional and research points of view, especially in the areas of sustainable development and energy saving (Evans et al., 2009; Jebaraj and Iniyan, 2006; Pohekar and Ramachandran, 2004; Jing et al., 2012). First the Kyoto Protocol of 1997 and, after that, the strategy of Europe 2020 (European Commission, 2010) can be mentioned as essential initiatives for the United Nations and European Union. According to the increasing impact of sustainability, new energy technologies become a key means of implementing sustainable energy systems as an important bridge between the EU sustainable development strategy and the Europe 2020 objectives. To achieve this, it is necessary to change our energy structure, integrating new sources and modifying the way we use fossil fuel to avoid damage to the environment (Terrados et al., 2009; Carrera and Mack, 2010; Streimikiene et al., 2012). Similarly, during the last decade many countries have been interested in the use of renewable energy sources and have committed themselves to include them in their energy systems. Renewable energy sources are considered environmentally friendly and capable of replacing conventional fuels at competitive price (Polatidis et al., 2006). An important decision for governments and businesses is whether or not to establish renewable energy systems in a given place and to decide which renewable energy source or combination of sources is the best choice (Baños et al., 2011). Because of their differences, each country must prepare its own energy policies based on geographical and environmental factors to address sustainability issues. For this reason, a variety of planning strategies have been utilized in different countries.

This thesis is framed around the study of developing suitable methods in energy planning problems. These kinds of problems are addressing conflicting economic, technological, social and environmental aspects to provide an appropriate equilibrium of energy production and consumption with minimum negative impact on the environment. Since social and economic development is affected by the appropriate energy planning problems, evaluating sustainable energy alternatives when determining valid energy policies is important. But, factors are not always certain and crisp. Instead, they include many qualitative variables that are difficult to analyze and quantify; the information needed for their evaluation is imprecise and involves uncertainty. Some of the currently used methods support the Decision Maker (DM) in all stages of the decision-making process by providing useful data to assess criteria with uncertain values (Kara and Onut, 2010).

Multi-Criteria Decision Analysis (MCDA) approaches are powerful tools used for evaluating problems in the process of making decisions with multiple criteria for finding a compromise solution. These methods have a strong decision support focus and interact with other disciplines such as intelligent systems dealing with uncertainty (Hwang and Yoon, 1981; Figueira et al., 2005; Ishizaka and Nemery, 2013). Multi-Criteria Decision Making (MCDM) methods under uncertainty and fuzzy systems are accepted as suitable techniques in conflicting problems that cannot be represented by numerical values, in particular in energy analysis and energy planning. Fuzzy MCDM techniques are capable of representing uncertainty, emulating skilled humans, and handling vague situations (Dubois and Prade, 1980; Tuzkaya et al., 2009). Frequently, this uncertainty is captured by using linguistic terms or fuzzy numbers to evaluate the set of criteria or indicators (Pedrycz et al., 2011).

The contribution in this Ph.D. thesis is the introduction of a new method for ranking different applications of energy alternatives (scenarios, technologies, strategies or policies). The thesis presents a qualitative MCDM method for Group Decision Making (GDM) with qualitative linguistic labels. This method addresses uncertainty with different levels of precision and ranks multi-criteria alternatives. Each DMs' judgment on the performance of alternatives with respect to each criterion is expressed by qualitative basic and non-basic labels. The proposed approach is compared with some MCDM methods such as modified fuzzy TOPSIS and Condorcet-based outranking methods. This comparison between the new method and other methods highlights the respective advantages and disadvantages of each, as evidenced in different aspects of decision making.

Some applications to energy planning problems are presented as case studies in which energy alternatives are ranked. First, the proposed method is applied in a case study of renewable energy alternatives selection. Second, a real case study in a social framework to find an appropriate place for wind farm location in Catalonia is presented. Third, a SEMANCO integrated platform application is used to assess the energy performance and $CO_2$ emissions of projected urban plans at the city level in Manresa.

This chapter is organized as follows. First, theoretical background is presented. Then, the motivation of the thesis and the research gap it aims to bridge are introduced. Finally, the objectives of the thesis are considered.

## 1.1 General framework of the thesis

Alternatives are characterized by several features which can be assessed by different scales; experts can evaluate them by means of qualitative or quantitative variables. The framework of this study is based on a hierarchical set of linguistic labels in which each expert can use different levels of precision to assess alternatives. DMs can make mistakes if they are forced to make more precise judgments than they are capable of. Conversely, a substantial loss of information can occur if the DMs are forced to make less precise judgments than the available data allow.

For this reason, in the presented method, evaluations are considered using ordinal scales with different sets of descriptors to capture the degree of uncertainty in the DM's perception. Therefore, this thesis is framed in the context of *multi-criteria decision making* and *Qualitative Reasoning (QR) techniques in Absolute Order-of-Magnitude (AOM)* as a theoretical framework of this study.

Techniques based on order-of-magnitude have provided theoretical models that can obtain results from non-numeric variables. One of the systematic tools for assessment is QR, which is a sub-field of research in Artificial Intelligence (AI). Reasoning techniques from the AI field are used in the development of alternatives; the resulting systems are referred to as intelligent decision support systems. These techniques attempt to understand and explain the skill of human beings in reasoning without precise knowledge (Doumpos and Grigoroudis, 2013). Qualitative AOM models were introduced into the QR field with the aim of using a linguistic approach to work with different levels of precision (Travé-Massuyès et al., 2005).

We believe that a combination of a linguistic approach with MCDM methods can be used as a systematic tool to help energy planners and policy makers to select strategies for energy assessments. In this way, from the application point of view, this thesis is defined in the scope of energy planning problems to use the benefit of the new method in this challenging area.

## 1.2 Motivations and research gap

According to the Renewable Energy (RE) plan 2011-2020, the increase in the use of RE in the Spanish energy mix will contribute to improving supply guarantee, reducing energy dependency, improving trade balance, and reducing greenhouse gas emissions. In general, it will have a positive effect on the creation of qualified jobs, stimulation of the economy and reduction of environmental impacts caused by the energy system (IDAE, 2010). All of these factors explain why RE has become a strategic sector in Spain and a key issue in the Spanish economic, political and social development strategy.

In 2005, the Spanish government approved the RE plan in the following sectors: wind power, hydroelectric, solar (solar photovoltaic, solar thermal, solar thermoelectric), biomass, bio-gas, and bio-fuels (San Cristóbal, 2011); in 2011 they added wave energy and geothermal energy to this plan. According to Europe Targets 2020, Spain should reach 20% of the total energy consumption covered by renewable sources in 2020 (IDAE, 2011). To do so, crucial decisions in energy sector are required.

Now, the questions are: how can Spain reach this goal? What energy assessment methods are needed? How can MCDM methods help decision makers to bring insight to problems and facilitate agreement among diverse stakeholders to improve decision making processes? The research carried out in this thesis adds value in these directions.

The key issue is *the development and use of a qualitative decision making method* to be applied in energy planning that is able to deal simultaneously with indicators of a qualitative nature alongside quantitative ones. Energy planning problems have multiple aspects, all of which should be considered to find the compromise solution which is acceptable to all the actors who are involved in a given problem. So, the primary goal of decision making should be capturing qualitative and quantitative aspects, especially in problems with high uncertainty.

Although many real applications with qualitative criteria use linguistic variables (e.g., in marketing), there are many numerical values in the technical areas of energy planning problems, yet there are also environmental and social aspects which cannot be easily quantified.

Since most of the indicators in energy planning problems are numerical, methods are basically quantitative in most of the literature, focusing on the technical and economic aspects of these problems. Such methods either ignore qualitative variables such as ecological concerns, social acceptance or environmental impact because it is difficult to quantify them, or they attempt to find numerical values for them. From a sustainability point of view, all aspects (technological, economic, social and environmental) are important and unavoidable.

Therefore, there is a need for methods that are able to analyze complex problems with multiple and conflicting criteria under uncertainty to determine solutions acceptable to all stakeholders. Such methods are necessary to fill the gap in experts' knowledge preferences by using linguistic terms rather than numerical values.

Although there are many studies in the MCDM area, interest in using linguistic variables via fuzzy sets and MCDM approaches has recently increased. The absolute order-of-magnitude reasoning, which is used in this thesis, is a useful method of artificial intelligent techniques using linguistic modeling. Linguistic terms help experts to express their preferences with different levels of precision based on their knowledge.

## 1.3 Contributions

In response to the need described in the preceding arguments, this thesis develops a decision-making method to give experts the ability to overcome uncertainty by using linguistic terms. It also takes into consideration that DMs prefer to use a method that is understandable and easy to use. To summarize, the main contributions of this thesis are as follows:

1. A new qualitative MCDM method is developed for addressing complex problems under uncertainty such as sustainable energy planning problems. This method takes into account intensity of preferences and gives experts the ability to assess alternatives using linguistic variables. The use of qualitative labels with different levels of precision is crucial to obtaining user-friendly systems to be used by energy planners for evaluation processes.

2. The proposed method is applied to three energy applications to show its potential and ease of use.

The advantage of using this type of hierarchical model is the fact that it permits multi-granular linguistic information to be expressed in a unified linguistic domain without losing information. The final ranking automatically aggregates all the information provided by the experts, computing words with different granularities and combining them to form a collective opinion. The method consists of 4 main steps:

1. Each expert rates or describes each feature using linguistic labels.

2. The system defines a “best fictitious alternative” and “worst fictitious alternative” by aggregating the best and the worst options for each feature.

3. The system then assigns the distance from the best and worst fictitious alternative to each alternative.

4. Finally, the system ranks alternatives (based on these distances).

The main advantages of the proposed method are:

- It takes into account the different degrees of strictness in the evaluators' opinions.
- It considers the evaluation of a group of experts and decision makers.
- It does not require evaluators to make pairwise comparisons between alternatives; this is advantageous when a large number of alternatives exist.
- It does not require averaging the evaluators' ratings.
- The method makes it possible to assign a different level of influence to each expert and different weights to attributes.
- And finally, it does not require interaction between experts or participation by a moderator to obtain a final ranking; this avoids the potential subjectivity caused by conflicts of interest among evaluators.

## 1.4 Objectives

The general aim of this study can be summarized as follows.

To define a new MCDM method able to deal with qualitative information and to illustrate the potential of this method through applications of renewable energy planning problems in Spain. To this aim, the following specific objectives have considered:

1. To review and study the different renewable energy sources.

2. To analyze the main features involved in energy planning problems (including technical, economic, environmental and social aspects)

3. To analyze existing decision-making methods and experiments in which energy DMs compared the usefulness, results and validity of several different MCDM methods.

4. To consider pilot examples to compare MCDM methods. These experiments, together with our reviews of a wide range of applications, have been helpful to develop the proposed method to test them against real problems.

5. To define a new MCDM method inspired by the ranking method in Agell et al. (2012) and TOPSIS method, suitable for application to energy planning problems. This new method incorporates to the existing MCDM method the ability to deal with uncertainty via qualitative DM assessments.

6. To apply the method to real cases in Catalonia.

The general hypothesis of the proposal is that the use of MCDM approaches incorporating linguistic variables will better capture the complexity of the energy planning problems. Using qualitative labels will simplify the experts' measurements and will help DMs to better understand the relevance of the variables involved and improve decision making.

## 1.5 Structure of the thesis

As previously stated, the purpose of this study is to elaborate a new multi-criteria method for the performance assessment of renewable energy systems taking into account the inherent complexity and uncertainty of the decision-making problem. To this end, the thesis is structured as follows.

Chapter 1 first introduces the context, theoretical framework, general and specific objectives, motivations and contributions of the thesis.

In Chapter 2, a literature review and in-depth study of criteria, subcriteria and indicators is carried out to obtain the set of qualitative and quantitative variables involved. Then, an analysis is performed of the existing MCDM methods especially appropriate for energy planning problems. The last part of this chapter presents a brief review of some applications in the energy sector, chosen to illustrate the very wide range of problems to which MCDM methods have been applied. The next two chapters detail the main contributions of this thesis.

Chapter 3 first presents a new model in MCDM approaches with qualitative labels. This method is based on an extension of a ranking method in QR with the absolute order of magnitude, and TOPSIS methods which have been introduced. Secondly, a detailed study and comparison of recent MCDM approaches based on fuzzy and QR techniques are performed. Finally, the new method is compared with another MCDM method based on outranking approaches.

The proposed method is applied in Chapter 4 to select the best investment alternatives for choosing the most sustainable renewable energy technologies. This application in energy planning is presented as an illustrative case example. In addition, two real case studies in specific areas of Spain are presented: a real case study in a social framework to find an appropriate place for a wind farm location in Catalonia, and a SEMANCO integrated platform application in order to assess the energy performance and $CO_2$ emissions of projected urban plans in Manresa.

Finally, in Chapter 5, conclusions are drawn and suggestions made for further work. Additional researches and publications derived from this thesis have been presented.

# Chapter 2

# State-of-the-art

There are, in the literature, a number of decision making approaches that are being applied in different energy planning problems. In this chapter these studies, which have been extensively used, are reviewed. Since one of the most important parts of decision making is finding the relevant criteria and variables, in the first part of this chapter a specific study in sustainable energy management and relevant criteria in literatures has been done. Taking into account this literature review, a list of all appropriate indicators to measure these criteria in energy problems is presented.

The second part of this chapter is related to the state-of-the-art in MCDM approaches, both from methodological and application point of view. These studies help DMs to find the suitable method among all others in different contexts. The last part is devoted to emphasize on various applications of MCDM approaches under uncertainty in the energy planning with the focus on using linguistic variables.

## 2.1 Sustainable energy assessments

In the broad discussion of sustainability, the Brundtland Report's principal definition of sustainability is the popular one, that is: "Development that meets the needs of the present without compromising the ability of future generations to meet their own needs". Meeting essential needs by achieving growth potential, and sustainable development clearly requires economic growth in places where such needs are not being met (World Commission on Environment and Development, 1987). The main concern in the concept of sustainability is the tension between the aspirations of human being towards a better life on the one hand and the limitations imposed by nature on the other hand.

There are two different point of views of sustainability; called "strong" and "weak" sustainability. These concepts are stated in Pearce et al. (1989), respectively:

1. That the next generation should inherit a stock of wealth, comprising man-made assets and environmental assets, no less than the stock inherited by the previous generation. *human capital* and *natural capital* are complementary. A constant stock of natural capital must be maintained because the productivity of one depends on the availability of the other.

2. That the next generation should inherit a stock of environmental assets no less than the stock inherited by the previous generation. It assumes that, *human capital* can substitute *natural capital*.

For instance, the depletion of fossil fuels is an issue of weak sustainability and strong sustainability as a space defined by a series of thresholds that must not be crossed. Weak sustainability can be shown which policy outcomes within that space are judged. Given that the conditions of strong sustainability are met, the most sustainable outcome will be that which leads to the largest amount of natural resources, such as environmental assets, valuable landscapes, science and technology, infrastructure, etc.

Thus, both weak and strong sustainability have a role to play in impact assessment. Generally, ecologists and other natural scientists will favor a larger role for strong sustainability (emphasizing non-substitutable ecosystem functions), whereas economists tend to like weak sustainability as this gives them ability of using their models.

Further, the balanced integration of societies' economic, social and environmental goals in a spirit of equity and with a concern to preserve the interests of future generations is often explained in discussions of sustainable business practices. A three-pillared approach has been shown in Figure 2.1:

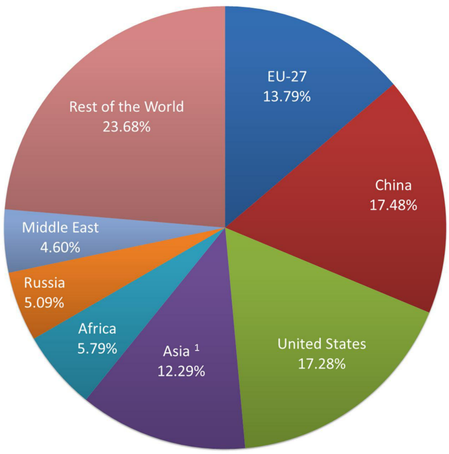
Figure 2.1: Three pillars of sustainability


Social, environmental and economic factors are interdependent in human development; and outcomes are dependent upon the interaction of these factors.

Finally, sustainable practices and planning has been considered as a set of processes and a component of an evolutionary paradigm in business. In general, sustainability in this sense (which is defined in the scope of this thesis), has a meaning of variety of economic, ecological or environmental and social sustainability in different concepts such as energy planning, urban planning, transportation and other managerial applications.

Energy is one of the most important elements of world economy. Most part of the energy comes from fossil fuel. Energy problems are serious problems caused by limited resources and human activity such as deforestation, water pollution or many long-term environmental impacts as well as greenhouse effect which produce global warming and climate change. Furthermore, the global energy demand is expected to increase about 50% percent between 2004 and 2030 especially in developing countries as a result of population growth and economic development. The global final energy consumption has been increasing for decades, it was 4674 Mtoe in 1973, and increased to 8918 Mtoe in 2011 (IEA, 2013). As it shown in Figure 2.2, EU-27 uses 13.8% of the total world energy (source in (European Commission, 2013)).

Figure 2.2: World final energy consumption by region (%)

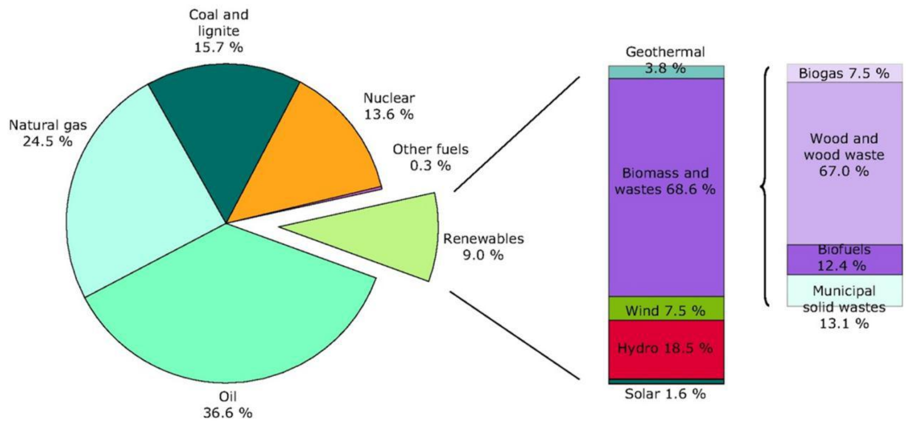



According to the importance of energy issues especially renewable energies as one of the important paths of our energy future, our focus in this thesis is applying suitable methods to help decision makers in renewable energy problems. It is evident that because of the limitations of fossil fuel supply and because of the environmental deterioration arising from its use, other sources of energy should be considered. Figure 2.3 shows that the vast majority of the world's energy is generated from non-renewable sources, which are oil, coal, gas and nuclear about 90%

[1] Excludng China and Middle East

and only 9% of the global energy is derived from renewable sources in European countries in 2010 (Stamford and Azapagic, 2011).

Figure 2.3: World final energy consumption by energy sources (%)




It is necessary to change the energy structure, integrating new sources and modifying the way we use fossil fuel, because of its damage to the environment. For this reason, several planning strategies have been utilized in different countries. On 11th November 2011, the new Renewable Energy Plan (REP 2011-2020) was approved by the Spanish Government for the years 2011 to 2020, establishing the development framework for the renewable energy sector during the next 10 years (IDAE, 2011). The REP 2011-2020 establishes the Spanish objectives and suggests the measures to be implemented in order to reach the 20% goal in 2020. It includes the Spanish vision on the evolution of the renewable energy sector regarding each of the type of renewable energy available in the coming years. The public entity in charge of the implementation of the Renewable Energy Plan 2011-2020 is the Institute for Energy Diversification and Saving (IDAE, 2010).

Table 2.1 shows the primary energy consumption from renewable sources in 2004, 2010, 2015 and the future plan in Spain (IEA, 2012).

The REP 2011-2020 specifically takes into account the different renewable sources such as wind power, bio-fuels and bio-liquids, hydro-energy, biogas, biomass, wave and tidal energy, geothermal energy, waste energy and solar technologies, including photo-voltaic (PV), thermal and concentrating solar power (CSP) (IDAE, 2011).

Table 2.1: Primary energy consumption from renewable sources in Spain

| Year | Percentage |
|---|---|
| 2004 | 6.30% |
| 2010 | 11.3% |
| 2015 | 14% |
| 2020 | 20% |

However the potential for renewable energy generation in Spain is remarkable and higher than the total national energy consumption, it seems that the objective of a 20% in 2020 is possible to reach. Renewable energy sources will allow future developments and investments in this sector. The key factors applicable in renewable energy planning are investment, energy capacity expansion and evaluation of energy alternatives (Pohekar and Ramachandran, 2004). Oil prices and the geographical distribution of energy reserves have shaped the energy options of developed countries for over three decades.

Different literatures studied various types of variables in energy planning. Different studies on energies will help the energy planners and policy makers to develop the necessary strategies for renewable energy system models. Solar, wind and biomass are accepted as reliable and widely available renewable energy. Habbane and McVeigh (1986); Akinoglu and Ecevit (1990); Maycock (1994); Meyer and van Dyk (2000); Cavallaro (2010a); Jain and Lungu (2002) presented solar energy models. Sfetsos (2000); Radics and Bartholy (2008); Ettoumi et al. (2003); Poggi et al. (2003) developed models in wind energy. Kimmins (1997); Haripriya (2000); Specht and West (2003) presented some models in biomass.

As stated in Chapter 1 about the importance of renewable energy, it is necessary to develop an efficient energy policy for each country (Topcu and Ulengin, 2004). Recently, several researches and planning of strategies have been done. Some articles aim to define different quantitative and qualitative indicators to evaluate sustainability of renewable energy generation technologies and energy planning. The use of criteria and indicators is a common way to describe and monitor complex systems and to provide information to DMs. According to sustainability point of view, four main criteria, technological, environmental, economic and socio-political are accepted by most of the researchers in energy planning area (Begic and Afgan, 2007; Doukas et al., 2007; Wang et al., 2008, 2009). Table 2.2 to Table 2.5 show the “sub-criteria” and “indicators” of these criteria that are commonly used in different studies. The most commonly used sub-criteria are considered for each criterion. Each indicator is assigned to a specific sub-criterion, and the corresponding studies citations are included.

Table 2.2: Review of technological indicators

| **Technological** | | |
|---|---|---|
| **Sub-criteria** | **Indicators** | **Citation** |
| Project feasibility | Technical feasibility. | (Goletsis et al., 2003); (Kahraman et al., 2009); (Nigim et al., 2004). |
| | Availability and, technological limitations. | (Evans et al., 2009). |
| | Resource availability. | (Nigim et al., 2004). |
| Technical safety, and security | Technical risk. | (Buytaert et al., 2011); (Goletsis et al., 2003). (Kahraman et al., 2009). |
| | Readiness of the local agents to, implement the project. | (Goletsis et al., 2003). |
| Technical maturity | Mastering of the technology, by local agents. | (Goletsis et al., 2003); (Jing et al., 2012). (Kahraman et al., 2009); (Beccali et al., 2003); (Kaya and Kahraman, 2011a); (Wang et al., 2009). |
| | Consistence of installation, and maintenance local Technical know how. | (Beccali et al., 2003); (Kahraman et al., 2009). |
| | Continuity and, predictability of performance. | (Beccali et al., 2003). |
| Property | Control property. | (Jing et al., 2012). (Kahraman et al., 2009). |
| | Regulation property. | (Jing et al., 2012). |
| Reliability | Reliability of resources. | (Jing et al., 2012). |
| | Reliability of technology. | (Goletsis et al., 2003); (Kahraman et al., 2009); (Beccali et al., 2003); (Wang et al., 2009). |
| | Reliability of energy. | (Evans et al., 2009); (Buytaert et al., 2011). |
| Operability factors | Response speed. | (Stamford and Azapagic, 2011). |
| | Power quality. | (Stamford and Azapagic, 2011). |
| | Efficiency. | (Beccali et al., 2003); (Begic and Afgan, 2007); (Evans et al., 2009); (Kaya and Kahraman, 2011a); (Wang et al., 2009). |
| | Energy payback time. | (Stamford and Azapagic, 2011). |
| | Capacity factor. | (Bhat et al., 2009). |

Table 2.3: Review of environmental indicators

| **Environmental** | | |
|---|---|---|
| **Sub-criteria** | **Indicators** | **Citation** |
| Land requirement | Occupied area. | (Buytaert et al., 2011); (Evans et al., 2009); (Kahraman et al., 2009); (Beccali et al., 2003); (Stamford and Azapagic, 2011); (Kaya and Kahraman, 2011a). |
| | Percentage of effective land use. | (Rovere et al., 2010). |
| Environmental impact | Deforestation. | (Beccali et al., 2003). |
| | Water consumption. | (Buytaert et al., 2011); (Evans et al., 2009). |
| | Soil quality. | (Rovere et al., 2010). |
| | Water quality. | (Buytaert et al., 2011). |
| Waste management | Minimization. | (Buytaert et al., 2011). |
| | Sorting. | (Buytaert et al., 2011). |
| | Need of waste disposal. | (Buytaert et al., 2011). |
| | Recycling. | (Kahraman et al., 2009). |
| Health risk | Noise. | (Streimikiene et al., 2012). |
| | Human health impact | (Kane driscoll et al., 2002); (Kiker et al., 2005). |
| Air quality and pollutant emission | $NO_x$ emission | (Buytaert et al., 2011); (Kahraman et al., 2009); |
| | $SO_2$ emission | (Begic and Afgan, 2007); (Kaya and Kahraman, 2011a); (Wang et al., 2009). |
| | $CO_2$ emission | (Begic and Afgan, 2007); (Kaya and Kahraman, 2011a); (Wang et al., 2009). |
| | Particles emission | (Begic and Afgan, 2007); (Kaya and Kahraman, 2011a); (Wang et al., 2009). |
| | Greenhouse pollutant emission | (Kaya and Kahraman, 2011a); (Wang et al., 2009). |
| | GHG emissions (global warming potential) | (Beccali et al., 2003). |

Table 2.4: Review of economic indicators

| **Economic Sub-criteria** | **Indicators** | **Citation** |
|---|---|---|
| Cost of the Project | Investment cost. | (Begic and Afgan, 2007); (Bhat et al., 2009); (Evans et al., 2009); (Goletsis et al., 2003); (Kahraman et al., 2009); (Streimikiene et al., 2012); (Kaya and Kahraman, 2011a); (Wang et al., 2009). |
| | Operation and maintenance cost. | (Begic and Afgan, 2007); (Evans et al., 2009); (Goletsis et al., 2003); (Jing et al., 2012); (Kahraman et al., 2009); (Stamford and Azapagic, 2011); (Kaya and Kahraman, 2011a); (Wang et al., 2009). |
| | Fuel cost. | (Stamford and Azapagic, 2011); (Kaya and Kahraman, 2011a); (Wang et al., 2009). |
| | Electric cost (energy cost). | (Stamford and Azapagic, 2011). |
| | Cost of grid connection. | (Begic and Afgan, 2007); (Wang et al., 2009). |
| | Equivalent annual cost. | (Streimikiene et al., 2012). |
| Viability of the business | Net Present Value. | (Buytaert et al., 2011). |
| | Payback | (Buytaert et al., 2011). |
| | Service life. | (Doukas et al., 2007); (Jing et al., 2012); (Kaya and Kahraman, 2011a); (Wang et al., 2009). |
| | Security of supply. | (Streimikiene et al., 2012). |
| | Peak load response. | (Streimikiene et al., 2012). |
| Financial incentives and assistance | Tax player burdens. | (Stamford and Azapagic, 2011). |
| | Availability of funds. | (Stamford and Azapagic, 2011). |

Table 2.5: Review of socio-political indicators

| **Socio-Political** | | |
|---|---|---|
| **Sub-criteria** | **Indicators** | **Citation** |
| Social acceptance | Acceptance of the business by producer. | (Buytaert et al., 2011); (Goletsis et al., 2003); (Kahraman et al., 2009). (Kaya and Kahraman, 2011a); (Wang et al., 2009). |
| | Consumer and local population. | (Buytaert et al., 2011). |
| Labor impact | Freedom of association. | (Kahraman et al., 2009); (Beccali et al., 2003). |
| | Minimum wages. | (Buytaert et al., 2011). |
| | Average level of job income. | (Buytaert et al., 2011). |
| | Discrimination. | (Rovere et al., 2010). |
| Job | Job creation | (Begic and Afgan, 2007). (Rovere et al., 2010); (Kaya and Kahraman, 2011a). |
| | Technology-specific job opportunities. | (Rovere et al., 2010). |
| Safety | Protection of human health. | (Buytaert et al., 2011). |
| | Food safety risk. | (Buytaert et al., 2011). |
| | Fatal accidents from the past experience. | (Streimikiene et al., 2012). |
| | Safe and healthy work environment. | (Streimikiene et al., 2012). |
| Political acceptance | | (Goletsis et al., 2003); (Kahraman et al., 2009). |
| | Consistency of the project with the National energy policy objectives. | (Beccali et al., 2003). |
| | Compatibility with political, legislative and administrative situation. | (Beccali et al., 2003). |

As mentioned before, these criteria such as technical, economic, social and environmental with their suitable indicators should be considered in complex problems. Since social and economic development is affected by the appropriate energy planning, evaluating sustainable energy alternatives when determining valid energy policies is essential. Assessment and selection of the most suitable types of energy in a geographical area is a complex problem. For governments and businesses, important decisions include whether to establish energy systems in a given place and deciding which energy source, or combination of sources, is the best option when considering potentially conflicting criteria with different aspects (Baños et al., 2011; Karimi et al., 2011). These criteria in energy planning problems involve different qualitative and quantitative variables and require specific techniques to aggregate and summarize assessments made in such complex situations. In addition, energy planning problems usually involve multiple DMs.

To do so, MCDM methods are considered suitable techniques in such complicated problems. These methods are introduced in Section 2.2 in detail.

## 2.2 Multi-criteria decision-making approaches

Multi-Criteria Decision-Making (MCDM) approaches, introduced in the early 1970s, are powerful tools used for evaluating problems and addressing the process of making decisions with multiple criteria. MCDM problems typically are quite complex, but the distinguishing characteristic is the fact that various conflicting criteria and the interactions between them have to be modeled explicitly in order to gain an understanding of the problem or to provide a solution to the problem. MCDM as a multi-disciplinary field of Operations Research (OR), uses mathematical approaches involving the following steps (Meier and Hobbs, 1994; Carlsson and Fullér, 1996; Yilmaz and Dagdeviren, 2011):

1. Structuring decision processes,
2. Defining and selecting alternatives,
3. Determining criteria formulations and weights,
4. Applying value judgments and evaluating the results to make decisions in design or selecting alternatives with respect to multiple conflicting criteria.

In the MCDM, three kinds of problems are distinguished: choice problems, ranking problems and sorting problems. The goal of the DM in each type of problem is different (Vincke, 1992; Roy, 1996; Doumpos and Grigoroudis, 2013):

- In **choice problems** the objective is to aid the decision maker by the choice of the subset of the "best" solution or alternative. The final output is a choice or selection procedure.

- The objective of **ranking problems** is to aid decision maker to simplify the "most attractive" actions in to equivalent classes. The ranking consists in ordering a set of solutions. The aim is finding the goodness of all alternatives, which is usually presented as a ranking from the best to the worst. They are completely or partially ordered with respect to the preferences. The final output is the ordering procedure.

- In **sorting problems** we want to know which alternatives belong to each class of a predefined set of ordered classes. Decision makers assign each action to a category. The result is an assignment procedure.

In general, MCDM methods are divided into Multi-Objective Decision Making (MODM) and Multi-Attribute Decision Making (MADM). The main distinction between the two groups of methods is based on the determination of alternatives (Pohekar and Ramachandran, 2004). MODM has been widely studied with mathematical programming methods, which have a well-formulated theoretical frame because this method is aimed at optimal design problems, in which several objectives are to be achieved simultaneously (Diakaki et al., 2010). The alternatives are not predetermined but instead a set of objective functions is optimized subject to a set of constraints. More information on MODM can be found in Hwang and Masud (1979); Lai and Hwang (1996); Ehrgott and Gandibleux (2002).

MADM methods evaluate a set of alternatives that are predetermined against a set of criteria to select the alternative that has the highest score. The best alternative is usually selected by making comparisons between alternatives with respect to each attribute (Wang et al., 2009). In this thesis, according to the aim of ranking energy alternatives, the method considered is in the group of MADM approaches and ranking problems, because the goal is making decision between "alternatives" that are described by several attributes (criteria). In ranking problems, the DM(s) want to find an order structure of alternatives. This order depends on the importance of each criterion and the performance of alternatives on particular criteria.

Moreover, MCDM approaches have a strong decision support focus and interact with other disciplines such as intelligent systems dealing with uncertainty. MCDM methods deal with the study of decision processes to help human beings. In many cases, these decision processes are based on data and information, which are not free of subjectivity and imprecision and have to manage uncertainty. The selection of the most suitable alternatives from the obtained (or considered) ones can be faced as a MCDM problem, in which each alternative is assessed according to a set of criteria.

There are some main concepts in the field of MCDM approaches used in this thesis. A brief summary of what is meant by certain terms and foundational concepts is presented as:

*Alternatives:* also referred to as actions, options, strategies or plans, are the possible solutions or a set of potential actions for the decision problem. Alternatives are represented as:
$A = \{ a_1, a_2, ..., a_m \}$, $A$ is the finite set of alternatives and $m$ is the number of alternatives in $A$.

*Criteria:* also called attributes or key factors, which will be measured for each alternative in order to find the solution. Criteria are the tools to define the goodness or attractiveness of an alternative. For instance, they allow to compare alternatives in terms of suitability based on the DMs' needs. Each criterion corresponds to a point of view considered in the decision process. Criteria are represented as:
$C = \{ c_1, c_2, \ldots, c_n \}$, $C$ is the finite set of criteria and $n$ is the number of criteria in $C$. Each $c_j(a)$ represents the performance value of alternative $a \in A$ on criterion $c_j \in C$, in which $j \in \{1, 2, 3, \ldots, n\}$. This performance value can be either in an *ordinal scale*: which is represented in a numerical or verbal/linguistic scale or in an *quantitative scale*: The order of the val-

ues are not only given, but also there is a clear defined quantity in a way that it gives a measure of the gap between two performances.

*Weights:* The concept of weights is also interpreted slightly differently in MCDM than in other fields. While the mathematical expressions of, for instance, preference structures appear to be weighted sums, the interpretation of the weights are much more subjective that just "the importance" indicated by the weights. The weights are in fact subjective expressions of trade-off which could roughly be equated to an expression of the importance of one compared to another. It should also be noted that the interpretation of weights could differ between different MCDM techniques, being seen as close to trade-off within some techniques based on value measurement, but seen more as strength of evidence in the outranking techniques. Weights are represented as $W = \{ w_1, w_2, \ldots, w_n \}$. $W$ is the finite set of weights.

The performance matrix $M$ is built for $A \times C$, where $c_j(a)$ is the performance in row $a$ and column $j$.

$$M = \left( \begin{array}{c|ccccc} & c_1 & c_2 & c_3 & \ldots & c_n \\ & w_1 & w_2 & w_3 & \ldots & w_n \\ \hline a_1 & a_{11} & a_{12} & a_{13} & \ldots & a_{1n} \\ a_2 & a_{21} & a_{22} & a_{23} & \ldots & a_{2n} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ a_m & a_{m1} & a_{m2} & a_{m3} & \ldots & a_{mn} \end{array} \right)$$

*Decision Maker (DM):* The person or group who satisfy certain objectives or values through the decision. DM provide an acceptable choice or ranking of alternatives and experience the decision problem or working to find an MCDM solution.
*Uncertainty:* Decision problems often involve an element of uncertainty. This could affect a MCDM problem situation. It could refer to the fact

that criteria, preferences or trade-off cannot be exactly measured or quantified. This type of uncertainty therefore has an impact in terms of measurements used. In this thesis this uncertainty captured by qualitative reasoning techniques implemented in a proposed MCDM method. The fact is some criteria have qualitative nature rather than quantitative ones and need to be incorporated into the model.

Since the criteria that measure the alternatives are often in conflict with one another, it is necessary to determine trade-off between them. It is important that these trade-off be quantified correctly to correspond to the preferences of the decision-maker. Trade-off may also be referred to as inter-criteria comparisons or compensation as in Guitouni and Martel (1998). Although they mentioned the following categories of compensation:

*Compensatory methods:* These methods allows trade-off (or compensation) between criteria, so that an improvement in one criterion can be counter-balanced with a decline in performance on another criterion.

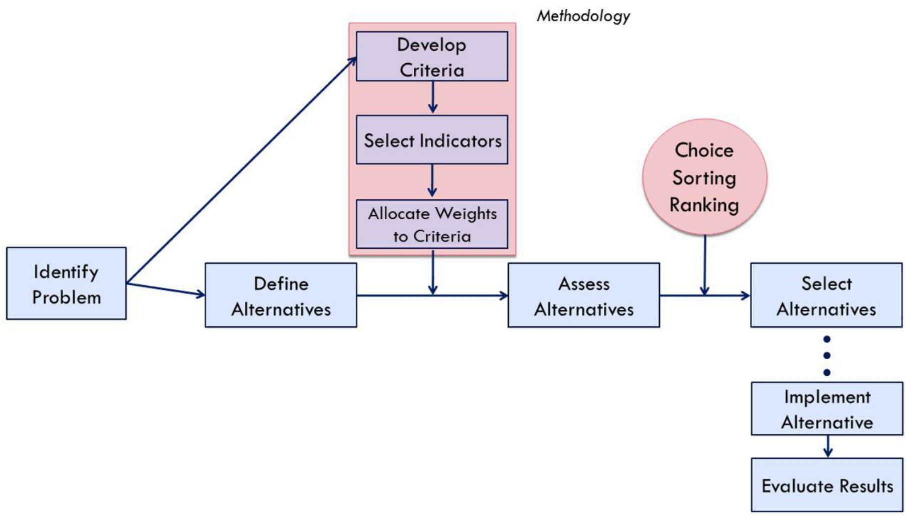
*Non-compensatory methods:* In these methods no trade-off between criteria are allowed, for instance when the decision-maker indicates that criteria are so important that trade-off between them cannot be considered.

*Partially compensatory methods:* Some form of trade-off can be accepted between criteria, and the major problem is to evaluate the degree of compensation between criteria.

Here, the whole process of decision making has been showed in Figure 2.4: from defining the problem as a goal, defining alternatives and developing criteria, selecting indicators and assigning weights, constructing an evaluation matrix, as it mentioned before, applying the appropriate method to evaluate alternatives, and finally, selecting alternatives according to the kinds of problems. Then, the selected alternatives can be implemented and evaluated in the particular application.

Different aggregation procedures with their own required information and mathematical procedure lead to different Multi-Criteria Deci-

Figure 2.4: The Decision-Making Process




sion Analysis (MCDA) approaches. Basically, there are two main research schools where MCDA were initially developed, the *American school*, which is more descriptive such as MAUT, AHP and TOPSIS commonly known as MCDM, and the *French school*, which developed methods more constructivist like ELECTRE and PROMETHEE, commonly known as multi-criteria decision aiding methods. According to these two schools, different classification of MCDM can be found in literature.

MCDM approaches are classically divided to three main groups as Belton and Stewart (2002) mentioned in their book: value measurement methods, goal aspiration and reference level methods, and outranking methods.

Guitouni and Martel (1998) proposed these four following categories: (i) elementary methods; (ii) the single synthesizing criterion approach; (iii) the outranking synthesizing approach; and (iv) the mixed methods. Table 2.6 shows the main methods belonging to each of these categories.

Combination methods that use different MCDM methods can also be found in the literature (Loken, 2007). MCDM methods can also be considered as deterministic, stochastic, fuzzy methods and combinations of them (Cai et al., 2009). In addition, the methods can be classified as single or group decision-making methods (Carlsson and Fullér, 1996; Jelassi et al., 1990).

Table 2.6: MCDM classification by Guitouni and Martel (1998)

| Category | Methods |
|---|---|
| Elementary methods | Weighted sum, Lexicographic method, Conjunctive methods, Disjunctive method, Maximin method |
| Single synthesizing criterion | TOPSIS, MAUT, MAVT, SMART Utility Theory Additive (UTA), AHPEVAMIX, Fuzzy weighted sum, Fuzzy Maximin. |
| Outranking methods | ELECTRE, PROMETHEE, MELCHIOR, ORESTE, REGIME |
| Mixed methods | QUALIFLEX, Martel & Zaras method, Fuzzy conjunctive/disjunctive method |

Although many specifications and categorizations exist, recently a new classification with non-classical MCDM approaches in the studies of Slowinski et al. (2002); Figueira et al. (2005) is presented which we highlight in this thesis. Referring this classification, three families of preference modelling (aggregation) methods are as below:

1. Methods based on the utility theory, determined by maximize utility or value introduced by Keeney and Raiffa (1976)

2. Outranking methods, based on the principle that one alternative may have a degree of dominance over another, introduced by Roy (1996).

3. Rule based methods based on rough set theory formulated by Pawlak (1982) and the decision rule approach to MCDA presented by Greco et al. (2005).

The main concepts of the most important methods of each category are introduced in the following sub-sections. The value measurement methods and outranking methods from the American and European schools record a considerable number of MCDM applications in the literatures.

### 2.2.1 Value measurement approaches

The objective of the methods in this group is to define mathematical models or rules that copy the human way of making decisions. The output of this method is a *value* or *score* for each alternative. A score is evaluated for each criterion and these are synthesized into a global score. A bad score for one criterion is compensated by a good score in another. So, these approaches assume compensable scores. The methods based on value are divided to full aggregation and reference level models. The main methods of each group are presented in the following subsections:

#### 2.2.1.1 Full aggregation methods

In full aggregation methods a numerical score (or value) $V$ is assigned to each alternative. These scores produce an order of preference for the alternatives such that $a$ is preferred to $b(a < b)$ if and only if $V(a) > V(b)$. Weights are assigned to the various criteria that represent their partial contribution to the overall score, based on how important this criterion is for the DMs Cavallaro (2010a). Methods such as the AHP, the MAUT, the Simple Multi-Attribute Rating Technique (SMART), the MACBETH and the Simple Additive Weighting (SAW) are classified into full aggregation models.

#### 2.2.1.1.1 Multi-attribute utility theory

Multi-Attribute Utility Theory (MAUT) is concerned with the theory developed to help DMs assign utility values to outcomes. These assignments are made by evaluating outcomes in terms of multiple attributes and combining these individual assignments to obtain overall utility measures, taking into consideration the DMs preferences. It is based on the idea that any DM attempts unconsciously to maximize some function that aggregates the utility of each different criterion (Keeney and Raiffa, 1976).

Utility theory is a systematic approach for quantifying an individual's preferences. It represents a way of measuring the desirability of the preference of alternatives, which can be represented as goods or services (Ishizaka and Nemery, 2013).

MAUT is founded on this approach, assigning a preference value to each alternative each attribute or criterion (Keeney and Raiffa, 1993). Therefore, the purpose of this approach is to associate a rating, generally a real-valued number to alternative $a$ on criterion $j$, representing the degree of "satisfaction" on criterion $g_j$ according to the DM's expectation and desired values. A utility function is applied to convert numerical attribute scales to value unit scales, allowing direct comparison of diverse measures. In this context, it is generally acknowledged that value functions represent the preference under certainty; and utility functions refer to preference under risk.

Ratings are used to compare the alternatives so that $r_j(a)$ is associated to each alternative $a \in A$ in such a way that $a$ is judged to be preferred to $b$ if $r_j(a) > r_j(b)$ and indifferent if $r_j(a) = r_j(b)$.

Once the real-valued function $r_j(a)$ is set to each alternative for all criteria, the aggregation of these uni-dimensional utility functions results in a global utility. Several aggregation operators have been proposed, requiring the mathematical properties (Idempotency, monotonicity, commutativity, compensativity, associativity and decomposability).

The additive model is the most used aggregation model of MAUT and a particular model is the weighted sum model. The advantages of methods in this group are, the fast calculation of the global utility, considering intensity of preferences and finally, the utility scores lead to a complete ranking. However, finding a specific utility function in complex problem is a major shortcoming of MAUT methods.

#### 2.2.1.1.2 Analytic hierarchy process

Analytic Hierarchy Process (AHP) developed in (Saaty, 1980), is a technique that evaluates the importance of each criterion in relation to the others in a hierarchical manner. The AHP method is based on structuring the model, a comparative judgment of criteria and a synthesis of the priorities (Karimi et al., 2011). It is considered a single synthesizing criterion approach which needs ratio scales. Ratio scales are the only possibility for aggregation measurement in a same unit way.

The AHP is a suitable method when it is difficult to find a utility function. Two main phases are problem structuring and elicitation of priorities through pair-wise comparisons. The problem is structured based on a hierarchy (Ishizaka and Nemery, 2013). In the first step, a complex problem is broken into a hierarchy with goal as an objective, criteria at levels and sub-criteria at sub-levels like a family tree. In more complex problems, more levels can be added. The second step begins with prioritization procedure in order to determine the relative importance of the criteria within each level. The evaluation of the hierarchy is based on pairwise comparison to assess the DM preferences from the second level to lowest one (Amiri, 2010). At the last step, the relative weights for each matrix are found and normalized. Furthermore, a consistency check and a sensitivity analysis to confirm the robustness of the result are recommended.

Generally, pairwise comparison is evaluated on the fundamental five level scale. For example, judgments might be indicated in the verbal scale of "equal importance", "moderately more important", "strong importance", "very strong importance" and "Extreme importance", then a corresponding number is associated with that judgment. For each comparison matrix $\frac{(n^2-n)}{2}$ comparisons are required; where $n$ is the number of criteria. The consistency index of a matrix is computed.

The main advantage of this method is reducing a multi-dimensional problem into one-dimensional problem. Also, there is a possibility to combine the final choices from a group to agree on a single outcome (Zopounidis and Pardalos, 2010).

This process can be performed with both qualitative and quantitative criteria. In addition, to deal with the uncertainty involved in some complex problems, a fuzzy approach of AHP method, where linguistic variables are used to represent the experts' opinion, was developed (Laarhoven and Pedrycz, 1983). The fuzzy AHP allows fuzziness and vagueness of the DMs' assessments (Kuo et al., 2015; Russo and Camanho, 2015). In general, experts use linguistic terms, which are translated into fuzzy evaluation scores and weights are finally expressed via fuzzy numbers.

#### 2.2.1.2 Reference level models and distance based approaches

Reference level models introduced by Yu and Zionts in 1990s, are based on priority and distance aggregation function. It defines a goal on each criterion, then identifies options to the ideal goal or reference level(s).

TOPSIS, VIKOR and goal programming method are considered the most well-known reference level models for ranking the alternatives. This group is the most suited with our objective in this study for ranking alternatives. Among these methods, TOPSIS methods have various applications especially in energy planning.

##### 2.2.1.2.1 Goal programming method

Goal Programming (GP) can be categorized according to the type of mathematical programming model (linear programming, integer programming, nonlinear programming, etc.) that is used when having more than one objective. GP, called also compromise programming, is a standard multi-criteria method that has a wide range of real-world applications. It is an extension of linear programming in order to handle conflicting objectives. This method consist of minimizing the distance between alternatives and a certain target point that models the best performance for each criterion considered (Agell et al., 2012).

In the modelling of the problem with GP, first, the decision variables should be identified. These variables are independent variables. Then, goals and after that soft and hard constraints are identified. According to Ishizaka and Nemery (2013), the difference between a goal with a soft constraint and the goal with a hard constraint is:

A goal with a soft constraint has a threshold as an ideal point. It can be exceeded because solutions are feasible even if they are not attractive. But a goal with a hard constraint has a threshold which is an ideal point and cannot be exceeded, the nearest solutions to the ideal point are preferred. A hard constraint is an inequality which describes a threshold that cannot be exceeded as it represents an infeasible solution. Therefore, all solutions less than threshold have the same preference.

As there are more than one goal in GP method, all goals are not always satisfied simultaneously. The main advantages of this method are related to the psychologically appealing idea that we should set a goal in objective space and try to come close to it and its simplicity and ease of use. This accounts for the large number of goal programming applications in many and diverse fields. It has an ability to handle relatively large numbers of variables, constraints and objectives. GP does not use any weight. This method can solve the problems with continuous solution scale.

#### 2.2.1.2.2 TOPSIS method

The Technique for Order Preference by Similarity to the Ideal Solution (TOPSIS), developed by Hwang and Yoon (1981), is one of the most well-known distance-based approaches for decision making. TOPSIS ranks the alternatives with respect to their geometric distance from the positive and negative ideal solutions. This approach is categorized as one of the MCDM methods in which value judgments of criteria are expressed through crisp values. TOPSIS is based on an aggregating function of the evaluation scores of the experts and determines the best alternative by calculating the distances from the positive and negative ideal solutions (Opricovic and Tzeng, 2004; Shih et al., 2007).

This method has been introduced as a principle method of our study in Chapter 3.

### 2.2.2 Outranking approaches

Outranking methods are characterized by the limited degree to which a disadvantage on a particular viewpoint may be compensated by advantages on other viewpoints, in comparison to MAUT that allows trade-off of performances. The aim is to build a binary relation, obtained from the pairwise comparison of alternatives with respect to each criterion. The degree of dominance of one option over another is indicated by outranking. The concept of outranking methods was first proposed by Roy (1996) with the original ELECTRE method. Vincke (1992) states that the underlying idea of introducing the outranking methods is that it is better to accept a result less richer than that yielded by utility-based methods, if one can avoid mathematical hypotheses which are too strong and requiring complex information from the DM (Del Vasto-Terrientes, 2015).

Every outranking method includes two phases: 1) the construction of the outranking relation, and 2) the exploitation of this relation in order to provide a recommendation to the DM (Figueira et al., 2009). The next sections introduce the PROMETHEE and ELECTRE methods which are the most widespread outranking methods.

#### 2.2.2.1 PROMETHEE method

The Preference Ranking Organization MeTHod for Enrichment Evaluations (PROMETHEE) proposed by Brans (1982), is a well-established decision support system which deals with the appraisal and selection of a set of options on the basis of several criteria, with the objective of identifying the pros and the cons of the alternatives and obtaining a ranking among them. This simple outranking method, both in conception and application, is well adapted to problems where a finite number of alternative actions are to be ranked considering several criteria.

The PROMETHEE method can handle data that are known with a reasonable degree of accuracy and have fixed numerical values. This method construct a valued outranking relation based on a preference index $P_j(a,b) \in [0,1]$ representing the degree of preference of $a$ over $b$ for each criterion on $G$. It is calculated from the difference between the performance of the alternatives, so that $P_j(a,b) = f(g_j(a) - g_j(b))$. The closer $P_j(a,b)$ is to 0, the greater the indifference between $a$ and $b$ is; while the closer to 1, the greater the preference of $a$ over $b$ is. Brans and Mareschal (2005). This preference index can be defined in different ways. In Brans and Vincke (1985), 6 functions that are commonly used in practical applications were presented:

1. Usual criterion: The indifference only applies when $g_j(a) = g_j(b)$. If not, then DM is indicating a strict preference of the alternative with the best performance.

2. Quasi criterion: The criterion is associated to a threshold $q$. If the difference between $g_j(a)$ and $g_j(b)$ do not exceeds this threshold, then $a$ and $b$ are indifferent. Otherwise, the alternative with the best performance is strictly preferred.

3. Criterion with linear preference: The function is associated to a threshold $p$. If the difference between $g_j(a)$ and $g_j(b)$ is lower than

$p$, the DM is indicating a progressive preference of the best performance. Otherwise, it is strictly preferred.

4. Level criterion: In this function, the DM has to set the two thresholds $q$ and $p$. If the difference between $g_j(a)$ and $g_j(b)$ do not exceeds $q$ the alternatives are indifferent, between $q$ and $p$ there is a weak preference (0.5), and after this value becomes strict preference of the alternative with the best performance.

5. Criterion with linear preference and indifference area: In this function, $a$ and $b$ are considered indifferent as long as $g_j(a) - g_j(b)$ do not exceeds $q$ and the preference increases linearly from this $q$ until $p$. After $p$, the strict preference applies.

6. Gaussian criterion: This function ($\rho$) is made easily according to the experience obtained with the normal distribution in statistics.

The principles of the PROMETHEE approach are, assigning a preference function, alternatives are compared pairwise with respect to every single criterion. Then results are expressed by the preference functions, the outranking degree of the options are estimated and a matrix of global preferences is calculated.

taking into account a weight $w_j$ of each criterion $j$, the preference indices $P_j(a,b)$ and the overall preference $\Pi(a,b)$ are calculated as follows:

$$\Pi(a,b) = \frac{\sum_{j=1}^{m} w_j P_j(a,b)}{\sum_{j=1}^{m} w_j} \tag{2.1}$$

The preference indices $\Pi$ for all pairs in $A$ are represented as a valued graph. For a certain alternative "entering flow" and "leaving flow" represent the origin and destination, which are calculated as follows, respectively:

$$\eta^{+}(a) = \sum_{b \in A} \Pi(a,b) \tag{2.2}$$

$$\eta^{-}(a) = \sum_{b \in A} \Pi(b, a) \tag{2.3}$$

These positive and negative flows for all alternatives is used to provide the best solution depending the problem that the DM is facing. The two most known PROMETHEE methods are PROMETHEE I and PROMETHEE II, applied for ranking problems. PROMETHEE I for partial ranking and PROMETHEE II for complete ranking.

#### 2.2.2.2 ELECTRE method

The ELimination Et Choix Traduisant la REalité (ELECTRE) methods, introduced by Bernard Roy in the late 60s, were designed according to a constructivist conception of MCDA. The analyst should try to obtain a coherent structured set of results in order to guide the decision aiding process and facilitate the communications about the decisions. ELECTRE methods have been widely used as a well-known decision aiding tool, with several applications in different contexts (Beccali et al., 1998, 2003; Cavallaro, 2010a; Papadopoulos and Karagiannidis, 2008). The decision aiding activity is based on three fundamental pillars in this binary outranking method (Roy et al., 2014):

1. The **actions** (formal definition of the possible actions or alternatives).

2. The **consequences** (aspects, attributes or characteristics of the actions that allow to compare them).

3. The **modeling of a preference system** (it consists of an implicit or explicit process, that for each pair of actions envisioned, assigns one and only one of the three possibilities: indifference, preference, or incomparability). Preferences in this method are modeled by relation $S$, where $aSb$ means "$a$ is at least as good as $b$".

Four main comprehensive preference situations can be performed in ELECTRE methods, which has been defined as follows, when $(a,b) \in A \times A$ are two possible alternatives.

- Strict preference ($aPb$): $a$ is strictly preferred to $b$
- Weak preference ($aQb$): $a$ is weakly preferred to $b$, corresponds to hesitation situation
- Indifference ($aIb$): $a$ is indifferent to $b$, corresponds to a situation where there are clear and positive reasons that justify an equivalence between the two actions,
- Incomparability ($aRb$): $a$ is incomparable to $b$, corresponds to an absence of clear and positive reasons that would justify any of the three preceding relations.

The analyst must follow an approach that leads or aims to produce knowledge from a certain number working hypotheses defined a *priori*. This approach should be based on models that are, at least co-constructed interactively with the DM.

$g_j(a_i)$ is the performance of action $a_i$ on criterion $g_j$. A performance matrix $M$ can thus be built. The uncertainty of the DM preference model can be represented with the following intra-criteria parameters (Del Vasto-Terrientes, 2015):

- indifference threshold $q_j[g_j(a)]$, below which the DM is indifferent to two alternatives in terms of their performances on criterion $g_j$;
- preference threshold $p_j[g_j(a)]$, above which the DM shows a clear strict preference of one alternative over the other in terms of their performances on criterion $g_j$.

This method is based on the concepts of concordance and discordance. *Concordance* correspond to validate $aSb$, a sufficient majority of criteria in favor of this assertion must occur. *Discordance* refers to the situation in which the assertion aSb cannot be validated if a minority of criteria is strongly against this assertions.

To build the outranking relations of two criteria parameters, weights $w_j$ and the veto threshold $v_j[g_j(a)]$ are required. A weight $w_j$ expresses the relative importance of criterion $g_j$, as it can be interpreted as the voting power of each criterion to the outranking relation. The weights of criteria do not represent substitution rates as in the case of compensatory aggregation operators.

The concept of veto threshold, $V_j$, gives the possibility to the criterion $g_j$ to impose its veto power. It means that $g_j(b)$ is so much better than $g_j(a)$, that is not possible to allow that $aSb$. When criterion $g_j$ opposes strongly to the assertion $aSb$, $g_j$ puts its veto to this assertion. ELECTRE methods can handle such situations through the partial discordance indices of criteria. The veto threshold, where a discordant difference in favor of one alternative greater than this value will require the DM to negate any possible outranking relationship indicated by the other criteria.

ELECTRE II, ELECTRE III, and ELECTRE IV are generally used in ranking problems. The main advantages of ELECTRE methods are:

- They have the possibility of taking into account the qualitative nature of some criteria. They allow thus to consider the original data.
- They are adequate to take the imperfect knowledge of the data and the arbitrariness related to the construction of the criteria. This is modeled through the indifference and preference thresholds.
- The compensatory effects are not pertinent. This is due to the fact that the weights cannot be interpreted as substitution rates. Contrarily to other methods there is no need in ELECTRE methods to use, from the starting point of their application, identical and commensurable scales.
- They can deal with very heterogeneous scales to model noisy, delay,

aesthetics, cost, etc. Every procedure can run by preserving the original performances of the actions for different scales.

On the other hand, outranking methods have some disadvantages that occur in certain contexts when it is required to assign a score to each action. In this way, when the decision makers require each action should appear associated with a score, the outranking methods are not adequate for such a purpose and the scoring based methods should be applied instead. The decision makers should be, however, aware that they cannot provide information that leads, for example, to intransitivities or to incomparabilities between certain pairs of actions.

Moreover, When all the criteria are quantitative it is better to use other methods. But, if we want to take into account a completely or even a partial non-compensatory method, or the imperfect character of at least one criterion, even under such conditions, we can use outranking methods.

The last point is, intransitivities may also occur in these methods. It is also well-known that methods using outranking relations do not need to fulfill the transitivity property. This aspect represents only a weakness if we impose a priori that preferences should be transitive (Figueira et al., 2013; Del Vasto-Terrientes et al., 2015a).

### 2.2.3 Decision rule approaches

Despite that the two major models used in multi-criteria decision analysis are the ones based on Utility functions and Outranking relations; there are other approaches which deal with the problem from decision rule point of view. This section provides some details about these approaches.

One way to Make decisions is searching for rules which provide good justification of people choices. The preference model is defined in terms of "if, then" rules. The acceptance of the rules by the DM justifies their use for the decision support. The set of rules can be applied to a set of alternatives in order to obtain specific preference relation. From the exploitation of these relations, a suitable recommendation can be obtained to support decision makers.

Next subsections are introduced decision rule approaches based on classic rough sets theory and the dominance-based rough set method.

#### 2.2.3.1 Rough set theory

The rough sets theory was formulated by Pawlak (1982) to deal with inconsistency and vague description of objects. Slowinski (1993) applied rough sets theory to MCDM methods. The theory is based on the concept of **indiscernibility** relation, which induces a partition of the objects into elementary sets. Any subset of elementary sets can be expressed in terms of **precisely** or **approximately**. The subset may be represented by two sets called the lower and upper approximations. A rough set is defined using these approximation sets. Decision rules induced from rough approximations are defined as below:

1. **Certain decision rule:** supported by objects from lower approximation of one class (such as "good") or discriminant rule. For example considering some students who we are evaluated by their performances in literature, physics and mathematics using "good", "medium" and "bad" marks. if a student is good in literature (Lit=-good), then Student is **certainly** good.

2. **Possible decision rule:** supported by objects from upper approximation of a class "good" or partly discriminant rule e.g. if the student is good in physics (Phys=good), then Student is **possibly** good

3. **Approximate decision rule:** supported by objects from the boundary of class "medium" or "good". In this case if Phys=good and Lit=medium, then Student is medium or good

The lower and upper approximation sets are built from a data matrix of examples. In decision making, an example is formed by a description of an alternative in terms of different criteria and the final decision value given to the alternative by the DM after solving the problem. That is, if we use the concepts of machine learning, the rough sets approach is a supervised method, because we require the knowledge of some solved problems in order to build a model to solve new ones. In fact, the rough sets method was introduced as a method to infer decision rules from a set of examples. An interesting characteristic of the rough set approach is that it is possible to deal with heterogeneous data sets without having to use a unified domain. The rules are generated from the analysis of the elements in the lower, upper and boundary approximations of the different solutions. That is, the values of the elements in these sets define the conditions of the rules for the different conclusions.

Rough set theory classically mainly used in the approach so called Classic Rough Set Approach (CRSA) or indiscernibility-based Rough Set Approach, Which is based on indiscernibility principle that if $x$ and $y$ are indiscernible with respect to all relevant attributes, then $x$ should classified to the same class as $y$.

In CRSA, certain decision rules based on indiscernibility are inconsistent with respect to the dominance principle (monotonicity constraints). The thing that is missing in CRSA is it does not detect inconsistency with respect to dominance (Pareto principle). In the case of multi-criteria choice and ranking problems, other extensions, detailed in following subsection, are needed because the data matrices used in the CRSA do not allow the representation of preferences between alternatives.

#### 2.2.3.2 Dominance-based rough set approach

Dominance-based Rough Set Approach (DRSA) is an extension of rough set theory for multi-criteria decision analysis as one of the common way to represent preferential rules, introduced by Greco et al. (2001). The original rough set approach is not able to deal with preference-ordered criteria and decision classes. In Greco et al. (2001, 2005) there are good explanations of how rough sets theory can be adapted to deal with the particular characteristics of sorting, choice and ranking decisions. The main modification is the substitution of the indiscernibility relation by a dominance relation, because indiscernibility is not able to deal with ordinal properties. DRSA permits representation and analysis of all phenomena involving monotonicity relationship between specific measures or perceptions, e.g. “the more a tomato is red, and the more it is soft, the more it is ripe”, “the older the car, the more likely its breakdown” or “the more similar are the causes, the more similar are the effects one can expect”.

In DRSA, information about objects is represented in a data matrix, in which rows are labelled by objects and represent the values of attributes for each corresponding object, whereas columns are labelled by attributes and represent the values of each corresponding attribute for the objects. Let $U$ denote a finite set of objects (universe), $Q$ a finite set of attributes, $V_q$ a domain of the attribute $q$, and $f(x,q)$ a function assigning to each pair object-attribute $(x,q)$ a value from $V_q$ . The set $Q$ is, in general, divided into set $C$ of condition attributes and a decision attribute $d$. In multi-criteria classification, condition attributes are criteria. The notion of criterion involves a preference order in its domain while the domains of attributes, usually considered in machine discovery, are not preference-ordered.

There are three most remarkable advantages of DRSA over classical rough set approach. The first one is the ability of handling criteria, preference-ordered classes and inconsistencies in the set of decision examples that CRSA is not able to discover inconsistencies in the sense of violation of the dominance principle. In consequence, the rough approximations separate the certain part of information from the doubtful one, which is taken into account in rule induction. The second advantage is the analysis of a data matrix without any preprocessing of data, in particular, any discretization of continuous attributes. The third advantage of DRSA lies in a richer syntax of decision rules induced from rough approximations. The elementary conditions of decision rules resulting from DRSA use rel. $\in \{\leq, =, \geq\}$, while those resulting from Classic RSA use rel. $\in \{=\}$. The DRSA is more understandable to practitioners and makes the representation of knowledge more synthetic, since minimal sets of decision rules are smaller than minimal sets of decision rules resulting from CRSA.

So, Value measurement, outranking and decision rule approaches are three main categories of decision analysis techniques based on mathematical aggregation functions and their preference modelling. On the other hand, we can separate methods with a single DM and methods with a group of DMs. The methods involving more than one DM are included in the research field of GDM methods; an introduction to the field can be found in (Jelassi et al., 1990).

It should firstly be noted that there are different ways of choosing suitable MCDA methods to solve specific problems. Ishizaka and Nemery (2013) say that "none of the methods are perfect nor can they be applied to all problems. Each method has its own limitation, particularities, hypotheses, premises and perspectives.". To do so, we should check the required input information, the output and the modelling effort. The modelling effort defines the richness of the output.

On the other hand, in some cases, the alternatives can be assessed by means of precise numerical values. However, such an approach may be much harder or even impossible when the alternatives bear on qualitative aspects. Such knowledge is usually imprecise and involves uncertainties. This uncertainty has been framed in terms of preferences with interval or fuzzy values through a linguistic approach. We are going to introduce these approaches in Chapter 3 as a method that we are going to use.

## 2.3 MCDM energy applications under uncertainty

Energy planning problems are quite suited to the use of MCDM as a way of evaluating environmental sustainability (Doukas et al., 2007; Karvetski et al., 2011; Nigim et al., 2004; Tsoutsos et al., 2009; Wang et al., 2008). A large number of multi-criteria techniques have been developed to deal with problems with different objectives such as choice, ranking and sorting or “classification” problems. As mentioned in previous section, there are several methods base on priority, outranking, distance or mixed methods which can be applied to these problems. A DM is required to choose the relevant method for each problem. In the case of energy planning problems, multi-criteria methods should be simple to promise transparency, consider the intensity of preferences and be partial or complete. These features are difficult to gather in one specific method simultaneously.

Among all categorizations in MCDM, reference point and outranking methods are widely used in the case of ranking problems in energy management (Beccali et al., 2003; Loken, 2007). Table 2.7 shows the most important MCDM methods used for assessing energy policy and management: AHP; PROMETHEE; ELECTRE; and TOPSIS (Pohekar and Ramachandran, 2004). Pohekar and Ramachandran presented a review and analysis of several published papers on MCDM and highlighted their applications in the renewable energy area (Pohekar and Ramachandran, 2004).

Hobbs and Horn used different MCDM methods to develop a set of recommender systems in energy planning and policy through an interview process and several group discussions between stakeholders. The authors discussed the difference between using MCDM for criteria and alternatives evaluation instead of monetizing all criteria and concluded that the best approach is a combination of the two methods (Hobbs and Horn, 1997).

Afgan and Carvalho defined energy system elements and indicators which are used in the analysis and assessment of the relationship between energy systems and their environment. The authors considered five indicators and presented the effect of priority rating and given weight to each criterion on the selected alternative energy system (Afgan and Carvalho, 2000). Enzensberger et al. emphasized on the importance of engaging all stakeholder groups in the criteria evaluation process and explained how considering different points of view can help policy planners to anticipate possible problems at an early stage. Renewable energy is foreseen as a sustainable, economic alternative to conventional energy resources and can be utilized in different ways (Enzensberger et al., 2002).

A review of the various types of renewable energy models such as solar, wind, biomass and bio-energy can be found in Jebaraj and Iniyan (2006). Diakoulaki et al. used MCDM to examine the relative contribution of different factors and characteristics in reaching the desired level of energy efficiency and how it can be further exploited in energy policy making Diakoulaki and Karangelis (2007).

Shih et al. (2007) analyzed the competitiveness of Korea among 30 other nations in hydrogen energy technology development using AHP and two potential scenarios to determine criteria. Begic and Afgan (2007) used multi-criteria evaluation in the assessment of different options of conventional hydrogen energy systems, comparing them with renewable energy systems. Wang et al. (2009) conducted a literature review on MCDM methods used for the selection of energy and their applications to energy issues. The review shows that there are four main criteria categories for the evaluation of energy source and site selection problems: technical, economic, environmental, and social.

In energy planning area, a group of studies address to the significant potential of MCDM techniques in the urban energy systems or direct relevance to the use of energy in cities, which can be found in Blondeau et al. (2002); Chang et al. (2008); Dutta and Husain (2009); Hsieh et al. (2004); Keirstead et al. (2012); Medineckiene et al. (2014); Mosadeghi et al. (2015); Qin et al. (2008); Wang et al. (2014); Wright et al. (2002); Zavadskas and Antucheviciene (2004, 2006).

The study of ranking processes is considered also an interesting issue in computer science and artificial intelligence. One of the active sub-fields of research in AI is linguistic modeling. It refers to some variables which nature is not crisp (especially for social and environmental aspects) when uncertainty is occurred due to either lack of information or imprecision in DM' assessments (Kahraman et al., 2010; Pohekar and Ramachandran, 2004). Frequently, these uncertainties are captured by using linguistic labels or fuzzy sets to evaluate the set of criteria or indicators (Nieto-Morote et al., 2010). It is also necessary to distinguish between internal uncertainties (related to DM values and judgments) and external uncertainties (related to imperfect knowledge concerning consequences of actions) (Figueira et al., 2005). Taking into account that reasoning based on imperfect knowledge, three kinds of uncertainty can be defined (Zadeh, 1999):

- Uncertainty from a random change of *veristic* variables, which can be modeled by probability (probability theory),
- Uncertainty of subjective judgement or "possibilistic" uncertainty which can be modeled by fuzzy sets,(possibility theory and fuzzy set theory)
- Uncertainty caused by granularity of information or"inconsistency" which can be modeled by rough sets (rough set theory).

Fuzzy sets introduced by Zadeh are commonly used in decision making techniques (Zadeh, 1965). Fuzzy sets can be applied to overcome uncertainty in human judgments, which involve vague information since often it is difficult to obtain exact numerical values for some criteria and indicators (Abu-Taha, 2011). In this way, several studies have attempted to implement the evaluation of renewable energy sources with MCDM methods using linguistic variables.

Beccali et al. (1998) introduced a methodological tool able to organize the large set of variables of several specific assessments that help the DM in a complex problem. The authors used the ELECTRE methods , either involving the use of fuzzy set concepts or not in the Italian island of Sardinia for renewable energy diffusion strategy planning. The case study explored the advantages and drawbacks of each ELECTRE method. In 2003, Beccali et al. used ELECTRE III to select the most suitable innovative technologies in the energy sector (Beccali et al., 2003). Three decision scenarios were supposed, each representing a coherent set of actions, and different fuzzification strategies were analysed. In the study of Boran et al. (2012), intuitionistic fuzzy TOPSIS was introduced to evaluate renewable energy technologies for electricity generation in Turkey.

Linguistic approaches have been widely used in MCDM methods in several fields such as power generation for tri-generation systems (Jing et al., 2012; Nieto-Morote et al., 2010; Wang et al., 2008), urban planning (Chang et al., 2008; Hsieh et al., 2004; Mosadeghi et al., 2015), Life Cycle Impact Assessment (Cherubini and Strømman, 2011) and many others. In energy planning, different aspects of environmental assessments have been considered in various studies, for example developing the local energy sources to rank energy alternatives (Goumas and Lygerou, 2000), evaluating water resources (Dai et al., 2010), assessing renewable energy alternatives (Doukas et al., 2010; Kahraman et al., 2010; San Cristóbal, 2011) and finding optimal locations for energy projects (Aras et al., 2004; San Cristóbal, 2012a; Yeh and Huang, 2014). Furthermore, different applications of fuzzy MCDM methods in energy planning can be found in Kahraman (2008).

Moreover, qualitative reasoning techniques as one of the sub-area of AI, tries to understand and model human beings' ability to reason without having exact information. The main objective of QR is to develop systems that permit operating in conditions of insufficient or without numerical data. Criteria cannot be given precisely and the evaluation data of the suitability of alternatives for subjective criteria are usually expressed in linguistic terms by the DMs preferences. These techniques have been introduced in the next chapter in detail.

| Method | Focus | Reference |
|---|---|---|
| AHP | Ranking energy alternatives | (Akash et al., 1999); (Kablan, 2004; Nigim et al., 2004) |
| MAUT | Examining energy policy | (Buehring et al., 1978) |
| | Strategic energy planning | (Pan and Rahman, 1998) |
| Goal Programming | Energy resource planning | (Meier and Hobbs, 1994) |
| | Renewable energy planning | (San Cristóbal, 2012a) |
| TOPSIS | Evaluating renewable energy | (Boran et al., 2012); (Cavallaro, 2010b) |
| | Assessing energy policy objectives | (Doukas et al., 2010) |
| | Selecting the best energy alternative | (Kaya and Kahraman, 2011a,b) |
| PROMETHEE II | Ranking energy alternatives | (Georgopoulou et al., 1998); (Goumas and Lygerou, 2000); (Haralambopoulos and Polatidis, 2003) |
| PROMETHEE I & II | Assessing renewable energies | (Topcu and Ulengin, 2004); (Cavallaro, 2005) |
| | Sustainable energy planning | (Tsoutsos et al., 2009) |
| | Assessing energy technologies | (Tzeng et al., 1992); (Oberschmidt et al., 2010) |
| ELECTRE III | Energy planning | (Georgopoulou et al., 1997); (Beccali et al., 2003); (Cavallaro, 2010a) |

Table 2.7: Review of MCDM applied to energy issues

# Chapter 3

# Methodology

Some methods support decision makers in the process of decision making by providing useful data to assess criteria with uncertain values. AI was intended to help people understand how the brain makes decisions. Decision support systems, which began appearing toward the end of the 1960s, served the latter goal, specifically targeting the practical needs of managers. Over the next decades, decision makers applied these techniques to decisions about investments, pricing, advertising, logistics and planning among other functions.

In this chapter, first, Section 3.1.2 discusses the main two approaches in AI to model and represent linguistic information: fuzzy set representation and ordinal qualitative representation. The method proposed in this thesis is framed in the absolute order-of-magnitude qualitative reasoning approach. These techniques can be integrated with MCDM methods, such as TOPSIS, to evaluate alternatives with respect to different criteria for ranking problems. Section 3.2 introduces one of the most commonly used MCDM methods, TOPSIS, and Section 3.3 presents a new qualitative TOPSIS method together with some preliminary concepts. The proposed method is compared in Section 3.4 with two other MCDM methods. The discussion of their advantages and disadvantages has been provided in these comparisons.

## 3.1 Artificial intelligence for linguistic modeling

AI techniques (including reasoning, knowledge engineering, planning, learning, communication, perception and the ability to move and manipulate objects) is an inter-disciplinary field of study in computer science, mathematics, psychology, linguistics, philosophy and neuroscience, as well as other specialized fields such as artificial psychology. The connections of MCDA with other disciplines such as AI, is particularly interesting for providing integrated decision support systems in complex contexts (Doumpos and Grigoroudis, 2013). Intelligent Decision Support Systems (IDSS) refers to the resulting systems when AI techniques are used in the assessment of alternatives. These systems assist decision makers to utilize data, models and knowledge to solve semi-structured or unstructured problems.

Recently, several studies have been done in the field of AI in areas such as expert systems, knowledge-based systems, fuzzy sets and data mining. AI techniques were firstly used by Poh (1998) to help decision makers in order to select a MCDA method based on series of user inputs. Poh suggested a knowledge-based system, which allowed the DM to select the most appropriate method among available 11 multi-attribute decision making methods. The knowledge-based intelligent system simplifies the methods selection problem with simple questions by allowing direct selection or automated selection based on DM's inputs.

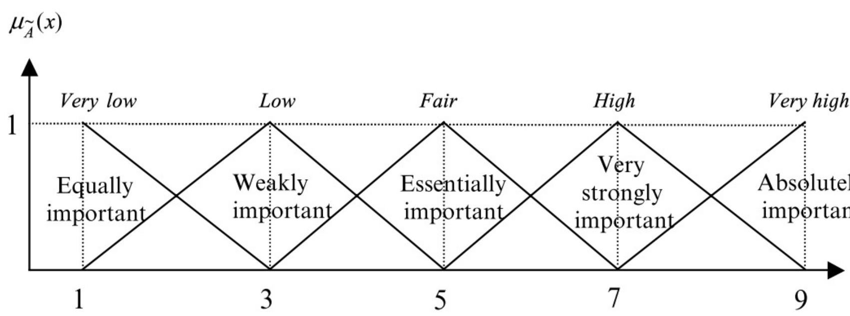
Moreover, the linguistic modeling or "computing with words" is an approximate technique which represents qualitative aspects as linguistic values by means of linguistic variables. In this way, these are variables whose values are not numbers but words or sentences in a natural or artificial language Zadeh (1975). Each linguistic value is characterized by a syntactic value or label and a semantic value or meaning. Linguistic variables have been used in different studies mentioned in Section 2.3. Since words are less precise than numbers, the concept of a linguistic variable approximately characterizes the situation that quantitative terms are poorly defined (Tang and Zheng, 2006; Aliev and Pedrycz, 2013; Roselló et al., 2010, 2011). Zadeh (1975) characterized a linguistic variable by the following five elements: $\{X; T(X); U; G; M\}$ where:

- $X$ is the name of the variable,
- $T(X)$ is the finite set of terms of $X$ (the set of linguistic values),
- $U$ is the universe of discourse,
- $G$ is the syntactic rule that generates $T(X)$ elements,
- $M$ is the semantic rule which associates a fuzzy number or qualitative label with each of the linguistic terms of $X$.

Given a set of words of natural language which define the performance of an alternative for each of the criteria, we need to also obtain a linguistic output $T(X)$, which is the output of the aggregation process of all the values.

In classic linguistic modeling, the fuzzy set or membership function associated with each linguistic term is used to represent its semantic. The theoretic foundation of this modeling is fuzzy logic. Figure 3.1 shows the membership function for the five levels of linguistic variables.

Figure 3.1: The membership function for the five levels of linguistic variables



It is also possible to build a linguistic modeling with ***qualitative labels*** in absolute order-of-magnitude qualitative reasoning. In order to appropriately express linguistic variables, first fuzzy sets, and after that qualitative reasoning techniques (which is a main focus of this thesis), are introduced in the following sections.

### 3.1.1 Fuzzy sets

Fuzzy sets, introduced by Zadeh (1965), extend decision support by allowing a representation of variables in a way that human reason about them. Decision makers encounter problems in which inputs are uncertain and imprecise and the flexibility of fuzzy sets representations, allows them to have a range of choices. This branch of artificial intelligence proposes more flexible membership functions for a set (Dubois and Prade, 1980; Cables et al., 2012). Boolean sets or "crisp sets" are based on a binary system which values can be 0 or 1 in the terms of strict membership "false" or "true" values. In contrast, fuzzy sets allow inputs in a range of values between 0 and 1 i.e., the membership function is $\mu_c : X \to [0,1]$.

Fuzzy sets are commonly used in decision making techniques. They can be applied to overcome uncertainty in human judgments, which involve vague information in the situation that crisp values cannot be obtained easily. The concept of fuzzy numbers can be defined as follows (Zadeh, 1999):

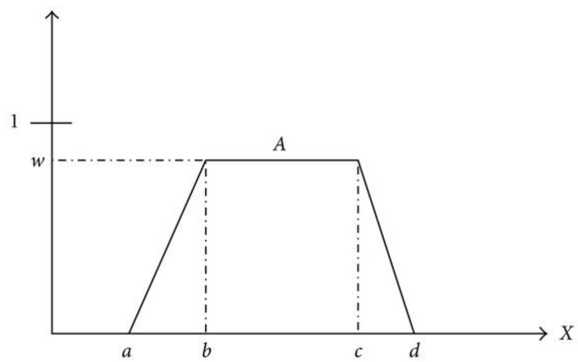
The membership function can take different forms but it must be convex. The most usual ones are *triangular* and *trapezoidal* fuzzy numbers. Triangular and trapezoidal membership functions can be easily defined with three/four points. A real fuzzy number $A$ is described as a fuzzy subset in a universe of discourse $X$ of the real line $\mathbb{R}$ with membership function $f_a$ values in the interval $[0,1]$ with the following properties:

- $f_a(x)$ is a continuous mapping from $\mathbb{R}$ to the closed interval $[0,1]$;
- $f_a(x) = 0$, for all $x \in (-\infty, a]$;

- $f_a(x)$ is strictly increasing on $[a, b]$;
- $f_a(x) = w$, for all $x \in [b, c]$;
- $f_a(x)$ is strictly decreasing on $[c, d]$;
- $f_a(x) = 0$, for all $x \in (d, \infty]$,

where a, b, c, d are real numbers and often $w = 1$. Fuzzy sets with this trapezoidal membership functions are commonly used in linguistic modeling (see Figure 3.2).

Figure 3.2: Trapezoidal membership function




Different linguistic modelings can be found in several fuzzy set theory extensions in recent literature, such as *2-tuple*, *unbalanced*, *hesitant*, *intuitionistic* and *interval valued fuzzy sets* (Herrera and Martínez, 2000; Herrera et al., 2008; Liu and Rodríguez, 2013; Boran et al., 2012; Ashtiani et al., 2009; Guereca et al., 2007). These approaches can be used by the experts to express their preferences about a particular problem.

According to Turban and Aronson (1998), the advantages of using fuzzy sets in decision making are:

- Flexibility to make allowances for imprecise inputs and different options for intuitions such as "very good",

- Ability to have “what-if” scenarios,
- Low risk for incorrect choices,
- Modeling approaches for problems with uncertainty.

The weaknesses of this approach are (Dubois et al., 2003):

- Fuzzy sets are difficult to develop in each specific context and difficult to estimate membership function,
- It requires numerous simulations before use.

### 3.1.2 Qualitative reasoning techniques

Qualitative Reasoning (QR) techniques as sub-area of artificial intelligence try to understand and explain human beings ability to reason without having exact information. According to (Ali et al., 2003), the main aims of these techniques are:

- First to address the need to deal with physical systems where some magnitudes are not easy to quantify, for example the numerical data is not available,
- Second to be able to reason at a qualitative or symbolic level, for instance reasoning directly in terms of order-of-magnitude.

QR develops systems that permit operating in conditions of insufficient or no numerical data. These techniques capture many features of human commonsense reasoning. They have been extended by several authors to encompass reasoning about the order-of-magnitude of quantities. QR reduces the quantitative precision of behavioural description retaining the crucial distinctions. Real valued variables are replaced with qualitative variables in which interval and qualitative algebras may form a simple basis for order-of-magnitude reasoning (Parsons, 1993).

QR also deals with problems in such a way that the principle of relevance is preserved, that is, each variable is valued with the level of precision required Forbus (1984). In group decision evaluation processes, it is not unusual for a situation to arise in which different levels of precision have to be worked with simultaneously depending on the information available to each evaluator. QR tackles the problem of integrating the representation of existing uncertainty within the group and, in addition, it allows the definition of the concept of entropy for qualitative evaluations. This allows us to calculate each evaluator precision and the degree of consensus within the decision group. If there is no consensus within the group, an automatic process to achieve this consensus can be activated and then the degree of consensus can be computed Roselló et al. (2011).

The limitation of this technique refers to the fact that the level of imprecision can dramatically grow after some computations. Order-of-magnitude models are an essential piece among the theoretical tools available for QR. They aim at capturing order-of-magnitude commonsense inferences, such as used in engineering world (Traves-Massuyes and Pierra, 1989).

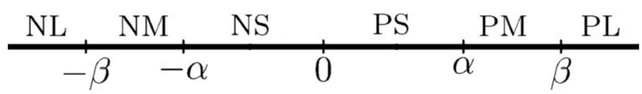
There exist two distinct approaches to the formalisation of human order-of-magnitude in QR which focus on reasoning with *relative* and *absolute* order-of-magnitude. The Relative Order-of-Magnitude (ROM) approach is introduced by Mavrovouniotis and Stephanopoulos (1987), as a family of binary order-of-magnitude relations which performed different comparisons such as *comparability*, *negligibility* and *closeness* relations (Burrieza et al., 2006). ROM are relations that qualify the relative position of a quantity with respect to another quantity. The absolute order-of-magnitudes are represented by a discretization or partition of $\mathbb{R}$, each element of the partition standing for a basic qualitative class. These models have been detailed in Section 3.1.2.1. The conditions under which an AOM and a ROM are consistent are analyzed in Travé-Massuyès et al. (2005).

#### 3.1.2.1 Absolute order-of-magnitude approach

Qualitative absolute order-of-magnitude (AOM) models were introduced by Traves-Massuyes and Pierra (1989), they use QR models by means of a linguistic approach in terms of an interval algebra. The absolute order-of-magnitude models are constructed via a partition of the real line $\mathbb{R}$ which provides the basic labels in a space. The partition is defined by a set of real landmarks. A general algebraic structure called qualitative algebra (Q-algebra) is defined; it provides a mathematical structure which unifies sign algebra and interval algebra through a continuum of qualitative structures built from the rougher to the finest partition of the real line. This structure has been extensively studied by Trave-Massuyès et al. (2005).

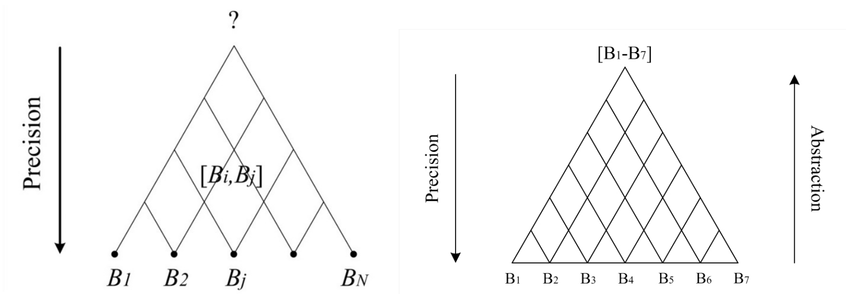
The most referenced order-of-magnitude qualitative algebra partitions the real line into seven classes, corresponding to the basic labels: Negative Large (NL), Negative Medium (NM), Negative Small (NS), zero (0), positive small (PS), positive medium (PM), positive large (PL) (see Figure 3.3). It can be defined via intuitive landmark values, and it is capable of working at different levels of precision (Forbus, 1984; Roselló et al., 2010, 2011).

Figure 3.3: Partition of the real line




The complete universe of description, allows the representation of alternatives from linguistic evaluations of experts by basic or non-basic labels with different granularity (see Figure 3.4). Multi-granular linguistic modeling is defined to deal with situations in which the linguistic information is assessed on different label sets. Different levels of precision for different experts based on their certain or uncertain knowledge helps to keep all the information of their assessments instead of allowing some information to be ignored. In this way, the precision increases according to experts' knowledge by different granularity from top of the hierarchy to the bottom. Each expert can use the level of precision required. In group decision evaluation processes, it is not unusual for a situation to arise in which different levels of precision have to be used simultaneously depending on the information available to each expert.

Figure 3.4: Labels with different granularity




For instance, let us consider the absolute order-of-magnitude model with granularity 7 from strongly agree to strongly disagree (see Table 3.1). In this case, for instance the linguistic label "not strongly disagree", is defined by the non-basic label $[B_2, B_7]$.

Table 3.1: Linguistic label description

| **Linguistic labels** | **Basic labels** |
|---|---|
| Strongly disagree | $B_1$ |
| Disagree | $B_2$ |
| Moderately disagree | $B_3$ |
| Neither agree nor disagree | $B_4$ |
| Moderately agree | $B_5$ |
| Agree | $B_6$ |
| Strongly agree | $B_7$ |

In this way, experts are not forced to make more precise judgments than they are capable of; as mentioned earlier, sometimes decision makers can make mistakes if they are required to make more precise judgments than the available information allows Parreiras et al. (2010). Therefore, if decision makers do not have enough knowledge about one criterion, they can indicate a range between two different assessments instead of an exact assessment. Even if a decision maker does not have any idea of the value for a specific attribute, he/she can use the label "I don't know"; e.g. in this example $[B_1, B_7]$. A detailed preliminaries about AOM models can be found in Subsection 3.3.1.

In the following section TOPSIS methodology is introduced as a MCDM method which is based on a distance function and TOPSIS method is fitted to integrate with AOM approach to capture uncertainty in real problems and ranking alternatives to resolve the vagueness, ambiguity, and subjectivity of human judgement.

## 3.2 TOPSIS Methodology

TOPSIS is a well-known method in the group of reference level models developed by Hwang and Yoon (1981). TOPSIS is particularly useful for the problems in which the valuations of alternatives are not represented in the same units. The basic idea is the alternative should have the shortest distance from the ideal solution and the farthest distance from the negative ideal solution (Opricovic and Tzeng, 2004; Shih et al., 2007). According to Cables et al. (2012), the main steps of this methodology are:

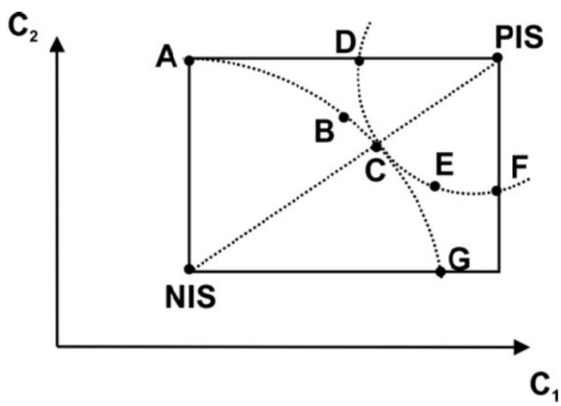
1. Decision matrix construction.
2. Normalized decision matrix construction.
3. Weighted normalized decision making construction.
4. Determining the Positive Ideal Solution (PIS) and Negative Ideal Solutions (NIS).
5. Calculating the distances of each alternative to the positive an negative ideal solutions.

6. Calculating the Closeness Coefficient (CC) aggregation function.

7. Ranking the alternatives.

Note that the weights in TOPSIS are obtained by trade-off and consistency of judgments should be checked. In final step, when alternatives are at the same distance from the NIS, the alternative that moves farthest away from the line that joins PIS with NIS (closer to PIS) has a better performance in Figure 3.5.

Figure 3.5: PIS and NIS representations




So, the order of alternatives with this situation with respect to criteria $C_1$ and $C_2$ is: $C > B > G > A$.

On the contrary, the best within the same distance to PIS, should be the one which is nearest to the PIS-NIS line (farthest from NIS) and the order is: $C > E > D > F$.

TOPSIS is one of the widely used compensatory decision analysis methods considering its simplicity and systematic calculation procedures. A comprehensive literature review on methodologies and applications of TOPSIS can be found in Behzadian et al. (2012). The main advantages of this method are:

- It can work with quantitative data with different units.
- It has a simple process.
- It needs only a minimal number of inputs from the user.
- It is easy to use and programmable and their output is very easy to understand.
- The advantage of its simplicity and its ability to maintain the same amount of steps regardless of problem size or number of alternatives has allowed it to be utilized quickly as a suitable decision-making tool.

However, it has some limitations:

- It assumes that each criterion's utility is monotonic, which is not appropriate for problems where a particular criterion value is desired to be achieved.
- It is rather sensitive to the weighting factors.
- It has a compensatory character in the aggregation. For this reason, it is not used when the weakness of one criteria should not be compensated by the strength of other criteria in a problem.
- The main disadvantage of classic TOPSIS is that it handles crisp data which cannot be used in problems under uncertainty.

Recently, in most of the studies, authors are interested in using linguistic variables to overcome the last shortage. However, linguistic variables and TOPSIS often have been studied with fuzzy sets called "fuzzy TOPSIS" in many literatures (Chen, 2000; Chen and Ben-Arieh, 2006; Ashtiani et al., 2009; Cavallaro, 2010b; Amiri, 2010; Kaya and Kahraman, 2011b; Chamodrakas and Martakos, 2011; Abo-Sinna and Abou-El-Enien, 2011; Baysal et al., 2011; Kahraman et al., 2010; Cables et al., 2012; Yuen, 2013; Kowkabi et al., 2013; Kuo et al., 2015), but the use of TOPSIS with linguistic variables modeled through absolute order-of-magnitude qualitative labels has not been previously considered. Therefore, the next section, introduces the new qualitative TOPSIS method as the methodological contribution of this thesis.

## 3.3 The proposed method: Qualitative TOPSIS

In order to considering linguistic rather than numerical values, a new function in which linguistic terms are associated to qualitative labels is needed to operate the alternatives. To do so, the new algorithm takes this premise into account in this section. A mathematical formulation is developed that contributes to decision analysis in the context of *multi-granular linguistic labels* and *group decision making* for ranking problems.

Agell et al. (2012) introduced a qualitative approach for ranking alternatives that was inspired by the reference point method. This approach ranks a set of alternatives by using a distance function. It uses linguistic assessments of alternatives and minimizes the distance between them and a certain target point that models the best performance for each criterion considered.

The method used in the study of Agell et al. (2012) for ranking alternatives, based on comparing distances against "a single optimal reference point", has been modified in the method proposed in this thesis, to capture the idea of the TOPSIS approach according to the "best" and "worst" reference points. To do so, the proposed method called Qualitative TOPSIS (Q-TOPSIS) is defined after some preliminaries are introduced.

### 3.3.1 Preliminaries

The absolute order-of-magnitude models are constructed via a partition of an interval in $\mathbb{R}$ which defines the set of basic labels. The partition is defined by a set of real landmarks. These evaluations are given by means of a set of qualitative labels with different levels of precision belonging to a certain order-of-magnitude space $\mathbb{S}$.

**Definition 3.1.** *Let $[a_1, a_{n+1}]$ be a real interval and $\{a_1, \ldots, a_{n+1}\}$ a set of real landmarks, with $a_1 < a < a_{n+1}$. The basic labels are defined by $B_i = [a_i, a_{i+1}]$, $i = 1, \ldots, n$.*

Each basic label $B_i$ corresponds to a linguistic term. In a generic sense, if $r < s$, then $B_r < B_s$, meaning that $B_s$ is strictly preferred to $B_r$, such as "extremely bad" < "very bad".

**Definition 3.2.** *The non-basic labels describing different levels of precision are defined as $[B_i, B_j] = [a_i, a_{j+1}]$ where $i, j = 1, \ldots, n$, and $i < j$. The label $[B_i, B_j]$ corresponds to the concept "between $B_i$ and $B_j$".*

Considering a set of alternatives $\{A_1, \ldots, A_l\}$, each alternative is defined by a set of $r$ criteria, and each criterion is evaluated by the judgments of a team of $m$ experts. These evaluations are given by means of a set of qualitative labels with different levels of precision belonging to a certain order-of-magnitude space $\mathbb{S}_n = [B_i, B_j] \quad i, j = 1, \ldots, n+1, i \leq j$, considering $[B_i, B_i] = B_i$.

In this way, each alternative $A_i$, $i = 1, \ldots, l$ is represented by a k-dimensional vector of labels in $(\mathbb{S}_n)^k$, $A_i \longleftrightarrow (A_{i_{11}}, \ldots, A_{i_{1m}}, \ldots, A_{i_{r1}}, \ldots, A_{i_{rm}})$.

$k$ being the number of criteria times the number of experts: $k = r \cdot m$. Distances between linguistic k-dimensional vectors of basic and non-basic labels are computed by using the location function in $n$. Each linguistic label corresponds to a location. The AOM qualitative space is used for the process of moving from the ordinal scale of the original data set to a cardinal scale by codifying the labels using location function that is defined as follows.

**Definition 3.3.** *The location function definition in $\mathbb{S}_n$ is the function;*
*$l : S_n \to Z^2$ such that:*

$$l([B_i, B_j]) = (-\sum_{s=1}^{i-1} \mu(B_s), \sum_{s=j+1}^{n} \mu(B_s)) \tag{3.1}$$

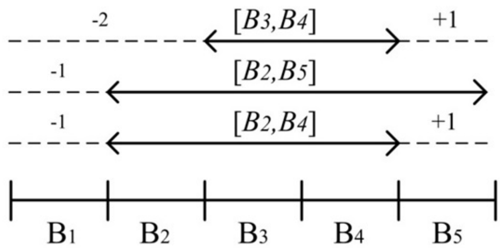
*where $\mu$ is any measure defined over the set of basic labels, for instance,* $(B_i) = ([a_i, a_{i+1}]) = a_{i+1} - a_i$.

In other words, the location function of a qualitative label $[B_i, B_j]$ is defined as a pair of real numbers whose components are, respectively, the opposite of the addition of the measures of the basic labels to its left and the addition of the measures of the basic labels to its right. By applying a function $l$ to each component of the k-dimensional vector of labels, each alternative $A_i$ is codified via a 2k-dimensional vector of real numbers:

$$L(A_i) = (l(A_{i_{11}}), \ldots, l(A_{i_{1m}}), \ldots, l(A_{i_{r1}}), \ldots, l(A_{i_{rm}}) \tag{3.2}$$

For example, the location of the basic label is $B_5$ defined by $(-4, 0)$ and the non-basic label, $[B_2, B_4]$, is the pair $(-1, 1)$ (see Figure 3.6).

Figure 3.6: Locations




### 3.3.2 Q-TOPSIS distances to reference labels

The Q-TOPSIS method proposed in this thesis, can process information represented by qualitative terms in the absolute order-of-magnitude that was introduced in previous subsection.

We consider the Qualitative Positive Reference Label (QPRL) as the $k$-dimensional vector $A^* = (B_n, \ldots, B_n)$, and the Qualitative Negative Reference Label (QNRL) as the $k$-dimensional vector $A^- = (B_1, \ldots, B_1)$, which are considered as reference labels to compute distances. Their location function values are in:

$$L(A^*) = (-\sum_{s=1}^{n-1} \mu(B_s), 0, \ldots, -\sum_{s=1}^{n-1} \mu(B_s), 0) \tag{3.3}$$

$$L(A^-) = (0, \sum_{s=2}^{n} \mu(B_s), \ldots, 0, \sum_{s=2}^{n} \mu(B_s)) \tag{3.4}$$

Both the Euclidean weighted distances of each alternative location $L(A)$ to $A^*$ and $A^-$ locations are then calculated, i.e. $d(L(A), L(A^*))$ and $d(L(A), L(A^-))$, by applying Eq. 4 to the vectors $(X, Y) = (L(A), L(A^*))$ and $(X, Y) = (L(A), L(A^-))$ respectively:

$$d(X, Y) = \sqrt{\sum_{i=1}^{r} w_i \sum_{j=1}^{2m} (X_{ji} - Y_{ji})^2} \tag{3.5}$$

Where $w_i$ is the weight corresponding to the $i-$th indicator, and $X_{ji}$, $Y_{ji}, j = 1 \ldots 2m, i = 1 \ldots r$, are respectively the components of $X$ and $Y$. Finally, the Qualitative Closeness Coefficient (QCC) of each alternative is obtained by Eq. 3.6, and the alternatives are ranked according to the decreasing order of $QCC_i$ values.

$$QCC_i = \frac{d_i^-}{d_i^* + d_i^-} \qquad i = 1, \ldots, m. \tag{3.6}$$

Where $d_i^*$ and $d_i^-$ are respectively the distance between the alternative location $L(A_i)$ and the QPRL location $L(A^*)$ and the QNRL location $L(A^-)$.

The ranking of alternatives can be determined according to the pre-order defined by the values of $QCC_i$, and the closer to $A^*$ and further from $A^-$ the alternative $A_i$, the greater the value of $QCC_i$.

In such a case, common in TOPSIS method, the alternative $A_i$ with the maximum $QCC_i$ is chosen as the best option.

## 3.4 Comparison with other methods

The aim of this section is to compare the proposed Q-TOPSIS method with two MCDM methods. The first comparison with modified fuzzy TOPSIS is based on the same characteristics of both methods using different types of linguistic variables to deal with uncertainty. The second comparison is with a Condorcet based method, which has different preference model and structure based on outranking method. In this subsection, we perform theoretical comparisons and in the next chapter the results obtained by these methods are compared in the first and second case studies respectively.

### 3.4.1 Comparing Q-TOPSIS with modified fuzzy TOPSIS

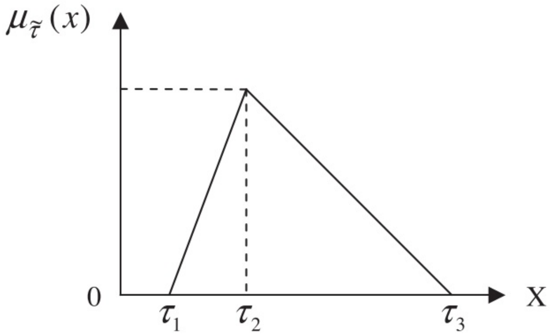
In this section, Q-TOPSIS is compared with modified fuzzy TOPSIS method developed by Chen (2000) in two different aspects. The main reasons for comparing the proposed method with modified fuzzy TOPSIS are, both methods use TOPSIS for ranking alternatives, and both capture uncertainty through linguistic variables. Therefore, as modified fuzzy TOPSIS method in some theoretical points is close to Q-TOPSIS, it has been selected for this comparison in order to show the new contribution of our method.

#### 3.4.1.1 Modified fuzzy TOPSIS method

Chen (2000) extends the TOPSIS method to fuzzy group decision making situations. The fuzzy TOPSIS is a popular tool to analyze the ideal alternative takes an evaluated fuzzy decision matrix as input. In fuzzy TOPSIS, linguistic preferences are converted to fuzzy triangle numbers. A Triangle Fuzzy Number (TFN) $\tilde{\tau}$ can be defined by a triplet $(\tau_1, \tau_2, \tau_3)$ shown in Figure 3.7. The membership function $\mu_{\tilde{\tau}}(x)$ is presented as follows:

$$\mu_{\tilde{\tau}}(x) = \begin{cases} 0, & x_1 \leq \tau_1 \\ \frac{x-\tau_1}{\tau_2-\tau_1}, & \tau_1 \leq x \leq \tau_2 \\ \frac{x-\tau_3}{\tau_2-\tau_3}, & \tau_2 \leq x \leq \tau_3 \\ 0, & x \geq \tau_3. \end{cases}$$

Figure 3.7: A triangular fuzzy number




Considering $\tilde{\rho} = (\rho_1, \rho_2, \rho_3)$ and $\tilde{\tau} = (\tau_1, \tau_2, \tau_3)$, two triangular fuzzy numbers, the distance between them is defined in Eq. 3.7.

$$d(\tilde{\rho}, \tilde{\tau}) = \sqrt{\frac{1}{3}[(\rho_1 - \tau_1)^2 + (\rho_2 - \tau_2)^2 + (\rho_3 - \tau_3)^2]}. \tag{3.7}$$

This method determines the best alternative by calculating the distances from the fuzzy positive and fuzzy negative ideal solutions according to an aggregation of the expert fuzzy evaluation scores. Linear normalization is used in this method, to transform the various criteria scales into a comparable scale to obtain the normalized fuzzy decision matrix. To summarize, in fuzzy TOPSIS these steps are given in the following:

1. A group of decision makers identifies the evaluation criteria.

2. Appropriate linguistic variables for the weights of the criteria and the alternatives are chosen.

3. A pairwise comparison matrix for the criteria is constructed and experts' linguistic evaluations are aggregated to get a mean value for each pairwise comparison.

4. The weights of the criteria are obtained by an appropriate approach and fuzzy weighted decision matrix is Constructed.

5. Fuzzy weighted decision matrix is normalized for the implementation of TOPSIS.

6. Weighted normalized fuzzy decision matrix is constructed.

7. Fuzzy Positive Ideal Solution (FPIS) and Fuzzy Negative Ideal Solution (FNIS) are determined.

8. The distance of each alternative from FPIS and FNIS are calculated, respectively.

9. The closeness coefficient of each alternative is calculated.

10. According to the closeness coefficient, the ranking order of all alternatives can be determined.

Yuen (2013) found that the classical fuzzy TOPSIS produces a misleading result due to some inappropriate definitions. According to the following section, the proposed Q-TOPSIS method avoids step 3 and step 5 by reducing prior aggregation and normalization.

#### 3.4.1.2 Theoretical comparing of methods

Table 3.2 shows the main differences between Q-TOPSIS and the modified fuzzy TOPSIS method. From our point of view, the differences noted in this table represent four significant improvements over modified fuzzy TOPSIS.

Table 3.2: Comparison of the Q-TOPSIS with fuzzy TOPSIS method

| Differences | Q-TOPSIS | Fuzzy TOPSIS |
|---|---|---|
| Scale | Qualitative labels | fuzzy triangle numbers |
| Granularity | Multi-granularity | Fixed granularity |
| Aggregation step | Without prior aggregation | Weighted mean |
| Normalization | Without prior normalization | Normalization |

In general, both methods use linguistic variables in different ways: Q-TOPSIS in the form of qualitative labels, and fuzzy TOPSIS by means of fuzzy triangle numbers. Furthermore, the final aggregation process of both methods finds the distance between each alternative and the best and worst solutions. However, there are some differences between these two methods. Firstly, the Q-TOPSIS method does not require any previous discretization or definition of landmarks for defining initial qualitative terms because the calculations are performed directly with the labels through the location functions. In contrast, in the modified fuzzy TOPSIS, fuzzy labels are defined by means of cut-points that have to be set before any aggregate triangle fuzzy numbers. Secondly, the Q-TOPSIS method can address different levels of precision, from the most precise and basic labels to the least precise labels $[B_1, B_n]$, which can be used to represent unknown values. Finally, the Q-TOPSIS method computations do not need to use an aggregation of expert assessments or a prior normalization. The first involves a loss of information, and the second concentrates expert assessments into a given range, which causes reduced differences. However, as can be seen in next chapter, the results obtained by applying both methods in the first application are similar.

### 3.4.2 Comparison of the Q-TOPSIS with a Condorcet based method

There are many multi-criteria models that can be used to obtain a ranking of the available alternatives Polatidis et al. (2006); Roy and Slowinski (2013). Each of them has its own advantages and disadvantages. The reason for selecting the C-K-Y-L method for this comparison is its simple adaptation for social choice and sustainability issues.

In addition, in this method a weakness of criteria is not compensated by strength of other desirable criteria, and using non-compensatory models in a social framework helps preserve all social actors' opinions. We assume this method can be further enhanced via combining it with QR methods. Let us first introduce the C-K-Y-L method briefly in the following subsection. Then compare the advantages and drawbacks of two methods.

#### 3.4.2.1 C-K-Y-L outranking method

The C-K-Y-L method was presented as a combination of the original Condorcet approach and the future attempts of Kemeny, Young and Levenglick Young and Levenglick (1978) in the study of social framework by Munda (2005). This model integrates social, economic and technical factors inside a coherent framework and is a powerful model for energy policy analysis. The underlying idea for the development of this method was to enrich the dominance relation by some elements based on preference aggregation. In the C-K-Y-L method, the DM compares two alternatives according to preferences and indifferences between them (expressed by indifference and preference thresholds defined for each criterion).

$$\begin{aligned} a_j P a_k &\Leftrightarrow g_m(a_j) > g_m(a_k) + q \\ a_j I a_k &\Leftrightarrow |g_m(a_j) - g_m(a_k)| q \end{aligned} \tag{3.8}$$

where $P$ and $I$ indicate a 'preference' and an 'indifference' relation, respectively and q is the positive indifference threshold. It means a higher value of criterion score is preferred to lower one (when criterion is for maximizing) and the same scores indicate an indifference relation when the difference between criteria is no more than the threshold. The maximum likelihood ranking of $N$ alternatives is the ranking supported by the maximum number of criteria for each pair-wise comparison, summed over all pairs of alternatives considered. The outranking matrix composed by $N(N-1)$ pair-wise comparisons between alternatives. By means of a pair-wise comparison between alternative $j$ and $k$, an outranking matrix with elements $e_{jk}$ is constructed using Eq. 3.9:

$$e_{jk} = \sum_{m=1}^{M} (w_m(P_{jk}) + \frac{1}{2} w_m(I_{jk})) \tag{3.9}$$

where $w_m$ indicates the weight of each criterion. Considering that there are $N!$ possible complete rankings of alternatives in the set of $\mathbb{R}$, the corresponding score $\varphi_s$ is computed for each one of them and the final ranking is the one that maximizes $\varphi_s$ Eq. 3.10.

$$\varphi_s = \sum e_{jk} \qquad j \neq k, \quad s = 1, 2, \ldots, N! \quad and \quad e_{jk} \in \mathbb{R} \tag{3.10}$$

This method ranking alternatives in a suitable way but the main drawback is the difficulty in aggregation step when the number of alternatives grows. The final best rankings obtained by this method is compared with the proposed method in the following subsection.

#### 3.4.2.2 Theoretical comparing of methods

Although these two methods have produced similar rankings, they have different characteristics in the structure of aggregation procedures. The qualitative TOPSIS method does not require the handling of the previous discretization or definition of landmarks to define initial qualitative terms because the calculations are performed directly with the labels; the computations are very fast and easy. This method considers the intensity of preferences. In contrast, the C-K-Y-L method uses a maximum likelihood approach as an aggregation function, which makes it more difficult to compute; in fact, and it becomes unmanageable as the number of alternatives rises.

Additionally, the qualitative TOPSIS method can address different levels of precision, from the basic labels representing the most precise ones to the least precise label which can be used to represent unknown values. This strength of the proposed method has not been used in this real example with given evaluation scores. On the other hand, C-K-Y-L avoids compensation and trade-off by representing the weights as the importance coefficients. Therefore, low scores on one criterion cannot be compensated by high scores on another. Table 3.3 shows the main characteristics of both methodologies.

Table 3.3: Comparison of the Q-TOPSIS with C-K-Y-L method

| | Qualitative TOPSIS | C-K-Y-L |
|---|---|---|
| Scale | Qualitative labels | Ordinal/interval/ratio |
| Structure | Compensatory Model | Non-Compensatory Model |
| Weights | Trade-off | Importance coefficients |
| Aggregation step | Based on distance function | Outranking<br>and pair-wise comparison |
| Aggregation function | Distance to the maximum<br>and minimum | Maximum<br>likelihood approach |

These differences suggest that both methods could be used together synergistically. For instance, using linguistic labels in Q-TOPSIS can more efficiently to process data when it is qualitative from the beginning; meanwhile C-K-Y-L can enforce the absence of compensation.

In the next chapter the results obtained by both methods are compared in the application to renewable energy alternatives selection and an application to a wind farm location problem in Catalonia, respectively.

# Chapter 4

# Applications of the Q-TOPSIS method

Ranking different alternatives to find the quality of them from the best to the worst is a crucial problem in energy planning. Multi-criteria ranking problems constitute one of the three main categories of decision problems, mentioned in Section 2.2. In ranking problems, the DM(s) want to find an order structure of alternatives. This order depends on the importance of each criterion and the performance of alternatives on particular criteria (Doumpos and Grigoroudis, 2013).

Applications of Q-TOPSIS method, introduced in Chapter 3, in energy planning problems provide the ordering of the alternatives, projects or scenarios in different cases. This chapter describes three applications of the proposed method addressing challenges in renewable energy planning, wind farm location planning and urban planning. The aim of these studies is to demonstrate the multi-disciplinary features of the proposed method in different energy applications and to illustrate the potential of the proposed method. These studies show the relation between the theoretical study of previous chapter and real applications. In Section 4.1, the application of the Q-TOPSIS method in a case study of renewable energy alternatives selection is presented. These alternatives are ranked and the results are compared with the modified fuzzy TOPSIS method.

The study of Section 4.2 refers to a real case which has been done in a research project of Universitat Autónoma de Barcelona, and the aim of this study is finding an appropriate place for wind farm location in Catalunya. Section 4.3, presents a real case study which has been co-financed by the European Commission within the 7th Framework Program of the European Union, under the coordination of the research group ARC from the School of Architecture and Engineering, Ramon Llull University and Universitat Autónoma de Barcelona. This study assesses the energy performance and $CO_2$ emissions of urban planning in Manresa using Semantic tools for carbon reduction in urban planning (SEMANCO) platform. The projects are completely ordered with respect to the preferences using Q-TOPSIS method.

## 4.1 An application to renewable energy alternatives selection

In the first application a case-example, based on data provided in a paper by Kaya and Kahraman (2011b), is used to illustrate how using qualitative labels rather than numerical values helps decision makers to evaluate alternatives. The results obtained by the proposed method and modified fuzzy TOPSIS, which was introduced in Section 3.4, are compared.

### 4.1.1 Determining alternatives, criteria and indicators

One of the main problems of energy planning is to choose among different energy sources or technologies such as solar energy, wind energy, biomass energy and wave energy in residential and industry sectors (Beccali et al., 2003; Tsoutsos et al., 2009). There are some other technologies with environmental drawbacks such as nuclear and conventional energy (oil, coal, natural gas) which can be considered among energy resources (Cai et al., 2009). On the other hand, selection of the energy technologies requires the consideration of quantitative and qualitative criteria. Wang et al. (2009) grouped energy criteria for evaluating energy sources into four main categories of technological, economic, environmental and social in terms of sustainability assessment, as detailed in Chapter 2.

Seven energy technologies were examined in the current study. Four renewable energies (wind, solar, biomass and hydraulic), two clean energies (nuclear and Combined Heat and Power (CHP)) and a conventional energy. A brief definition of each technology is following (World Commission on Environment and Development, 1987; Ulutas, 2005; Kaygusuz, 2002; Topcu and Ulengin, 2004):

1. *Conventional energy ($A_1$)* is referring to classic sources of energy such as coal, oil, petroleum and natural gas. The energy obtained from these sources is not environmental friendly because it release a large amount of carbon dioxide into atmosphere. It is clear that in this study the aim is considering sustainable factors to evaluate the order of this source among others.

2. Nuclear energy ($A_2$): is one of the modern form of energy generation nowadays. This form of energy is clean but dangerous without well-controled potential effects for energy generation. This energy produced by the quick and dangerous release of energy produced from joining atoms. The amount of energy could supply all of our energy demands problems.

3. *Solar energy ($A_3$)* (including solar thermal, Photo Voltaic (PV), Solar Power and concentrating solar power) captures the energy of the sun directly and turns it into electricity, a great extension of land will be needed to make a significant contribution. PV modules can convert diffused light as well as direct sunlight (which is more productive and cheaper) into electricity, so they could be used anywhere. PV modules generate electricity directly from light without emissions, noise, or vibration. Sunlight is free but power generation cost is exceptionally high, although prices are starting to come down.

4. *Wind energy ($A_4$)*: causes no emissions and it is free if the wind available. The site should be remote from habitation and bird migration

routes. Power generation by wind is noisy and unsightly. Equipment is expensive to maintain.

5. *Hydraulic energy ($A_5$)*: is a proven technology for electricity production capable of generating large amounts of power. It is entirely renewable and causes no CO2 emissions. Once a hydroelectric plant or a dam is built, it is very inexpensive to operate. The plant can cause some damage to the landscape and affect fish. Water is a renewable resource and many dams available are already in use in most countries.

6. *Biomass energy ($A_6$)*: is biological material derived from living, or recently living organisms. Most commonly, biomass refers to plants matter grown for use as bio-fuel. It also includes plant or animal matter used for production of fibres, chemicals or heat, and biodegradable wastes that can be burnt as fuel. It excludes organic material which has been transformed by geological processes into substances such as coal or petroleum.

7. *CHP energy ($A_7$)*: is the use of a heat engine or power station to generate electricity and useful heat simultaneously. CHP generation requires less fuel to produce a required output than conventional energy. Combining this with sustainable fuels such as biomass can provide low cost heating that has a minimal carbon footprint.

Nine indicators, with reference to the most frequently used technical, economic, environmental, and social criteria in evaluating energy options, were selected to assess the given alternatives. These indicators are detailed in Table 4.1. These indicators are explained briefly as follows:

*Energy efficiency*: or "first law" measures the useful energy from an energy source. It shows how well an energy conversion or process is accomplished. Energy efficiency is essential to reduce the energy demand growth and increase the clean energy supplies. It can be measured by the ratio of output to the input energy (Kanoglu et al., 2007; Sovacool, 2009).

*Exergy*: or "rational efficiency", also called "second low", is the energy that is available to be used. It is defined as the ratio of the benefit

Table 4.1: Criteria and indicators

| Criteria | Indicators |
|---|---|
| Technical | Efficiency ($c_1$) |
| | Exergy ($c_2$) |
| Economic | Investment cost($c_3$) |
| | Operation and maintenance cost ($c_4$) |
| Environmental | $NO_X$ emission ($c_5$) |
| | $CO_2$ emission ($c_6$) |
| | Land use ($c_7$) |
| Social | Social acceptability ($c_8$) |
| | Job creation ($c_9$) |

exergy to the consumption exergy. The thermodynamic performance of power plants (especially in CHP) improve this indicator (Kanoglu et al., 2007; San Cristóbal, 2012b).

*Investment cost*: This essential economic indicator includes all purchase and installation cost of energy technologies such as mechanical equipment, engineering services and construction costs (Wang et al., 2008).

*Operation and maintenance cost*: In order to measure operation and maintenance cost both fixed and variable costs of products and services during each period of time, should be considered.

$NO_X$ *emission*: $NO_X$ produced from the reaction among nitrogen, oxygen and even hydrocarbons which is harmful for health and causes acid rain. The major source of $NO_X$ production is the conversion of fuel in nitrogen during combustion of nitrogen-bearing fuels such as coals, oil and biomass (Streimikiene and Sivickas, 2008).

$CO_2$ *emission*: produced GreenHouse Gas (GHG) in the atmosphere which leads to a global warming. According to the Kyoto protocol in 1997, some countries agreed to reduce GHG emissions in their future plan (Mostashari, 2011; San Cristóbal, 2012b).

*Land use*: Each plant requires specific land from natural source. This indicator has a strong influence on environment directly by the energy systems. Thus, energy decision makers must pay attention to this factor in their evaluations (Mosadeghi et al., 2015).

*Social acceptability*: It shows the degree of local population agreement to accept energy systems. This indicator heavily influences the amount of time to finish the project (Kaya and Kahraman, 2011b; Wang et al., 2014). Note that it can be only measured by qualitative variables.

*Job creation*: Energy systems employ many people during the cycle life of projects. The sustainable energy system creating more jobs improves the quality life of local people (Wang et al., 2009).

In the first step, alternatives, criteria and indicators are determined. Then indicators are weighted by a group of three experts in energy technologies. Special attention has been paid to the definition of the criteria weights for aggregation functions in the MCDM literature. Weights given to different criteria are particularly important to obtain the overall preferential value of the alternatives (Choo et al., 1999). Based on aggregation procedures of MCDM models, the criteria weights can be used in different ways.

Weights can be defined as trade-off or importance coefficients. In value measurement MCDM methods based on distance functions, weights are obtained by trade-off among criteria such as pair-wise comparison. In particular, in this study, a fuzzy approach of the well-known AHP is used to obtain weights of indicators in order to evaluate energy alternatives. This method can deal with the uncertainty involved in some complex problems using linguistic variables to represent the experts' opinion (Chang, 1996). Table 4.2 gives the list of considered indicators weights obtained by using fuzzy AHP method. In the next section, the Q-TOPSIS method is performed on the basis of these indicators, which were introduced and weighted by a group of three experts.

### 4.1.2 Q-TOPSIS implementation

Once the evaluation criteria are determined and the indicators, weights, and alternatives are specified, the Q-TOPSIS algorithm steps are exe-

Table 4.2: Indicators' weights

| **Indicators** | **weights** |
|---|---|
| Efficiency | 0.09 |
| Exergy | 0.1 |
| Investment cost | 0.1 |
| Operation and maintenance cost | 0.11 |
| $NO_X$ emission | 0.13 |
| $CO_2$ emission | 0.15 |
| Land use | 0.11 |
| Social acceptability | 0.09 |
| Job creation | 0.12 |

cuted. The Q-TOPSIS approach considered in this example uses seven basic qualitative labels. Table 4.3 shows these qualitative labels together with their locations, considering the measure $\mu$ over the set of basic labels $\mu(B_i) = 1$, for all $i = 1, \ldots, 7$.

Table 4.3: Evaluation scores

| **Linguistic terms** | **Qualitative labels** | **locations** |
|---|---|---|
| Very poor (VP) | $B_1$ | (0,6) |
| Poor (p) | $B_2$ | (-1,5) |
| Medium poor (MP) | $B_3$ | (-2,4) |
| Fair (F) | $B_4$ | (-3,3) |
| Medium good (MG) | $B_5$ | (-4,2) |
| Good (G) | $B_6$ | (-5,1) |
| Very good (VG) | $B_7$ | (-6,0) |

Each expert assesses each alternative by means of nine qualitative labels (one for each indicator). Therefore, each alternative $A$ is represented by a 27-dimensional vector of qualitative labels.

$$A \longleftrightarrow (E_{1,1}, \ldots, E_{1,9}, E_{2,1}, \ldots, E_{2,9}, E_{3,1}, \ldots, E_{3,9}) \tag{4.1}$$

The location function then codifies each alternative by a 54-dimensional vector of real numbers.

$$A \leftrightarrow (X_{1,1},\ldots,X_{1,18},X_{2,1},\ldots,X_{2,18},X_{3,1},\ldots,X_{3,18}) \tag{4.2}$$

Considering separately the assessments made by the three energy planning experts, Table 4.4 shows the alternatives evaluation matrices and the vector in Eq. 4.2 for each alternative $A_i$, is obtained by combining the $i-th$ rows of the three matrices given in Table 4.5 via the locations of the nine indicators.

The two vectors $L(A^-) = L(B_1,\ldots,B_1) = (0,6,\ldots,0,6)$ and $L(A^*) = L(B_7,\ldots,B_7) = (-6,0,\ldots,-6,0)$ are considered as QPRL and QNRL reference labels to compute distances, respectively,. The qualitative Euclidean distance of each alternative from the QPRL and QNRL is then calculated by means of Eq. 4.3:

$$d(A,\tilde{A}) = \sqrt{\sum_{i=1}^{9} w_i \sum_{j=1}^{6} (X_{ji} - \tilde{X_{ji}})^2} \tag{4.3}$$

Applying the proposed method, Table 4.6 shows the values of the distances to the QPRL and QNRL of each alternative together with the values of the $QCC_i$.

According to the $QCC_i$ values, the best alternative is $A_4$ (wind energy). The ranking of alternatives is presented in Table 4.7.

Table 4.4: Qualitative decision matrices

| $E_1$ | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ | $C_7$ | $C_8$ | $C_9$ |
|---|---|---|---|---|---|---|---|---|---|
| $A_1$ | $B_6$ | $B_6$ | $B_5$ | $B_5$ | $B_1$ | $B_1$ | $B_2$ | $B_3$ | $B_5$ |
| $A_2$ | $B_7$ | $B_4$ | $B_1$ | $B_7$ | $B_3$ | $B_3$ | $B_3$ | $B_2$ | $B_6$ |
| $A_3$ | $B_4$ | $B_4$ | $B_4$ | $B_4$ | $B_7$ | $B_6$ | $B_7$ | $B_6$ | $B_4$ |
| $A_4$ | $B_3$ | $B_5$ | $B_6$ | $B_6$ | $B_6$ | $B_7$ | $B_7$ | $B_7$ | $B_4$ |
| $A_5$ | $B_5$ | $B_6$ | $B_5$ | $B_4$ | $B_3$ | $B_2$ | $B_3$ | $B_4$ | $B_6$ |
| $A_6$ | $B_4$ | $B_5$ | $B_4$ | $B_4$ | $B_6$ | $B_2$ | $B_5$ | $B_6$ | $B_6$ |
| $A_7$ | $B_4$ | $B_5$ | $B_4$ | $B_3$ | $B_4$ | $B_4$ | $B_5$ | $B_6$ | $B_5$ |

| $E_2$ | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ | $C_7$ | $C_8$ | $C_9$ |
|---|---|---|---|---|---|---|---|---|---|
| $A_1$ | $B_7$ | $B_5$ | $B_6$ | $B_4$ | $B_1$ | $B_3$ | $B_1$ | $B_2$ | $B_6$ |
| $A_2$ | $B_6$ | $B_7$ | $B_3$ | $B_7$ | $B_3$ | $B_3$ | $B_1$ | $B_3$ | $B_6$ |
| $A_3$ | $B_3$ | $B_4$ | $B_5$ | $B_4$ | $B_7$ | $B_6$ | $B_6$ | $B_6$ | $B_5$ |
| $A_4$ | $B_4$ | $B_5$ | $B_6$ | $B_6$ | $B_6$ | $B_7$ | $B_6$ | $B_7$ | $B_4$ |
| $A_5$ | $B_4$ | $B_6$ | $B_5$ | $B_4$ | $B_3$ | $B_2$ | $B_3$ | $B_4$ | $B_5$ |
| $A_6$ | $B_4$ | $B_4$ | $B_5$ | $B_4$ | $B_6$ | $B_6$ | $B_5$ | $B_6$ | $B_6$ |
| $A_7$ | $B_5$ | $B_4$ | $B_4$ | $B_3$ | $B_4$ | $B_4$ | $B_6$ | $B_5$ | $B_5$ |

| $E_3$ | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ | $C_7$ | $C_8$ | $C_9$ |
|---|---|---|---|---|---|---|---|---|---|
| $A_1$ | $B_7$ | $B_7$ | $B_5$ | $B_5$ | $B_3$ | $B_3$ | $B_2$ | $B_3$ | $B_5$ |
| $A_2$ | $B_7$ | $B_7$ | $B_1$ | $B_7$ | $B_2$ | $B_3$ | $B_3$ | $B_3$ | $B_6$ |
| $A_3$ | $B_4$ | $B_4$ | $B_4$ | $B_4$ | $B_6$ | $B_6$ | $B_6$ | $B_6$ | $B_4$ |
| $A_4$ | $B_2$ | $B_5$ | $B_6$ | $B_7$ | $B_7$ | $B_7$ | $B_6$ | $B_7$ | $B_4$ |
| $A_5$ | $B_6$ | $B_6$ | $B_5$ | $B_4$ | $B_3$ | $B_2$ | $B_3$ | $B_4$ | $B_6$ |
| $A_6$ | $B_4$ | $B_5$ | $B_5$ | $B_4$ | $B_6$ | $B_6$ | $B_5$ | $B_6$ | $B_5$ |
| $A_7$ | $B_5$ | $B_4$ | $B_4$ | $B_3$ | $B_4$ | $B_4$ | $B_5$ | $B_6$ | $B_5$ |

Table 4.5: Locations decision matrices

| $E_1$ | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ | $C_7$ | $C_8$ | $C_9$ |
|---|---|---|---|---|---|---|---|---|---|
| $A_1$ | (-5,1) | (-5,1) | (-4,2) | (-4,2) | (0,6) | (0,6) | (-1,5) | (-2,4) | (-4,2) |
| $A_2$ | (-6,0) | (-3,3) | (0,6) | (-6,0) | (-2,4) | (-2,4) | (-2,4) | (-1,5) | (-5,1) |
| $A_3$ | (-3,3) | (-3,3) | (-3,3) | (-3,3) | (-6,0) | (-5,1) | (-6,0) | (-5,1) | (-3,3) |
| $A_4$ | (-2,4) | (-4,2) | (-5,1) | (-5,1) | (-5,1) | (-6,0) | (-6,0) | (-6,0) | (-3,3) |
| $A_5$ | (-4,2) | (-5,1) | (-4,2) | (-3,3) | (-2,4) | (-1,5) | (-2,4) | (-3,3) | (-5,1) |
| $A_6$ | (-3,3) | (-4,2) | (-3,3) | (-3,3) | (-5,1) | (-1,5) | (-4,2) | (-5,1) | (-5,1) |
| $A_7$ | (-3,3) | (-4,2) | (-3,3) | (-2,4) | (-3,3) | (-3,3) | (-4,2) | (-5,1) | (-4,2) |

| $E_2$ | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ | $C_7$ | $C_8$ | $C_9$ |
|---|---|---|---|---|---|---|---|---|---|
| $A_1$ | (-6,0) | (-4,2) | (-5,1) | (-3,3) | (0,6) | (-2,4) | (0,6) | (-1,5) | (-5,1) |
| $A_2$ | (-5,1) | (-6,0) | (-2,4) | (-6,0) | (-2,4) | (-2,4) | (0,6) | (-2,4) | (-5,1) |
| $A_3$ | (-2,4) | (-3,3) | (-4,2) | (-3,3) | (-6,0) | (-5,1) | (-5,1) | (-5,1) | (-4,2) |
| $A_4$ | (-3,3) | (-4,2) | (-5,1) | (-5,1) | (-5,1) | (-6,0) | (-5,1) | (-6,0) | (-3,3) |
| $A_5$ | (-3,3) | (-5,1) | (-4,2) | (-3,3) | (-2,4) | (-1,5) | (-2,4) | (-3,3) | (-4,2) |
| $A_6$ | (-3,3) | (-3,3) | (-4,2) | (-3,3) | (-5,1) | (-5,1) | (-4,2) | (-5,1) | (-5,1) |
| $A_7$ | (-4,2) | (-3,3) | (-3,3) | (-2,4) | (-3,3) | (-3,3) | (-5,1) | (-4,2) | (-4,2) |

| $E_3$ | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ | $C_7$ | $C_8$ | $C_9$ |
|---|---|---|---|---|---|---|---|---|---|
| $A_1$ | (-6,0) | (-6,0) | (-4,2) | (-4,2) | (-2,4) | (-2,4) | (-1,5) | (-2,4) | (-4,2) |
| $A_2$ | (-6,0) | (-6,0) | (0,6) | (-6,0) | (-1,5) | (-2,4) | (-2,4) | (-2,4) | (-5,1) |
| $A_3$ | (-3,3) | (-3,3) | (-3,3) | (-3,3) | (-5,1) | (-5,1) | (-5,1) | (-5,1) | (-3,3) |
| $A_4$ | (-1,5) | (-4,2) | (-5,1) | (-6,0) | (-6,0) | (-6,0) | (-5,1) | (-6,0) | (-3,3) |
| $A_5$ | (-5,1) | (-5,1) | (-4,2) | (-3,3) | (-2,4) | (-1,5) | (-2,4) | (-3,3) | (-5,1) |
| $A_6$ | (-3,3) | (-4,2) | (-4,2) | (-3,3) | (-5,1) | (-5,1) | (-4,2) | (-5,1) | (-4,2) |
| $A_7$ | (-4,2) | (-3,3) | (-3,3) | (-2,4) | (-3,3) | (-3,3) | (-4,2) | (-5,1) | (-4,2) |

Table 4.6: Q-TOPSIS results

| | $d_i^-$ | $d_i^*$ | $QCC_i$ |
|---|---|---|---|
| $A_1$ | 8.514 | 9.033 | 0.485 |
| $A_2$ | 9.278 | 8.657 | 0.517 |
| $A_3$ | 10.528 | 5.420 | 0.660 |
| $A_4$ | 12.119 | 4.435 | 0.732 |
| $A_5$ | 8.204 | 7.973 | 0.507 |
| $A_6$ | 10.490 | 4.876 | 0.682 |
| $A_7$ | 9.136 | 6.495 | 0.584 |

Table 4.7: Ranking energy sources

| **Ranking** | **Alternatives** |
|---|---|
| 1 | wind ($A_4$) |
| 2 | biomass ($A_6$) |
| 3 | solar ($A_3$) |
| 4 | CHP ($A_7$) |
| 5 | nuclear ($A_2$) |
| 6 | hydraulic ($A_5$) |
| 7 | conventional energy ($A_1$) |

### 4.1.3 Comparison of Q-TOPSIS and modified fuzzy TOPSIS results

Kaya and Kahraman (2011b) applied modified fuzzy TOPSIS to the data summarized in previous subsection. Three experts evaluated the seven energy technologies, mentioned in Section 4.1.1, with respect to each one of the nine indicators using other linguistic semantics, which is defined by the triangle fuzzy numbers given in Table 4.8.

Considering weights of Table 4.2 as a particular and first scenario ($w_1 = 0.09$; $w_2 = 0.1$; $w_3 = 0.1$; $w_4 = 0.11$; $w_5 = 0.13$; $w_6 = 0.15$; $w_7 = 0.11$; $w_8 = 0.09$; $w_9 = 0.12$), the modified fuzzy TOPSIS provided the following alternatives ranking: wind >biomass >solar >CHP >hydraulic >nuclear >conventional energy.

Table 4.8: Fuzzy evaluation scores for the alternatives

| **Linguistic terms** | **Fuzzy numbers** |
|---|---|
| Very Poor(VP) | (0,0,1) |
| Poor(p) | (0,1,3) |
| Medium Poor(MP) | (1,3,5) |
| Fair(F) | (3,5,7) |
| Medium Good(MG) | (5,7,9) |
| Good(G) | (7,9,10) |
| Very Good(VG) | (9,10,10) |

Both algorithms were implemented using the same data, and wind energy was found to be the best alternative among other energy technologies on both studies for this particular scenario. Although both MCDM linguistic approaches process uncertainty in different ways, their results produce similar rankings.

### 4.1.4 Sensitivity analysis

In this section, a sensitivity analysis that considers four other scenarios, randomly changing the weights for each criterion (Table 4.9), was carried out to analyze the results when applying both approaches. It is a crucial issue in any multi-criteria method to determine if the final ranking is dependent and sensitive to the estimates of the criteria weights.

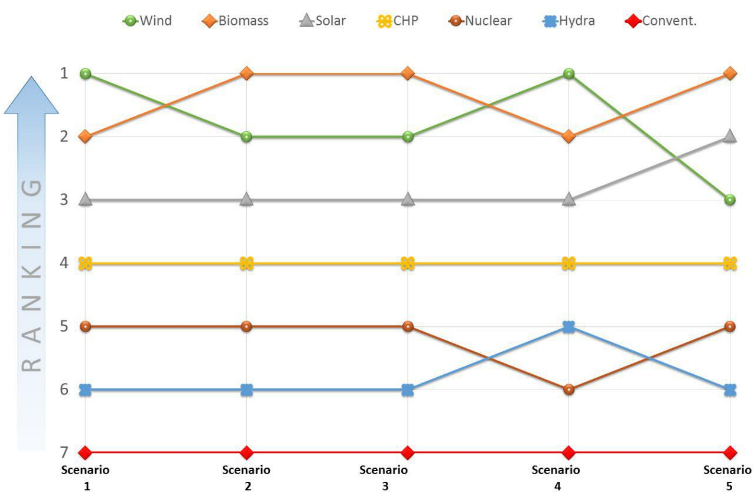
The rankings after applying Q-TOPSIS method using different random weights has been shown in Figure 4.1. Wind and biomass energy and, after that hydra and nuclear, are the most sensitive alternatives to weights. The reason lies on the fact that their $QCC_i$ are the closest ones, in this way, a small change in their weights produces a switch on the ranking. Conventional energy is always the worst alternative and CHP is not sensitive to the estimates of the criteria weights.

In addition, the results applying both Q-TOPSIS and modified fuzzy TOPSIS approaches are summarized in Table 4.10. Differences were found just in the shaded cells. In each shaded cell, the first item always shows the Q-TOPSIS result, and the second item shows the modified fuzzy TOPSIS result.

Table 4.9: Different weights of indicators for five scenarios

| | **Scenario1** | **Scenario2** | **Scenario3** | **Scenario4** | **Scenario5** |
|---|---|---|---|---|---|
| $C_1$ | 0.09 | 0.2 | 0.2 | 0.05 | 0.3 |
| $C_2$ | 0.1 | 0.1 | 0.15 | 0.05 | 0.05 |
| $C_3$ | 0.1 | 0.05 | 0.05 | 0.1 | 0.05 |
| $C_4$ | 0.11 | 0.05 | 0.05 | 0.1 | 0.05 |
| $C_5$ | 0.13 | 0.1 | 0.2 | 0.15 | 0.2 |
| $C_6$ | 0.15 | 0.1 | 0.05 | 0.15 | 0.05 |
| $C_7$ | 0.11 | 0.1 | 0.05 | 0.15 | 0.05 |
| $C_8$ | 0.09 | 0.1 | 0.05 | 0.15 | 0.05 |
| $C_9$ | 0.12 | 0.2 | 0.2 | 0.1 | 0.2 |

Figure 4.1: Rankings in different scenarios




This table shows that the results obtained from both methods always coincide in the first option, and in general, they produce compatible rank-

Table 4.10: Sensitivity analysis

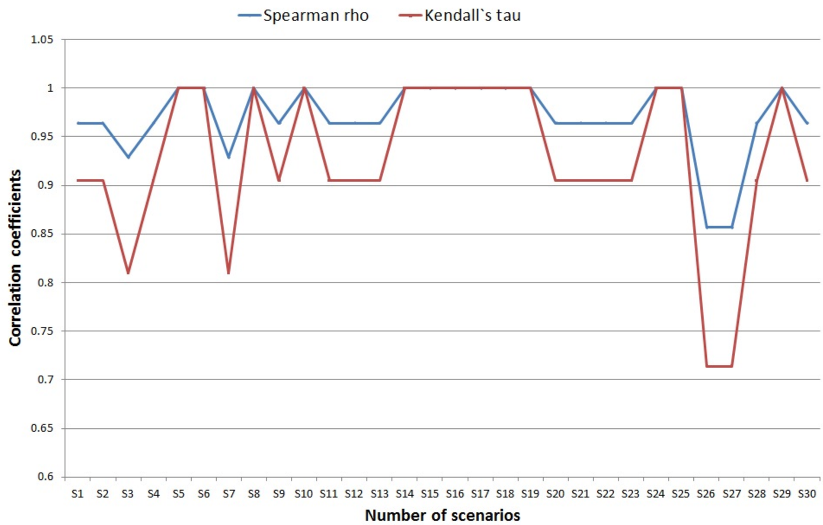
| Scenario1 | Scenario2 | Scenario3 | Scenario4 | Scenario5 |
|---|---|---|---|---|
| Wind | Biomass | Biomass | Wind | Biomass |
| Biomass | Wind | Wind | Biomass/Solar | Solar |
| Solar | Solar | Solar | Solar/Biomass | Wind |
| CHP | CHP | CHP/Nuclear | CHP | CHP/Nuclear |
| Nuclear/Hydra. | Nuclear | Nuclear/CHP | Hydra. | Nuclear/CHP |
| Hydra./Nuclear | Hydra. | Hydra. | Nuclear | Hydra./Convent. |
| Convent. | Convent. | Convent. | Convent. | Convent./Hydra. |

ings of alternatives. In particular, in Scenario 2, both methodologies produce exactly the same ranking. Greater differences were found in the last scenario. A plausible reason for this finding is that the variability (standard deviation) of the weights used in the last scenario is significantly greater than in the rest of the scenarios. Moreover, increasing the criteria weight of $C_1$, changes the position of the wind energy alternative in the last scenario, meaning that this option is largely dependent on the weights of efficiency indicator.

Finally, to study the similarity between both ranking methods, a simulation was conducted including 30 other scenarios in which the weights considered changed randomly for each criterion. Figure 4.2 shows the correlation coefficient values obtained in the 30 scenarios.

To this end, the Spearman's rho and the Kendall's tau correlation coefficients were computed for each of the 30 scenarios. In all the scenarios, highly significant values (p-value $<0.05$) were obtained. The mean and the standard deviation for these coefficients were: $\bar{\rho} = 0.97$ and $\bar{\tau} = 0.93$ and, $s_\rho = 0.037$ and $s_\tau = 0.082$, respectively. The results indicate a high correlation between the results obtained using both methods.

Figure 4.2: Spearman's rho and Kendall's tau correlation coefficients




### 4.1.5 Allowing experts to use different levels of precision

To highlight the ability of the method presented in this Thesis to capture the inherent uncertainty existing in human reasoning, we present a simulated extension of the previous Scenario 1 where experts are allowed to use different levels of precision in their assessments. In general, costs, social acceptability and job creation are usually the criteria involving more uncertainty, meaning that their results and predictions can present greater differences. For this reason, we consider that Expert 1 expresses uncertain judgments when assessing criteria ($C_3$, $C_4$, $C_8$ and $C_9$) in Scenario 1. Table 4.11 presents the previous values considered for Expert 1 assessments with respect to these four criteria, whose locations were presented in Table 4.4, along with the new assessments allowing different levels of precision.

Considering these new assessments of Expert 1, the final order of ranking is the same as the previous one: wind > biomass > solar > CHP > nuclear > hydraulic > conventional energy (see Table 4.10). Note that

Table 4.11: Expert 1 assessment using non-basic labels

| $E_1$ | $C_3$ | | $C_4$ | | $C_8$ | | $C_9$ | |
|---|---|---|---|---|---|---|---|---|
| | basic labels | non-basic lables | basic lables | non-basic lables | basic lables | non-basic lables | basic lables | non-basic lables |
| $A_1$ | $B_5$ | $[B_2-B_6]$ | $B_5$ | $B_5$ | $B_3$ | $B_3$ | $B_5$ | $[B_3-B_6]$ |
| $A_2$ | $B_1$ | $B_1$ | $B_7$ | $B_7$ | $B_2$ | $[B_1-B_3]$ | $B_6$ | $B_6$ |
| $A_3$ | $B_4$ | $[B_3-B_5]$ | $B_4$ | $[B_3-B_5]$ | $B_6$ | $B_6$ | $B_4$ | $[B_3-B_5]$ |
| $A_4$ | $B_6$ | $B_6$ | $B_6$ | $B_6$ | $B_7$ | $B_7$ | $B_4$ | $B_4$ |
| $A_5$ | $B_5$ | $[B_4-B_6]$ | $B_4$ | $[B_1-B_7]$ | $B_4$ | $[B_3-B_5]$ | $B_6$ | $B_6$ |
| $A_6$ | $B_4$ | $[B_3-B_5]$ | $B_4$ | $[B_3-B_5]$ | $B_6$ | $[B_5-B_6]$ | $B_6$ | $B_6$ |
| $A_7$ | $B_4$ | $[B_1-B_7]$ | $B_3$ | $[B_1-B_4]$ | $B_6$ | $B_6$ | $B_5$ | $[B_4-B_5]$ |

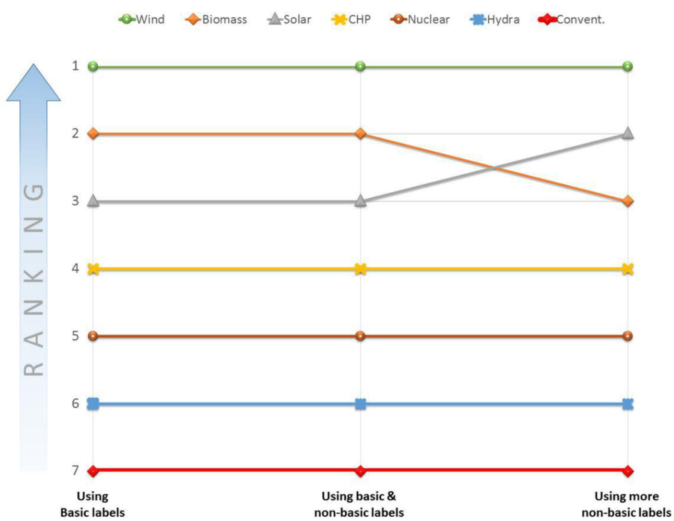
the modified fuzzy-TOPSIS method is not able to deal with these types of assessments; therefore these results can only be computed using the method proposed in this paper. This example clearly shows the originality and the contribution of the proposed method because, although it allows experts to express their uncertainty through imprecise assessments, it yields the same final ranking; thus, the same results can be obtained with less information. In addition, this reinforces the idea that the proposed method is more adaptable to real situations and requires less cognitive effort on the part of the experts. However, obviously, if the assessments are more imprecise, the obtained ranking can be different, as can be seen in the situation presented in Table 4.12.

Table 4.12: Expert 1 assessment using more non-basic labels

| $E_1$ | $C_3$ | | $C_4$ | | $C_8$ | | $C_9$ | |
|---|---|---|---|---|---|---|---|---|
| | basic labels | non-basic lables | basic lables | non-basic lables | basic lables | non-basic lables | basic lables | non-basic lables |
| $A_1$ | $B_5$ | $[B_4-B_6]$ | $B_5$ | $B_5$ | $B_3$ | $B_3$ | $B_5$ | $[B_3-B_5]$ |
| $A_2$ | $B_1$ | $[B_1$-$B_2]$ | $B_7$ | $[B_1$-$B_3]$ | $B_2$ | $[B_1$-$B_3]$ | $B_6$ | $[B_4$-$B_6]$ |
| $A_3$ | $B_4$ | $[B_4$-$B_7]$ | $B_4$ | $[B_4$-$B_6]$ | $B_6$ | $[B_6$-$B_7]$ | $B_4$ | $[B_4$-$B_6]$ |
| $A_4$ | $B_6$ | $[B_6$-$B_7]$ | $B_6$ | $[B_6$-$B_7]$ | $B_7$ | $B_7$ | $B_4$ | $[B_4$-$B_6]$ |
| $A_5$ | $B_5$ | $[B_5$-$B_6]$ | $B_4$ | $[B_4$-$B_6]$ | $B_4$ | $[B_4-B_6]$ | $B_6$ | $[B_4$-$B_7]$ |
| $A_6$ | $B_4$ | $B_4$ | $B_4$ | $[B_3$-$B_5]$ | $B_6$ | $[B_4$-$B_6]$ | $B_6$ | $[B_4$-$B_6]$ |
| $A_7$ | $B_4$ | $[B_2$-$B_6]$ | $B_3$ | $[B_4$-$B_5]$ | $B_6$ | $B_6$ | $B_5$ | $[B_4$-$B_6]$ |

The ranking based on these last assessments is wind > solar > biomass > CHP > hydraulic > nuclear > conventional energy. In the new order the respective places of solar/biomass and hydra./nuclear are switched (see Figure 4.3).

Figure 4.3: Ranking using basic and non-basic labels



## 4.2 An application to a wind farm location problem in Catalonia

The rapid development in wind energy technology has led to consider it promising alternative to conventional energy systems. It is argued that wind energy is one of the most promising tools for confronting global warming, being a powerful source of renewable energy with rapid and simple installation, lack of emissions and low water consumption Afsordegan et al. (2015). Wind power is an important renewable energy source with positive social and economic benefits. In addition, the technology is deemed to be revolutionary and has been selected as the main power source for Europe's 2020 goals to attain 20% renewable energy in their energy mix (European Commission, 2013). It has recorded a consistent growth of global installed wind generation capacity by more than 20% a year, in the last 10 years of the world (Torres Sibille et al., 2009).

However, even tough investment in this renewable energy has a potential to improve the economic development especially in rural places and public residences and this energy is more environmentally friendly than conventional energy, it also imply some negative impacts on a local scale. Wind farms have a strong influence on their local environment such as the poor integration of turbines into the landscape view with aesthetic and visual impacts. Landscape is a directly tangible and important asset for people and it is not be easily accepted by local people. So, the point is "properly" sited wind farms do no harm to property values or to those who live in the neighbourhood.

Nevertheless, wind farm location is a problem that involves multiple and conflicting factors related to public opinion and interest. Different stakeholders may have different expectation and conflicting requirements with each others. Therefore, these problems deal with high conflict on a local scale and social actors. According to the need for public participation together with MCDA methods, Social Multi-Criteria Evaluation (SMCE) framework is proposed by Munda (2004). The main advantage of this framework is the flexibility and adaptability to real-world high dynamic situation (Bergh and Brunisma, 2008). In this framework alternatives are constructed considering information from several sources such as *focus group* and *interviews to key persons*, in order to have an idea of social actors. In the next section, alternatives and indicators which have been studied in this case is presented.

### 4.2.1 Study of wind farm locations and indicators

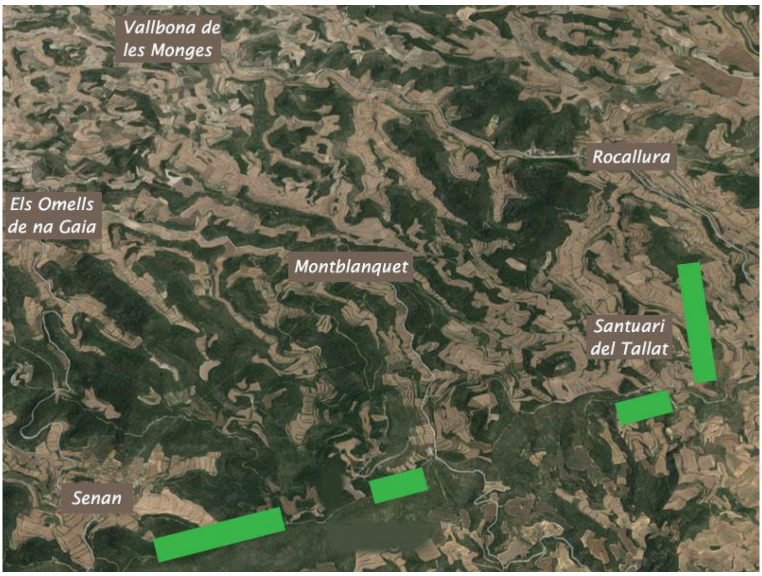
This application is a case of selecting the best wind farm location in Catalonia (northeast of Spain), located in a region between the counties of *Urgell* and *Conca de Barberá* (Figure 4.4). This case study has been done based on data provided by the research group in the project of Universitat Autónoma de Barcelona.

Figure 4.4: *Urgell* and *Conca de Barberá* counties


Considering two alternatives corresponding to *Coma Bertran* (CB) and *Serra del Tallat* (ST) projects, and combination of them, three preliminary alternatives CB-Pre, ST-Pre and CBST-Pre were defined. These basic alternatives only taken into account the study of technical and economical aspects. After further discussion only CB-Pre were left for evaluation.

Other alternatives (CB, ST, CBST) were generated based on the technological and economic feasibility, and "acceptance of some social actors" involved in this project. Considering the worry of some people about the visual impact of the wind farms, two modified projects L and R take into account the reduction of visual impact of the original proposals. The basic feasibility zones based on two preliminary projects CB and ST, together with two modified projects L and R have been shown in Figure 4.5. The last alternative is the possibility of not constructing wind park at all (NP), which is the Business as Usual (BaU) situation. Table 4.13 indicates the proposed alternatives for the location of the desired wind farms. The detailed features of these alternatives is presented in Table 4.14. Figure 4.6 shows the specific locations of wind mills for each alternative.

Figure 4.5: Technical feasibility zones




Some municipalities and some citizens were in favor of constructing wind farm plants in the two preliminary projects as a good opportunity to increase their income and to improve social services and some others were against it. The main social and economic actors participating in this project are detailed in Table 4.15.

To find the best wind farm location, the relevant economic, social,

Table 4.13: Alternatives for the location of wind farm

| **Alternatives** |
|---|
| **CB-Pre**: Coma Bertran Preliminary project. |
| **CB**: Coma Bertran project. |
| **ST**: Serra del Tallat project. |
| **CBST**: Combination of CB and ST projects. |
| **L**: Based on CB and ST projects, considers the windmills located at least more than 1.5 km far from population centres and potential tourist attractions (Santuari del Tallat). |
| **R**: This option attempts to move the windmills away from population centers presenting higher resistance to the wind farms (Senan and Montblanc) |
| **NP**: the possibility of constructing no project at all. |

Table 4.14: Alternatives features

| **Alternatives** | **CB-Pre** | **CB** | **ST** | **CBST** | **L** | **R** | **NP** |
|---|---|---|---|---|---|---|---|
| Number of windmills | 16 | 11 | 33 | 44 | 26 | 24 | 0 |
| Power capacity (MW) | 13.6 | 16.5 | 49.5 | 66 | 39 | 36 | 0 |
| Rotor height (m) | 55 | 80 | 80 | 80 | 80 | 80 | 80 |
| Blades diameter (m) | 58 | 77 | 77 | 77 | 77 | 77 | 77 |

technical and environmental perspectives must be taken into account in the decision-making process to reach a possible solution. Environmental and social assessment are mainly carried out to satisfy all social actors. Some studies have examined different key factors and indicators which are involved in the wind farm selection such as wind availability, site advantage, policy support, advanced technologies, wind turbine cost, connection cost and technical risks Enzensberger et al. (2002); Lee et al. (2009); Wolsink (2010); Yeh and Huang (2014). Lee et al. (2009) proposed six dimensions for evaluating the best wind location: safety and quality, economic, social impression, environment and ecology, regulation, and policy.

Figure 4.6: Locations of wind mills

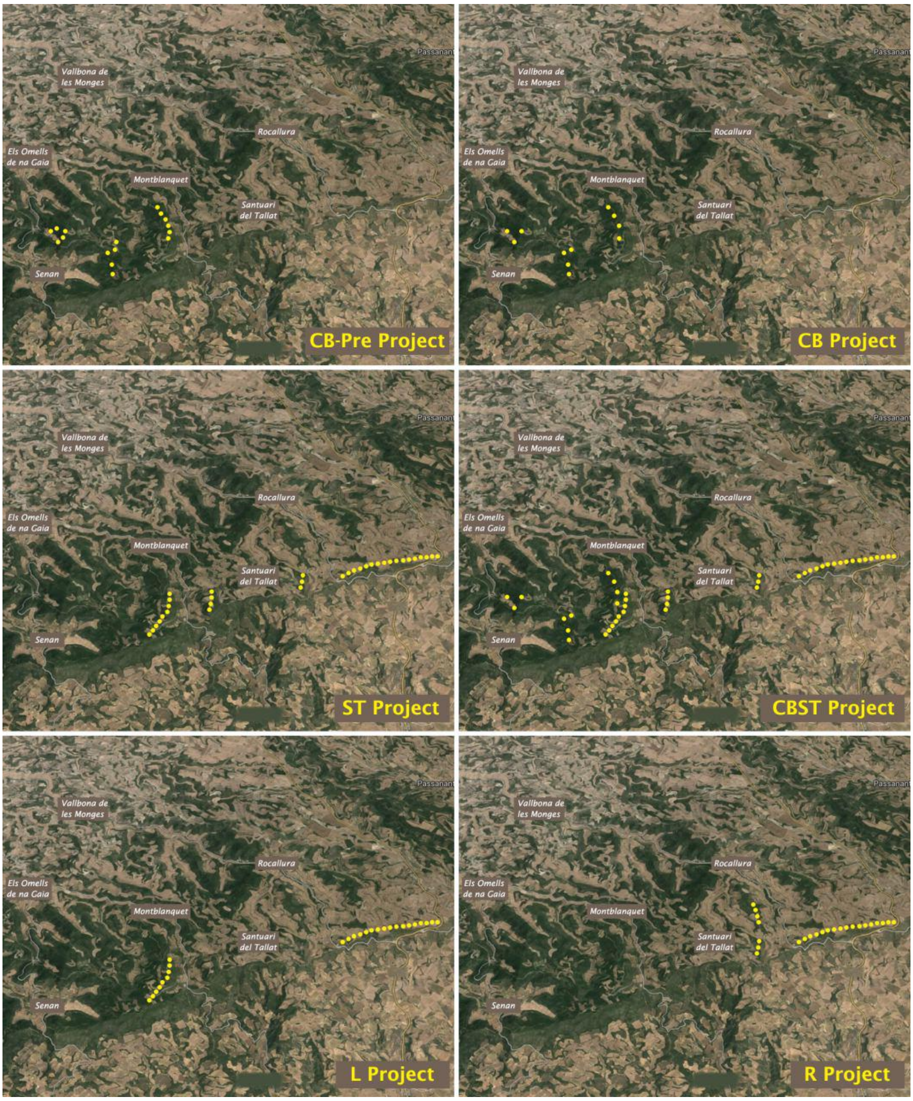


Table 4.15: Actors in wind farm project

| Actors | Level of action |
|---|---|
| **National social actors** | Catalunya government |
| | Environmental non-governmental organization |
| | Enegiá Hidroelećtrica de Navarra (EHN) |
| | Gerrsa (The promoter of the Coma Bertran project) |
| **Province actors** | President of the Consell comarcal de l'Urgell |
| | Politic representatives |
| | Coordinating committee to defend the land |
| | Plataform for Senan |
| **Local-Province actors** | Municipality of Vallbona de less Monges |
| | Municipality of Rocallaura |
| | Municipality of Els Omells de Na Gaia |
| | Town council od Senan |
| | Association of friends and neighbors of Montblanquet |

In the study of Yeh and Huang (2014) the summary of the decision criteria in the literature for determining wind farm location can be found. In this study, alternatives are evaluated on the basis of nine indicators which are defined by combining information from participatory processes, interviews and a review of the projects in regional scale performed by the research group (see Table 4.16).

*Social and ecological criteria:*

Social issues affect the permission process for project approval and include public acceptance and visual impact. The attitude of people about wind farm location is different from place to place. In some countries a lot of developers have been forced to invest on offshore projects because people do not want to see wind turbines near their towns. While it could make economic sense to site a wind farm near an urban centre, the social impact would prevent such proximity.

People often see visual impact and noise impact ecological indicatoras aa main factors in fuelling social resistance to wind farm development. Activists who oppose wind farm developments have coined slogans like NIMBY (Not in My Back Yard), and BANANA (Build Absolutely Noth-

Table 4.16: Evaluation Criteria

| **Criteria** | **Indicators** | Units | **Direction** |
|---|---|---|---|
| Economic | Land owner's income ($C_1$) | € /year | + |
| | Economic activity tax ($C_2$) | € /year | + |
| | Construction tax ($C_3$) | € | + |
| Social | Number of jobs ($C_4$) | Per person | + |
| | Visual impact ($C_5$) | $km^2$ | - |
| Ecological | Deforestation ($C_6$) | $ha$ | - |
| | Avoided $CO_2$ emissions ($C_7$) | ton $CO_2$ /year | + |
| | Noise ($C_8$) | $dB(A)$ | - |
| Technical | Installed capacity ($C_9$) | $MW$ | + |

ing Anywhere Near Anything) in their campaigns (PennWel, 2012). In fact, on the global scale everyone agrees that GHG should be reduced and the share of renewable energy should be increased, but on the local scale many people are not willing to suffer the disadvantages.

*Economic and technical criteria:*

Economic factors do not only affect the locations of the wind farms but also the sizes of the farms themselves. The economic and technical criteria include site accessibility, proximity to the grid, availability of installation equipment, income and taxes and installed capacity. All these indicators have been considered in this study. The best is to locate wind farm as close to an existing grid as possible. It is also necessary that the grid can handle the capacity you plan to generate. If not, the wind farm developer or transmission company has to extend it.

Wind farms can only be located in areas with good wind regimes, these are sometimes remote or isolated areas, thus the grid improvements turn out to be expensive. Another issue that technically affects generating wind power is installed capacity. The size of a wind farm or the amount of power that can be generated is determined by the capacity that can be installed.

### 4.2.2 Q-TOPSIS computations and results

The criteria scores were computed to construct the multi-criteria impact matrix. Table 4.17 presents the impact matrix of the problem we are dealing with. The criteria scores are obtained from a study of Gamboa and Munda (2007).

These scores must be aggregated by means of the proposed algorithm to achieve the final ranking of the alternatives. Note that in this study, equal weights for indicators are considered.

The steps of the Q-TOPSIS algorithm, detailed in Chapter 3, are executed. The highest and lowest scores of each criterion are respectively considered, as the maximum and minimum elements of the qualitative space, and therefore as reference labels. The first step of this algorithm is assigning qualitative labels to the quantitative scores to simplify the computation in the process of ranking.

Table 4.17: Multi-criteria impact matrix

| **Criteria** | **CB-Pre** | **CB** | **ST** | **CBST** | **L** | **R** | **NP** |
|---|---|---|---|---|---|---|---|
| $C_1$ | 48000 | 33000 | 99000 | 132000 | 78000 | 72000 | - |
| $C_2$ | 12750 | 15470 | 46410 | 61880 | 36570 | 33750 | - |
| $C_3$ | 61990 | 55730 | 96520 | 152250 | 81890 | 67650 | - |
| $C_4$ | 2 | 1 | 4 | 5 | 3 | 3 | - |
| $C_5$ | 76.057 | 71.465 | 276.55 | 348.015 | 220.4 | 163.29 | - |
| $C_6$ | 8.04 | 8.1 | 6.6 | 14.7 | 3.9 | 2.6 | - |
| $C_7$ | 4680 | 6010 | 19740 | 25750 | 14740 | 13760 | 30000 |
| $C_8$ | 14.64 | 23.86 | 18.6 | 23.84 | 20.88 | 14.66 | - |
| $C_9$ | 13.6 | 16.5 | 49.5 | 66 | 39 | 36 | - |

Table 4.18 shows these qualitative labels together with their locations, where the considered measure $\mu$ over the set of basic labels is $\mu(B_i) = 1$, for all $i = 1, \dots, 7$.

Table 4.18: Different levels of qualitative labels

| **Linguistic terms** | **Qualitative labels** | **locations** |
|---|---|---|
| Very Poor (VP) | $B_1$ | (0,6) |
| Poor (p) | $B_2$ | (-1,5) |
| Medium Poor (MP) | $B_3$ | (-2,4) |
| Fair (F) | $B_4$ | (-3,3) |
| Medium Good (MG) | $B_5$ | (-4,2) |
| Good (G) | $B_6$ | (-5,1) |
| Very Good (VG) | $B_7$ | (-6,0) |

The Q-TOPSIS approach considered in this example uses seven basic qualitative labels for each criterion. The basic qualitative labels correspond to seven intervals defined from minimum and the maximum values of the corresponding raw scores in Table 4.17 and their lengths, which are one seventh of the distance between these two values. For instance, land owner's income indicator has the same label ($B_4$) in projects L and R, because both of them stand on the same interval $B_4$. Labels in the qualitative impact matrix are provided in this way (Table 4.19).

Table 4.19: Qualitative impact matrix

| **Criteria** | **CB-Pre** | **CB** | **ST** | **CBST** | **L** | **R** | **NP** |
|---|---|---|---|---|---|---|---|
| $C_1$ | $B_3$ | $B_2$ | $B_5$ | $B_7$ | $B_4$ | $B_4$ | $B_1$ |
| $C_2$ | $B_2$ | $B_2$ | $B_5$ | $B_7$ | $B_4$ | $B_4$ | $B_1$ |
| $C_3$ | $B_3$ | $B_3$ | $B_5$ | $B_7$ | $B_6$ | $B_3$ | $B_1$ |
| $C_4$ | $B_3$ | $B_2$ | $B_6$ | $B_7$ | $B_5$ | $B_5$ | $B_1$ |
| $C_5$ | $B_6$ | $B_6$ | $B_3$ | $B_1$ | $B_4$ | $B_5$ | $B_7$ |
| $C_6$ | $B_3$ | $B_3$ | $B_4$ | $B_1$ | $B_6$ | $B_6$ | $B_7$ |
| $C_7$ | $B_2$ | $B_2$ | $B_6$ | $B_7$ | $B_5$ | $B_4$ | $B_7$ |
| $C_8$ | $B_3$ | $B_1$ | $B_2$ | $B_1$ | $B_1$ | $B_3$ | $B_7$ |
| $C_9$ | $B_2$ | $B_2$ | $B_5$ | $B_7$ | $B_4$ | $B_4$ | $B_1$ |

Each alternative ($A$) is represented by a 9-dimensional vector of qualitative labels $A = (C_1, \ldots, C_9)$, obtained from the assessment of indicators

($C$). As mentioned in Section 3, each label is represented via a vector in $\mathbb{R}^2$. Therefore, the location function $L(A)$ codifies each alternative by an 18-dimensional vector of real numbers representing the location of the vector A, $L(A) = (X_1, \ldots, X_{18})$.

Table 4.20 shows the alternative evaluation matrices via the locations of the nine indicators. The two vectors $L(A^-) = L(B_1, \ldots, B_1) = (0, 6, \ldots, 0, 6)$ and $L(A^*) = L(B_7, \ldots, B_7) = (-6, 0, \ldots, -6, 0)$ are considered as reference labels to compute distances (worst and best options).

Table 4.20: Location impact matrix

| **Criteria** | **CB-Pre** | **CB** | **ST** | **CBST** | **L** | **R** | **NP** |
|---|---|---|---|---|---|---|---|
| $C_1$ | (-2,4) | (-1,5) | (-4,2) | (-6,0) | (-3,3) | (-3,3) | (0,6) |
| $C_2$ | (-1,5) | (-1,5) | (-4,2) | (-6,0) | (-3,3) | (-3,3) | (0,6) |
| $C_3$ | (-2,4) | (-2,4) | (-4,2) | (-6,0) | (-5,1) | (-2,4) | (0,6) |
| $C_4$ | (-2,4) | (-1,5) | (-5,1) | (-6,0) | (-4,2) | (-4,2) | (0,6) |
| $C_5$ | (-5,1) | (-5,1) | (-2,4) | (0,6) | (-3,3) | (-4,2) | (-6,0) |
| $C_6$ | (-2,4) | (-2,4) | (-3,3) | (0,6) | (-5,1) | (-5,1) | (-6,0) |
| $C_7$ | (-1,5) | (-1,5) | (-5,1) | (-6,0) | (-4,2) | (-3,3) | (-6,0) |
| $C_8$ | (-2,4) | (0,6) | (-1,5) | (0,6) | (0,6) | (-2,4) | (-6,0) |
| $C_9$ | (-1,5) | (-1,5) | (-4,2) | (-6,0) | (-3,3) | (-3,3) | (0,6) |

Then, the weighted Euclidean distance of each alternative from the two reference labels is calculated as follows:

$$d(A, \tilde{A}) = (\sum_{j=1}^{9} w_j (X_j - \tilde{X}_j)^2))^{1/2} \tag{4.4}$$

The considered weights in this case are equal. Table 4.21 shows the values of the distances to the reference labels of each alternative together with the values of the $QCC_i$.

Table 4.21: Qualitative closeness coefficient factors

| | $d_i^-$ | $d_i^*$ | $QCC_i$ |
|---|---|---|---|
| CB-Pre | 3.26 | 5.88 | 0.35 |
| CB | 2.90 | 6.56 | 0.30 |
| ST | 5.33 | 3.88 | 0.57 |
| CBST | 6.92 | 4.89 | 0.58 |
| L | 5.12 | 4.26 | 0.54 |
| R | 4.73 | 4.13 | 0.53 |
| NP | 4.89 | 6.92 | 0.47 |

According to the maximum $QCC_i$ values, the best alternative is CBST and the order of the remaining of alternatives is ST > L > R > NP > CB-Pre > CB. Alternative CBST and after that alternative ST are selected as first and second best options because of the good performance in economic terms and intermediate environmental impacts.

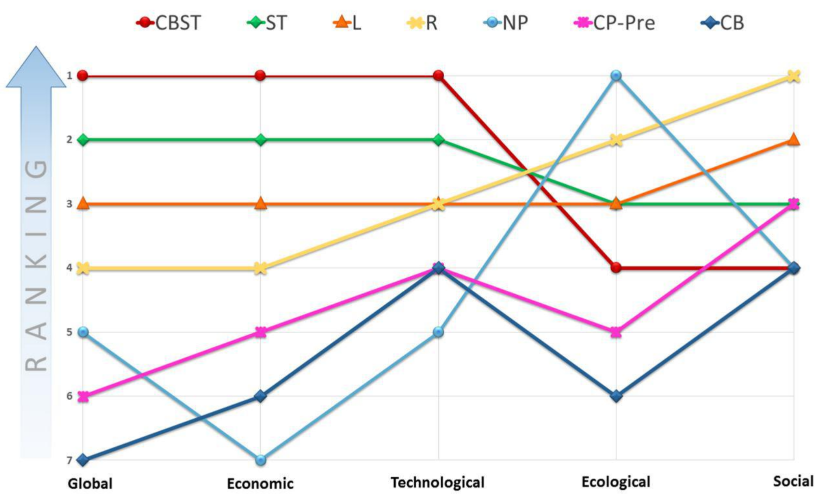
In addition, the analysis of ranking in the level of criteria is performed. This analysis shows that however some alternatives have the best performance in one criteria, but they have the worst performance in another, such as NP. Table 4.22 and Figure 4.7 show the ranking of alternatives based on each economic, social, ecological and technical criteria in comparison with the general ranking.

Table 4.22: Rankings of alternatives according to each criteria

| Alternatives | Goal Ranking | Economic criteria | Technical criteria | Ecological criteria | Social criteria |
|---|---|---|---|---|---|
| CBST | 1 | 1 | 1 | 4 | 4 |
| ST | 2 | 2 | 2 | 3 | 3 |
| L | 3 | 3 | 3 | 3 | 2 |
| R | 4 | 4 | 3 | 2 | 1 |
| NP | 5 | 7 | 5 | 1 | 4 |
| CB-Pre | 6 | 5 | 4 | 5 | 3 |
| CB | 7 | 6 | 4 | 6 | 4 |

Changing the orders of alternatives in different criteria shows that when the preferences of the group of actors are for example in favor of ecological benefits alternatives NP, R and L are stands on as better choices than CBST and ST. Here the same weights used for all criteria according to the social actors' agreements, but increasing weights of these criteria can be affected the final ranking. Furthermore, some alternatives such as R and L have similar positions in different criteria. It means that these alternatives could be generally good options, if we are going to consider all the social actors preferences. For example, in CBST the weak performance in social value compensated by economic and technical high values. In this way, in order to avoid compensation, alternatives R and L have better performances because for instance, R is ranked as a best alternative according to social criteria and second and third in ecological and technical criteria. The only weak performance is its intermediate ranking in economic aspects which is not compensated by other criteria.

Figure 4.7: Rankings in the global and criteria levels




It is concluded that the rankings are depended on the preferences of social actors to avoid this compensation or not.

### 4.2.3 Results comparison

In this section, the results obtained by Q-TOPSIS is compared with the C-K-Y-L results, which their main theoretical features have been introduced in Section 3.4.2. This comparison has been done in order to take into account the result obtained by MCDM methods with different perspectives and different aggregation ranking functions. In this method a threshold for each indicator is defined and the pair-wise comparisons between alternatives are performed according to these threshold values. The results provided by the C-K-Y-L method in Gamboa and Munda (2007) present the five best rankings with the maximum score among all 7! (5040) possible rankings according to the seven alternatives (see Table 4.23).

Table 4.23: Rankings obtained by C-K-Y-L method

| C-K-Y-L | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| Ranking 1 | CBST | ST | L | R | CB | CB-Pre | NP |
| Ranking 2 | CBST | ST | L | R | CB-Pre | CB | NP |
| Ranking 3 | CBST | L | ST | R | CB | CB-Pre | NP |
| Ranking 4 | CBST | ST | R | L | CB | CB-Pre | NP |
| Ranking 5 | CBST | ST | L | R | CB | NP | CB-Pre |

To sum up, Table 4.24 shows the final ranking produced by the Q-TOPSIS method together with the first ranking obtained by applying the C-K-Y-L method.

Table 4.24: Comparison of ranking results

| Ranking | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| Qualitative TOPSIS | CBST | ST | L | R | NP | CB-Pre | CB |
| C-K-Y-L | CBST | ST | L | R | CB | CB-Pre | NP |

As shown in Table 4.24, the differences of rankings occurred in the case of the NP and CB options. In the proposed Q-TOPSIS method, the option of No Project (NP) is not considered as a worst option because it depends on the distance of this alternative from the best and the worst scores. So, the intensity of preferences is considered. In contrast, C-K-Y-L method does not consider this intensity and this alternative always loses in the pair-wise comparison against all the others.

Also C-K-Y-L explores $N!$ possible rankings and this is the difficulty in computing when there are many alternatives. In contrast, Q-TOPSIS has a simple process, as mentioned in Section 3.4.2.2, to provide the final ranking. Q-TOPSIS also can performed rankings for each economic, technical, social and ecological criteria.

## 4.3 An application to urban energy systems: Energy efficiency in buildings

Urban energy systems present multiple identities with multiple criteria, which are subject to non-equivalent descriptions and the relevant aspects cannot be captured using a single perspective. For example in the case of buildings, an architect would describe the criteria in terms of volumes, shapes, materials and orientation. By contrast, sociologist would look at the people living in the buildings, and describe it according to demographic, cultural and socio-economic characteristics. Different persons with different backgrounds would focus on different aspects of the buildings according to what they consider relevant for the analysis.

In order to deal with this issue, this study introduces the proposed method applied to the SEMANCO (Semantic tools for carbon reduction in urban planning) project to assess the energy performance of urban plans and to compare them against the baseline and each other. Urban energy system models analyze the impacts of various scenarios, evaluate different policy measures, test technological level solutions (i.e. using CHP, using renewable energy sources, etc.) and finally identify opportunities for energy efficiency by comparing and ranking possible scenarios (Keirstead et al., 2012). Therefore, an integration of these models with MCDM support policy-makers, city planners and businesses such as suppliers, and technology manufacturers for making decisions.

As economy advances and human society requires more energy, the problem of reducing $CO_2$ emissions in cities has given rise to a serious contradiction among energy supply, environment protection and economic development. It is necessary to change the energy structure, integrating new models and modifying the way we use energy such as improving the energy efficiency of buildings by means of an urban energy system model. The buildings sector has significant impacts on communities. At the same time, it is the sector with the highest cost and environmental saving potentials provided effective strategies are implemented.

Buildings are responsible for 33% of worldwide energy-related GHG emissions; also it has been identified as a sector where huge savings can be made. For example, the 40% of energy consumed by buildings in the European Union (EU), estimates reveal that the implementation of energy-efficiency measures could lead to cost-saving of around 28% (Ekins and Lees, 2008). From an energy perspective, buildings are complex systems. Households, in particular, have a share of 29% of the total energy consumed and release 21% of the total emissions (International Energy Agency, 2008). Therefore, the built environment is arguably a sector that can play an important role in mitigating climate change impacts, reducing energy use and natural resources (Abanda et al., 2013; Robert and Kummert, 2012).

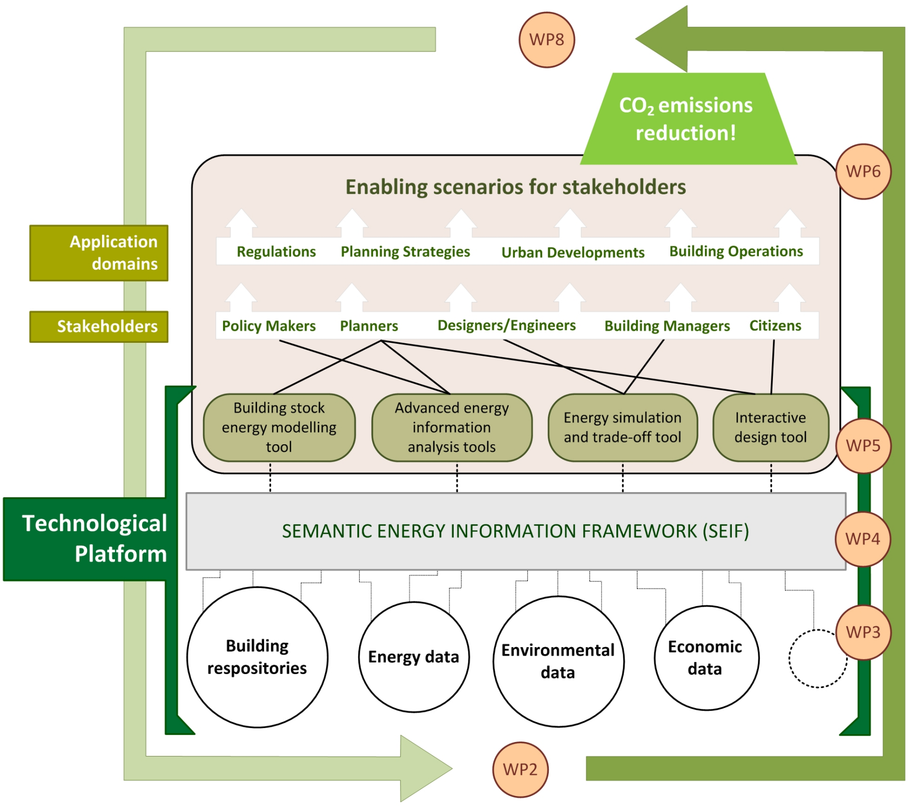
### 4.3.1 The SEMANCO platform

Recently, in small and big cities, sustainability practitioners focus their attention on improving buildings performance. In the SEMANCO project, semantic technologies have been used to create models of urban energy systems able to assess the energy performance of an urban area to make informed decisions about how to reduce $CO_2$ emissions in cities.

The goal of the SEMANCO research project is to create a comprehensive framework in which semantic energy information brings the data sources at different scales from different domains. This integration of data from multiple sources with different tools is handled by a Semantic Energy Information Framework (SEIF), as a key technological component developed in this project (Madrazo et al., 2013). This framework is the connection between the different data sources and the tools which use the semantically modeled data Figure 4.8.

In the integrated platform, the experts' knowledge is captured through the use case method, as well as the links to the external data sources which are available via the SEIF. This combination of knowledge and information constitutes the base for creating energy models for a specific urban area. The SEMANCO integrated platform is based on the following components (see Figure 4.9):

Figure 4.8: Structure of the SEMANCO project. Source: Sicilia et al. (2012)




1. **Urban Energy System (UES)**. The creation of a UES is the first step in considering a given urban area within the SEMANCO platform. A UES refers to an urban area being studied using the SEMANCO platform. It conveys a definition of the energy efficiency objectives, and the identification of the actors involved, physical components and the available data resources.

2. **Urban Energy Models (UEM)**. These models are created using semantic data and tools to assess the actual baseline energy perfor-

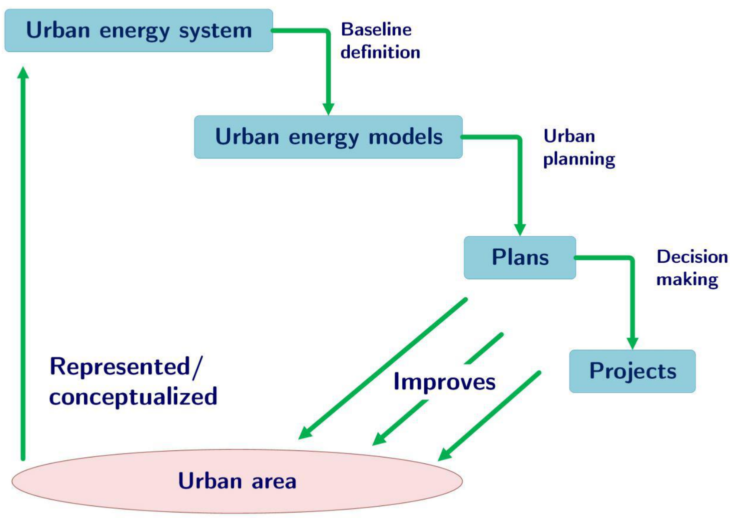
mance of the area.

3. **Plans** are developed from a given UEM. For the UEM being considered, there can be any number of plans. Each plan involves the selection of a specific area, or set of buildings.

4. **Projects** are developed from plans, by selecting a set of proposed energy efficient interventions and applying these using the tools of the SEMANCO integrated platform.

5. **Analysis** refers to the use of the multi-criteria evaluation tool within the SEMANCO integrated platform in order to assess how the different projects for a given plan compare to each other and to select the best among them.

Figure 4.9: Platform components. Source:

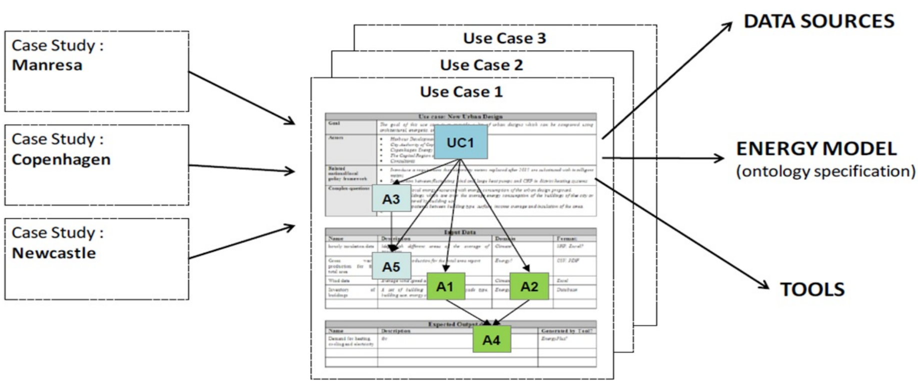



Ontology can be used to create shared vocabularies which help experts from different fields to establish relationships between certain objects of an urban energy system according to their knowledge and experience (Gruber, 1993). It can serve to promote communication between the semantically modeled data and the various software applications used by experts. This ontology has been applied to three case studies in the SEMANCO project, first at the buildings scale and later on at the urban level (Corrado et al., 2015). Different scenarios located in Copenhagen (Denmark), Manresa (Spain) and the Newcastle (United Kingdom) will enable defining the scope of the research and outlining the specifications for the tools needed by stakeholders in different domains (Figure 4.10).

Use cases defined by means of these templates are a foundation in the ontology buildings process. This study focusing is on the city of Manresa, the capital of the region of Bages, located in the geographic centre of Catalonia, with a population of 76,558. The urban energy model contains 2415 buildings with a total surface built of 2062537 $m^2$. Within this urban energy model 13 plans and 21 projects have been developed.

The platform shown in Figure 4.11 has been designed to support services for different user groups. Real energy and different information such as socio-economic information can be obtained before and after implementation of some actions. The description of buildings typologies will consider the energy carriers used and final use within the buildings and neighbourhood levels.

Figure 4.10: The SEMANCO project case studies. Source: Madrazo et al. (2013)



Experts can represent the existing conditions of the urban system (descriptive model), analyze the future evolution of the system (predictive model), explore different scenarios for future development (exploratory model) and propose improvement plans and evaluate projects to improve the performance of the urban energy system (planning model) using MCDM tools (Madrazo et al., 2014). The MCDM methods compares alternatives in order to decide which improvements might be most suitable by generating a new plan. Figure 4.12 shows that each plan has a set of project attached to consider the effect of different measures for example window improvement, heating system improvement, roof isolation and adding renewable thermal energy supply. The user can switch back to the plan interface and use the multi-criteria tool developed to compare the interventions contained within each project. This helps them decide which project they would prefer in practice. These measures can be categorized in the following groups:

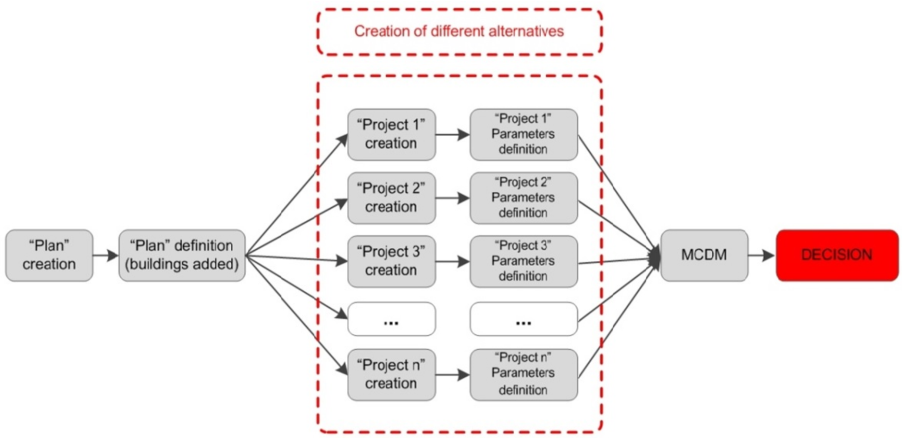
Figure 4.11: Integrated platform and buildings selection in the platform interface. Source: Madrazo et al. (2014)


- Measures for the improvement of the buildings' envelope (addition or improvement of insulation, change of color, placement of heating-insulating and cooling techniques and buildings shaping)
- Measures for reducing the heating and cooling loads

- Use of renewable energy (solar thermal systems, buildings' integrated PV and hybrid systems)
- Use of intelligent energy management (advanced sensors and monitoring systems)
- Measures for the improvement of the indoor conditions (improvement of boilers and air-conditions efficiency
- Use of energy efficient appliances and compact fluorescent lighting.

according to variety of proposed measures, the main problem is to choose the more effective and reliable alternative or a feasible solution in the long term.

Figure 4.12: Work-flow for decision making within the platform. Source: Carpenter et al. (2014)




In order to illustrate the use of the MCDM methods within the SEMANCO integrated platform, let us consider a baseline case to refit the set of buildings and three projects proposing different ways of saving energy efficiency have been created. The basic results can be seen in the following section.

Table 4.25: Relevant indicators

| Indicators | Definition |
|---|---|
| Energy demand heating ($kWh/m^2$) | The total annual consumption of energy spend on heating per $m^2$ for households and office buildings is needed to find this indicator along with the number of $m^2$ in households and office buildings in the scenario. |
| $CO_2$ emission ($kgCO2/m^2$) | Input needed is $CO_2$ emission-factors for heat produced, the total heat produced and total heat consumed, all within the city district, along with $CO_2$ emission-factors for heat produced outside the city district. |
| Heating cost €$/m^2$ | The total cost of supplying heat (investments, running costs, profit margin, etc.) and the total amount of heat produced from different sources. |
| Ease of implementation | Qualitative indicator based on expert's opinion |
| Social acceptability | Qualitative indicator based on social opinion |

### 4.3.2 Implementation of Q-TOPSIS for selecting an appropriate project

In this section, the results provided by Q-TOPSIS applied to SEMANCO platform are presented to show the ability of using multi-granular lables for evaluations and ease of use. Indicators are crucial components in the overall assessment of progress towards sustainable development. In this study, the indicators shown in Table 4.25 are considered according to the input needed. On the other hand, two qualitative criteria which are ease of implementation and social acceptability are also considered to use the advantage of expert's assessment by means of Q-TOPSIS approach (Afsordegan et al., 2014).

According to the given relative importance via experts, possible improvement: using heat pumps, using solar PV or using extra insulation are defined as project A, project B and project C, respectively. The baseline (current plan), which is denoted by the plan's name "Policy changes", is also considered in the analysis (Figure 4.13). The calculated baseline will be a reference to assess the effectiveness of the improvement

Figure 4.13: New plan sample platform

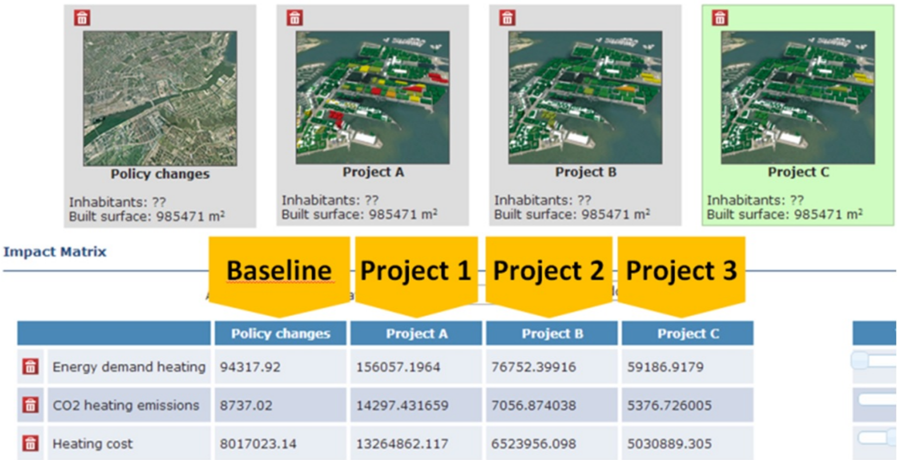



Table 4.26: Different indicators with different granularity

| Indicators | Granularity | Reference label locations | |
|---|---|---|---|
| | | QPRL | QNRL |
| Energy demand heating | $(B_1, \cdots, B_{10})$ | $(-9, 0)$ | $(0, 9)$ |
| $CO_2$ emission | $(B_1, \cdots, B_8)$ | $(-7, 0)$ | $(0, 7)$ |
| Heating cost | $(B_1, \cdots, B_5)$ | $(-4, 0)$ | $(0, 4)$ |
| Ease of implementation | $(B_1, \cdots, B_7)$ | $(-6, 0)$ | $(0, 6)$ |
| Social acceptability | $(B_1, \cdots, B_7)$ | $(-6, 0)$ | $(0, 6)$ |

plans developed for the last round of demonstration scenarios.

The highest score of each criterion are respectively considered as the reference label of the qualitative space. Table 4.26 shows these qualitative labels together with their locations.

The first step of this algorithm is assigning qualitative labels to the quantitative scores to simplify the computation in the process of ranking. The Q-TOPSIS method considered in this example uses different basic qualitative labels *with different granularity* for each criterion which corresponds to several intervals whose length is defined via the distance of

Table 4.27: Indicator's values

| **Indicators** | **Baseline** | Project A | Project B | Project C |
|---|---|---|---|---|
| Energy demand heating | 94317.92 | 156057.19 | 76752.39 | 59186.91 |
| $CO_2$ emission | 8737.02 | 14297.43 | 7056.87 | 5376.72 |
| Heating cost | 8017023.14 | 13264862.11 | 6523956.09 | 5030889.30 |
| Ease of implementation | VP | MG | G | F |
| Social acceptability | F | MG | MP | P |

Table 4.28: Basic linguistic labels

| **Indicators** | **Baseline** | Project A | Project B | Project C |
|---|---|---|---|---|
| Energy demand heating | $B_5$ | $B_1$ | $B_6$ | $B_7$ |
| $CO_2$ emission | $B_4$ | $B_1$ | $B_5$ | $B_6$ |
| Heating cost | $B_3$ | $B_1$ | $B_3$ | $B_4$ |
| Ease of implementation | $B_1$ | $B_5$ | $B_6$ | $B_4$ |
| Social acceptability | $B_4$ | $B_5$ | $B_3$ | $B_2$ |

minimum and maximum scores. Then, the Euclidean distance of each alternative from two reference labels is calculated. Finally, these values are combined to give a single ranking for each improvement type. The intention is not that the output from this tool should be followed in an absolute manner but rather that it should serve to aid decision makers by clarifying their intentions.

The values of three first quantitative indicators are provided from the simulation of new plan in platform, which can be transformed to the basic labels according to their specific granularity. In addition, the two second qualitative indicators, ease of implementation and social acceptability, are obtained by the assessment of one expert in urban planning. These values are presented in Table 4.27 and 4.28 using seven basic linguistic labels: Very Poor ($B_1$), Poor ($B_2$), Medium Poor ($B_3$), Fair ($B_4$), Medium Good ($B_5$), Good ($B_6$), Very Good ($B_7$).

Table 4.29 shows the values of the distance of each alternative to the reference labels. According to the maximum $QCC_i$, the following ranking, using same weights, is presented: Project C > Project B > Baseline > Project A. This ranking shows that the policy of using extra insulation and after that using solar PV are more efficient than baseline and using heat pumps policies in the simulated plan of energy efficiency of buildings in Manresa.

Table 4.29: Distances aggregation

| **Ranking** | $QCC_i$ |
|---|---|
| Project C | 0.56 |
| Project B | 0.54 |
| Baseline (Policy changes) | 0.39 |
| Project A | 0.31 |

On the basis of the current plan, project C is better in all indicators except social acceptability which has a minimum importance among other indicators. In the comparison of best options, project C is a winner in quantitative indicators and project B in qualitative ones. So, being the weights of qualitative indicators more important can cause a ranking reversal between these two options (see Table 4.30 and 4.31).

The proposed method for ranking these projects, does not require the handling of the previous discretization or definition of landmarks to define initial qualitative terms because the calculations are performed directly with the labels so the computations are very fast and easy.

Table 4.30: Using different weights

| **Indicators** | **Weight1** | **Weight2** | **Weight3** |
|---|---|---|---|
| Energy demand heating | 1 | 5 | 1 |
| $CO_2$ emission | 1 | 2 | 2 |
| Heating cost | 1 | 5 | 1 |
| Ease of implementation | 1 | 1 | 5 |
| Social acceptability | 1 | 1 | 3 |

Table 4.31: Different rankings

| **Ranking 1** Using same weights | **Ranking 2** More weights for quantitative indicators | **Ranking 3** More weights for qualitative indicators |
|---|---|---|
| Project C | Project C | Project B |
| Project B | Project B | Project C |
| Baseline | Baseline | Project A |
| Project A | Project A | Baseline |

Additionally, the Q-TOPSIS method can address different levels of precision, using multi-granular basic labels in this case, which represent the most precise ones to the least precise label which can be used to represent unknown values. So, it is possible to guarantee transparency and the intensity of preferences is considered.

# Chapter 5

# Conclusions

This chapter presents a summary of the most important contributions of this thesis together with suggestions for future development of the presented work and possible extensions for future applications. Finally, additional research, projects and publications derived from this thesis have been presented.

In this work a new TOPSIS method is introduced based on classic TOPSIS and qualitative reasoning techniques. TOPSIS methods need only a minimal number of inputs from the user and their output is very easy to understand. These methods offer an important advantage over other reference level methods such as goal programming and VIKOR. Specifically, when two alternatives are equidistant from the ideal solution, the one with greater distance from the anti-ideal solution is the better alternative. Previous methods only considered the distance to the ideal solution. The classic TOPSIS method first gathers the performance of each alternative according to different criteria, and then it normalizes these performances. Finally, it provides an output result by means of an index with values in $[0, 1]$ for ranking alternatives.

Even though classic TOPSIS method provides several advantages, a weakness is that it handles crisp data which cannot model many real life problems. The new method introduced in this thesis, called qualitative TOPSIS (Q-TOPSIS), is more suitable for problems in which qualitative information for evaluating some indicators is required. This method could deal with both quantitative and qualitative input data and could support uncertainty in decision-making process. It offers decision makers the possibility of working with qualitative scales in their assessments. The proposed method is especially suitable for energy planning problems, since they usually require analysis and quantification of different types of variables involving imprecision in social and environmental aspects.

Moreover, in this new (Q-TOPSIS) method, different levels of precision for different experts based on their certain or uncertain knowledge help to keep all the information of their assessments instead of allowing some information to be ignored. In this way, if decision makers do not have enough knowledge about one criterion, they can indicate a range between two different assessments instead of an exact assessment. Even if a decision maker does not have any idea of the value for a specific attribute, he/she can use the label "I don't know".

## 5.1 Theoretical and managerial implications

Energy is a crucial factor for the economic development of nations. As economies and human societies advance, more energy is required. The increasing scarcity of fossil fuel energy and its pollution of the environment have given rise to serious contradictions among the competing priorities of energy provision, environmental protection, and economic development. Since the importance of renewable energies has increased, a crucial decision for governments and businesses is deciding the best choice of energy source policies for investment. According to the importance of energy issues, especially renewable energies, as one of the important paths of our energy future, our focus in this thesis is applying suitable methods to help DMs solve energy problems. Energy planning problems are serious problems caused by limited resources and human activities.

Sustainable energy planning problems require critical decisions in a variety of dynamic complexities with respect to conflicting criteria. In addition, energy planning problems usually involve multiple decision makers. These problems require the use of MCDM approaches, as useful tools in energy problems, to evaluate sustainability. In this thesis many literatures based on MCDM methods and energy planning have been studied. Moreover, an in-depth study of criteria and indicators in the energy area has been presented.

Considering environmental, technical, economic and social aspects, it is crucial to analyze and quantify different types of variables that involve imprecision. These factors, especially social ones, are not always precise, as uncertainty is feature of the real world. Therefore, in order to provide useful data from experts' assessments, a new MCDM method to support decision makers in all stages of the decision-making process with uncertain values is presented.

This approach, based on order-of-magnitude QR, provides a model that can obtain results from non-numeric variables. So, the main contribution of this thesis is the qualitative TOPSIS (Q-TOPSIS) method, which is introduced and applied in energy case studies with following features:

- This method is an adequate approach for dealing with high degree of conflict (sustainable development is a multi-dimensional concept: social, ethical, technical and environmental).
- This method takes into account intensity of preferences and gives experts the capability to assess alternatives under uncertainty by expressing their judgments using linguistic variables involving qualitative labels.
- The use of qualitative labels with different levels of precision is essential to obtaining user-friendly systems to be used by decision makers, especially energy planners, for evaluation processes. This method is able to capture the existing ambiguity inherent in human reasoning and addresses the problem in such a way that the principle of relevance is preserved: Each variable is valued with the level of precision required.

- It requires neither interaction between experts nor the participation of a moderator to obtain a final ranking. This avoids the potential subjectivity caused by conflicts of interest among evaluators.
- An expert can make mistakes if he/she is forced to make more precise judgments than the available information allows. On the other hand, a substantial loss of information may happen if the experts are forced to make less precise judgments.
- The output of the method is very easy to understand for decision makers and it has very low computational costs.
- It does not need previous normalization or previous aggregation before using a distance function.
- Problems can be evaluated by more than one expert. This method is suitable for multi-criteria group decision-making problems involving experts with strong knowledge and experts with weak knowledge in some aspects. The method makes it possible to assign different levels of influence to each expert and different weights to attributes.
- It permits multi-granular linguistic information to be expressed in a unified linguistic domain without losing information. The final ranking automatically aggregates all the information provided by the experts, computing words with different granularities and combining them to form a collective opinion.

The second contribution of this thesis is the proposed method has been applied to energy applications to show its potential and ease of use. Three applications of Q-TOPSIS in energy planning are presented in this research in order to show the simplicity of Q-TOPSIS in group decision making problems involving multi-dimensional concepts. First, the proposed method is applied in a case study of renewable energy alternative selection and compared with the modified fuzzy TOPSIS method. This comparison is performed using an example based on data provided by Kaya and Kahraman (2011b). The fuzzy AHP method is used to obtain weights of criteria to evaluate energy alternatives. We can conclude that, basically, both methods use linguistic variables: Q-TOPSIS in the form of qualitative labels with different levels of precision, and fuzzy TOPSIS by means of linguistic labels corresponding to the triangle fuzzy numbers. Furthermore, the final aggregation process of both methods finds the distance between each alternative and the best and worst solutions. However, the Q-TOPSIS method does not require any previous discretization or definition of landmarks for defining initial qualitative terms; in contrast, in the modified fuzzy TOPSIS, fuzzy labels are defined by means of cut-points that have to be set before any aggregation. The Q-TOPSIS method can address different levels of precision, from the most precise and basic labels to the least precise label, which can be used to represent unknown values. However, as can be seen in the Section 4.1, despite the flexibility of Q-TOPSIS in allowing imprecise assessments, the results obtained by applying both methods are similar. In addition, a simulation of 30 scenarios using different weights demonstrates that the simplicity and interpretability of Q-TOPSIS provides a general improvement in TOPSIS in the case of ordinal assessments.

Second, a real case study in a social framework to find an appropriate location for wind farms in Catalonia is presented. In this case different alternatives were proposed for the location of the desired wind farms in a region between the counties of Urgell and Conca de Barberà. These alternatives are evaluated on the basis of nine indicators which are defined by combining information from participatory processes, interviews and a review of the projects performed by the research group. Additionally, the qualitative TOPSIS method is used for evaluating these alternatives using basic labels. Ranking alternatives concludes that an alternative combining two different initial projects is the best option. Using the proposed method to handle a high degree of conflict in group decision making involving multi-dimensional concepts simplified the experts' measurements.

Finally, an application to energy efficiency in buildings using the SEMANCO platform is presented in order to assess the energy performance and $CO_2$ emissions of projected urban plans at the city level in Manresa.

The proposed qualitative TOPSIS approach is applied to the urban energy system to help policy makers and users in making appropriate decisions. This application of Q-TOPSIS helps decision makers to rank different projects with respect to both quantitative and qualitative criteria and offers outputs which are very easy for decision makers to understand.

## 5.2 Future work

Several directions of future work have been identified both in the theoretical part of the method and in applications for energy planning.

From the *theoretical point of view*, an extension of the proposed method using a hierarchical structure to capture the inherent ontology of decision makers' preferences should be considered in future research. This problem modeling based on sub-goals in a hierarchy helps DMs to understand complex problems and find a better model based on the DMs' knowledge in various subjects. It may help the DMs to have a better image of the problem's implications as a whole, as it allows DMs to represent the overall influence of each of these dimensions in an optimal way as well as to better understand the relevance of the variables involved.

We can also highlight the open problem of introducing the proposed method to group decision-making consensual processes, analyzing the degrees and solutions of agreement among groups of decision makers in energy planning problems. All the stakeholders involved in the project, should be evaluated alternatives with respect to criteria, until a high degree of global consensus was reached.

Research as to the role of the criteria weights also would be interesting. Special attention has been paid to use of criteria weights for aggregation functions in the MCDM methods. Based on compensatory or non-compensatory types of MCDM models, the criteria weights can be used as trade-off or importance coefficients. Considering methods based on distance functions, weights are obtained by trade-off among criteria such as pair-wise comparison. This is a very important issue, since different calculations of the criteria weights can change the ranking of the possible alternatives.

In addition, the use of different vocabularies to make assessments will be considered. Q-TOPSIS can use different levels of precision, but it might be interesting to extend it in order to also combine different semantics by defining a comparability relation to compare and combine them.

Finally, the theoretical framework considered for energy planning can be extended to more qualitative energy sustainability indicators such as waste management, public health risk and the impact of possible accidents which were not considered in our framework.

Although the proposed method is applied in this dissertation to energy planning problems, it can also be applied to many other management decision problems. Such flexibility shows the multi-disciplinary nature of this method.

From the *application point of view*, the use of qualitative descriptions could be relevant to improving usersínteraction, allowing more human-like assessments in decision making. In particular, Q-TOPSIS is currently starting to be applied in two real cases framed in two different research projects.

1. An extension of the Optimization Water-Energy Model by means of the Q-TOPSIS method

   Our proposed method also can be used to improve the output part of energy optimization models as a qualitative multi-criteria layer. In particular, the use of this method to assess the selection of the most suitable types of renewable energy and water consumption models in a geographical area should be considered. Optimization models to analyze the use of renewable energies and water consumption have received increasing attention not only for the research community but also for the industry and business world. Therefore, as a future study, this method will apply in a real energy case of a tourist destination in Costa Brava, Catalonia, with different dimensions focused on tourism activities as one of the main sources of income for the area.

In tourism management, criteria which are potentially harmful to the environment must be taken into account. In addition, objectives for improving the competitive position of tourist destinations encourage reflection on the need to adapt tourism products to environmental trends which are in demand. As a consequence, tourist destination planning requires integrating economic development with land conservation. For this reason, an important decision for a tourism destination is whether or not to establish renewable energy and water consumption systems in a given place or area. To do so, the combination of energy models and the proposed method helps to decide which renewable energy source or combination of sources is the best choice, not only to avoid environmental harm but also as a way to attract customers who find "green" features appealing.

The study and viability of a software tool to help tourism destination managers in the assessment of alternatives for energy planning and water resource management is being considered for application to future projects. The energy model that is planned to be used assesses the cost of carbon emissions reduction through renewable energies or energy efficiency based on the demand for energy services. It contains a complete representation of the energy system using a bottom-up optimization model to analyze energy policy. The final outputs generate alternatives and possible energy technologies according to the current demands of the case study. The limitation of quantitative energy models is that they work with numerical data to measure alternatives. As a result, many qualitative criteria are not considered in these models; the introduction of Q-TOPSIS will make them more complete by allowing this consideration. In addition, Q-TOPSIS will allow the alternatives generated by energy models to be ranked, which will further help decision makers to select the best option.

2. A hierarchical assessment to find the most sustainable wind farm sites

   In further research, other multi-criteria decision-making approaches must be used to select the most suitable site for the wind farms (Wind as a major source of renewable energy was studied in this thesis as one of the applications). To this aim, specifically, the hierarchical ELECTRE-III-H method, an extension of an outranking approach ELECTRE, proposed in Del Vasto-Terrientes et al. (2015b) is selected. This method helps DMs when they interested in analyzing not only overall suitability but also the preferential relationships between different sites in relation to several sub-parts of the problem. A robustness analysis compares different scenarios with strict, normal and optimistic preference, indifference and veto thresholds. These results could be compared with the results obtained by the qualitative TOPSIS method presented in 4.2.

   The main advantage of ELECTRE-III-H is that it is able to construct a partial pre-order at different levels of a hierarchy of criteria. Therefore, it allows the decision maker to build the model that best represents the overall influence of each of these dimensions to find an order structure of alternatives. This structure depends on the importance of criteria to generate several order structures at each intermediate node, and then these criteria are aggregated at their parent node. First, the importance of each aspect to be considered in the decision at different levels is defined, then the strictness in the action's comparison for each individual criterion is determined (using the indifference and preference thresholds). Finally, the possibility of vetoing permits the decision maker to control the compensative effect of other decision support methods, in which the evaluations given by minorities are always ignored in favor of those given by the majority. With ELECTRE-III-H, minorities can also veto the majority if there are enough arguments to do so. This hierarchical structure is planned to be considered in our qualitative TOPSIS method.

## 5.3 Additional research, projects and publications

The first part of this thesis is related to the theoretical aspect of the new method, which is applied in the second part to different case studies in the energy sector in order to plan and find the best solution among other alternatives. These applications come from the ideas introduced in conferences, seminars and schools which I attended during my Ph.D. program.

### 5.3.1 Pre-doctoral stages and doctoral schools

1. *Visiting period at ESADE Business School, Ramon Llull University, Department of Management Science, Nov 2013-March 2014, Sant Cugat, Spain.*

   I had an opportunity to improve the progress of my Ph.D. thesis in one the best business schools in management science, and to apply my method to managerial problems. Some final results from the research started from this time period have been:

   - Submitting the first publication derived from the thesis, which was accepted.

   - Participating in seminars and conferences.

   - Attending the GREC Advanced Ph.D. Seminars in AI Techniques for Decision Making in Management and presenting the progress of the thesis there.

2. *European Multiple Criteria Decision Aiding (MCDA) Spring School; Multiple Criteria Decision Making: a Key for Sustainability. 25-31 May 2014, Perugia, Italy.*

   The urban planning applications using MCDM approaches and decision support systems as a key for sustainability in Perugia spring school, motivated the researcher to find an application of this method in this area. To do so, the SEMANCO integrated platform in the city of Manresa, Spain, was developed. This application finds the best solution in order to maximize the energy efficiency of buildings to reduce $CO_2$ emissions using MCDM methods.

3. *Energy transition SEEEP Summer School. 1-15 March 2015, Shanghai-Hangzhou, China.*

   The topic of this school was energy transition to reduce carbon emissions in China. This course completed the pathway of the thesis by inspiring the integration of energy system analysis models with decision-making methods. The objective of the school was to improve the multi-disciplinary skills of researchers in idea-driven projects such as increasing the amount of renewable energy using suitable methods, using sustainable transport technologies to reduce carbon emission, and implementing smart micro grids for demand-side management with big data and the Internet of Things (IoT).

   One of the valuable experiences of the SEEEP Summer School was the opportunity to work on a team project to address the challenge of increasing renewable energy in Chinese energy systems based on the country's policy target-2020 with the focus on photovoltaic solar energy and large-scale wind energy, and taking European power systems into consideration. So, the research question of this project was: which policies can help China to meet its energy demands in the future? The aim of this project was finding the answer to this question by using energy analysis models and decision-making tools. These kinds of energy models are powerful tools for finding an optimal energy mix and energy technology solutions over the long term, as they consider current technological and political limitations to generate alternatives. Integrating such models with decision making tools accelerates the process of making right decisions for DMs. This new work has been described in more detail in the future research section.

### 5.3.2 Publications derived from this thesis

1. Afsordegan, A., Agell, N., Sánchez, M., Zahedi, S., Cremades l. (2015). Decision making under uncertainty using a qualitative TOPSIS method in sustainable energy planning. ***Journal of Environmental Science and Technology***, under review.

2. Afsordegan, A., Agell, N., Sánchez, M., Aguado J.C., Gonzalo G. (2015). Absolute-order-of-magnitude reasoning applied to a social multi-criteria decision framework. ***Journal of Experimental and Theoretical Artificial Intelligence***. DOI:10.1080/0952813-$X$.2015.1024489.

3. Afsordegan, A., Agell, N., Sánchez, M., Cremades l., Gonzalo G. (2014). Using linguistic description with multi-criteria decision aid approaches in urban energy systems. ***BDC Journal-Bollettino del centro Calza Bini***, Vol. 14(3): 285-300.

4. Afsordegan, A., Agell, N., Sánchez, M., Aguado J.C., Gonzalo G. (2014). A comparison of two MCDM methodologies in the selection of a wind farm location in Catalonia. ***Artificial Intelligence Research and Development***, Vol.269: 227-236.

### 5.3.3 Conferences and seminars

1. Afsordegan, A., Del Vasto-Terrientes L., Valls A., Agell N., Sánchez M. (2015). A hierarchical assessment to find the most sustainable wind farm location. ***82nd Meeting of EURO Working Group on MCDA***, September 24-26, Odense, Denmark.

2. Afsordegan, A., Agell, N., Sánchez, M., Aguado J.C., Gonzalo G. (2014). A new MCDM method in the selection of a wind farm location in Catalonia. ***Proceedings of the 17th International Conference of the Catalan Association of Artificial Intelligence (CCIA2014)***, 22-24 October, Barcelona, Spain.

3. Afsordegan, A., Agell. N.(2014). Order-of-Magnitude reasoning for MCDM methodologies: An application to the assessment of renewable. ***Seminar***, *Universitat Rovira i Virgili, Department of Computer Science and Mathematics*, Tarragona, Spain.

4. Afsordegan, A., Agell, N., Sánchez, M., Zahedi, S., Cremades l. (2014). Multi-criteria decision making with linguistic labels. ***Proceedings of the XVII International Conference on Technologies and Fuzzy logic (ESTYLF2014)***, 5-7 February. P:21-26. Zaragoza, Spain.

5. Afsordegan, A., Agell, N., Sánchez, M., Zahedi, S., Cremades l. (2013). Assessment of renewable energies based on fuzzy and qualitative multi-criteria decision making. ***22nd International Conference on Multiple Criteria Decision Making***, 17-21 June, Malaga, Spain.

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