UNIVERSITAT POLITÈCNICA DE CATALUNYA
BARCELONATECH
Departament d'Arquitectura de Computadors

An Approach to Pervasive Monitoring in Dynamic Learning Contexts: Data Sensing, Communication Support and Awareness Provision

ESUNLY MEDINA MEDINA

UNIVERSITAT POLITÈCNICA DE CATALUNYA
Department of Computer Architecture

An Approach to Pervasive Monitoring in Dynamic Learning Contexts: Data Sensing, Communication Support and Awareness Provision

BY

ESUNLY MEDINA MEDINA

December 2015

ADVISORS

ROC MESEGUER, PHD.

DOLORS ROYO, PHD.

COMPUTER NETWORKS AND DISTRIBUTED SYSTEMS GROUP

DEPARTMENT OF COMPUTER ARCHITECTURE

UNIVERSITAT POLITÈCNICA DE CATALUNYA

CASTELLDEFELS

SPAIN

Dissertation for the degree of Doctor

from the Universitat Politècnica de Catalunya

2015

An Approach to Pervasive Monitoring in Dynamic Learning Contexts: Data Sensing, Communication Support and Awareness Provision. *December 2015*.

Esunly Medina Medina
esunlyma@ac.upc.edu

Computer Networks and Distributed Systems Group
Universitat Politècnica de Catalunya
Esteve Terradas 7
08860 - Castelldefels (Spain)

To God,
the owner of my heart,
the saviour of my life,
the one who makes all things possible,
in whom I wait

To my husband, Joaquín,
my life travelling companion, the seal over my heart,
the mighty fire that cannot be extinguished,
the man whose love brought peace, happiness and growth to my life

To my parents, Humberto and Esther,
who taught me the most important things of life,
who gave me the most valuable gift,
who have always been there for me

To my brothers, Humberto, David and Daniel,
with whom I have grown and laughed,
who make me feel that together we are like The Fantastic Four
the ones who I love until the moon and back

To those few, relatives and friends,
who have shared a piece of life,
who laughed, cried and prayed with me

Acknowledments

First and foremost, I would like to thank my supervisors. I am grateful to Roc Meseguer for his support, guidance and encouragement all these years and throughout all the steps of this PhD. He has continuously provided invaluable advice and feedback on my research. I also want to express my gratitude to Dolors Royo for her support and stimulating discussions as well as for her continuous help with the experiments.

I would also like thank the members of the jury, Davinia Hernández-Leo, Bart Braem, Esther Salamí, Rodrigo Santos and Eduard Ayguadé, who kindly accepted to participate of this thesis, as examiners. I wish to gratefully acknowledge the enthusiastic contributions of the reviewers of my thesis as well as the members of my pre-defence jury Miguel Valero and Cristina Barrado.

I do not want to forget the invaluable help of my research partners Sergio Ochoa, Humberto Medina, Carlos Molina and Davide Vega, they have been also been instrumental in my development as a researcher. Their feedback on my research, papers, and dissertation has also been priceless.

There are three special projects which have enormously influenced and partially funded my work: CONFINE, ALLOW and P2PGRID. Special thanks to Leandro Navarro for his enthusiastic supervision during my time working for the CONFINE and P2PGRID projects as well as for his advice about my thesis. While working for the ALLOW project, Fahim Kawsar provided me with invaluable advice and enthusiasm that has shaped my research. I am also grateful for his supervision during my research stay in Lancaster University, which opened new research horizons for me.

Special thanks to David López for his help with the development of the prototypes and with the experiments, and to Joana Murera who has been very patient and helpful with all the administrative process. I am also thankful to the students that participated in the user studies.

My sincere thanks to my colleagues at the Department of Computer Architecture and at the Computer Networks and Distributed Systems Group Ester López, Isabel Gallego, Antonia Gallardo and Pablo Royo, for their support and encouragement.

This work would have not been possible without the contribution of many: family, friends and colleagues, who have continuously shown interest in my evolution throughout the PhD and that have personally supported this work one way or another. I would like to take advantage of this opportunity to thank them all.

Finally, I deeply thank each of my family members my husband, parents, brothers and parents in law for their unconditional love, support and sacrifices. They have been constantly encouraging, tolerating and supporting me during all this process.

Abstract

It is within the capabilities of current technology to support the emerging learning paradigms. These paradigms suggest that today's learning activities and environments are pervasive and require a higher level of dynamism than the traditional learning contexts. Therefore, we have to rethink our approach to learning and use technology not only as a digital information support, but also as an instrument to reinforce knowledge, foster collaboration, promote creativity and provide richer learning experiences.

Particularly, this thesis was motivated by the rapidly growing number of smartphone users and the fact that these devices are increasingly becoming more and more resource-rich, in terms of their communication and sensing technologies, display capabilities battery autonomy, etc. Hence, this dissertation benefits from the ubiquity and development of mobile technology, aiming to bridge the gap between the challenges posed by modern learning requirements and the capabilities of current technology.

The sensors embedded in smartphones can be used to capture diverse behavioural and social aspects of the users. For example, using microphone and Bluetooth is possible to identify conversation patterns, discover users in proximity and detect face-to-face meetings. This fact opens up exciting possibilities to monitor the behaviour of the user and to provide meaningful feedback. This feedback offers useful information that can help people be aware of and reflect on their behaviour and its effects, and take the necessary actions to improve them.

Consequently, we propose a *pervasive monitoring system* that takes advantage of the capabilities of modern smartphones, using them to support the awareness provision about aspects of the activities that take place in today's pervasive learning environments. This pervasive monitoring system provides (i) an *autonomous sensing platform* to capture complex information about processes and interactions that take place across multiple learning environments, (ii) an *on-demand and self-managed communication infrastructure,* and (ii) a *display facility* to provide *"awareness information"* to the students and/or lecturers.

For the proposed system, we followed a research approach that have three main components. First, the description of a *generalized framework for pervasive sensing* that enables collaborative sensing interactions between smartphones and other types of devices. By allowing complex data capture interactions with diverse remote sensors,

devices and data sources, this framework allows to improve the information quality while saving energy in the local device. Second, the evaluation, through a real-world deployment, of the suitability of ad hoc networks to support the diverse communication processes required for *pervasive monitoring.* This component also includes a method to improve the scalability and reduce the costs of these networks. Third, the design of two *awareness mechanisms* to allow flexible provision of information in dynamic and heterogeneous learning contexts. These mechanisms rely on the use of smartphones as adaptable devices that can be used directly as *awareness displays* or as communication bridges to enable interaction with other remote displays available in the environment.

Diverse aspects of the proposed system were evaluated through a number of simulations, real-world experiments, user studies and prototype evaluations. The experimental evaluation of the data capture and communication aspects of the system provided empirical evidence of the usefulness and suitability of the proposed approach to support the development of *pervasive monitoring* solutions. In addition, the proof-of-concept deployments of the proposed awareness mechanisms, performed in both laboratory and real-world learning environments, provided quantitative and qualitative indicators that such mechanisms improve the quality of the *awareness information* and the user experience.

Resumen

La tecnología moderna tiene capacidad de dar apoyo a los paradigmas de aprendizaje emergentes. Estos paradigmas sugieren que las actividades de aprendizaje actuales, caracterizadas por la ubicuidad de entornos, son más dinámicas y complejas que los contextos de aprendizaje tradicionales. Por tanto, tenemos que reformular nuestro acercamiento al aprendizaje, consiguiendo que la tecnología sirva no solo como mero soporte de información, sino como medio para reforzar el conocimiento, fomentar la colaboración, estimular la creatividad y proporcionar experiencias de aprendizaje enriquecedoras.

Esta tesis doctoral está motivada por el vertiginoso crecimiento de usuarios de smartphones y el hecho de que estos son cada vez más potentes en cuanto a tecnologías de comunicación, sensores, displays, autonomía energética, etc. Por tanto, esta tesis aprovecha la ubicuidad y el desarrollo de esta tecnología, con el objetivo de reducir la brecha entre los desafíos del aprendizaje moderno y las capacidades de la tecnología actual.

Los sensores integrados en los smartphones pueden ser utilizados para reconocer diversos aspectos del comportamiento individual y social de los usuarios. Por ejemplo, a través del micrófono y el Bluetooth, es posible determinar patrones de conversación, encontrar usuarios cercanos y detectar reuniones presenciales. Este hecho abre un interesante abanico de posibilidades, pudiendo monitorizar aspectos del comportamiento del usuario y proveer un feedback significativo. Dicho feedback, puede ayudar a los usuarios a reflexionar sobre su comportamiento y los efectos que provoca, con el fin de tomar medidas necesarias para mejorarlo.

Proponemos un *sistema de monitorización generalizado* que aproveche las capacidades de los smartphones para proporcionar información a los usuarios, ayudándolos a percibir y tomar conciencia sobre diversos aspectos de las actividades que se desarrollan en contextos de aprendizaje modernos. Este sistema ofrece: (i) una *plataforma de detección autónoma,* que captura información compleja sobre los procesos e interacciones de aprendizaje; (ii) una *infraestructura de comunicación autogestionable* y; (iii) un *servicio de visualización* que provee *"información de percepción"* a estudiantes y/o profesores.

Para la elaboración de este sistema nos hemos centrado en tres áreas de investigación. Primero, la descripción de una *infraestructura de detección generalizada,* que facilita interacciones entre smartphones y otros dispositivos. Al permitir interacciones

complejas para la captura de datos entre diversos sensores, dispositivos y fuentes de datos remotos, esta infraestructura consigue mejorar la calidad de la información y ahorrar energía en el dispositivo local. Segundo, la evaluación, a través de pruebas reales, de la idoneidad de las redes ad hoc como apoyo de los diversos procesos de comunicación requeridos en la *monitorización generalizada.* Este área incluye un método que incrementa la escalabilidad y reduce el coste de estas redes. Tercero, el diseño de dos *mecanismos de percepción* que permiten la provisión flexible de información en contextos de aprendizaje dinámicos y heterogéneos. Estos mecanismos descansan en la versatilidad de los smartphones, que pueden ser utilizados directamente como *displays de percepción* o como puentes de comunicación que habilitan la interacción con otros displays remotos del entorno.

Diferentes aspectos del sistema propuesto han sido evaluados a través de simulaciones, experimentos reales, estudios de usuarios y evaluaciones de prototipos. La evaluación experimental proporcionó evidencia empírica de la idoneidad del sistema para apoyar el desarrollo de soluciones de *monitorización generalizadas.* Además, las pruebas de concepto realizadas tanto en entornos de aprendizajes reales como en el laboratorio, aportaron indicadores cuantitativos y cualitativos de que estos mecanismos mejoran la calidad de la *información de percepción* y la experiencia del usuario.

Publications from this Dissertation

A. Core Publications

While preparing research findings for this dissertation, some of the work performed for this PhD thesis has been published on several peer-review conferences and indexed journals. Next, there is a list of publications that form part of the core of this dissertation:

Conferences

- *CC1* **Medina, E.**, López, D., Royo, D., Meseguer, R.,& Ochoa, S. F. (2015). CoSP: A Collaborative Sensing Platform for mobile applications. In Computer Supported Cooperative Work in Design (CSCWD), 2015 IEEE 19th International Conference on (pp. 377-382). IEEE.
- *CC2* López, D., Royo, D. **Medina, E.**, Meseguer, R. (2015). OIoT: A Platform to Manage Opportunistic IoT Communities. In Intelligent Environments (IE), 2015 International Conference on (pp. 104-111). IEEE.
- *CC3* **Medina, E.**, Meseguer, R., Ochoa, S. F., & Medina, H. (2015). A Behaviour Awareness Mechanism to Support Collaborative Learning. In Collaboration and Technology (pp. 95-110). Springer International Publishing.
- *CC4* **Medina, E.**, Kawsar, F., Meseguer, R., & Ochoa, S. F. (2014). Situated micro-displays for activity-aware systems. In Distributed, Ambient, and Pervasive Interactions (pp. 450-461). Springer International Publishing.
- *CC5* **Medina, E.**, Meseguer, R., Molina, C., & Royo, D. (2011). OLSRp: Predicting control information to achieve scalability in OLSR ad hoc networks. In Mobile Networks and Management (pp. 225-236). Springer Berlin Heidelberg.
- *CC6* Rodríguez-Covili, J., Ochoa, S. F., Pino, J., Meseguer, R., **Medina, E.**, & Royo, D. (2010). HLMP API: a software library to support the development of mobile collaborative applications. In Computer Supported Cooperative Work in Design (CSCWD), 2010 14th International Conference on(pp. 479-484). IEEE.

CC7 Meseguer, R., Ochoa, S. F., Pino, J. A., **Medina, E.**, Navarro, L., Royo, D., & Neyem, A. (2009). Building real-world ad-hoc networks to support mobile collaborative applications: lessons learned. In Groupware: Design, Implementation, and Use (pp. 1-16). Springer Berlin Heidelberg.

Journals

CJ1 Meseguer, R., **Medina, E.**, Ochoa, S. F., Pino, J. A., Neyem, A., Navarro, L., & Royo, D. (2012). Communication Support for Mobile Collaborative Work: An Experimental Study. International Journal of Information Technology & Decision Making, 11(06), 1035-1063.

CJ2 Rodríguez-Covili, J., Ochoa, S. F., Pino, J. A., Meseguer, R., **Medina, E.**, & Royo, D. (2011). A communication infrastructure to ease the development of mobile collaborative applications. Journal of Network and Computer Applications, 34(6), 1883-1893.

B. Related Publications

In addition to the core publications, a number of other scientific papers have been published. These papers include research that is related with the topics covered in this thesis but that is not central to it. Following, there is a list of such publications:

Conferences

RC1 Millan, P., Molina, C., **Medina, E.**, Vega, D., Meseguer, R., Braem, B., & Blondia, C. (2014). Tracking and predicting link quality in wireless community networks. In Wireless and Mobile Computing, Networking and Communications (WiMob), 2014 IEEE 10th International Conference on (pp. 239-244). IEEE.

RC2 Vega, D., **Medina, E.**, Meseguer, R., Royo, D., & Freitag, F. (2011). A node placement heuristic to encourage resource sharing in mobile computing. In Computational Science and Its Applications-ICCSA 2011 (pp. 540-555). Springer Berlin Heidelberg.

RC3 Vega, D., **Medina, E.**, Meseguer, R., Royo, D., Freitag, F., Ochoa, S. F., & Pino, J. (2011). Characterizing the effects of sharing hardware resources in mobile collaboration scenarios. In Computer Supported Cooperative Work in Design (CSCWD), 2011 15th International Conference on (pp. 465-472). IEEE.

RC4 Meseguer, R, **Medina, E.** , Royo, D., J. Navarro, L., Damian-Reyes & P., Favela (2010). Supporting context-aware collaborative learning through automatic group formation. In Ubiquitous Computing & Ambient Intelligence. (UCAmI) (pp. 325–334).

RC5 Meseguer, R., **Medina, E.**, Royo, D., Navarro, L., & Juárez, J. P. (2010). Group Prediction in Collaborative Learning. In Intelligent Environments (IE), 2010 Sixth International Conference on (pp. 350-355). IEEE.

Journals

RJ1 Millan, P., Molina, C., **Medina, E.**, Vega, D., Meseguer, R., Braem, B., & Blondia, C. (2015). Time series analysis to predict link quality of wireless community networks. Computer Networks.

RJ2 Vega, D., Baig, R., Cerdà-Alabern, L., **Medina, E.**, Meseguer, R., & Navarro, L. (2015). A Technological overview of the guifi.net community network. Computer Networks.

RJ3 Vega, D., Meseguer, R., Ochoa, S. F., Pino, J. A., Freitag, F., **Medina, E.**, & Royo, D. (2013). Sharing hardware resources in heterogeneous computer-supported collaboration scenarios. Integrated Computer-Aided Engineering, 20(1), 59-77.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Motivation

Advances in ICT and particularly in mobile technologies have changed how we live our lives. Nowadays, technology is blurring the boundaries between work and personal life. It is possible to work on the move, while you are on a plane or bus or just while walking. Also, you can almost simultaneously send a work-related email and check your friends' updates on Facebook.

These changes in life and work have to lead inevitably to a dramatic change in the way we learn. The easy availability of information on the Internet and the emergence of initiatives, such as *Creative Commons*, online universities and *Wikipedia*, to promote resource and information sharing as well as the appearance of new technological tools, have created the need to reinvent the way we teach and learn. However, in practice, the use of ICT in education tends to support more individualistic and passive forms of learning, and technology is mainly and merely used to provide digital information support to traditional learning methodologies.

There have been, nevertheless, a raised awareness of the need of developing new learning paradigms that encourage active participation of students and foster collaboration with teachers and fellow students. This has caused the appearance of new learning practices based on existing theories, such as *Collaborative Learning, Situated Learning, and Informal and Lifelong Learning* [206, 51, 244]. The basic ideas behind these learning methods are the following:

- Knowledge is not centralized but distributed between individuals and collaboration and social interactions are an essential part of the learning process. Students are not merely consumers of information but active participants in the learning process.
- Meaningful learning can take place not only in a dedicated learning environment and formal curriculum but it can also happen in ad hoc, informal and opportunistic situations outside pre-established learning settings. Therefore, learning is also lifelong and happens all the time, not only in a confined space-time context.
- Learning occurs within a relevant or authentic context and not in isolation from it. Therefore, it is extremely important to connect knowledge acquisition with the specific context in which it will be applied.

These learning paradigms especially highlight the great value of social interactions, emphasising the importance of extensive, diverse and sustained interpersonal relationships to facilitate and improve learning [58]. In that line, research works in other fields have studied the influence of social interactions on people satisfaction and productivity. For instance, in [117] the authors stress the importance that interpersonal interactions have to achieve better teamwork outcomes. In [195] the authors also provide evidence that strong social interactions among people have a positive impact on their productivity. Some studies also investigate the role of informal social interactions in organizations, observing that the quality of such interactions influences work performance and job satisfaction positively at no cost for the organizations [118, 235].

Considering these facts, it seems evident that, in order to be successful and satisfactory, learning should rely on strong social interactions and therefore be highly collaborative. However, in learning contexts, teachers and students usually have low visibility of the collaboration processes that are taking place while they are being conducted. Therefore, the assessment of such processes is done once they have concluded, when it is too late to try intervene (e.g.,by providing feedback). This situation shows a need to count on automatic mechanisms that monitor team members' activities and provide feedback accordingly. As a result, the monitoring, analysis and assessment of social interactions and collaboration processes captures the interest of many researchers in the area of Collaborative Learning (CL) [80, 201].

There are several interesting examples of the use of monitoring techniques in learning environments. For example, in [197], the communication patterns of the students taken from email communication and forum discussions were used to measure team cohesion in collaborative distance-learning. Another interesting study is presented in [13], where interaction patterns between students are studied through log files of computer-mediated collaborative activities. Results show relationships between such interactions and the quality of the collaboration process (measured by rating of human experts) and the students' performance (grades). In [217], the social roles and information flow between learners and educators in a distance learning system is monitored in order to understand their impact on the collaboration process and the learning activities. A different approach is followed in [147] where collaborative interactions between students are monitored through their speech and their physical actions on an interactive tabletop. The findings indicated a relationship between speech and physical activity patterns and the degree of collaboration of different groups of students.

In a society where the Internet of Things (IoT) is gradually becoming a reality, there is an increasing need to integrate learning activities into everyday life by embedding smart systems into the environment, which could create more opportunities for lifelong and ubiquitous learning. In addition, the introduction of the IoT technology into the educational system could contribute to a more contextualized knowledge acquisition, which is also promoted by the new learning paradigms. This fact suggests the potential and possibility of creating seamless learning environments that combine the physical environment with the digital world. This would provide digitally augmented physical spaces that create richer perceptual experiences for the students, which could benefit and reinforce his learning process. Several research works present interesting proposals to integrate IoT in the learning environment [52, 240].

The diversity and complexity of contexts where, according to the new paradigms, learning may occur [211] makes the monitoring of learning activities and collaboration processes in this context very challenging. Thus, in order to understand complex individual and collective behavioural patterns of the students, monitoring techniques should capture, analyse and visualize different types of learning activities and interpersonal interactions across multiple scenarios and involve several types of students and devices. For that reason, the development of pervasive monitoring systems is necessary to allow the collection of information about learning processes that are taking place not only within the classroom but also in all the different contexts that the students encounter throughout the course of their daily routines. In that line, the ubiquity of mobile devices such as smartphones, tablets and laptops provides a unique opportunity to increase the pervasiveness of the monitoring activities and gather great amounts of information on human interactions and behaviour [17, 210] by capturing data from the sensors embedded in modern devices.

Typically, smartphones have multiple embedded sensors, such as accelerometer, gyroscope, GPS, camera or microphone and several built-in wireless interfaces, such as Bluetooth, infrared, NFC (Near Field Communication) or Wi-Fi, which makes it possible to establish communication between several mobile devices and many other types of devices, such as IoT devices, sensors in smart buildings, shared displays, etc. This communication between devices can be used to observe relationships in the data collected by them. For example, we can establish connections between data sensed using smartphones (e.g., from electronic exchanges through calls records, application being currently in use, SMS logs, email headers, accelerometer measures, GPS data, etc.) and the data generated by IoT devices and objects embedded in the environment (e.g., users access records, documents in the users' printing queue, etc.). Furthermore, since smartphones are mobile networked devices that can send and receive information over the Internet, they can be considered as IoT devices [93] that add portability and pervasiveness to an environment enriched by IoT objects [169]. As a result, the sensors and interfaces existing in modern smartphones facilitate the performance of pervasive data sensing activities by capturing complex data streams collected from diverse sensors and devices and throughout various contexts and environments.

The data streams collected using smartphones reflect on the context, activities and routines of the smartphone' owners and therefore, can be used to capture and monitor diverse behavioural and social aspects of the users. Thus, raw sensor data can be processed to draw inferences and create high-level representations of the users' behaviour and interactions [190]. For example, the microphone can be used to determine if the user is speaking [135] and to detect conversation groups [140], the accelerometer can be used to measure the intensity of the physical activities conducted by the user, and the Bluetooth can be used to detect face-to-face meetings or to discover the physical proximity of the user to objects or to other people [175]. In the field of learning, this fact creates opportunities to take account of the students surroundings, contexts, activities or interactions and therefore, to create lifelong and ubiquitous learning environments [52, 240].

Various studies have used the data gathered from smartphone' sensors in order to model the users' behaviour and try to understand its influence on people's activities. For instance, a study presented in [142] uses smartphones to analyse the social interactions of undergraduate students, trying to identify the interactions patterns of the community and its relationship with their health status and political opinions. Another study performed among students and faculty at the *MIT* demonstrates that Bluetooth-enabled mobile phones can be used to recognize social patterns, infer relationships between people and model organizational behaviour [65]. The information for this study was collected mainly from the cellular phones of the involved people while they were performing their ordinary work activities. One further example is reported in [154], an application running in off-the-shelf mobile phones that infers various aspects from the user context, such as activity or social setting. The inferred information is automatically exported to social network applications such as *Facebook* or *Myspace*.

These research studies demonstrate that the technological advances in sensing, communication and computation of modern-day smartphones and their continuous presence and usage in everyday life activities makes them ideal for the pervasive monitoring. Furthermore, the information monitored by smartphones can be used to provide detailed and meaningful feedback to users about their activities and behaviour patterns. This feedback delivers useful information that can help people to be aware of and reflect on their behaviour in order to take the necessary actions to improve it.

Feedback has been regarded as an extremely important awareness mechanism, which influences positively the learning process by providing learners with information that allows them to improve their performance and learning behaviour [207]. Awareness about the information monitored using smartphones can help students (and also lecturers) to make reasonable inferences about the learning process, and also to gain insights into the nature of collaboration performed during a learning activity or process. This feedback can help foster collaboration, allowing students to reflect on their own and their mates learning practices, and based on that, react on time and adapt their attitude accordingly. Therefore, pervasive monitoring systems should include appropriate awareness mechanisms that provides students and lecturers with meaningful statistics and feedback about the students' daily routines, which can influence the learning experience. Moreover, the use of these systems to automatically monitor and model the students' behaviour and communication and collaboration patterns, and share this information with their peers and lecturers would open up new possibilities to enhance the learning experience and academic achievement, not only by making students aware about their current behaviour, but also supporting lecturers in the monitoring of collaborative learning activities. The monitoring results can be used to facilitate the lecturers' intervention in order to take corrective measures to redirect the development of specific learning activities. The monitored information can also inform the design of future learning activities to promote interpersonal interactions and collaboration.

Although there is a considerable body of research which suggests that current digital and communication technologies make possible to establish the emerging new learning paradigms, the challenge is to make use of the opportunities that advances in ICT have created and fully integrate them as pedagogical tools in both inside and outside the classroom. We have to rethink our approaches to learning and education and use technology as an instrument to reinforce knowledge, foster collaboration, promote creativity and increase productivity. It is important to find ways to take full advantage of the technological advances to ensure that learning is highly social, collaborative, situational and long term.

This is one of the goals of this thesis. We intend to facilitate the integration of the promising new learning methodologies with the existing technological capabilities. Therefore, we propose a pervasive monitoring system that benefit from the ubiquity and technological development of today's smartphones to support and encourage these new learning paradigms.

1.2 Objectives and Approach

The main objective of the proposed pervasive monitoring system is to provide a mechanism to support complex data collection and awareness provision about diverse activities and processes that can take place in dynamic learning environments, characterized by a diversity of contexts, devices, individuals and collaborative interactions. Nevertheless, there is an overwhelming amount of aspects to consider for the development of such a monitoring system [153, 190], such as data processing and inference, privacy and security concerns, adaptation of machine learning algorithms, sensing services discovery, computation offloading, etc. For that reason, our approach to pervasive monitoring is restricted to the aim of providing (i) an autonomous sensing platform to capture information about processes and interactions that are taking place in pervasive learning environments, (ii) a self-managed and autonomous communication infrastructure to ensure a flexible, interoperable and highly available communication support, and (ii) a display facility to provide awareness information to the students in a dynamic way and considering diverse contexts and devices. To this end, we take advantage of the technological capabilities of modern smartphones toward a threefold aim:

- Make use of their ***sensing capabilities*** to capture information about learning activities and practices. Moreover, we enhance such sensing capabilities by facilitating the interaction of smartphone with other remote sensing devices (e.g., IoT devices, sensors in smart buildings, etc.). This way, we intend to capture complex information from diverse data sensors to allow the monitoring the students communication, collaboration and behavioural patterns.

- Utilize their wireless communication technologies to dynamically create ***mobile ad hoc networks*** when convenient or when no other network infrastructure is available, allowing students' devices to interact among them or with other type of devices (e.g., IoT devices, shared displays, etc.) in real-time, anytime and anywhere.

- Take advantage of their display capabilities to use them as ***awareness displays*** to show, in the appropriate context, information related with the students' activities, interaction patterns or learning routines. We also make use of the interactions between smartphones and other displays available in the environment (i.e. shared displays) to enable flexible awareness provision across different types of displays. The main objective is to raise awareness, helping students to reflect on their activities and behaviour, which can help promote better learning practices.

Considering these opportunities offered by mobile technology, for the proposed pervasive monitoring system, we followed an approach that includes three main components that match with the distinguishing features of smartphone technology presented above:

i ***A pervasive sensing framework***: we design a framework that allows collaborative sensing interactions between smartphones and other types of devices. This framework provides an autonomous sensing platform to capture information about processes and interactions that take place in dynamic learning environments, , allowing the collection of complex and accurate data from the smartphone's local sensors and other remote sensors while saving energy and ensuring the autonomy of the sensing devices.

ii ***An autonomous communication support:*** we propose the use of Mobile Ad hoc Networks to provide a self-managed and autonomous infrastructure that is available across the diversity of environments and situations where learning processes can take place. This infrastructure supports the diverse communication processes between smartphones and other devices required for pervasive monitoring activities, including both data collection and awareness provision.

iii ***A flexible awareness mechanism:*** we propose two types of smartphone-mediated awareness methods designed to allow a flexible provision of targeted and personalised feedback information in dynamic learning contexts.

1.3 Thesis Statement and Research Questions

In the previous sections we presented the limitations of the current use of technology to support pervasive monitoring of students in the diversity of potential contexts and environments considered by the new learning paradigms. We also discussed some of the advantages and challenges posed by the development of pervasive monitoring systems that use smartphones to capture the activities and behaviour of users and to provide appropriate awareness and feedback. Consequently, to address these issues, the main aim of this thesis is:

Each of the components of this thesis statement raises research questions that need answering. Such research questions are the following:

> ***To propose, define, develop and evaluate suitable technological solutions to support the data collection, communication and awareness provision processes required for the development of pervasive monitoring solutions for dynamic learning contexts.***

- ***Research Question 1:*** How can we capture diverse and complex data from both the sensors embedded in smartphones and other remote sensors in an accurate and energy-efficient way?
- ***Research Question 2:*** How can we provide a pervasive network infrastructure that meets the communication requirements to support data collection and awareness provision processes?
- ***Research Question 3:*** How can smartphones be helpful to provide flexible awareness methods that could be adapted to diverse dynamic learning contexts?

In support of our thesis statement and to answer these questions, this research focuses on the development of data collection, communication and awareness provision solutions to support the pervasive monitoring of behavioural, social and contextual factors that can influence the quality of the learning process, in highly dynamic learning contexts that involve diverse situations, interactions and environments. The main reasons to select this context for the research work presented in this thesis are the following: (i) there is a need to provide timely visibility of the activities, interactions and collaboration processes that influence the learning experience, (ii) there is a lack of comprehensive monitoring solutions that provide the autonomy and flexibility required to operate across the diversity of contexts where learning processes can take place, (iii) smartphone sensing applications are becoming more and more common every day, and (iv) there is a conviction in the research community that awareness provision can produce a great positive impact on the learning process and the performance of the students.

Consequently, our thesis is based on the hypothesis that this research work will help increase the technical viability, reduce the development effort and increase the quality of solutions in the area of pervasive monitoring in dynamic learning contexts.

1.4 Methodology

This section presents the basic research methodology applied in this thesis.

1.4.1 Research Approach

The general research approach followed was a compound of ***theoretical work*** with a ***systematic empirical investigation,*** combined with ***quantitative*** and ***qualitative*** analytical methods.

As depicted in Figure 1.1, the main research methodology employed follows these three essential phases:

1. The combination of theoretical analysis and empirical evidence to identify critical factors that influence pervasive monitoring.
2. The design of controlled experiments to isolate and understand the effects of the data sensing processes, the communication support and the awareness provision upon those factors.
3. The deduction of design principles and recommendations to build real-world pervasive monitoring systems that help enrich the learning experience.

According to this figure, we can say that we primarily used a ***deductive method*** to conduct our research. That is, we used a top-down approach, basing our work on existing theories or technological solutions to formulate

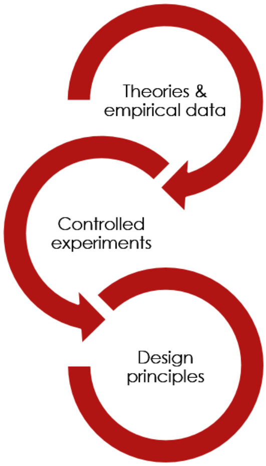


Figure 1.1: Stages of the research methodology

hypotheses and perform experiments to confirm them. Nevertheless, some aspects of our work required inductive methodologies to be able to make generalizations or develop explanations as result of empirical observations.

A detailed representation of the workflow applied to the different components of our research is depicted in Figure 1.2.

As we can observe, six main stages were followed in order to achieve each one of the specific research goals of this thesis:

1. First, a study of related works is done in order to understand the state of the art on the particular research topic that is being addressed.

2. After the literature review, we can isolate open research questions and challenges and therefore, make a specific problem statement.

3. Following, we have the design stage, in which we make a careful experimental design, specifying variables, measurement methods and requirements, and also selecting the appropriate technologies.

4. Next, a preliminary assessment is executed in order to verify if everything is ready for the next stage of experimentation or if we need to make fur-

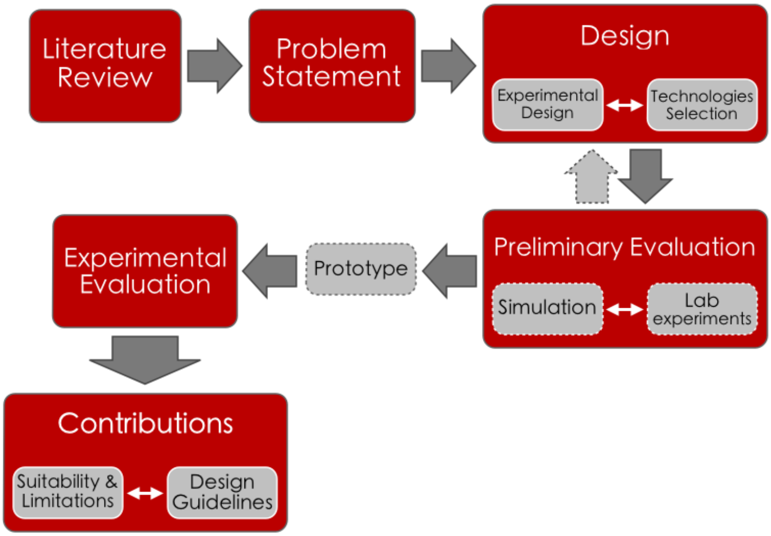


Figure 1.2: Research workflow

ther adjustments to the proposal and go back to the design phase. This evaluation can be performed through simulations or laboratory experiments, depending on the nature of the problem to be addressed. In addition, in many cases a prototype solution will be developed for experimentation, but it will not always be the case.

5. At this point, the experimental evaluation is done, collecting data and analysing the obtained results. During the analysis phase, we search for patterns, identify relationships or simply perform statistical studies.

6. Finally, based upon the empirical results, we can confirm or refute our hypotheses. We also draw some conclusions about the suitability and limitations of the solution proposed, which can help us to provide some suggestions for improvements and design guidelines for researchers working on similar solutions.

1.4.2 Experimental Research Components

This dissertation is composed of four main experimental components:

1. An empirical understanding of the suitability of using ad hoc networks as communication support for pervasive monitoring.
2. Evaluation of the technological solutions proposed to facilitate pervasive data collection and to improve the efficiency of the communication support.
3. Evaluation of the proposed awareness mechanism to assess their usability and impact on the users.

Each one of these components is a distinct piece of work and contributes to different aspects of the overall purpose of this dissertation. Therefore, to achieve our research goals, we employ several experimental and analytical methods and apply the appropriate ones to each component of this work. Table 1.1 summarizes the methodologies applied.

Table 1.1: Experimental methods applied to each research component

Component	**Experimental Method**	**Analytical Method**	**Research Approach**	
(1)	Lab Experiment	Quantitative	Deductive	Theoretical & Empirical
(2)	Simulation			
(3)	Lab/Field User Study	Quantitative & Qualitative		

1.5 Thesis Organization

The remainder of this PhD thesis is structured as follows. Chapter 2 covers the state of the art and background of the main research topics addressed in this thesis. In Chapter 3, we present and evaluate the pervasive sensing framework designed to collect sensor data among smartphones and other devices. Chapter 4 presents the study of the viability of using Mobile Ad hoc Networks as communication support for pervasive monitoring as well as some recommendations and solutions to improve the efficiency of these network infrastructures. We then provide, in Chapter 5, a description and evaluation of the awareness mechanism proposed to provide feedback to students. Finally, Chapter 6 presents the conclusions and main contributions of the research work presented in this dissertation.

Figure 1.3 shows a detail of the structure of this thesis that includes the research questions addressed, the three main areas of contributions that each one of them target and the associated chapters where they are described.

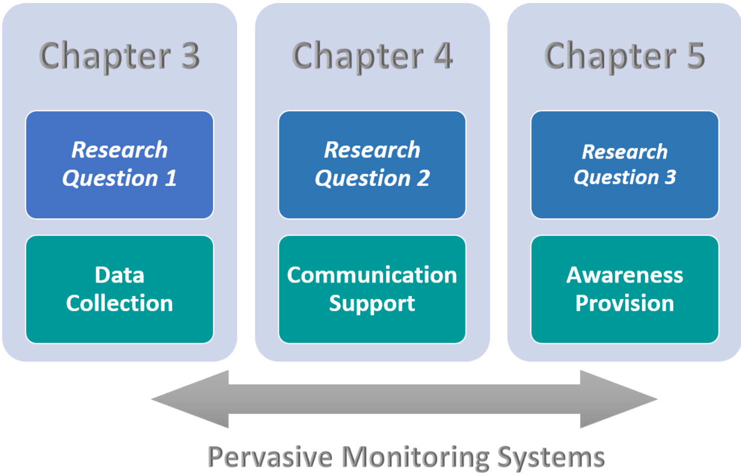


Figure 1.3: Organization of the contributions of the thesis

Chapter 2

Background and Literature Review

2.1 Background on Monitoring Systems

As discussed in Chapter 1, the objective of the monitoring system proposed in this thesis is to automatically monitor and model the students' behaviour and interaction patterns in order to provide appropriate awareness information and feedback to encourage reflection and promote actions that lead to behaviour improvements. Next sections present a review of research studies in the literature that use sensor data to model, monitor and shape the behaviour of individuals and groups.

2.1.1 Using Sensor Data to Model Behaviour

The fast-growing developments in mobile computing, ubiquitous sensing devices and particularly, the proliferation of sensor-enabled smartphones, have created new opportunities to gather information about people's context and activities. Typically, smartphones have multiple embedded sensors, such as accelerometer, gyroscope, GPS, video or microphone and several built-in interfaces, such as Bluetooth, infrared, or Wi-Fi. In addition, the increasing number of smartphone users have made possible to establish communication between many types of sensing devices and observe relationships in the data collected by their sensors. This fact has driven the development of *smartphone-based context recognition systems* [97, 45].

These systems acquire knowledge about the user context through sensor-enhanced smartphones. Examples of this contextual information are physical location, noise level, proximity to other devices, type of physical activity, etc. An example of a smartphone-based context recognition system is *CenceMe* [154], an application running in off-the-shelf, sensor-enabled smartphones. *CenceMe* fuses social networking with real-world sensing by inferring various aspects from the user context, such as activity or social setting and automatically exporting the results to social network applications, such as Facebook or Myspace.

Another interesting work is the *SoundSense* [134] framework for modelling sound events using smartphones. It is implemented for *Apple's IPhones* and can recognize everyday significant sounds in the life of the user. The system is scalable and runs only on the mobile phone with no back-end interactions. A similar study is presented in [140]. The authors propose*SocialWeaver,* a sensing service running on smartphones that uses a clustering algorithm to build conversation networks automatically. The evaluation performed show that the system achieved high accuracy in the detection of fine-grain conversation groups.

A different type of application is explored in [214], where smartphones are used to model the usage patterns of their owners. This work presents the *MobileMiner* a general-purpose mobile service that uses contextual data, which includes applications usage and places, to predict user patterns. The results of this prediction are used to adapt the *UI,* showing appropriate shortcut icons, and improve the user experience.

Researchers have investigated the potential to use the information inferred by these types of smartphone-based systems and other sensor-based context recognition solutions to understand the context of the user's activities, environment and social interactions [97, 23]. Consequently, there have been much work focused on using data gathered from sensors embedded in diverse types of mobile devices in order to model the behaviour of the users and try to understand its influence on people's activities. Many of these types of studies investigate factors about how people communicate and interact to each other.

In that line, much research work the *MIT Media Lab* has concentrated on collecting data about interactions among people in organizations using the *Sociometric badge* [178], a custom-made sensing platform (in the form of an employee' badge). The *Sociometric badge* uses several sensor technologies: (i) accelerometer to recognize common human activities (e.g., walking, standing, sitting, etc.), (ii) microphone for voice capture in order to extract speech features in real-time, (iii) Bluetooth to detect proximity to other users and to communicate with Bluetooth-enabled devices (e.g., smartphones, tablets, etc.), (iv) IR sensor to identify face-to-face interactions and (v) 2.4 GHz radio to communicate with based stations (i.e. other badges in fixed locations or other compatible devices) and perform indoor localization. The objective is to capture individual and collective patterns of behaviour in order to understand how such patterns shape individuals and organizations.

For example, in the study presented in [177] 22 employees of a real organization used the *Sociometric badge* to capture and model their social interactions and communication patterns. Results from the study revealed that these devices were able to predict the users' perceptions about their productivity and the quality of their interactions. In [175], the authors also present two studies based on the *Sociometric badge.* The first one, conducted in a hospital, demonstrated that high variations across the daily activity levels (i.e., alternating periods of high and low activity during the day) of the nurses can be used to predict an increase in the daily average number of delays in the Post Anaesthesia Care Unit. The second study, performed among the participants of an entrepreneurship program, revealed that the *Sociometric badge* was useful to capture the features of successful teams with regards to physical activity levels, speech features and proximity to other. Similarly, in [235] the authors report a study that determines, through sensed data, the social interactions between workers at a call centre. The study results show a positive correlation between the quality of the individuals' interactions and their productivity.

The work presented in [182], uses the *Sociometric badge* to model communication patterns among people. Researchers were able to identify, from the sensor data, three factors of the communication patterns of team members that affect their performance. They isolated engagement (i.e. number and frequency of interactions), energy (i.e. the degree to which the conversations flow among people followed a close loop) and exploration (i.e. number of additional interactions outside the core group) as predictors of team success. Another appealing study [176] shows that is possible to model both individual and group behaviour from sensor data. Therefore, data from the *Sociometric badge* was used to capture high level descriptions of human behaviour in terms of physical and speech activity, face-to-face interactions, physical proximity and social network attributes, which allowed the identification of personality traits and group performance features.

There are similar studies from a different research group. For instance, [35] presents a study where RFID wearable tags are used in a research laboratory to collect face-to-face interactions and location data. By modelling user behaviour, researchers observed that social interactions varied across physical locations and were also influenced by cultural factors. Similarly, in [36] RFID wearable tags are also used to model interpersonal interactions between people different subgroups of the formal hierarchy of an organization. This information is used to study how the design of physical spaces has an impact on social interactions.

2.1.2 Using Sensor Data to Monitor Behaviour

In order to model the behaviour of individual and groups, it is necessary to track and monitor people's activities over a certain period of time, which usually requires the collection of different pieces of information from diverse data sources using mobile or ubiquitous sensing technologies. Consequently, several sensor-based monitoring solutions have been proposed in the literature.

The *FriendSensing* framework, reported in [189] uses short-range radio technologies to monitor face-to-face encounters between people. Particularly, Bluetooth data collected by mobile phone users to infer social networks and recommend friends on social-networking sites. The evaluation of this framework showed that it was also able to identify current friendship relationships of the users.

Another group of interesting research studies on the topic were performed by researchers from *The University of Cambridge.* In *EmotionSense* [191] the authors exploit the fact that smartphones offer an unobtrusive means of obtaining information about the users. Therefore, they explore the use of smartphones to support experimental sociology research as an alternative to the traditional methods, such as cameras or self-reports, where the participants of the research experiments are aware of being constantly monitored. *EmotionSense* is a smartphone-based sensing platform that captures the user's emotions (happiness, sadness, fear, anger and neutral), patterns of conversation and social interactions.

In another study, *WorkSense* [190] is used for workplace monitoring by capturing data from smartphone sensors (i.e. accelerometer, Bluetooth and microphone) and infrastructure sensors (i.e. desk sensors, Bluetooth scans and microphones), and combining them with work-related data about the users (i.e. from application logs and calendars). The *WorkSense* application was used to automatically infer meetings and collaborations among users at the workplace and to model the interaction patterns of workers.

In [78] the authors propose an integrated sensing system to perform complex and simultaneous audio inferences. This system is used to monitor the user behaviour by continuously capturing the audio environment. The audio data collected enabled the identification of speakers, emotions, common ambient sounds the number of people in a room.

One initiative aimed at monitoring and modelling behaviour in educational contexts using sensor data is reported in [209]. Here, the authors introduce a study that involves tracking students in a university campus to model their behaviour and mobility patterns. They propose a monitoring system that use information gathered from the access points (AP) distributed in different locations of the campus buildings. The system collects in a central server, information about the time when a particular MAC address (corresponding to a specific wireless mobile device) is associated to any of the APs deployed. The authors suggest that the information provided by this monitoring system can be used to make an effective planning and distribution of the network bandwidth as well as of other university services offered to the students.

A different approach is used in *Reality Mining,* reported in [65]. In this study, logs from Bluetooth MAC addresses were collected, using two different systems. The first one, is the *BlueAware,* an application that runs in the background of Symbian Series 60 phones and collects Bluetooth data, cell tower identifiers and information about the use of applications and the device state (e.g., charging, idle, etc.). The second system, the *Bluedar,* is composed by a Bluetooth beacon and a Wi-Fi bridge. *Bluedar,* which was placed in a public location, performs Bluetooth scans periodically and sends the results to a central server. The *Reality Mining* application was used to monitor the behaviour of students and faculty at the *MIT* over the course of an academic year. The resulting monitoring data was used to infer interpersonal relationships and to analyse individual and group behaviour patterns.

The empirical study described in [66] explores the controversial issue of the privacy concerns related to the use of monitoring systems. This study involved the deployment of a sensor-enhanced social sharing service in a work environment. The service used data collected from smartphone sensors and static sensors embedded in the environment to monitor location, conversation and interaction with physical objects. The information monitored was used to provide awareness to the users about the social interactions in the workplace and about the location of their colleagues as well as personal statistics about their social behaviour. Results from the study showed that there are contradicting trends regarding the acceptability of this type of monitoring systems. Although users found value in the information provided by the monitoring system, the loss of control over what was reported about their own behaviour raised some privacy concerns.

2.1.3 Using Sensor Data to Shape Behaviour

The ultimate goal of most monitoring systems is to deliver awareness information and feedback to users in order to promote behavioural changes that impact positively on their activities. For example, the concept of *Socially Aware Interactive Playgrounds* [157], describes the idea of enhancing playground installations with sensors, displays, interactive objects and wearable sensors to provide engaging and immersive game experiences. Most of these playgrounds use custom-made solutions, such as pressure sensors located in the floor, camera-based tracking systems, toys and objects with wireless motion sensors to model and monitor the children's behaviour and promote physical activity, social interactions and cognitive development. To provide awareness about negative behaviour patterns and promote positive social interactions these playgrounds typically use visual signals from projectors and sounds that encourage the children to change their patterns.

Another example is *VibeFones* [141], a software that uses smartphones to infer social interaction patterns of a conversation and provide feedback to users. It uses location, proximity and voice data to create a sophisticated understanding of the verbal communication patterns of the users. It measures signs of conversational interest, such as speaking time, number of back-and-forth interactions and tone of voice to predict the outcome of the conversation according to the specific context where it is taking place. The system also displays information about the speech characteristics and provide direct instructions to the user of how he should change his conversational behaviour (e.g., "Maybe you could speak a little slower").

Jabberwocky [180] was designed to facilitate introductions or collaboration between strangers with similar interests or profiles. The *Jabberwocky* was developed as both a wearable device and a smartphone-based application. Both implementations use Bluetooth to monitor and "digitally tag" places or people that have been previously encountered by the user. The monitored information is used to provide simple visualizations of the general state of familiarity among users, showing, for example, the amount of people previously tagged by a user that are also in his current location.

It is also interesting the application of these systems to shape the organizational behaviour. For example, in the *Meeting Mediator* [116], a smartphone application that uses data sensed using the *MIT's Sociometric badge* [178]. The goal is to promote a more balanced speech pattern by displaying information about the dominance of each person participating in a face-to-face conversation. The system detects dominance expressed through verbal and non-verbal cues using sensor-collected data about speaking time, volume, turns and movement status. Moreover, the application provides real-time feedback to change collaboration patterns and reduce the difference between dominant and non-dominant people, which also leads to a mood contagion effect.

Another example, is *SociableSense* [192], a smartphone-based platform that captures the user behaviour in an office environment. It provides awareness of the sociability of the user and of his colleagues using a quantitative feedback mechanism. This mechanism provides awareness about the strength of the user's relationships in the workplace with the purpose of promoting changes in his social interactions patterns. *SociableSense* also informs the user about relationships that need specific attention and about opportunities to interact with colleagues in particular social locations.

BeWell [125] is an example of the application of monitoring systems to provide feedback and shape behaviour in the healthcare domain. It runs on *Android* smartphones and monitors several dimensions of the behaviour of the users that influence their health and well-being, such as sleep patterns, social interaction and physical activity. The platform informs the users about changes in their state of well-being, making them self-aware of their current state and therefore, promoting behaviour patterns that will impact positively in their future well-being.

An interesting study in the educational area in presented in [244], where a smartphone-based monitoring application is used to support a situated learning activity. In this case, the GPS sensor is used to track the location of the students while participating in an outdoor learning activity. The application display information in the students' devices to make them follow specific activity patterns. It is also used by the teachers to monitor the progress of the students and provide real-time feedback.

2.2 Requirements of a Pervasive Monitoring System

From the studies presented in the previous section and from the challenges derived from the features of the types of learning scenarios described in Chapter 1, we can deduce several requirements for the design and implementation of a technological solution for pervasive monitoring:

- ***Ubiquity:*** monitoring solutions must provide sensing and feedback services across diversity of environments and contexts. Therefore, they must ensure high information availability, considering both the collection of sensor data and the provision of feedback to the user.
- ***Autonomy:*** to ensure a high availability of monitoring services, these solutions should not rely on fixed or centralized components that could become potential Single Point of Failure (SPOF). For this reason, the system must make sure that both its sensing and communication services are autonomous.
- ***Diversity:*** to guarantee information heterogeneity and quality, monitoring systems must have access to multiple data sources and sensing

devices. Therefore, collaborative sensing interactions between multiple and diverse devices is required.

- ***Interoperability:*** to allow interactions between devices we these types of systems must provide interoperable communication and data services.
- ***Cost-efficiency:*** due to the continuous sensing operations required by pervasive monitoring applications, monitoring solutions must be energy-aware and make an appropriate use of the computing and network resources.
- ***Context-aware*** and ***Social-aware:*** for cost-efficiency reasons, to provide appropriate awareness information and detect opportunities for collaborative sensing, monitoring solutions must be aware of the context of the local monitoring device and of surrounding devices the user, of the user and of his social interactions.
- ***Connectivity:*** to provide access to remote information, to optimize the resources of the local devices and to perform complex inferences, monitoring systems must provide Internet and Cloud connectivity.
- ***Flexibility:*** due to the heterogeneity of devices and environments considered in monitoring applications, they must provide flexible awareness mechanisms as well as adaptable sensing methods.
- ***Unobtrusiveness*** and ***Interactivity:*** both features must be supported by monitoring systems to avoid interruptions that could disrupt the user but at the same time allow the possibility of collecting quantitative information and user-entered data.

This thesis offers technological solutions that contribute with the fulfilment of all the requirements listed above from the data sensing, communication and awareness provision perspectives. Next sections describe the related work on topics associated with such aspects and therefore with the main contributions of this dissertation.

2.3 Collaborative Sensing for Pervasive Monitoring

Due to the fact that most pervasive monitoring solutions rely on collaborative sensing interactions between different types of devices. This section describes some related work on collaborative sensing.

The widespread penetration of smartphones in the society has opened several opportunities to perform mobile collaborative sensing. In the literature we can find different approaches to the topic.

Participatory sensing [190, 41] usually involves the voluntary cooperation between smartphone users in order to collect, analyse and share information about their local context. These processes usually require explicit participation of the user, who is actively involved in the data collection process. An example of this voluntary information sharing is when an individual use his smartphone to take a picture, provide descriptions of his particular context (e.g., in a meeting, cycling, etc.) or tag his current place (e.g., my favourite cafeteria, my brother's place, etc.). Similarly, *mobile crowdsensing* [76, 84, 85] also requires user intervention to provide sensor information. However, it reuses user-entered data from Internet services and social networking sites. These capabilities have allowed people to become active participants of these processes and get a benefit for that. Some services based on these sensing paradigms allow people, for example to identify opportunities for hitchhiking [219] or to evaluate their personal security [46]. Typically, these sensing approaches use infrastructure-based communication that allows mobile sensors to access centralized data repositories, which are in charge of supporting the data sharing process.

These approaches are not particularly designed to perform opportunistic sensing, where heterogeneous mobile devices (i.e., devices with distinct sensing capabilities) collaborate to provide each other with contextual data that each device alone could not otherwise sense. For this reason, a different sensing approach is also necessary. *Opportunistic sensing* [190, 153], provides a method to capture contextual information automatically from sensor available in the smartphone. In this case, the user is not directly involved in the data collection process and the information is sensed unobtrusively.

Next, we present some examples of solutions designed to provide support to the collaborative sensing approaches described above.

The *CoMon* [128] platform was proposed to address the energy drain problem caused by continuous sensing and processing tasks required by monitoring applications. It supports cooperation by sharing sensed data among nearby smartphone users, focusing in the detection of potential collaborators (mobile users) and trying to maximize the mutual benefits for the people involved. The platform was also evaluated to show the energy benefits of collaborative sensing. The authors also highlighted additional advantages of collaborative, such as extending the sensed information beyond the capabilities and context of the local device.

METIS [193] is an adaptive smartphone-based sensing platform designed to support social sensing applications. The platform follows a mixed approach, combining smartphones with other devices. Therefore, it decides whether to perform sensing tasks on the local smartphone or on fixed remote sensors, considering the energy costs and the mobility patterns of the user.

In [132], the authors propose a collaborative sensing middleware that allows smartphones to delegate part of their sensing activities to other nearby devices, which leads to an overall reduction in the battery drain of the group of devices involved. This middleware is centralized and aggregates sensor information to serve multiple devices distributed in a particular physical area. It also uses an algorithm to find the best combinations of sensors that could be activated on the available devices and uses a cloud server to process or store sensor data.

The framework presented in [69], models collaborative interactions between a mobile *crowdsensing* platforms and the smartphones. It was conceived to provide incentive mechanisms that encourage users to join and interact with *crowdsensing* applications.

A novel application of collaborative sensing systems is described in [72]. In this case, collaborative interactions between sensing devices are envisioned for health monitoring applications based on *Body Sensor Networks (BSN).* The authors also propose and evaluate the *C-SPINE* framework, specifically designed to support Collaborative BSNs.

Collaborative sensing systems have also been used for the collection of traffic information. In [237] the *EasiSee* system for real-time counting and classification of vehicles is described. For the development of this system, the authors propose a collaborative sensing mechanism that coordinates sensing tasks between a camera and magnetic sensors, and minimizes the energy consumption of the system.

2.4 Mobile Ad hoc Networks for Autonomous Communication

This section presents related work on Mobile Ad hoc Networks (MANET) due to the fact that we propose the use of these types of networks to provide autonomy to the communication processes required for pervasive monitoring. We introduce some studies in collaborative learning over Mobile Ad hoc Networks and also some works on real-world deployments of these types of networks.

2.4.1 MANETs in Collaborative Learning

Advances in mobile computing and wireless communications have created a shift in the development of collaborative applications from a mainly stationary focus to more dynamic contexts and mobile forms of collaboration. This have been the case for a large number of application domains, such as design [243], healthcare [220], construction work [172], emergency management [155], productive activities [164] and education [47, 226, 57, 218, 60, 194], this last being considered as one of the main application areas.

According to [67], having an effective communication support is essential to assist groups of people working together towards a common goal. Therefore, if we want to develop mobile collaborative learning applications we have to enable coordination and collaboration by providing a suitable communication support among mobile users, regardless of their physical location. As explained in the introduction of this dissertation, meaningful learning can take place in an informal and opportunistic way. Therefore, the context in which opportunities for collaborative learning may arise can frequently be uncertain. For that reason, to appropriately support the new learning paradigms we need flexible, autonomous and interoperable solutions that do not rely on pre-existing communication infrastructure and provide smooth and transparent integration among all the participating devices. Despite this, many studies does not consider the fact that mobile collaborative applications are usually deployed in scenarios where the permanent availability of fixed communication infrastructures is hard to predict. Various research studies, however, advocate for the use of MANETs in collaborative learning applications [165, 42, 228, 74, 12, 227] as an interesting contribution to support communication between mobile students.

For example, in [158], the authors propose a collaborative learning environment that uses MANETs as communication support to provide coordination, information exchange and location and notification services. They also explore the challenges in terms of security and bandwidth availability posed by the use of MANETS in such an environment. Moreover, the authors propose some solutions to deal with secure group establishments in MANETs.

The work presented in [77] highlights that MANETs provide a technological base for the development of *context-aware learning environments* due to the fact that they integrate communication, collaboration and content exchanging services. In this study, the *CAFLA* framework is developed to facilitate the deployment of mobile collaborative learning activities. This framework, which implements ZigBee as communication protocol, enables interaction with RFID-enabled devices and objects.

2.4.2 Real-world implementations of MANETs

Many recent research studies focus on the use of MANETs, as these networks are gaining more and more attention due to their low implementation cost and flexibility [121, 174], which make them ideal for diverse applications that involve mobility and ad hoc deployments. Most of these studies use simulations to evaluate the performance of these networks to assess their suitability for real-world applications [121, 122, 114, 224]. These simulation tools provide a simple and inexpensive method to gain understanding of algorithms and protocols. Nevertheless, their reliability and accuracy to represent real systems and contexts is limited [222, 174, 122, 181, 20]. For that reason, simulations should only be used as a preliminary evaluation method and its results must be verified and assessed through real-world experiments [174]. Consequently, in this section we report studies performed using real-world implementations of MANETs.

A recent study presented in [174], an indoor MANET testbed was implemented and evaluated. The testbed evaluated the performance of the *Optimized Link State (OLSR)* protocol for MANETs in terms of throughput when transmitting UDP traffic at 500 Kbps (generated using the D-ITG open source traffic generator). For this evaluation, five static nodes running a *CentOs Linux* distribution were configured to work in the IEEE 802.11b band (2.4 GHz and channel 1). The indoor environment considered was free from obstacles.

In [144] the authors present an implementation of the *Dynamic Source Routing (DSR)* protocol, tested in a MANET composed of five mobile nodes installed in cars moving at a maximum speed of 40 km/h and two stationary nodes. The stationary nodes were installed 700 m apart at opposite ends of the course travelled by the mobile nodes. The authors provided some general lessons learned from these tests, such as the fact that control packets of the routing protocol should be delivered with high priority, that the management of human participants of the experiment is difficult and time consuming and that the wireless signal propagation is highly variable.

The *DSR* prototype implementation was extended to support real-time traffic such as audio and video in [98]. In this study, the network is composed of one mobile and seven fixed nodes. Then, audio and video streams were transmitted over up to three hops from the mobile node to one of the fixed nodes. The experiment showed that the transmission of real-time traffic over an ad hoc network is possible if the routing protocol is adapted to the specific application scenario.

The experiments presented in [63] study the impact of the routing strategy, which is based on various network metrics, on the performance of ad hoc networks. Therefore, three different link-quality metrics (*ETX, per-hop RTT, and per-hop packet pair*) were compared with the *minimum hop-count* metric. These metrics were evaluated using a DSR-based routing protocol running in a wireless network with 23 nodes. The experiments show that the *ETX* metric has the best performance when all the nodes are static and the *hop-count* metric outperforms all the link-quality metrics in a scenario where the sender is mobile, because it reacts more quickly to fast topology changes.

An experiment conducted with implementations of *Ad hoc On-demand Distance Vector (AODV)* and *Destination-Sequenced Distance Vector (DSDV)* routing protocols is described in [53]. These protocols were tested in a scenario with four fixed and one mobile node. The fixed nodes were set up in a chain topology and the mobile node moved alongside this chain, from one end to the other. The main objective of these experiments was to identify which one of the two protocols considered reacted faster to changes in the network topology.

The authors of [43] report an experimental evaluation of four MANET routing protocols (*DSR, OLSR, TORA and AODV*). The performance of these protocols was compared in a scenario where coded video was transmitted over UDP. The results showed that the appearance of burst of packet loss caused by route changes is a major problem, which should be handled by the routing protocol.

The use of MANETs for real-world emergency support is explored in [121]. In this study, a robot moves around different locations of an office environment searching for things to be saved in case of fire. A MANET is established between the robot and eight static nodes using the IEEE 802.11b. protocol. The nodes operate on Ubuntu and use the OLSR routing protocol. In this study, the performance of the network is evaluated in terms of throughput received when transmitting UDP traffic at 200 Kbps. This scenario could be used, for example, to support information sharing between firemen located in different locations of the building, where the communication can be affected by walls and other obstacles from the physical environment.

In recent years, the application of MANETs to support communications between vehicles has gain interest. An interesting example of the use of MANETs in this area is explained in [20]. Here, a real-world testbed that allows extensive testing of network protocols in vehicular networks is described. The testbed allows remote network control, code deployment and distributed data collection from moving vehicles. Although it was initially designed for testing purposes, the testbed is currently in use as communication infrastructure to support harbour operations.

2.5 Smartphones for Flexible Awareness Provision

The two awareness mechanisms proposed in Chapter 5 take advantage of the flexibility that smartphones offer to provide awareness in dynamic and heterogeneous learning contexts. The first mechanism proposed is intended to support awareness provision in collaborative learning scenarios, whereas the second mechanism uses smartphones as a bridge to provide information in a multi-display environment. Consequently, this section present related works on both topics.

2.5.1 Awareness in Collaborative Learning

Many studies have addressed the feasibility of providing visual awareness functions in software systems supporting collaborative learning activities. Some of these studies aim at providing awareness and feedback in e-Learning environments. For example, in [123] a Web-based group coordination tool for an online course is described and evaluated. The tool includes functions to visualize the assessments of the members of a team about their group processes and performance. It also allows comparing theses values with those from other teams. A different approach is proposed in [124], which involves the provision of social awareness. In this case, a field study explores the usefulness of providing indicators of presence, participation and interactions among students on a forum hosted on *Moodle.* Such indicators were offered to the students as visualizations of social networks, participation graphs and dialogue quality descriptions. Results from the study indicated that active participation and the quality of the students' contributions can be increased by the use the social awareness tools proposed.

Awareness systems have also been used to support face-to-face collaborative learning activities. For instance, in [151] the authors propose and evaluate several task-specific visualizations designed to provide awareness during a gamified location-based learning activity. The visualizations were evaluated through a real-world collaborative learning activity, where 23 secondary school students had to answer a number geo-located questions using a gamified mobile application. This application allowed the collection of data about the interactions of the students with the application, which was used later for the design of the visualizations. Such visualizations were designed to provide information about the performance of the students during the learning activity, facilitating the students' self-assessment as well as the teachers' evaluation of the activity design.

Other types of systems have been proposed to offer awareness of various kinds of conflicts that can arise between students while they are collaborating. For instance, the work presented in [238] proposes the introduction of two different tools in wiki systems to increase awareness of each editor's contribution and of task conflict. The first tool offers paragraph-based edit history and word-based content authorship information to increase awareness of the contributions of a group of students that are working on a common wiki article. The second tool provides feedback of task conflicts by assigning different background colours to words or sentences, based on the computation of the severity of the conflict. The authors of [39] proposed a rating-based group awareness tool to support conflict resolution in collaborative learning. This tool, which was embedded into a text-based online discussion environment that allowed teams of students to reach an agreement about a specific topic in a physics course, was primarily intended to be used in scenarios of majority-minority conflicts. It also enabled students to compare their own contributions to the discussion with the contributions of other group members in a synchronous way. The evaluation of the proposed group awareness tool involved 64 undergraduate students arranged in small groups of four students.

Another work that explores the role of awareness in CSCL environments is introduced in [185]. The authors enhance an existing groupware application with services for supporting peer feedback and reflection. The Radar tool, for peer feedback, facilitates the collection and display of information about the social and cognitive performance of a student, from a personal and team perspective. Moreover, Radar was evaluated to assess its usefulness in providing individual and group awareness about the students' collaborative behaviour.

Some awareness solutions offer a complementary approach to the studies described previously. This approach is based on the use of visualizations to regulate the structure or flow of specific collaborative learning activities. The authors of [152] explore this idea by using these types of solutions to support shared planning of collaboration. They integrated a scripting tool, which structured the collaborative interactions required to complete collaborative assignment, with a group awareness tool that displayed a summary of the goals and perceptions of each group member. The goal was to promote individual and group regulation of the assignments. Another interesting example is presented in, [145]. This study, proposes a software system to structure collaborative learning in a smart classroom. This architecture enables the integration of smartphones, a smart display and wearable devices but it can also be extended for integration with other classroom technologies. The applicability of the proposed architecture is illustrated by the authors through a scenario where secondary students have to perform an activity using the Jigsaw Collaborative Learning Flow Pattern (CLFP) at a secondary educational context.

2.5.2 Awareness in Multi-display Environments

Traditionally, most of our computing has been confined to environments with a single display and focused activities. However, much of the recent research is related to *multi-display environments,* as displays become embedded throughout our environment and daily lives. Examples include peripheral or ambient displays, where a person can be aware of the information provided while attending some other primary activity [105, 87], the exploration of co-located collaboration across handheld devices, where multiple users with handheld computers share information during a collaborative activity [198], work related to single-user interactions with multiple-monitor systems [146] and work about design aspects of *Distributed Display Environments (DDEs)* [199, 102] and DDEs research related to the placement or location of on-screen objects and information [81, 100].

Many research studies have centred on situated displays and on the use of public displays. There are a number of interesting papers in the literature focused in awareness and interaction with large public displays. In [184] the authors conducted a study with 14 participants about information displays available in office environments and they developed a taxonomy of visual display-based activity in office spaces using this field data.

Another example is the work presented in [34], focused on improving the design of public interaction. In this paper, a system designed to encourage social interaction is described. The authors placed this system in two social real-world settings and presented their findings in terms of physical and social engagement that take place around it.

The study in [215] also presents a software architecture designed to support the coordinated scheduling of rich media content on networks of situated public displays. In contrast to the previous pieces of research, where the use of public displays have focused on providing information across remote locations or among people who are loosely connected and lack awareness of the activities of each other, recent research has focused on collaboration issues. For example, [99] presents *Semi-Public Displays,* a suite of applications to support and enhance awareness and collaboration in co-located groups.

Another interesting approach is the groupware system presented in [79], where distributed and co-located users can post media elements onto a real-time and collaborative public surface. The authors also highlight the differences in the users' behaviour when their system is displayed on a large public screen than when it appears on a personal computer.

Another active area of research, deals with *user interruptibility and attention management.* For instance, [149] present a toolkit that provides structured support for managing user attention in the development of peripheral displays. In [161] the authors describe two user studies to explore how the users' expectations towards what is presented on public displays has a relationship with their selective attention towards these displays. The study presented in [103] proposes a strategy for using context-aware computing to minimize the perceived information change. The authors, propose a reasoning module that accepts requests to display information from multiple applications and controls how the information is presented to minimize visual disruptions to users.

The system presented in [145] is an interesting example of multi-display environments in a learning context. It was designed to structure learning patterns in a classroom environment by using a combination of fixed, mobile and wearable displays. This system displays awareness information in a smart TV and provides feedback in the screens of the student's smartphones. It also guides the students through specific activity patterns using wearable displays.

Another example is the system described in [159] intended to provide a rich and varied experience with video contents and activities for learning purposes. It is based on a public display, with which students can interact through an *Android* application that grants access to the display's contents. Two applications were developed using this system: the *Quiz Application,* to show video and quiz elements in the public display and allow students to interact with the quizzes using their smartphones, and the *Video Rating Application,* which displays information about the students' ratings of diverse educational videos.

In [31] the authors present a literature review on the use of *ambient displays* in learning applications. The focus of this study is the use of such displays for situational awareness and feedback. The majority of the works review are focused at understanding the psychological effects of ambient displays instead of design aspects of the displays themselves. In addition, the majority of prototypes developed handle only a low capacity of information.

Chapter 3

A Framework for Pervasive Data Sensing

3.1 Introduction

In order to perform pervasive monitoring in learning scenarios, we need to extract metrics that allow the characterization of the features of the students learning practices and patterns. It is, therefore, necessary to capture raw data from different kinds of sensors continuously and across the different situations and contexts that the students might encounter in their everyday lives. Furthermore, in order to make high-level inferences about the students' behaviour from this raw sensor data, several processing and classification tasks must also take place.

As discussed in previous chapters modern smartphones are ubiquitous and powerful sensing devices that can help to draw inferences about social interactions and learning processes. However, the data collection and inference processes involved are not trivial mainly because of three reasons:

- The sensors available in a specific device can be limited and/or not have the accuracy that is required for a specific sensing task.
- The continuous sensing process necessary to perform monitoring activities have a high energy cost, leading to a rapid battery drain, especially if there are several sensing tasks active concurrently [24].
- The smartphone computing resources can be limited to perform some computationally intensive classification and inference tasks (e.g., speech or image recognition) [190].

These challenges have promoted the appearance of collaborative sensing techniques to improve data quality and save energy [136, 137, 62, 153]. Nevertheless, although there are many collaborative sensing software platforms that can help developers to create monitoring applications for smartphones, it is not clear the sensing model that these platforms implement and the range of scenarios in which they can provide a solution.

Most sensing platforms involve the use of centralized components, or assume homogeneity of devices capabilities or stability of the communication link among the participants [55, 128, 187]. Most of these sensing solutions use infrastructure-based communication that allows mobile sensors to access centralized data repositories, which are in charge of supporting the data sharing processes. Moreover, they usually require the explicit participation of the people and allow them to become active participants of these processes and get a benefit for that.

These assumptions do not represent a problem for conducting several monitoring activities; for instance, crowdsensing [76, 84] or participatory sensing [41] in urban scenarios where the application can assume a continuous access to the cellular network. However, it does not take into consideration scenarios with loosely-coupled interactions between smartphone users (i.e. when the users perform their activities autonomously and only collaborate when is necessary or an opportunity arises [173]) in uncertain communication contexts or those scenarios where users share information both implicitly and explicitly.

This partial mismatch is because comprehensive pervasive monitoring applications should consider the dynamism of contexts and interactions that smartphone users can encounter. Therefore, pervasive data sensing solutions should provide services for implicit and explicit data sharing, and these services should work in both infrastructure-based and ad hoc networks. Although there are several applications that provide specific solutions for addressing particular problems, most of them are not easy to use in other contexts, and also require specialized development expertise. For this reason, the development of these types of applications requires to address several challenges related to the limitations of the communication networks and types of interactions in certain contexts, such as unstable communication links, devices heterogeneity, energy constraints, user mobility patterns, etc.

There are also platforms that consider unstable communication scenarios and provide autonomy to the devices participating in a sensing activity, for example, using ad hoc networks. Nevertheless, they do not take advantage of the long-range communication infrastructures (e.g., Internet connection, cellular networks, etc.) when they are available [128, 61]. This is why, the ideal solution should not only provide autonomy, but also the capability to interact with remote components when they are available.

Provided that pervasive monitoring scenarios usually entail diverse types of sensing devices and are dynamic in terms of communication support and mobility patterns of the people involved, the monitoring platform should also provide context-awareness [26] and support for device heterogeneity (i.e. allowing interoperability and considering hardware and energy limitations).

Considering all the challenges introduced in the previous paragraphs, we propose a framework especially designed to deal with data collection and sharing processes involved in smartphone-based pervasive sensing. Although this framework was conceived to meet the special requirements of pervasive monitoring in learning contexts as the ones envisioned by the new learning paradigms, it also provides a technological model that is suitable for a variety of pervasive monitoring scenarios.

The proposed framework has the following features:

- ***Autonomous:*** since it preserves the independent operation of the mobile devices but also enables it to work collaboratively with other devices.
- ***Context-aware:*** because it considers the characteristic of the hardware components of the devices as well as the network conditions.

- ***Energy-aware:*** due to the fact that considers the battery level of devices for the assignation of sensing tasks and intends to minimize the energy costs for the overall group of devices involved.
- ***Infrastructure-independent:*** since it can work regardless of the underlying network infrastructure. It can also work in scenarios where there is no fixed communication infrastructure available. This feature also contributes to the autonomy of the framework.
- ***Support for dynamism:*** because it adapts to changes in the network, mobility and hardware conditions.
- ***Flexible operation:*** since it provides autonomy to the devices but also allows access to fixed network infrastructures or remote components when they are available.
- ***Interoperable:*** because it enables collaborative sensing interactions between different types of smartphones and various kinds of sensors and devices, independently of their hardware characteristics.

After exploring the viability and usefulness of the framework through a simulation tool, a prototype of the framework was developed and evaluated. The evaluation processes were helpful to assess the framework's performance and determine its associated costs in terms of energy, computation and network traffic. The preliminary results indicate that this infrastructure is useful not only for data gathering and sharing, but also for reducing the battery consumption involved in the sensing tasks.

Chapter Overview

This chapter describes and evaluate a framework for pervasive data sensing, involving both autonomous and collaborative sensing activities. The framework was evaluated empirically using both, simulations and a prototype. Both types of evaluations provided various insights on the performance of the framework under diverse hardware, networking and mobility conditions. The remainder of the chapter is organised as follows: in Section 3.2 we describe the design of the pervasive sensing framework proposed, including details about its architecture, services, interaction protocols, messages and data retrieval mechanism.

In Section 3.3 we present the evaluation of the framework and discuss the results of the simulations as well as of the evaluation of the prototype. We also propose some improvements to enhance the performance of the framework in Section 3.4. Finally, we present the conclusions in Section 3.5.

3.2 The MASU Framework for Pervasive Sensing

This thesis proposes the Mobile Autonomous Sensing Unit (*MASU*) framework for pervasive data sensing in learning scenarios. The aim of this framework is to support opportunistic information sensing and sharing among different types of devices regardless of the underlying network infrastructure. This infrastructure allows the creation of service-oriented pervasive sensing applications, providing complex collaborative sensing services while ensuring the devices autonomy. In addition, the *MASU* framework offers a common platform for the provision of pervasive monitoring services, allowing the interaction between smartphones and other types of sensors and IoT devices, such as smart objects, shared displays, networked printers, sensors in smart buildings, etc. This platform can be easily reused to support the development of collaborative sensing solutions for wide range of contexts and diverse applications. The design of the *MASU* framework is flexible, allowing both interoperability and autonomy. The following sections describe different aspects of the design of this framework.

3.2.1 System Overview

The *MASU* framework supports opportunistic mobile collaborative sensing activities performed over dynamic communication scenarios that include both stable and unpredictable communication links. This framework is based on what we called *MASU* units or nodes, which are smartphones or other devices that run the *MASU* software infrastructure. The *MASU* units can not only work autonomously and perform independent sensing tasks, but also interact opportunistically with other units to perform collaborative sensing. The framework allows smartphone users to act as both consumers and providers of sensing services while preserving their autonomy. The collaboration among a group of *MASU* units allows the provision of complex and high quality sensing services that could not be provided by individual sensing devices due to limitations in their capabilities (e.g., cpu, memory, sensor quality, etc.) or to the high cost involved in the sensing tasks. For this reason, the interaction between several units enables a number of collaborative sensing services that are beneficial for the overall group of devices involved in terms of hardware resources, energy consumption and information quality.

In order to model the different processes and services involved in a collaborative sensing activity the *MASU* framework defines a number of roles played by different units. A role can be seen as a particular set of services provided and/or consumed by a specific unit. A *MASU* unit participating in a collaborative sensing activity can play one or more roles within such an activity. Moreover, it can have several instances of the same type of role activated at the same time. A unit can also participate in several parallel collaborative sensing activities, interacting simultaneously with units that are part of different activities and playing the same or different roles in those activities. In other words, a *MASU* unit can be seen as a node playing one or more roles and therefore consuming and/or providing the services specified by those particular roles.

Figure 3.1 shows an overview of the *MASU* system when two collaborative sensing activities are being performed among a group of units. It shows two different groups of units that, according to the roles played by them, provide and/or consume diverse services within the activity they are participating. In addition, one of the units is participating in both sensing activities so that it can contribute to and benefit from both of them.

3.2.2 Architecture

The architecture of the *MASU* framework designed to support the development of pervasive data sensing applications, is represented in Figure 3.2. This framework has a modular design composed by two separate layers: the ***Control Tier*** and the ***Sensing Tier,*** which interact among themselves and define two different categories of roles. On the other hand, the *MASU* framework has also a crosslayer architecture, enabling interactions with other layers of the computing system. This enables the framework to have access data from such layers and benefit by the information that they provide (i.e. hardware and network information).

The ***Control Tier*** provides all the services required for the management and monitoring of the overall collaborative sensing activity, coordinating the tasks

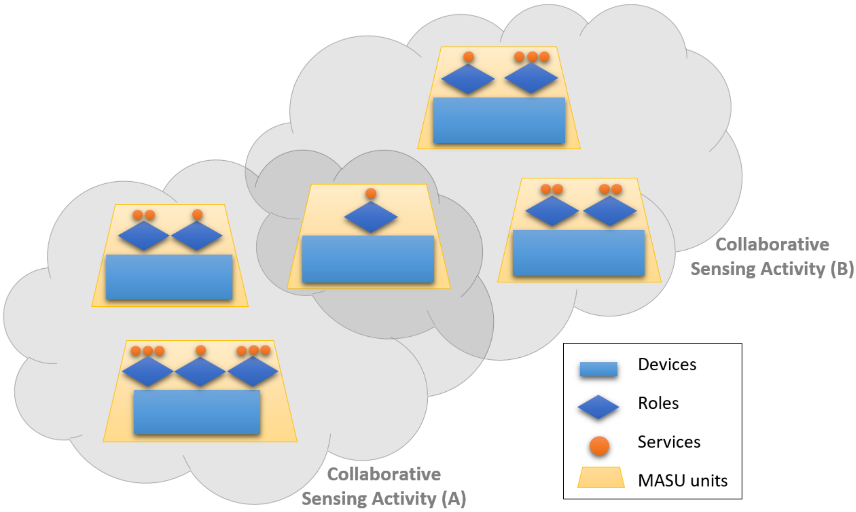


Figure 3.1: Overview of the MASU system

within the activity and also between several sensing activities, if required. The Control Tier is also in charge of managing the use of resources within each sensing device (*MASU* unit) participating in an activity.

This layer includes two roles: ***Manager*** and ***Monitor,*** which interact among themselves to coordinate the operation of this tier and to guarantee the provision of collaborative sensing services. Therefore, the Control Tier performs role selection and activation functions and has control over the Sensing Tier. It also monitors the state of different hardware components of the device, such as battery level, processor load, memory available and quality of the sensors available (***hardware monitoring***). Moreover, it keeps track of events related to the underlying network infrastructure, including topological changes, network traffic, congestion and delay (***network monitoring***). Such a careful monitoring allows the *MASU* units to be context-aware and to make appropriate role selection and activation decisions as well as to adapt to the unpredictability of dynamic environments, activating or deactivating roles accordingly.

The ***Sensing Tier,*** which is in charge of performing the specific data sensing and sharing tasks, has four distinct roles: ***Producer, Consumer, Storage*** and ***Relay***. These roles interact among themselves enabling the provision of complex data sensing services.

3.2.3 Node Structure

The node running the *MASU* platform can play one or more of the roles defined in each one of the tiers of the framework. Figure 3.3 represents the role composition structure of a MASU node.

A node can play one or more roles and it can also have several instances of the same type of role activated at the same time. Furthermore, these roles are dynamic and can evolve over time according to the characteristics of the network infrastructure, the mobility of the nodes or changes in the number of nodes involved in the activity or in the hardware resources available in such

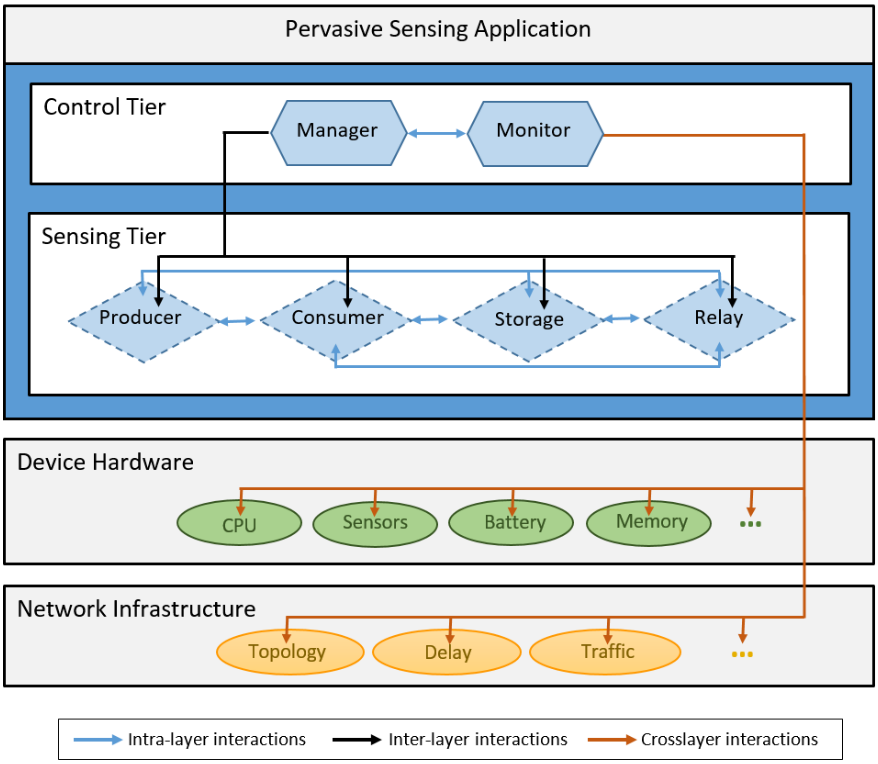


Figure 3.2: Architecture of the MASU Framework

nodes.

To have a collaborative sensing activity, it is necessary that at least two nodes are willing to collaborate and that such collaboration imply some benefit for the participating nodes. Otherwise, the *MASU* units would be working independently, in autonomous mode. A node performing sensing activities independently in a stand-alone fashion would be at the same time Producer and Consumer of its own sensing services. It would, therefore, only require the activation of particular Producer roles for the required services and the corresponding Consumers of such services. By contrast, in a scenario where a set of nodes is working collaboratively to perform a sensing activity, there can be diverse combinations on the number and type of roles that must be activated in different nodes, depending on the requirements of the activity and on the characteristics and capabilities of the participating devices. However, this collaborative sensing activity would require that at least one Manager, one Monitor, one Producer and one Consumer roles be activated in the activity.

Typically, most nodes collaborating in a sensing activity will have at least a Consumer role activated because we assume that they will be interested in at least part of the sensed data. Nevertheless, if some of the *MASU* units participating in the activity are IoT devices, there can be cases where they would require the activation of a Consumer role (e.g., a shared display receiving an image), but in other cases, they would only provide sensing services and would not have any Consumer role active (e.g., sensors in smart buildings).

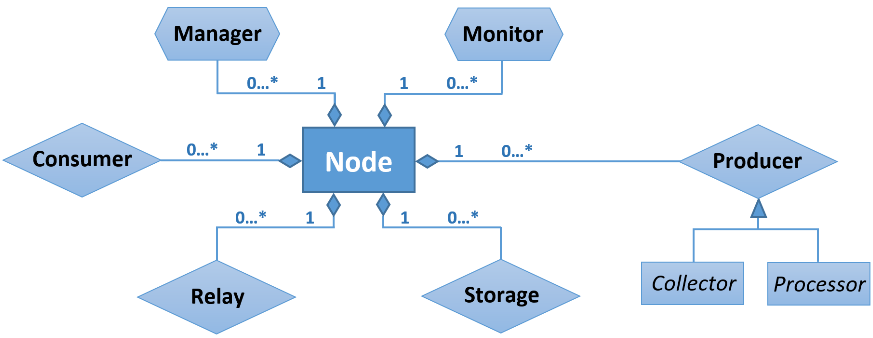


Figure 3.3: Structure of a MASU node

There can be two different kinds of Producer roles: Collector and Processor, depending on the type of information that they generate or in the method used by them to obtain it. Moreover, Relay and Storage roles can be activated depending on the network conditions and on the characteristics of the sensing activity and of the participating nodes.

3.2.4 Roles and Services

Each one of the roles of the *MASU* framework provides a number of services. *MASU* units playing some roles can interact with each other by subscribing to the services provided by specific roles. When a unit subscribes to a particular role, it is then, subscribing to all the services provided by such a role. Following we detail the roles included in the *MASU* framework and the services offered by them:

a ***Manager:*** This role acts as coordinator of the collaborative sensing activity. There can also be several Managers coordinating the activity. This role performs the following functions:

  i Runs a Cost Function to determine the viability and usefulness of performing the collaborative sensing.

  ii Divides the overall collaborative activity in a group of subtasks that will be performed by specific roles.

  iii Defines specific roles and the particular characteristics of the services that they must provide in order to perform all the subtasks required for the completion of the collaborative activity. The specification of these roles takes into consideration the requirements of the activity, including temporal and hardware requirements. To fulfil the temporal requirements of the activity, the Manager takes into account aspects related to the current state of the communication network, such as traffic, congestion and delay.

  iv Matches the roles specified with all the participating units. To make this match, the Manager considers the performance of both communication network (e.g., considering that some links can be more congested than others) and hardware components of the units (e.g., some units can have less battery lifetime). For the role-unit matching, the Manager also runs the Resource Optimization Algorithm (ROA) to optimise the use of the resources of the whole group of participating units.

v Activates the roles specified in the selected units. The roles will be activated according to the results of the ROA algorithm only in units that meet the particular requirements of the specific role.

vi Monitors the state of all the roles previously activated and their corresponding services (**service monitoring**). This way, The Manager can know when some of these roles have crashed or are not working properly. The service monitoring considers the characteristics of the underlying communication network, detecting when some units have unstable communication links or have left the network, and therefore the services offered by them are not available within the collaborative sensing activity.

vii Communicates with other Managers to reach consensus for the activation of roles in the *MASU* units that are taking part in the collaborative sensing activity. It can also communicate with other Managers from outside of the local collaborative sensing activity in the case that one or more local units are also taking part in external activities.

b ***Monitor:*** This role monitors the performance of *MASU* units. It offers various basic services:

i Monitors the hardware performance of all the units that are part of the activity (including the units acting as the Manager and the Monitor itself). This monitoring (**hardware monitoring**), takes into account hardware elements of the devices, for example, battery level, processor load, memory available and quality of the sensors available. Furthermore, the results of the hardware monitoring is used as input for the Cost Function and the Resource Optimization Algorithm in order to assess the usefulness of the collaborative sensing activity and make an appropriate management of the units' resources.

ii Keeps track of aspects related with the underlying communication network, such as network traffic, congestion and delay (**network monitoring**).

iii Performs service monitoring of the units selected to work as Managers. By doing so, the *MASU* framework can be aware of failures in the Managers of a collaborative sensing activity and take the appropriate measures.

iv Communicates with the Managers to notify changes in aspects related to hardware performance of the units.

c ***Producer:*** A unit playing this role performs sensing tasks using any of the sensors available in the device. Such sensors can be hardware or software components and can collect raw sensor data or higher level aggregated data or inferred information. According to the type of data produced by the sensing task, the Producer role can be classified into ***Collector*** and ***Processor***. Collectors sense raw data, whereas Processors produce higher level information, which can be generated by combining data from several sensors or making inferences from such data. Processors can use data sensed previously by other Producers, including both Collectors and Processors, to generate higher level information. The input data required by Processors can also be accessible through Storages or Relays. As a result, Processors have to subscribe to the services provided by the units that will deliver such input data. Thus, the performance of Processors can be affected by the performance of other roles. In general, a Producer has the following services:

i Produces sensor data according to the requirements of the sensing task following the specifications of the particular role as defined by the Manager.

ii Sends the data to Consumers, Storages and Relays subscribed to them to meet the temporal requirements specified by the Manager in the role definition. Producers respond to their subscribers in an asynchronous fashion (i.e. they do not respond to the subscribers' requests immediately, but when they have information available). They can send data periodically, only when the information sensed previously changes or only once (when it is available).

d ***Consumer:*** Consumers are service consumers that use the data sensed by Producers. They can access this data directly from the Producers but also through Storages or Relays. We assume that if the units participating in a collaborative activity are, for example, smartphones carried by students, all of them will be interested in receiving at least part of the sensed information. In this case, all the *MASU* units have at least one Consumer role activated. However, if the units are sensors located in smart buildings (e.g., motion sensors, access control systems, cameras embedded in the infrastructure, etc.), smart objects or other IoT devices, they will probably only be producers of information and therefore will not have any Consumer role activated. Notice that Storages, Relays and Processors that require data sensed previously by other *MASU* units are not only service providers, but also service consumers. Consequently, they also have one or more Consumer roles activated. Consumers performs the following functions:

i Subscribes to Producers, Storages or Relays receiving the information sent by them. This subscription is facilitated by the Manager, who informs Consumers about *MASU* units that can provide the services required as well as the specifications of the subscription.

ii Consumers use all the services provided by the roles they are subscribed to.

iii Specify the required data delivery rate if they are subscribed to Storages. The data rate is specified in the subscription request of the Consumer.

e ***Storage:*** This role provides two basic services:

i Subscription to Producers, from whom they will receive data.

ii Storage of historic shared data, considering the storage capabilities of the devices. This information can be used, for example, by nodes that have poor network connectivity and/or high mobility and therefore are likely to miss continuously information sent by Producers.

iii Retrieval of the information to Consumers subscribed to them. The information is retrieved according to the specifications and data rate defined in the subscription performed by particular Consumer roles.

f ***Relay:*** Relays retransmit recent data generated by Producers to Consumers that lost or could not receive the data sent by the Producers properly. Relays are similar to Storages but they usually store smaller amounts of recent information instead of larger amounts of historic data. In addition, they are selected due to their strategic characteristics in terms of network connectivity or mobility patterns in order to facilitate the data delivery to units that missed the information. The Relays perform two basic services:

i Subscribe to Producers and receive data from them.

ii Deliver information to subscribed Consumers. The information is forwarded from Producers to Consumers asynchronously, according to the data delivery rate specified by the Producer.

Figure 3.4 shows an example of a collaborative sensing activity involving four *MASU* units. We can observe the interactions between the different roles played by them. The Manager activates all the roles present in the activity and also performs service monitoring over them. On the other hand, the Monitor performs network monitoring, service monitoring over the Manager and hardware monitoring over the four participating units. In the activity we have two Producers: one acting as Collector and the other as Processor. In this case, the Processor receives the data sensed previously by the Collector, performs some classification or inferences tasks and sends the resulting information to the Storage. Finally, the Storage sends this information to the Consumer.

3.2.5 Interaction Protocols

In this section we describe the interaction protocols between the different roles defined in the *MASU* framework.

Once the set of devices that will take part in the collaborative sensing activity is determined (which is beyond of the scope of this thesis), all the participating units share their hardware capabilities. The next step is to select and activate the different roles in each one of the tiers of the framework. We will distinguish between two basic operations: (i) Role Selection and Activation in the Control Tier and (ii) Role Selection and Activation in the Sensing Tier.

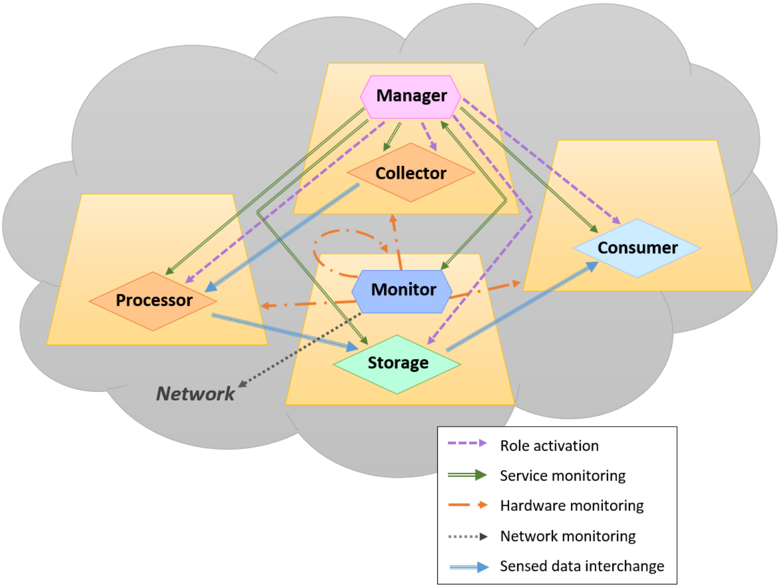


Figure 3.4: Interactions between MASU roles

3.2.5.1 Mechanisms for Role Selection and Activation in the Control Tier

Based in the hardware information shared and the network connectivity of the units, there are four different strategies for the selection and activation of roles in the Control Tier:

a ***Fixed Centralized:*** This approach determines that only one specific *MASU* node will play both Manager and Monitor roles. Thus, the first node joining the collaborative sensing activity will be selected to play the role. This role is static and does not change over time, and therefore, the node playing it is the single point of failure of the activity.

b ***Dynamic Centralized:*** In this case, the *MASU* framework also specifies one particular node to play the role. In order to determine the best suitable candidate for a particular role, a ***distributed leader election algorithm*** is executed. The criterion followed for the selection of the leader is different depending on whether the node will play a Manager or a Monitor role. The node with the best hardware capabilities will be selected as Manager, whereas network connectivity will be a more determining factor for the selection of the Monitor. However, both aspects will be considered for the selection of these two roles. For that reason, it is possible that the leader election algorithm for the selection of the Manager and the Monitor obtain the same result, which would imply that only one node will have to activate both roles. Nonetheless, in the case of a Dynamic Centralized Control Tier, the framework has to choose two different nodes to fulfil the functions of Manager and Monitor roles.

c ***Distributed:*** We can have a fully distributed Control Tier, where all the *MASU* nodes that are participating in the sensing activity will play both Manager and Monitor roles simultaneously.

d ***Hybrid:*** The Hybrid approach adds some restrictions to the Distributed Role Selection and Activation method. In this approach, most nodes participating in the collaborative sensing activity will activate the Manager and Monitor roles apart from those who have capabilities and/or connectivity that fall below some pre-established thresholds.

Due to the lack of dynamism and flexibility of the Fixed Centralized method, we consider that this approach is not part of our proposal. Nevertheless, we use it only as a baseline to compare the performance of the approaches included in our framework. Notice that all the other strategies adapt to the unpredictability of some types of networks and the heterogeneity of devices, and therefore the roles in the Control Tier are dynamic. Thus, the units selected to play a particular role or the number of active roles can change over time.

The Dynamic Centralized and Hybrid approaches can be appropriate in pervasive data sensing activities that involve small sensors or IoT devices. Typically, these devices are low power and resource constrained so they should not be selected to play Manager or Monitor roles since these roles might entail resource intensive tasks and also require high network connectivity.

Henceforth, for simplicity reasons we will refer to both Distributed and Hybrid approaches as Distributed since the Hybrid can be seen as a special case of the Distributed approach.

3.2.5.2 Mechanisms for Role Selection and Activation in the Sensing Tier

Once the Manager (or Managers) is selected and activated, it has to select and activate the different roles in the Sensing Tier. According to the strategy followed for the selection of the Manager in the Control Tier there are two different options for the selection and activation of the roles:

a ***The Manager decides:*** If the strategy for the selection and activation of the Manager was Dynamic Centralized (or Fixed Centralized), it would only be one Manager in the activity. Consequently, all the units must inform the Manager about their capabilities and characteristics. Using this information the manager will select the most appropriate units to fulfil each one of the roles of the Sensing Tier, taking into account the requirements of the activity. Moreover, the Manager will activate the required roles in the selected units.

b ***The Managers reach a consensus:*** In case of a Distributed approach, there are several units performing as Managers of the collaborative sensing activity. As a result, all these Managers have to agree on which nodes will be selected to play the roles required for the activity. Based on the hardware and network information of the units, once each Manager decides the most suitable units, all the Managers run a ***distributed consensus algorithm*** previously to the activation of the roles required by the activity. Notice that in this case most network nodes are Managers, and therefore they would only have to inform themselves or a neighbour node about what roles should be activated. As a result, there will only be a few role activation messages transmitted over the network. Thus, mainly only the messages of the consensus algorithm will be interchanged between the Managers.

Similarly than in the Control Tier, roles in the Sensing Tier are also dynamic and can evolve over time depending on the characteristics of the communication network and on the hardware capabilities of the *MASU* units that are participating in the collaborative sensing activity.

Table 3.1 shows a summary of the different methods followed for the selection of roles in the different Tiers and according to the role architecture of the

Control Tier. If the role architecture of the Control Tier is Dynamic Centralized, the selection of roles in this Tier will be determined by the results of the election algorithm. Furthermore, due to the fact that in this architecture we only have one Manager, the selection of roles in the Sensing Tier will be determined by such a Manager. Nevertheless, if the role architecture of the Control Tier is Distributed, all the units that are part of the collaborative sensing activity and that are active and have connectivity will play the roles of the Control Tier. In addition, the Selection and Activation of roles in the Sensing Tier will be determined by the results of the consensus algorithm.

Table 3.1: Role Selection and Activation Mechanisms for the different role architectures

	Role Architecture of the Control Tier	
Tier	**Dynamic Centralized**	**Distributed**
Control Tier	By leader election algorithm	All active units
Sensing Tier	By the Manager	By consensus algorithm

3.2.5.3 Cost Function and Resource Optimization

Before selecting and activating roles in the Sensing Tier, the Manager uses the information received from the *MASU* units to run a Cost Function. The output of this function will determine whether it would be beneficial for the whole group of units to work collaboratively or not. According to such output, the Manager will activate or not the Role Selection and Activation processes in the Sensing Tier. Consequently, if the output of the Cost Function is negative, there will not be collaborative activity and all the units will work independently. The Cost Function determines the viability and usefulness of performing collaborative sensing.

The Cost Function is also associated with the results of the Resource Optimization Algorithm (*ROA*), which helps optimise the use of the resources of the whole group of participating units. The *ROA* algorithm runs every time that the *MASU* framework wants to initiate the Role Selection and Activation process in the Sensing Tier. Such algorithm influences how roles are selected, calculating the estimated costs of the services provided by each one of the roles, and considering the specific requirements of the activity and the characteristics and state of the devices. The *ROA* determines, for a group of units, who has to activate a given role, who has to collect data from specific sensors and share the results with the rest of the members, etc. For example, the *ROA* can determine, depending on the battery level and the memory usage of the units that two units will be Producers, whereas the rest will act as Consumers. The *ROA* will also decide, between these two Producer units, which one have to capture data from microphone and which one have to sense *GPS* data. As a result, the rest of the units acting as Consumers will deactivate their sensors and wait until they receive the sensed information from these two Producer units.

The definition of specific cost functions and resource optimization algorithms to be used in particular application scenarios is beyond the scope of this work. Some examples of cost functions and resource optimization mechanisms used in similar contexts that the one presented in this dissertation can be found in [112, 128, 137].

3.2.5.4 Fault Tolerance Mechanisms

Due to the dynamism and uncertainty of some network infrastructures, the *MASU* framework defines several fault tolerance mechanisms to deal with changes and failures in active roles that are taking part in a collaborative sensing activity. Such mechanisms can be classified into two categories:

Mechanisms of Tolerance to Role Failure

The dynamic characteristics of the underlying communication network, the mobility patterns of the units or an application failure can make that some roles that are taking part in a collaborative sensing activity crash or disappear. To detect a role failure, the framework monitors the state of each one of the roles that were activated to perform the activity. As explained previously, the Manager role monitors the state and behaviour of the services offered by all the other roles. Similarly, both Manager and Monitor perform mutual ***service monitoring*** on each other.

The *MASU* framework defines two different tolerance mechanisms to deal with role failures: (i) *Mechanism of Tolerance for the Control Tier* and (ii)

Mechanism of Tolerance for the Sensing Tier.

(i) ***Mechanism of Tolerance for the Control Tier:*** This mechanism only applies when the role architecture of the Control Tier is ***Dynamic Centralized*** since in a Distributed approach, all the units play all the roles included in the Control Tier. For this reason, if a role fails, the rest of the units would keep working properly.

In case of a Dynamic Centralized architecture, if the Manager fails, the *MASU* framework restarts the Role Selection and Activation mechanisms for the Control Tier, which implies a ***distributed leader election algorithm.*** Consequently, both Manager and Monitor roles will be reassigned. In addition, the framework also restarts the Role Selection and Activation mechanisms for the Sensing Tier, which imply that the Manager will assign all the roles required in this tier. Nevertheless, if the architecture is Dynamic Centralized but only the Monitor fails, the Manager will be in charge of reassigning the Monitor role to a suitable unit.

(ii) ***Mechanism of Tolerance for the Sensing Tier:*** Contrary to the previous case, this mechanism only applies when the role architecture of the Control Tier is ***Distributed*** due to the fact that in a Dynamic Centralized architecture the Manager would be in charge of reassigning the roles that failed.

In case of failure of any of the roles in the Sensing Tier, only the Role Selection and Activation mechanisms for such a tier will be activated and the corresponding roles will be reassigned. Such mechanisms imply a ***distributed consensus algorithm*** so that all Managers could agree on the assignation of roles.

Notice that the *MASU* framework has three basic methods to deal with role failure and decide how to reassign new roles: (i) the Manager decides, (ii) the leader election algorithm decides or (iii) the consensus algorithm decides. These methods correspond to the ones used for Role Selection and Activation in the Sensing and Control Tiers.

Mechanisms of Tolerance to Resource Limitation

The mobility of the nodes, the characteristics of the network infrastructure (e.g., congestion, delay, etc.) or the limited hardware capabilities (e.g., low battery level, high CPU utilization, etc.) of the mobile devices that are operating as *MASU* units can make necessary to determine if the roles that are currently active must be reassigned or even if the collaborative activity must finish.

The Monitor and Manager keep track of any event in the collaborative activity: new units join, some disappear, others have poor network connectivity or run out battery, CPU or storage capacity, etc. If any of these changes occur, the Cost Function must be executed to determine the viability and usefulness of the collaborative sensing activity. If the output of this function is positive, the *MASU* framework will restart the Role Selection and Activation mechanisms for the Sensing Tier, reassigning roles as appropriated according to the results of the ROA algorithm.

In the case that many new units join the collaborative sensing activity, it is possible that the cost required to share the sensed data is too high, and therefore the output of the Cost Function is negative. This situation would imply that the collaborative sensing activity is not beneficial for the overall group of participating units so that it has to end. Howevhis situation could be solved by creating two parallel sensing activities.

3.2.6 Control Messages

According to the interaction protocols, the *MASU* framework defines five types of messages of the Control Tier:

1. ***Unit Detection Messages:*** these messages are used to detect the units that are present in the collaborative sensing activity. Therefore, the Unit Detection messages are used to monitor changes in the composition of the activity, regarding the units and roles that are present in such activity. These messages are used for textit**service monitoring** operations, which are required for the *Mechanisms of Tolerance to Role Failure*. The detection and monitoring of units is performed by observing changes in the connectivity of the units and the network topology

due to new units that join or existing units that leave the network.

2. ***Device Information Messages:*** these types of messages are used by the units to share information about their hardware capabilities, such as battery level, processor load, memory available and quality of the sensors available. The Device Information messages are necessary whenever a *Role Selection and Activation* Process takes place. Moreover, the information provided by these messages is used for the ***hardware monitoring*** functions required for the *Mechanisms of Tolerance to Resource Limitation* and also as input for the *Cost Function* and *ROA* algorithm. For hardware monitoring, the Device Information messages are sent by the units when the performance of the diverse hardware components considered falls under various pre-established thresholds.

3. ***Election messages:*** this category includes the messages of the *distributed leader election algorithm* that is used to select the Manager and Monitor roles in a Dynamic Centralized role architecture of the Control Tier de manager. Due to the fact that the leader election algorithm needs information about the devices in order to make a decision, we consider as Election messages (and not as Device Information messages) the messages with the hardware capabilities of the devices that are required by the leader election algorithm.

4. ***Consensus messages:*** these kinds of messages are used in a Distributed role architecture of the Control Tier so that all the Managers could agree on the selection of roles in the Sensing Tier. Therefore, these are the messages required for the *distributed consensus algorithm.* Similarly than in the previous types of messages, we include in this category messages with the hardware information of the devices that are required for the consensus algorithm.

5. ***Role Activation messages:*** these messages are only used in case of a Dynamic Centralized role architecture of the Control Tier. They are sent by the Manager to activate roles in the Sensing Tier or to activate the Monitor if it fails. In case of a Distributed role architecture of the Control Tier, all the units are Manager so they activate roles locally and do not need to send messages to other units.

6. ***Network Monitoring messages:*** this is a special type of message

that is necessary for the network monitoring functions performed by the Manager. The number of messages of this type depend on the kind of communication support used. For example, if we have a fixed wireless infrastructure composed by one or several Access Points (AP), a network monitoring process would involve that the APs have to collect several network statistics and send it to the Monitor. Typical solutions for these types of infrastructures require the installation of customised software in the APs and an external cloud server, which computes the network metrics required [29]. This process would require the interchange of messages between the APs and the units connected to them as well as between the different APs and the cloud server. In this case, the cloud server would probably act as Monitor since it has to collect and computer statistics from all the network nodes, which can be too heavy for a regular node. By Contrast, if we have an ad hoc network, we can perform a passive network monitoring using the same messages that are part of the routing protocols. Such protocols have metrics that allow the estimation of the number of packets or the traffic that a given link would be able to support [59, 204, 138]. Although these metrics only provide an approximation of the real network traffic or congestion, the use of ad hoc networks provide several advantages: (i) do not require additional hardware or software components but only an extension of the existing routing protocol, (ii) have an easy configuration since the routing protocol is already running in the nodes (it does not require changes in the fixed infrastructure) and (iii) do not require sending additional messages for the monitoring of the network since they are already included in the routing protocol. In this case, the Monitor can be any network nodes since the network monitoring does not require any additional messages or computation.

3.2.7 Data Retrieval Mechanism

The interactions between the different roles of the Sensing Tier enables the *MASU* units participating in the collaborative sensing activity to collect and share data so that all the units can have the information required by the activity. These interactions are mediated by the *Collaborative Sensing Mechanism (CoSM),* which is the data retrieval component of the *MASU* framework. What is more, the *CoSM* is the component of the framework that allows the differential activation of each one of the roles of the Sensing Tier (i.e. Consumer, Producer, Storage and Relay).

The *CoSM* mechanism offers four basic services for service discovery [233] and information distribution: *Publish, Find, Subscribe*, and *Data Dissemination.*

Publish Service. This service allows the units that are participating in the collaborative activity to publish their services. This function will be used by Producers, Storages and Relays to offer their services and share their sensed data with others. Consequently, the Publish service takes place when the Manager or Managers of the collaborative activity activate such roles in the Sensing Tier.

Find Service. This function enables Consumers, Storages and Relays to know what data they need to receive. Once again, this service is provided when the Manager activates these roles according to the specific requirements of the collaborative activity.

It is important to notice that the Manager works as a service registry performing service publishing and finding operations. This service registry can be centralized or distributed, depending on the strategy followed to elect the Manager in the Control Tier.

Subscribe Service. This function allows some roles to subscribe to the services offered by others. In this case, the role that want to receive the sensed data has to make itself the subscription to the particular role that offers it.

Data Dissemination Service. This service enables active roles in the collaborative activity to share data between providers and subscribers of a specific service.

The *CoSM* is composed by three main modules (Figure 3.5): the *Sensing Module (SM),* the *Data Source Manager (DSM)* and the *Data Dissemination Manager (DDM).* These modules are responsible of the services that enable the differential activation of the roles in the Sensing Tier. The *SM* interacts with the *DSM* and the *DDM* to determine the type of data that a particular unit has to sense and the method that it will use to obtain such data.

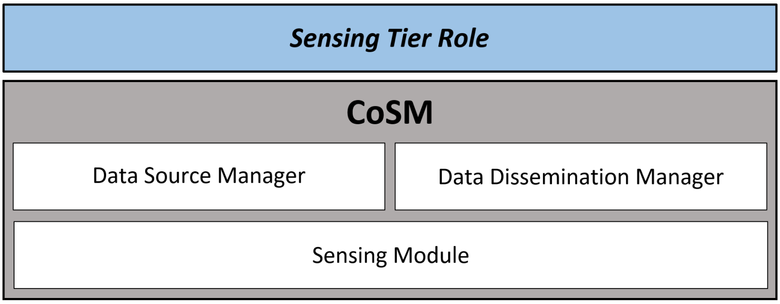


Figure 3.5: Modules of the CoSM mechanism

3.2.7.1 Sensing Module

The *Sensing Module (SM)* supports the data collection process. The data can be collected from the sensors available on the *MASU* unit as well as retrieved from other units. The *SM* has a modular design, where data can be collected from diverse independent sensors. For the *MASU* framework a sensor is any hardware or software component that act as source of information. Consequently, the *SM* module calls a number of services for accessing any type of sensor available on the unit.

This module can obtain raw sensor data from, for example, the unit's physical sensors but also high level information from other types of sensors. In the former case, a Collector role will be activated, while in the latter the role played by the unit will be a Processor. The *SM* also enables the use of data shared by other units as data source and establishes (for every sensor in the unit) the way how it will obtain the corresponding data. This way, the activation of particular Producer or Consumers roles can take place. Accordingly, the *SM* defines two basic data collection methods: ***direct*** and ***indirect.*** In the direct method the unit is responsible for capturing data without relying on any other source. In the second case, the sensor receives and processes data that has been previously collected by other units. In the former case the unit will play a Producer role, whereas in the latter it will be a Consumer.

The *SM* allows both, remote and local activation of the all the sensing services. This fact facilitates the activation of roles in the *MASU* units by the Manager for collaborative sensing activities as well as the independent operation of the units for individual sensing tasks. The *SM* also allows flexible configuration of the sensing frequency and waiting times.

The data collection methods specified by the *SM* allow a selective distribution of data from different sensors. That is, the *MASU* framework facilitates a flexible selection of the collection methods that will be used for each one of the sensors available on the units. For example, it can decide to use a direct method to capture data from the accelerometer of the unit but to use an indirect method to capture GPS data.

Figure 3.6 illustrates a data sharing process conducted by three different units. These units have activated three kinds of sensors. Unit A shares data from two sensors. This data was collected directly by the unit, which means that these sensors were activated in direct mode. On the other hand, this unit also has a sensor activated in indirect mode, receiving data from one of the sensors of Unit C. In addition, Unit B has all its sensors activated in indirect mode. Then, this unit will receive all the data from units A and C.

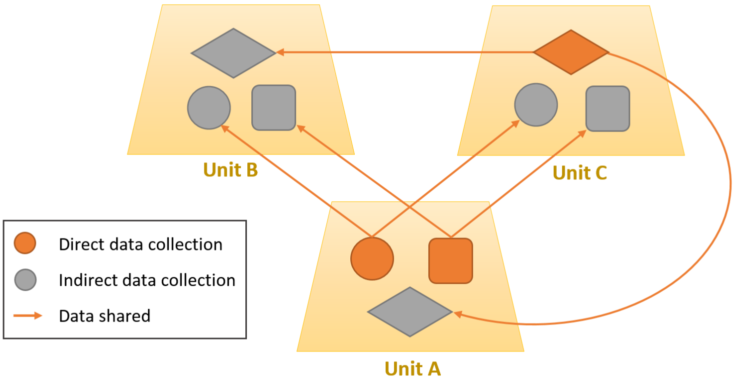


Figure 3.6: Example of data sharing between units

3.2.7.2 Data Source Manager

The *Data Source Manager (DSM)* is in charge of specifying the sensors that the unit will use to collect the input data. The *DSM* enables the units to capture diverse types of data from different sensors so that the *MASU* units can sense different kinds of information and share it with others.

The *MASU* framework supports diverse sensors or data sources, such as IoT devices, information repositories, sensors in smart buildings and sensors embedded in commercial smartphones. These sources must be able to provide information that is relevant for the applications and users (in our case, information that is relevant for pervasive monitoring and awareness). Moreover, as stated in [26], any modern mobile ubiquitous system must provide context-awareness and therefore information about the environment that is providing services to the users (in our case, the *MASU* unit). For this reason, the proposed framework supports a wide range of data sources that are necessary to provide context-awareness about the *MASU* units (what we previously called ***hardware monitoring***) as well as useful information for pervasive monitoring in learning scenarios. Next, we specify the different categories of data sources supported:

1. ***Physical sensors:*** We can differentiate between three kinds of physical sensors:

    a Hardware sensors, for example, accelerometer, GPS, ambient light, dual microphones, proximity sensor, dual cameras, compass and gyroscope.

    b Communication sensors that correspond to the several built-in communication interfaces of modern devices, e.g., Bluetooth, infrared, Wi-Fi and cellular antennas.

    c Performance sensors, such as battery level, network traffic, and CPU, memory and disk utilization.

2. ***Virtual sensors:*** In this group we consider information that can be obtained from the device's applications and services; e.g., the screen status, the user's touch inputs, applications status, log files and notifications.

3. ***Human-based sensors:*** We include in this category any custom application used to collect information that require explicit user intervention. These types of sensors require the participation of a human user to provide information and create new knowledge [171]. Human-based sensors complement the implicit sensing process performed automatically by unobtrusive sensors. This way we can obtain both objective (e.g., a picture, a quantitative datum, etc.) and subjective (e.g., perception, opinion, etc.) information from the user.

4. ***Context sensors:*** These are modules that collect information related to the user context [26] from existing repositories; for instance, the user's profile, preferences, schedule or performance indicators.

5. ***Logical sensors:*** These sensors provide high-level information and they can combine data from several sources. Information from this category usually involves some type of aggregation and processing to interpret the sensed data and contextual information. An example of logical sensors could be a service that interprets raw data from an accelerometer to infer the type of physical activity that the user is performing (e.g, sitting, walking, running, etc.).

In the *MASU* framework there can be units that act as Producers and/or Consumers of the different types of data that these categories of sensors provide. *MASU* units that use an indirect method to collect input data from any of these sensors will act as Consumers, whereas units that use a direct method will fulfil a particular Producer role. In this later case, the *MASU* units that sense data using physical, virtual, human-based or context sensors can have a Collector or Processor role, depending on whether this data require some level of interpretation (e.g., classification, aggregation, processing, etc.) or not. On the other hand, those units that retrieve data from logical sensors to perform further interpretation tasks always play a Processor role.

3.2.7.3 Data Dissemination Manager

As shown in Figure 3.7, the *Data Dissemination Manager (DDM)* establishes three data dissemination mechanisms: Broadcast, Point-to-Point and Server-Mediated.

The ***Broadcast*** and ***Point-to-Point*** mechanisms offer different methods to create Peer-to-Peer proximity networks amongst devices. It allows the *MASU* units to share information directly among them, without depending on any centralized server. This fact opens up the possibility to integrate the *MASU* framework with IoT, allowing that the units could interact with nearby networked objects and sensors. In the case of broadcast data dissemination, the data sent by a unit can be received by all the others. On the other hand, the Point-to Point mechanism only allow data transfer between pairs of units and therefore only the particular unit that was specified as destination of the data can receive and use it.

Finally, the ***Server-Mediated data dissemination*** allows communication between units that are not in the same local network. This mechanism enables data transfer between two independent groups of units connected to different local networks but reachable through the Internet. For example, this two groups could be units that are participating in two different collaborative sensing activities. Furthermore, the *MASU* framework can decide to make use of this server to perform some resource intensive aggregation, processing or classification tasks to optimize the use of local hardware resources of the units. For example, to perform complex inference tasks that are computationally intensive, such image or voice recognition. It can also be used to play the role of Storage if required, for example, because there is a reduced number of units participating in the activity or because none of the participating units has enough space available.

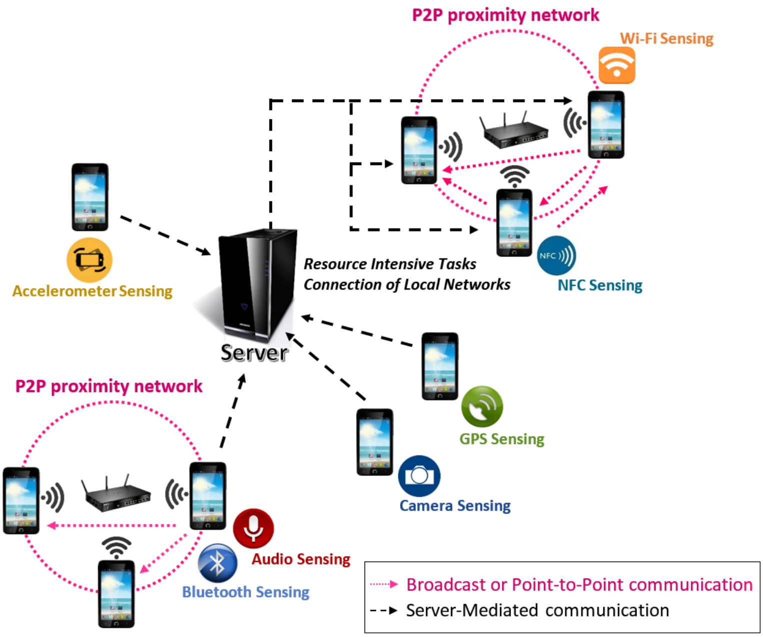


Figure 3.7: Example scenario of data dissemination

3.3 Evaluation of the MASU Framework

The *MASU* framework was evaluated empirically to assess its usefulness and performance under diverse networking, hardware and mobility conditions. To evaluate different aspects of the behaviour of the framework in diverse scenarios we carried out a study based on both simulations and an empirical evaluation of a prototype of the framework.

3.3.1 Simulations Setup

To evaluate the performance of the *MASU* framework we used the *ns-3* simulator [6]. This simulation tool allowed us to represent diverse scenarios and collect a number of metrics with the purpose of assessing the impact on the performance of the framework of the underlying network infrastructure as well as the mobility patterns of the *MASU* units existing in the scenario.

The *ns-3* enables the configuration of the nodes that run the *MASU* framework, the communication network that supports them and the physical space where they are placed. Consequently, the hardware capabilities of the nodes, their wireless network interfaces, physical position and mobility patterns were configured using this simulation tool. We performed 20 simulations for each one of the particular scenarios configured in the *ns-3*. This allowed us to have several samples of the measures performed over each scenario. All the simulations had a duration of 20 minutes.

3.3.1.1 Nodes and Physical Space

We defined a 360x360 meters outdoor area to place the nodes. Such an area represents an outdoor physical space where diverse everyday activities can take place. The size of this space was set to allow the mobility of the nodes and the creation and evolution of different network topologies.

In this area, we placed 40 nodes that represent the units running the *MASU* framework. We considered that all the nodes were similar and had the same technical features. Therefore, the simulations do not consider the effect of device heterogeneity, which will be addressed in the evaluation of the prototype. Particularly, we configured the nodes to have the capabilities of an iPhone 5. These devices have an effective Wi-Fi communication range of approximately

80 metres in open areas.

Table 3.2 summarizes the general parameters configured in the ns-3 for the simulations.

Table 3.2: Simulation general parameters

Parameter	Value
Simulation time	1200 s
Simulation area	360 x 360 m
Number of nodes	40
Node model	Iphone 5
Wi-Fi standard	IEEE 802.11g
Propagation model	YansWifiChannel
Transmission power	0.66 W
Transmission range	80 m

3.3.1.2 Mobility Patterns

The simulations allow the evaluation of the framework under dynamic conditions, considering different nodes' mobility patterns and a high number of nodes.

The nodes' movements were modelled using the BonnMotion tool [22]. BonnMotion includes well-known models that represent people's mobility patterns [44]. For the simulations, the nodes' speed was set between 0 m/s (static nodes) and 1.5 m/s (walking speed) and three mobility patterns were used: *Random Walk, SLAW,* and *Nomadic.*

- The *Random Walk Model (RandomWalk)* considers people moving randomly in terms of both direction and speed, within a certain area [44]. This model typifies the movements of people who walk without using formal paths and their walking speed and direction can change randomly at any time. Figure 3.8 shows an example of the mobility of the nodes in a simulation that uses the RandomWalk mobility model, where the movements of all nodes are represented in lines of different colours.

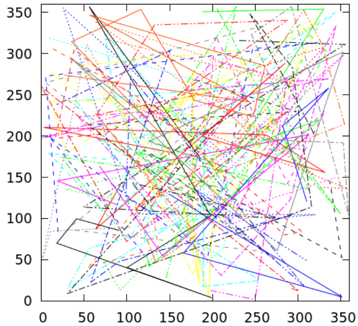


Figure 3.8: Sample of the RamdomWalk mobility model

- In the *Self-similar Least Action Walk Model (SLAW)* people move quite freely but with some limitations in speed and direction. This mobility pattern symbolizes a more realistic scenario, where people walk following dedicated walking paths. This model also includes a probability for the formation of groups between people that move together. For this reason, the SLAW model is effective in representing casual encounters among members of the same community; e.g., students at the University Campus or friends in a park [126]. Figure 3.9 shows a sample representation of the mobility of the nodes in a simulation that uses the SLAW mobility model.

- The *Nomadic Community Mobility Model (Nomadic)* considers people moving in groups from one location to another. This model considers several groups of people and, for each group, an invisible node that acts as reference for all the other nodes within the group. This reference node determines the next position towards which the group will go as well as the path and speed at which it will move to reach such a place. In the Nomadic mobility pattern, allows the representation of several groups of nodes, which follow the direction and speed of their corresponding reference nodes. However, the nodes belonging to each group move randomly

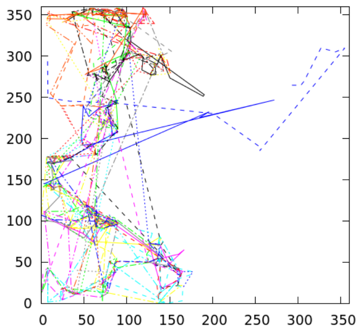


Figure 3.9: Sample of the SLAW mobility model

within a maximum distance from the reference. In addition, this model allows that some nodes could leave their current group and join others. In a real-world scenario, this mobility pattern can be representative of guided tours in a city or museum, where the tourists move together visiting several points of interest [44]. In this scenario, the reference node can be, for example, the tour guide. Figure 3.10 depicts an example of the mobility of the nodes in a simulation that uses the Nomadic mobility model.

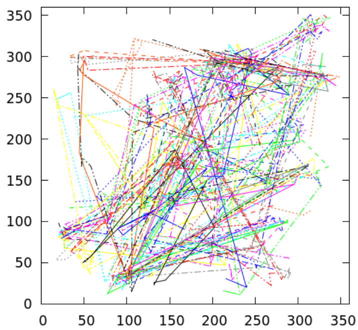


Figure 3.10: Sample of the Nomadic mobility model

In Table 3.3 we can find an overview of the parameters used for the setup of the mobility models considered.

Table 3.3: Parameters of the mobility models of the nodes

RandomWalk	
Max. speed	1.5 m/s
Max. pause	60 s
SLAW	
Cluster ratio	25 m
Max. pause	60 s
Nomadic	
Avg. nodes per group	4
Group size deviation	2
Max. distance	15 m
Max. speed	1.5 m/s
Max. pause	60 s

This configuration of the physical area and the nodes' mobility patterns helped us simulate a dynamic network, where some existing communication links can be lost and new links can appear. Such configuration represents a realistic scenario where people move within a physical space and eventually interact with other people that they meet within such a space.

3.3.1.3 Network Infrastructures

In order to evaluate the performance of the *MASU* framework when the units communicate using diverse network infrastructures, we configured the simulator to use three different types of networks to support the communication between the nodes: ***AP-based, Terminal-to-terminal (T2T) and Mobile Ad hoc Networks (MANET).*** These wireless network infrastructures, based on the IEEE 802.11 standards, were selected from the proposed by [196] and [37] and adapted to be simulated on *ns-3*.

- ***AP-based network (AP):*** In this case we have a fixed network infrastructure, where a static Access Point (AP) provides network connectivity to all the nodes that are within its coverage zone. All the nodes have their wireless interfaces configured in infrastructure mode and are connected to the AP. Only those nodes connected to the AP and that are within its coverage range and in mutual coverage range can communicate between them. For this reason, the mobility of the nodes has a significant impact in their possibility of establishing communication among themselves. Figure 3.11 shows an example of the AP network used in the simulations.

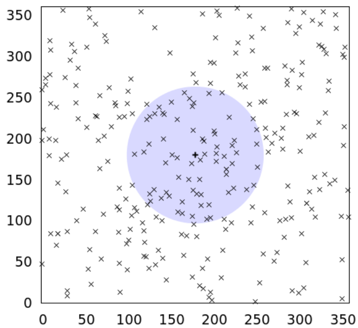


Figure 3.11: Example of AP network

- **Terminal-to-terminal network (T2T):** It relies on direct Wi-Fi communication between mobile nodes, without any need for a fixed network infrastructure. This type of network allows a mobile coverage zone due to the fact that the network is created by one node that acts as AP. In an T2T, all the nodes that move following the node that created the network and that are within its coverage range (and in mutual coverage range) can communicate directly between them. In this case, the nodes' wireless interfaces were configured to work in ad hoc (no infrastructure) mode. Figure 3.12 depicts an example of the T2T network used in the simulations.

- **Mobile Ad hoc network (MANET):** In a mobile ad hoc network all the nodes create the network and act as routers without relying in any fixed network infrastructure. Therefore, we have a mobile network and all the nodes connected to this network can communicate between

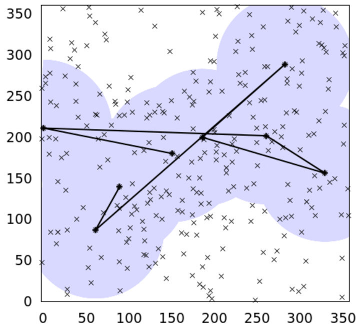


Figure 3.12: Example of T2T network

them at any time and place. The configuration of this kind of network requires the configuration of the nodes' wireless cards in ad hoc mode and also that the nodes run an ad hoc routing protocol. This protocol allows multi-hop communications between any pair of nodes within the network even if they are not within their mutual coverage range as other nodes act as routers, retransmitting messages from the source node to the destination. For our simulations we used the OLSR routing protocol. Figure 3.13 depicts an example of the MANET network used in the simulations.

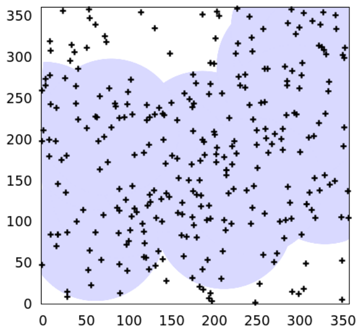


Figure 3.13: Example of MANET network

In case of AP-based and T2T networks we used UDP broadcast (for 1 to N communication) control messages. These messages are used to monitor any change in the network topology (new nodes that join or existing nodes that leave the network), as proposed in [83, 231, 113], as well as for the leader election and the consensus algorithms. We also use UDP broadcast for messages of the Sensing Tier (i.e. containing the data sensed).

In case of MANETs, it was not necessary to use additional messages to monitor topology changes, since these messages are already included in the routing protocol (HELLO and TC messages of the OLSR protocol). The messages of the routing protocol are also UDP broadcast as well as the messages of the leader election and the consensus algorithms. Nevertheless, the messages used to exchange the data sensed in MANETs are UDP unicast (for 1 to 1 communication).

Table 3.4 shows a detail of the configuration of the ns-3 simulator for the different types of messages interchanged in the three network infrastructures considered.

Table 3.4: Messages Setup for AP, T2T and MANET networks

AP and T2T	
Control messages	UDP broadcast
Data messages	UDP broadcast
MANET	
Control messages	UDP broadcast
Unit detection messages	-
Data messages	UDP unicast
Routing Protocol messages (HELLO & TC)	UDP broadcast
HELLO interval	2 s
TC interval	5 s

3.3.1.4 Role Selection and Activation Methods

The simulations consider both ***Dynamic Centralized*** and ***Distributed*** role architectures of the Control Tier. Therefore, we implemented in the *ns-3* simulator the three methods defined in the framework for Role Selections and

Activation in the Sensing and Control Tiers: (i) the Manager decides, (ii) the leader election algorithm decides or (iii) the consensus algorithm decides. We implemented a *distributed leader election algorithm* based on the proposals of [230] and [148]. Similarly, the *distributed consensus algorithm* used in the simulator was based on the presented in [234] and [239].

3.3.2 Prototype Implementation

A prototype of the *MASU* framework was implemented with the purpose of evaluating the performance of the Sensing Tier of the framework and its effects on the devices that are running it, in terms of resource consumption.

This prototype was implemented as a mobile application that provides a number of services for automatic collection and collaborative distribution of the data gathered from sensors embedded in mobile devices. Such services facilitate access to the sensors available on the device, enabling data collection and sharing between devices according to the specifications of the *Collaborative Sensing Mechanism (CoSM)* of the *MASU* framework.

3.3.2.1 Role Selection and Activation Methods

The prototype implements the Role Selection and Activation processes according to the following procedure:

- The Manager is fixed for the duration of the collaborative sensing activity and it is responsible of selecting and activating roles in the Sensing Tier (i.e. Consumer, Producer and Storage), sending messages to other units accordingly.
- When a new node access the network, it announces its state, capabilities and the sensing services that can provide. As a result, the Manager knows which sensors are available in the network and therefore which units are suitable candidates to play Producer roles.
- In case that several units meet the requirements to play a particular Producer role, the Manager takes the decision considering the quality of the sensor and the battery level of the device. Thus, the units that have sensors with the highest quality and the highest battery level, will be selected as Producers.

- After a specific Producer role is selected and activated, the Manager automatically activates Consumers of the information sensed by that Producer in all the units connected to the network.
- Consumers can receive information from Producers (i) periodically or (ii) only when the information changes, receiving a notification as well as the new data when it is available.
- Every time a new node joins the network, the Manager starts the Role Selection and Activation process in the Sensing Tier, activating a Consumer role in the new node.
- The Manager selects and activates a unit to act as Storage of the data collected by a specific Producer. This unit stores all the information sent by such a Producer in a SQLite database.
- Consumers receive data from the Storage periodically, according to the data rate specified by the Consumers in the data request.

3.3.2.2 Data Retrieval Methods

Our prototype of the *MASU* framework implements three different methods for the provision of the data retrieval services (***Publish***, ***Find***, ***Subscribe***, and ***Data Dissemination*** services) included in the *CoSM* mechanism of the *MASU* framework. The three methods implemented are: AllJoyn [3], CoAP [5] and GCM [1, 241].

Alljoyn and CoAP communication systems offer different mechanisms to create a Peer-to-Peer proximity networks, enabling devices to share information directly among them, without depending on any centralized server. By contrast, if the devices are not physically close but have Internet connectivity, they can share information using the GCM service, which is connected to the *CoSM Server*. Following we describe each one of the data retrieval methods and how they have been implemented in the prototype.

1) ***AllJoyn*** is an open source software system, originally developed by Qualcomm, and promoted by the Allseen Alliance. AllJoyn offers a very thin but efficient client and more sophisticated services than other communication frameworks, such as device discovery, permanent connectivity and session management. This features makes AllJoyn too heavy for very small devices, but it

is a highly suitable option for devices with higher capabilities like smartphones or tablets. Moreover, AllJoyn is cross platform and allows interoperability among devices from different manufacturers.

In our prototype we use AllJoyn for the creation of the ***Peer-to-Peer proximity network***, for both AP-based and T2T architectures. Furthermore, AllJoyn allows network and service discovery operations. These operations enable the discovery of nearby devices and is used by new units to announce their services. Therefore, AllJoyn is the component of the prototype that implements the ***Publish*** and ***Find*** services of the *MASU* framework. It also allows service ***Subscription*** and ***Broadcast data dissemination*** (using TCP messages).

Consumers that want to receive the information sensed by a Producer or Relay using AllJoyn, have to subscribe to them, which allows them to receive data every time that it changes or periodically. In case that Consumers want to receive data from a Storage, they would have to specify the required data reception rate in the subscription.

AllJoyn is also used to send the messages of the Control Tier that make possible the dynamic selection and activation of roles in the Sensing Tier. Thus, AllJoyn allows the Manager to select and activate roles according to the dynamics of the network.

AllJoyn is always active detecting every time a *MASU* unit joins or leaves the network. Consequently, Alljoyn is used by the framework to detect failures due to network dynamism as well as due to the resource limitations of the devices.

2) ***CoAP*** *(Constrained Application Protocol)* is an application layer protocol designed by the Internet Engineering Task Force (IETF) for IoT devices. CoAP is a web transfer protocol for use with devices and networks with limited resources and capacities. CoAP implements a REST model where services provided by servers are available under an URL and clients can access them. Moreover, CoAP enables devices to play both the server and the client roles in a peer-to peer network and offers a request/response asynchronous interaction model with multicast support and low overhead.

The prototype implements CoAP as service ***Subscription*** and ***Point-to-***

Point data dissemination (using UDP unicasts messages) mechanism to enable *MASU* units to interchange information between roles of the Sensing Tier. Thus, CoAP is only used for the distribution of the sensed data. Particularly, Producers create CoAP services to offer the data and Consumers subscribe to such services.

Consumers subscribed to a particular Producer using CoAP receive the information every time that it changes. If they want to receive information from the Producer periodically, they have to send periodic subscription messages to the Producer (otherwise, they would receive the information only once). In case of subscription to Storages, the data rate required by the Consumers will be determined by the periodicity of their subscription messages.

For the sake of simplicity and because our prototype was designed to be deployed in smartphones, we used the AllJoyn protocol for network and service discovery to avoid the development costs that the implementation of a new protocol would bring. Nonetheless, as mentioned previously, AllJoyn can be too heavy for very small devices. This issue is addressed in our prototype because it provides a hybrid platform that uses both AllJoyn and CoAP, allowing communication with other hybrid devices as well as with AllJoyn-only devices and CoAP-only devices. Therefore, we could use only CoAP in cases where AllJoyn is inappropriate, such as small IoT devices or sensors, but another device running the hybrid system could be used as "CoAP-to-AllJoyn Control Tier Proxy" enabling CoAP-only devices to publish their services.

3) ***GCM****(Google Cloud Messaging)* [1, 241] is a free service developed by Google that allows a client/server communication between a server and mobile devices (currently available for Android or IOS). The GCM is a HTTP connection server protocol that allows sending push messages to mobile devices from a server (downstream messaging) as well as sending messages back from the devices to the server (upstream messaging). GCM provides a flexible messaging method that allows sending data to a single device, to groups of devices or to devices subscribed to particular topics. It also provides a reliable and battery-efficient communication channel between the server and the devices. The GCM service handles the message queuing and the delivering operations until the messages are appropriately fetched by the target applications on the devices.

The GCM service provides the ***Server-Mediated data dissemination*** method of the prototype. The devices must register through the GCM service to get a registration ID. Once the ID is received by the device's application, it must be sent to the *CoSM Server,* which can then use the GCM service to send messages back to the devices. The devices can also decide to utilise the *CoSM Server* to perform some resource intensive aggregation or processing tasks to optimise the use of local hardware resources. For instance, if a group of users want to share high-level representations of their collaboration or interaction patterns, they would typically require the *CoSM Server* to perform some processing on their behalf. As a consequence, they would also have to use the GCM service to disseminate data.

3.3.2.3 Prototype Versions

Two different versions of the prototype were developed in order to evaluate the performance of the framework for distinct software implementations, network infrastructures and data retrieval mechanisms. Table 3.5 summarizes the main features of both versions of the prototype.

Regarding software implementations, the first version of the prototype was implemented using the Unity [10] development platform, whereas the second version was implemented as a native *Android* application. Due to the fact that Unity is crossplatform, the second version of the prototype was deployed in both *Android* and *Windows OS.*

Concerning the network infrastructures, the two versions of the prototype provide to distinct methods to create peer-to-peer proximity networks among a group of *MASU* units in order to perform collaborative sensing activities. The first version of the prototype allows the group of units to connect to an existing AP, while the second version configures automatically the first unit that joins the activity as AP to provide wireless access for the whole group of units. As a result, AP-based (AP) and Terminal-to-terminal (T2T) networks are established, respectively. In both versions, the first unit that joins the network uses AllJoyn to create the peer-to-peer proximity network. Such a unit will also act as Manager for the overall duration of the collaborative sensing activity. Therefore, we have a ***Fixed Centralized*** role architecture of the Control Tier without any mechanism for the dynamic selection and activation of roles in such a tier. For this reason, the prototype implemented was only useful to evaluate the Sensing Tier of the *MASU* framework.

In reference to the data retrieval mechanisms, the first version of the prototype implements AllJoyn, whereas the second version implements CoAP.

Table 3.5: Implementation details of the two versions of the prototype

	Prototype v1	**Prototype v2**
Type of implementation	Embedded into Unity	Native Android application
Network infrastructure	AP	T2T
Mechanism for the p2p network creation	AllJoyn	AllJoyn
Location of the Manager role	In the first node that joins	In the node that acts as AP
Data retrieval mechanism	AllJoyn	CoAP
Data message type	TCP	UDP unicast

3.3.3 Results of the Simulations

This section presents results from the simulations that show the behaviour of the Control Tier of the *MASU* framework for the different network infrastructures and mobility patterns considered. It also considers the costs, in terms of network utilisation, involved in each one of the actions performed by such a tier.

3.3.3.1 Justification of the Control Tier

The Control Tier is an essential component of the *MASU* framework since it ensures availability of the information sensed by units participating in a collaborative sensing activity. We performed several simulations showing the behaviour of the framework when the Control Tier is not available. For these simulations we used several network infrastructures and a ***RandomWalk*** mobility pattern. In addition, we applied Consumer roles to 40 nodes, which represent all the *MASU* units existing in the scenario. We also assigned Producer roles to specific nodes manually, who play this role till the end of each simulation, sending the sensed information to the Consumers every 60 seconds. This means that when a Producer moves away from the coverage range or leaves the network, the Consumers subscribed to it will not receive the data.

Figure 3.14 shows results from simulations when only one Consumer is assigned. This figure represents the percentage of time during which the Producer and the Consumers were present in the network throughout the simulations. The Producer presence was calculated by counting the proportion of data messages sent by the Producer that were received by the Consumers that were present in the network.

In order to facilitate an easy interpretation of the results and at the same time provide some information about their statistical significance, most of the figures that represent the simulation results are composed of two different graphs. The first graph represents the average of the results and the second graph is a box-and-whisker diagram. This diagram shows the distribution of a dataset in three quartiles that separate the lowest 25%, 50% and 75% of the values from the rest (box) and the variability of the values outside the upper and lower quartiles (whiskers).

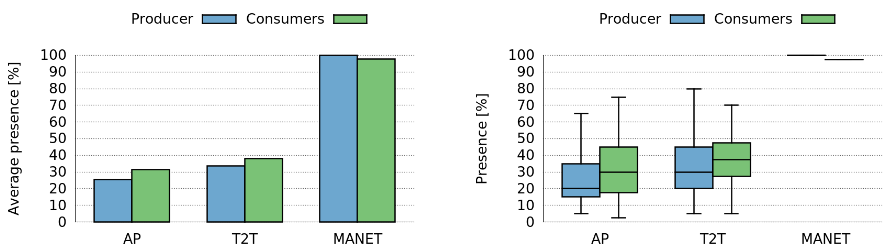


Figure 3.14: Presence of the Producer and the Consumers for different network infrastructures when the Control Tier is not available

In AP and T2T networks the presence of both the Consumers and the Producer is low and there is a high dispersion of values. In these networks the Producer is within the network only a 25% and a 33% of the time (in average) respectively. Only a few number of simulations show an acceptable percentage of presence of the Producer. By contrast, MANETs achieve large values of presence (around a 100% in average) with a very small dispersion.

Similarly, Figure 3.15 shows the percentage of presence of Producers when the number of nodes playing such a role increases. In AP and T2T networks when the number of Producers increases, the percentage of time during which they are reachable within the network decreases. On the other hand, in MANET networks the presence of Producers remains stable at the maximum value.

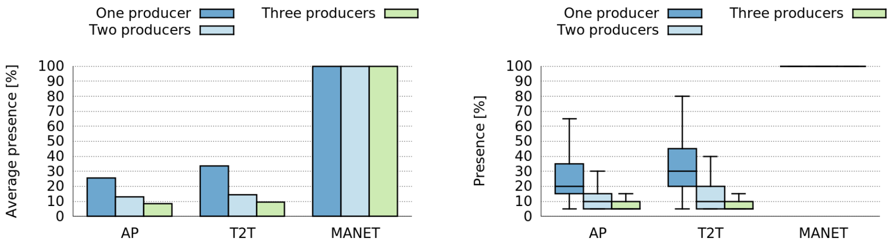


Figure 3.15: Presence of Producers and Consumers for different network infrastructures when the Control Tier is not available and the activity has several Producers

These figures reveal that there is a significant amount of time when the node or nodes that are acting as Producers will not be reachable within the network. This fact would make the collaborative sensing activity useless since the Consumers will not receive the information generated by the Producers. Therefore, the previous results provide evidence that clearly points to the necessity of the Control Tier as a mechanism to deal with mobility and failures that can affect the availability of the Producers. They also show that MANET infrastructures provide an interesting technological alternative to support pervasive data sensing activities in scenarios where the network coverage is limited.

In order to justify the usefulness of the Control Tier works, we performed several simulations considering a scenario when such a Tier is active and we have an ideal Control Tier algorithm that performs automatic and dynamic Role Selection and Activation processes in both Control and Sensing Tiers. Thus, every time a Manager or Producer fail or leave the network, the Control Tier will reassign these roles always that there are suitable candidates. Figure 3.16 shows the results of these simulations in terms of the achieved average presence of the Producer and the Consumers.

As expected, the activation of the Control Tier increases considerably the Producer presence in AP and T2T networks. By contrast, the presence of the Producer for MANETs as well as the presence of Consumers for all the three types of networks considered, remains similar than in simulations where the

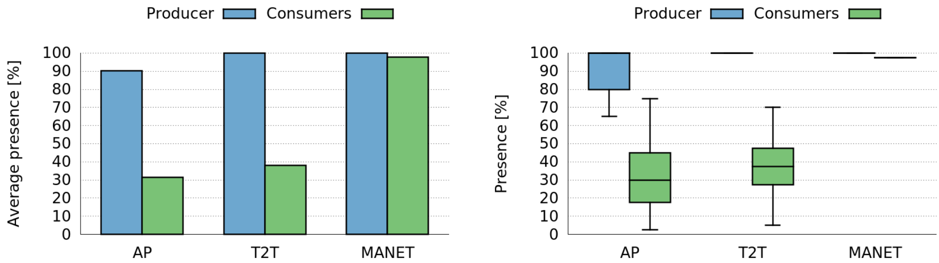


Figure 3.16: Presence of the Producer and the Consumers for different network infrastructures using an ideal Control Tier

Control Tier was deactivated.

The previous results show that the Control Tier provides a useful mechanism to deal with the dynamism of the network and guarantee a high average presence of Producers within the collaborative sensing activity. Despite this, the average presence of Consumers is low in AP and T2T networks. In addition, as shown in Figure 3.17, the number of nodes that are present at the same time in the collaborative activity is very low for such networks. This fact suggests the necessity of providing a method to deal with data losses due to the dynamism of the network, especially when the number of Producer increases. The *MASU* framework includes the ***Storage*** and ***Relay*** roles in order to deal with this issue and ensure high data availability.

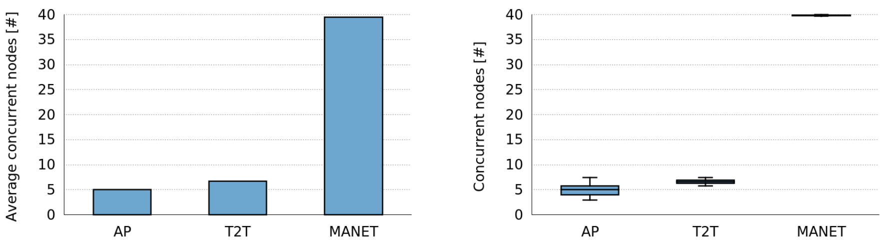


Figure 3.17: Number of nodes that are present in the collaborative sensing activity concurrently for different network infrastructures

3.3.3.2 Evaluation of the Control Tier

Following we introduce the results of the simulations performed to evaluate the performance of the Control Tier of the *MASU* framework. These results consider the performance of the Control Tier in isolation, without considering the behaviour of the Sensing Tier. The main objective is to evaluate the performance of the different types of role arquitectures of the Control Tier, considering several network infrastructures and mobility patterns. We also evaluated the cost of maintaining such tier in terms of number of messages sent to the network.

To verify that the Control Tier works as expected, we performed several simulations of the Dynamic Centralized and the Distributed role architecture approaches considered by the *MASU* framework and compared them with a Fixed Centralized method (used as baseline), where there is no dynamic selection and activation of roles in the Control Tier. For both approaches we implemented real algorithms in order to confirm that the *MASU* framework behaves as expected. In case of the Dynamic Centralized approach, we implemented a ***distributed election algorithm*** for the selection of a Manager every time it fails. Similarly, in the Distributed approach we implemented a ***distributed consensus algorithm*** for the selection of a Producer when necessary.

Following we present the evaluation of the different role architectures of the Control Tier considered for different (i) network infrastructures and (ii) mobility patterns.

For different network infrastructures

For this first set of simulations we used the ***RandomWalk*** mobility pattern and evaluated the performance of the *MASU* framework for several network infrastructures: AP, T2T and MANET.

As we can observe in Figure 3.18, for AP and T2T networks in the Dynamic Centralized and the Distributed approaches, the average presence of the Producer increases in comparison with the results of Figure 3.14, when no Control Tier was active. Nevertheless, in the Fixed Centralized method the results for both types of networks are not as good with less than 60% and 70% of average

Producer presence, respectively.

The results obtained using real algorithms for the Dynamic Centralized and the Distributed approaches are similar to those obtained when considering an ideal performance of the Control Tier (Figure 3.16), which confirms that the Control Tier behaves as expected, obtaining an optimum performance. Notice that the results obtained for MANETs are always the same, independently of the approach followed.

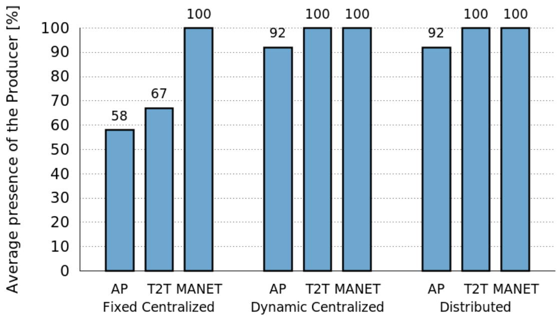


Figure 3.18: Performance of the Control Tier for different network infrastructures

The Dynamic Centralized and Distributed approaches considered in the *MASU* framework achieve significant improvements in comparison to a Fixed Centralized approach. Following we evaluate the cost required for such improvements in terms of the number of messages sent by the algorithms used for dynamic role Selection and Activation.

For this evaluation, we considered the four (i.e. Unit Detection, Device Information, Election and Consensus messages) of the six types of control messages defined by the *MASU* framework as well as the particular messages required by the routing protocol in MANET networks (routing messages). However, in the Device Information messages, we did not consider the messages required for hardware monitoring because we cannot measure changes of the hardware components of the devices in the simulator. We only considered the Device Information messages sent after a role Selection and Activation process in the Sensing and/or in the Control Tiers takes place. Thus, we only included the messages sent by new network nodes that are unknown for the new Manager selected. Therefore, the number of Device Information messages is associated with the number of nodes that are concurrently active when a new Manager is selected.

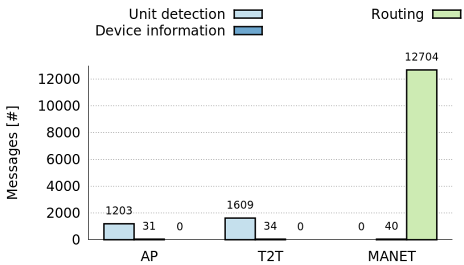
Figure 3.19, shows a comparison of the number of messages required for the Dynamic Selection and Activation of roles in Fixed Centralized, Dynamic Centralized and Distributed role architectures of the Control Tier. These figures show that the number of messages is very similar for both Dynamic Centralized and Distributed approaches. Nonetheless, the number of messages is slightly smaller for the Fixed Centralized approach. This can be explained by the fact that in the Fixed Centralized approach, the first node that join the network plays both the Manager and the Monitor roles and when such a node fails, the system stop counting the messages that this node was monitoring.

Notice that in MANET networks in addition to the control messages we have routing messages. This situation is possible due to the fact that the *MASU* framework considers a crosslayer approach, which means that we can use the routing messages (routing layer) to substitute the Unit Detection messages (application layer). Nevertheless, the number of routing messages could seem too high in comparison with the number of other types of messages. However, it is important to consider that in MANETs there is a much higher number of nodes that are active concurrently in the collaborative sensing activity than in AP and T2T networks (as represented in Figure 3.17). Consequently, the number of routing messages is directly proportional to the number of active nodes, which is only a sign of the high data availability provided by MANETs.

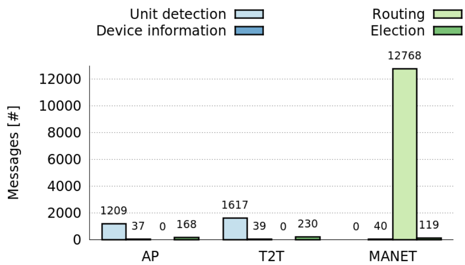
From Figure 3.19 we can conclude that the number of messages required by the framework depends on the network infrastructure and it is positively correlated with the number of nodes of the network. Thus, AP infrastructures produce a smaller number of messages, followed by T2T and MANET networks.

To be able to have more objective criteria to evaluate whether the number of the different types of control messages shown previously is reasonable or not, we computed the number of instances that each one of the actions of the Control Tier occurred in each one of the role architectures of the Control Tier considered. Such actions correspond to the various types of messages represented, and therefore the higher the number of times that an action takes place, the higher the number of messages of the corresponding type would be. Figure 3.20 presents the results obtained. If we compare these results with the presented in Figure 3.19, we can observe how the number of times that the different control actions take place is independent of the number of nodes and is similar for all the network infrastructures. As a result, we can conclude that the number of control messages is related to the actions of the control Tier and the number of times that such actions are executed by the nodes that are present in the network. As we can observe in Figure 3.20, although the number of control actions is slightly smaller in the Fixed Centralized architecture, it is relatively similar in all of the three architectures considered. Consequently, we can claim that the number of times that a control action takes place is mainly associated with the type of network infrastructure used.

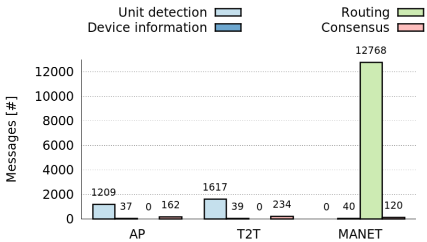
Considering the previous results, it seems reasonable to have a higher number of messages in Dynamic Centralized and Distributed architectures than in a Fixed Centralized one since the two former take more control actions to maintain the role structure of the collaborative sensing activity and ensure the availability of the information sensed. Furthermore, taking into account



(a) Fixed Centralized

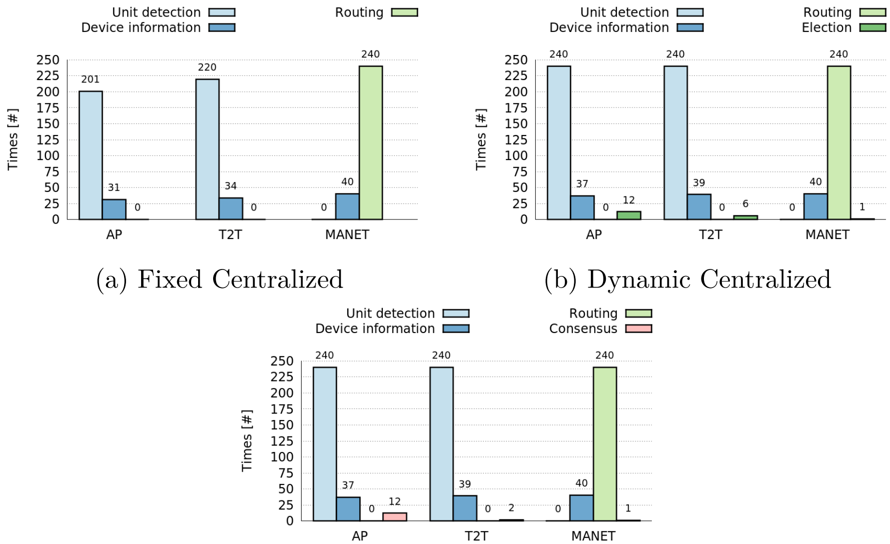


(b) Dynamic Centralized



(c) Distributed

Figure 3.19: Cost of the different role architectures of the Control Tier for different network architectures



(a) Fixed Centralized

(b) Dynamic Centralized

(c) Distributed

Figure 3.20: Number of instances that an action of the Control Tier takes place for different network infrastructures

that the number of messages is also positively correlated with the number of active nodes, we calculated the number of messages that a given node has to send every time that occurs an action of the Control Tier. By doing so, we pretend to find an objective method to assess the cost of the different actions of the Control Tier.

As shown in Figure 3.21, the different actions of the Control Tier have a small cost in terms of number of messages required (with a maximum of 3 messages per node). The Consensus and Election actions have the higher cost. Therefore, the highest costs of the Control Tier is caused by the role selection processes in both, Control and Sensing Tier.

In any of the three network infrastructures considered, any network node has to send a similar number of messages whenever a Control Tier action takes place. On the other hand, the number of routing messages used in MANETs is slightly higher than the number of Unit Detection messages that they substitute. Moreover, the number of Election and Consensus messages is also slightly higher in MANETs than in the other infrastructures considered. Consequently, we can claim that the cost of the Control Tier is similar for the three network infrastructures considered. This fact points to the consistent performance of the *MASU* framework regardless of the underlying network infrastructure and therefore its applicability to dynamic communication contexts. Nevertheless, if the number of nodes is too high, the higher cost of MANETs could produce a degradation in the performance of the framework.

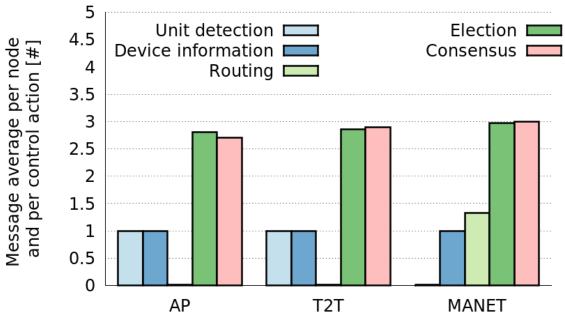


Figure 3.21: Average number of messages per action of the Control Tier and per node for the different network infrastructures considered

For different mobility patterns

This section presents the evaluation of the different role architectures of the Control Tier considered for different mobility patterns.

First, we evaluated the effect of the mobility patterns of the nodes when there is no Control Tier available. Figure 3.19 shows the average percentage of presence of the Producer of different network infrastructures for the mobility patterns considered. *RandomWalk* and *Nomadic* mobility patterns achieve a similar percentage of presence of the Producer in AP and T2T networks, whereas *SLAW* achieves a slightly higher percentage. Nevertheless, the improvement achieved by the *SLAW* mobility pattern is not significant. On the other hand, MANET networks achieve the maximum percentage, regardless of the mobility pattern. These results suggest that more realistic mobility patterns yield to higher presence of the Producer. This can be explained due to the fact that such patterns consider the social tendency of human interactions and therefore people's inclination to form groups.

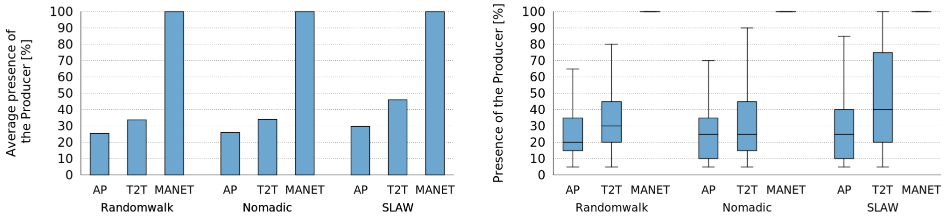


Figure 3.22: Presence of the Producer for different mobility patterns when no Control Tier is available

Next, we evaluated the performance of an ideal Control Tier as well as the average presence of Consumers for the different mobility patterns considered. Figure 3.23, shows that the presence of Consumers varies slightly across mobility patterns and network infrastructures. In addition, the performance of an ideal Control Tier in terms of presence of the Producer is similar for all mobility patterns in T2T and MANETs, while *RandomWalk* obtains slightly better results for AP networks. Thus, the variation in the results obtained for different mobility patterns are not significant.

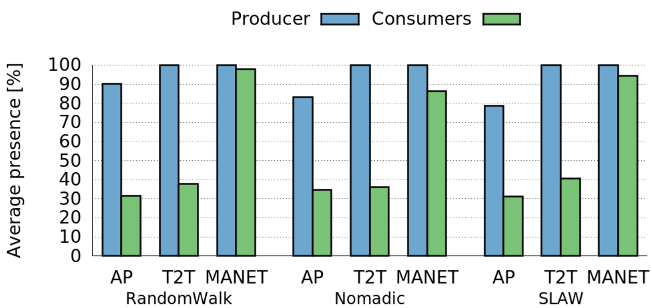
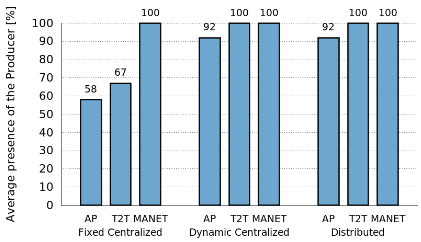


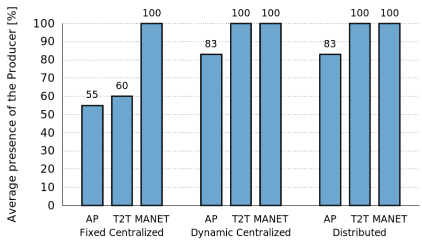
Figure 3.23: Presence of the Producer and the Consumers for different mobility patterns using an ideal Control Tier

Then, we evaluated the performance of the different Control Tier strategies considered in our proposal for different mobility patterns. Figure 3.24 shows that the performance of the Dynamic Centralized and Distributed architectures is similar to the performance of an ideal Control Tier (Figure 3.23). However, the performance of the Fixed Centralized architecture is worse than in the ideal case. On the other hand, although the variation in the results is not significant across mobility patterns, the *Nomadic* pattern achieves the worst results for all architectures in AP and T2T networks, while the *SLAW* pattern achieves the best ones. MANETs achieve the same results for all mobility patterns and architectures.

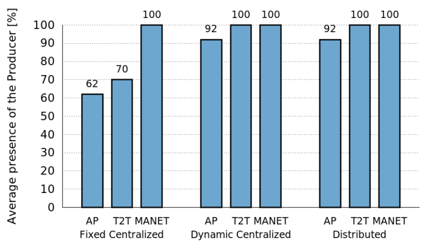
The fact that all the mobility patterns considered achieve very similar results suggests that the results of the evaluation performed in the previous section using the *RandomWalk* mobility pattern could be easily extrapolated to the *Nomadic* and *SLAW* patterns as well as to more realistic mobility patterns. This suggests that in a real world scenario, with real mobility patterns the performance of the *MASU* framework could be very similar that the performance obtained through simulations.



(a) RandomWalk



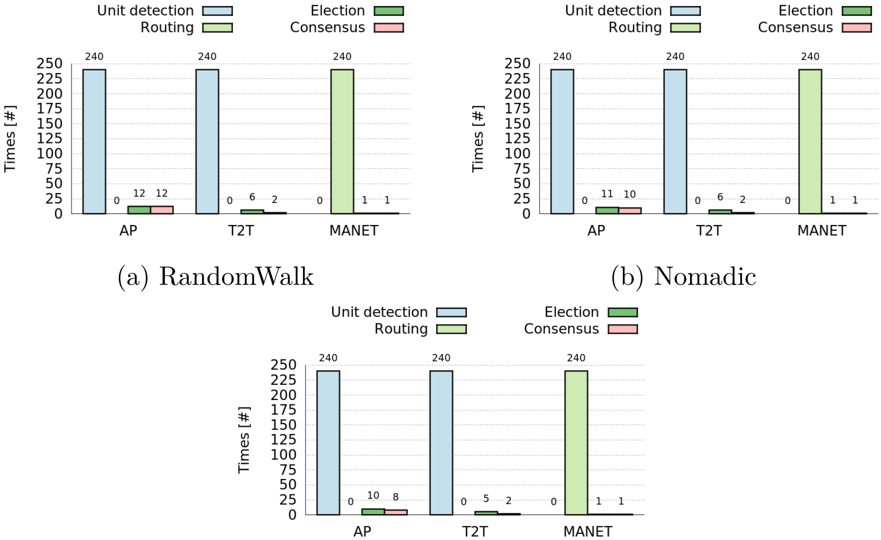
(b) Nomadic



(c) SLAW

Figure 3.24: Performance of the different role architectures of the Control Tier for different mobility patterns

In order to evaluate the differences in the costs required for the maintenance of the Control Tier that are caused by the different mobility patterns, we computed the number of instances that each one of the actions of the Control Tier occurred in each one of the mobility patterns considered. The results represented in Figure 3.25 show that the *SLAW* mobility pattern requires less number of Control Tier actions, which imply a lower cost in terms of number of messages required. Once again, this fact points to the benefit of taking advantage of the characteristics of realistic mobility patterns that consider the social nature of human interactions and their tendency to form groups.



(a) RandomWalk (b) Nomadic

(c) SLAW

Figure 3.25: Number of instances that an action of the Control Tier takes place for different mobility patterns

3.3.3.3 Evaluation of MANET Network Infrastructures

The results presented previously suggest that MANET networks can provide an interesting alternative to support pervasive data sensing in dynamic scenarios since they guarantee higher node presence values (especially, Consumers since the Control Tier of the framework already deals with the presence of Producers), regardless of the mobility patterns considered. This fact means that higher data availability is possible using this types of networks since Consumers can receive data from Producers regardless of the fluctuations in the communication links and the mobility conditions of the nodes.

The explanation for this high data accessibility can be found in Figure 3.26. It shows that more than 50% of the time that the Producer is present in the network is located more than one hop away from the Consumers. There are even cases where the Consumers receive data from the Producer when it is at four or five hops away.

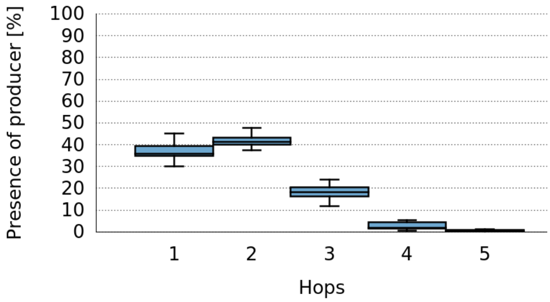


Figure 3.26: Percentage of presence of the Producer versus the number of hops in MANET networks

These benefits of MANETs come at the expense of a higher number of messages that have to be transmitted over the network, as represented in Figure 3.27. This figure shows the average number of messages that are transmitted over the network for different network infrastructures. The number of messages is significantly higher in MANETs due to the fact that the data messages transmitted from the Producer to the Consumers are UDP unicast (1 to 1). For this reason, the Producer has to send one message to each one of the Consumers that are within the network. Thus, the number of data messages has a direct correlation with the number of active Consumers. By contrast, in AP and T2T networks the data messages are UDP broadcast (1 to all) so the number of messages has a positive correlation with the number of active Producers.

The higher cost related to the number of messages in MANETs is compensated by the fact that these types of networks allow that a higher number of units could receive the information sensed by Producers. However, if the number of Consumers is too high, this cost could lead to network congestion, which would also suppose that the *MASU* framework will not be able to work properly under those conditions. As a result, it would be necessary to find a solution to deal with scalability problems related with the high number of messages sent through the network in MANET.

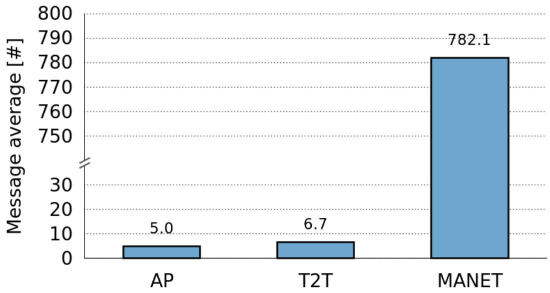


Figure 3.27: Average number of messages for different network infrastructures

3.3.4 Results of the Prototype Evaluation

In this section we discuss the results of tests performed for the evaluation of the prototype. These tests evaluate the performance of the Sensing Tier in terms of resource consumption and considering heterogeneous devices. Therefore, in contrast to the simulation tests, the prototype evaluation considers devices with diverse capabilities. In order to do that, we deployed the prototype in several different Android devices. We used smartphones and tablets with different OS versions and various kinds of CPU, battery and sensor chips. The features of the different types of devices used are detailed in Table 3.6. This device heterogeneity allows us to gain some insights about the changes in the performance of the framework across devices.

To evaluate the prototype we carried out several tests where some of devices sensed the environment and shared the data, and others only received the sensed information. The duration of all the tests was 20 minutes and in every test, the battery of all the devices was initially at the same charge level (100%). The tests performed consider an outdoor space, where the devices are moving constantly at walking speed.

In the tests conducted for the evaluation of the first version of the prototype, the devices remained within the coverage zone of a fixed AP. By contrast, in the tests performed using the second prototype, the devices are never outside

Table 3.6: Devices used in the evaluation of the prototype

	A1, A2, A3	B	C	D	E
Device type	Smartphone	Smartphone	Smartphone	Tablet	Tablet
Model	HTC Desire	HTC One	Samsung Note II	Google Nexus 7	Google Nexus 7
Android version	2.3.3	4.4.3	4.4.2	4.4.4	5.0.2
Chipset	Qualcomm QSD 8250 Snapdragon S1	Qualcomm APQ 8064T Snapdragon 600	Samsung Exynos 4412 Quad	Nvidia Tegra 3	Nvidia Tegra 3
CPU	1 GHz Scorpion	Quad-core 1.7 GHz Krait 300	Quad-core 1.6 GHz Cortex-A9	Quad-core 1.2 GHz Cortex-A9	Quad-core 1.2 GHz Cortex-A9
Battery capacity	5180 mWh	8510 mWh	11470 mWh	16000 mWh	16000 mWh
GPS technology	A-GPS	A-GPS, GLONASS	A-GPS, GLONASS	A-GPS, GLONASS	A-GPS

the coverage zone of the device that acts as AP or their mutual coverage zone. As a result, both types of tests do not consider dynamic network topologies or diverse mobility patterns.

3.3.4.1 Justification of the Benefits of Collaborative Sensing

Next, we present the results of the evaluation of the first version of the prototype. We performed several tests using the first prototype a version in order to assess the usefulness, for a group of *MASU* units, of sharing sensor data between them instead of working autonomously. This assessment only considers the advantages of collaborative sensing in terms of the battery consumption of the devices involved, but other aspects have also to be taken into account, such as better information quality and social welfare (the benefit of the entire community of users).

First, we evaluated the battery consumption produced by a sensing activity in different devices. Figure 3.28 shows the results obtained. The first set of bars represents the case when the devices are not performing any sensing or sharing activities, whereas the second set shows the results when the devices are sensing GPS data. This graph also shows that there is a significant cost in battery lifetime, due to the sensing operations. Moreover, this cost differs across devices, having the device A the highest cost. This difference in battery consumption can be caused by differences in the versions of the operating system or the GPS sensing chips.

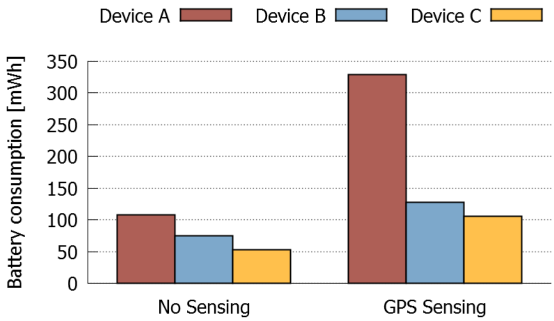


Figure 3.28: Sensing costs for different devices

Then, we evaluated the costs involved in a collaborative sensing activity in scenarios with heterogeneous devices. To that end, we compared the total battery consumption when sensing data and transmitting it using the two local data retrieval mechanisms used in our prototype: AllJoyn and CoAP. We conducted two different sets of experiments, where four different devices share GPS data, using AllJoyn and CoAP, respectively.

Figure 3.29 depicts the results when the device A1 is sensing GPS data and sharing it with the others. The device A1 is sensing and transmitting GPS data (Producer role) and devices A2, B and C are receiving it (Consumers). As expected, the energy consumption is higher in the transmitting device than in the receiving ones for both, AllJoyn and CoAP protocols. In addition, the energy consumption is higher in when using AllJoyn than when using CoAP for both, transmitting and receiving devices. Nevertheless, for some receiving devices, the energy drain is very similar for both protocols. Notice that the battery consumption differs for different types devices even when they have same role (Consumers) and protocol active, which shows the effect of the heterogeneity of devices in the collaborative sensing activity.

These results can be anticipated since the CoAP protocol is very simple and it is therefore, expected to consume less energy than a more complex protocol like AllJoyn that includes network and service discovery functionalities.

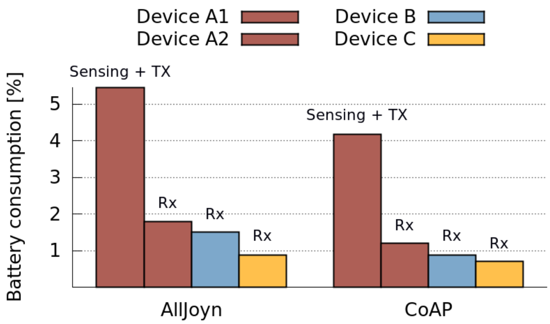


Figure 3.29: Comparison of the overall collaborative sensing costs of AllJoyn and CoAP for different devices

Next, we conducted several tests in order to verify the benefits of collaborative sensing. Unlike the previous tests, here we aim not only to evaluate the overall costs of collaborative sensing, but also to isolate the costs related to the data retrieval mechanisms used by the *MASU* framework. This way we intend to differentiate between the sensing costs (which are required even when the units work in a stand-alone fashion) and the costs caused by the collaborative activity itself. For these tests, we considered the worst case scenario, that is, when sharing data using the most energy-intensive protocol. Consequently, the application executing the *MASU* framework had only the AllJoyn protocol activated. The results are shown in Figure 3.30.

The first set of bars in Figure 3.30 shows a comparison of the maximum, minimum and average energy consumption when: (i) the devices are only sensing GPS, (ii) they only have the prototype application running and (iii) they have the application running and the AllJoyn service active, but they are not sharing any data. This way, we wanted to evaluate the cost of maintaining an AllJoyn session (16 mWh in average) in comparison with the cost of sensing. These results also show that the cost of sensing GPS is considerably higher than the cost of using AllJoyn.

The second set of bars in Figure 3.30 shows the average cost of sensing and transmitting GPS data (corresponding to a Producer role) using AllJoyn, versus the cost of receiving it (Consumer). From the figure it is clear that the cost of sensing and transmitting is slightly higher than the cost of sensing GPS, whereas the cost of receiving information is smaller (15.06 mWh in average). This result indicates that there is an obvious benefit for the receiving device (GPS Consumer), while the cost in the transmitting device (GPS Producer) is relatively low, which clearly points to the advantages of collaborative sensing in terms of social welfare because there is some benefit for the overall group of users (3.41 mWh in average). It seems reasonable to think that, if number of devices increases, these benefits could be increased too. Thus, we could compensate the communication cost introduced by maintaining the AllJoyn session. Nevertheless, further tests are necessary to be able to confirm this claim.

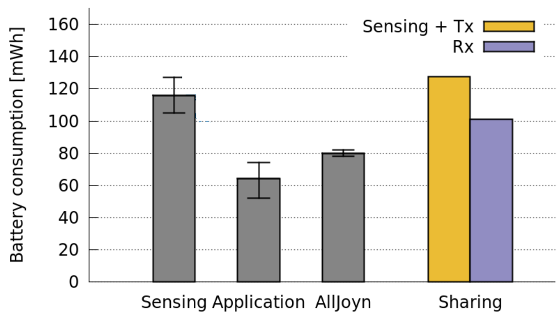


Figure 3.30: Evaluation of the cost of AllJoyn in a collaborative sensing activity

3.3.4.2 Battery Consumption of Producers and Consumers

Some additional tests were performed to evaluate the energy costs of Producer and Consumer roles. We compared the performance of Producers and Consumers in case of high and low intensity data sharing processes, when sharing data using AllJoyn. That is, the cost of sensing from sensors that generate low and high amounts of data, including the costs of sharing such data at low and high data rate, respectively.

The high intensity data process was established by sensing GPS data continuously and sharing it every time geolocation value changed. This implied that the GPS data was sent continuously due to the high precision of the GPS sensor and also because the devices were constantly moving. On the other hand, the low intensity data sharing process was established by sending an audio file captured from the smartphone microphone.

Figure 3.31 shows the results obtained. In the case of high intensity data sharing process, the cost of sensing is slightly smaller than the cost of sensing and transmitting the data, but higher than the cost of receiving it. Therefore, in case of high data-intensive Producers we can confirm the usefulness of sharing the sensed data using AllJoyn, even when the data is shared solely with one Consumer.

Contrarily, the cost of using AllJoyn for sharing small amounts of data, at a low transmission rate, is very high and considerably higher than the cost of sensing. For this reason, in case of low data-intensive Producers it would make much more sense to collect the information directly in the devices that are going to consume it. However, it seems reasonable to think that if the number of devices is high enough, this energy cost could be compensated. Nonetheless, further tests are necessary to confirm this claim.

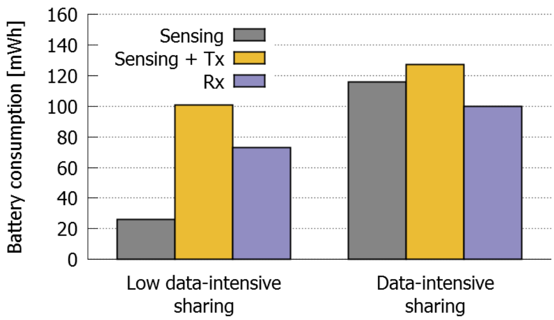


Figure 3.31: Comparison of the energy costs of high data-intensive and low data-intensive sharing processes

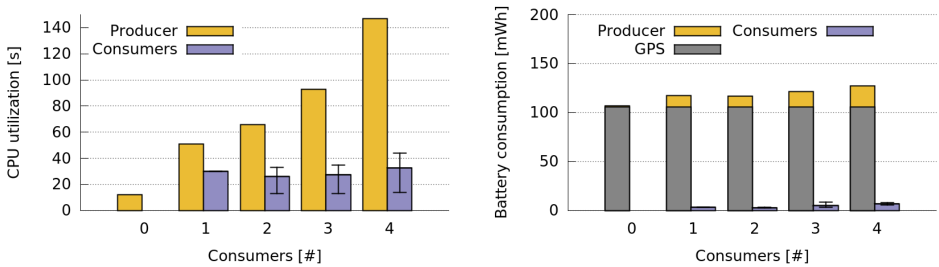
3.3.4.3 Resource Consumption for an Increasing Number of Nodes

The evaluation of the first prototype, provided some insights about the benefits of collaborative sensing and the costs involved. This evaluation represented a worst case scenario due to the poor efficiency of the software implementation embedded in the Unity platform as well as due to the higher costs of AllJoyn as data retrieval method. Thus, we conducted several tests using the second version of the prototype, which provides a more realistic experimental scenario with a more efficient implementation. In this case, CoAP is used as data retrieval method.

We performed several tests to evaluate the impact of increasing the number of Consumers of information in terms of CPU utilization and battery consumption of Producer and Consumer roles. These tests had only one Producer but several Consumers active. In this scenario, the Producer senses GPS data, creates a CoAP service and sends the GPS coordinates to the Consumers subscribed to the service.

Figure 3.32 shows the results of these tests when the Producer sends data to the Consumers every time the GPS data changes. Due to the fact that for these tests the GPS sensor was always active and the nodes were constantly moving, the GPS information changed frequently, and therefore the Producer was continuously sending messages to the Consumers. Figure 3.32 represents the CPU and energy consumption of both Consumers and Producers when the number of Consumers of GPS data increases. It shows that the CPU utilization of the Producer increases with the number of Consumers. This increment is mainly caused by the high number of CoAP messages that the Producer has to send due to the high change rate of the GPS data. Particularly, for each 20-minute test, the Producer had to send around 900 CoAP messages to each Consumer. We can also observe in this figure that the energy cost of the Producer (GPS sensing and transmitting) is slightly higher than the energy cost of sensing GPS, whereas the energy cost of the Consumer (receiving information) is significantly smaller. This indicates that there is a clear benefit for the Consumers, while the cost for the Producer is relatively low. Nevertheless, there is a slight battery consumption increase when increasing the number of Consumers. This was an expected result because the amount of energy should increase when more devices are added to the system, due to more the energy consumption required for the Wi-Fi subsystem maintenance. Despite this, if we consider the overall battery consumption of the system, we have an important reduction in the energy consumption (295 mWh in total for one Producer and four Consumers) when we use the prototype for sharing the sensed data, instead of sensing data independently, which once again shows the advantages of collaborative sensing. In this case, we achieved a 43% of reduction in battery drain, considering the overall group of devices involved. Therefore, both Consumer and Producer applications are energy-efficient and most of the energy cost of the Producer is caused by GPS sensing.

Comparing these results obtained with the case when we only have one Consumer (as presented in both Figure 3.30 and Figure 3.32), we can confirm that there is a higher benefit for the overall group of devices when the number of Consumers increases. Nonetheless, the tests performed only consider four Consumers. For this reason, more tests would be necessary to determine the maximum possible number of Consumers so that there is some energy savings for the overall system.



(a) CPU utilization (b) Battery Consumption

Figure 3.32: Resource consumption of Producers and Consumers when sharing GPS data continuously

We also evaluated the CPU utilization when the Consumers call the CoAP service of the GPS Producer periodically, every 60 seconds (Figure 3.33). In this case, the Producer does not send GPS data continuously. It only sends every 60 seconds the last GPS value measured. This means that, although the GPS sensor still active, the Producer only does a GPS reading every 60 seconds. Thus, the number of CoAP messages sent by the Producer decreases significantly (around 20 messages for each Consumer). As a result, the CPU utilization of the Producer is significantly smaller than when it was sending data continuously (Figure 3.32) and increases very slowly with the number of Consumers.

3.3.4.4 Resource Consumption of Storages and Relays

In order to assess the CPU consumption of the Storage and Relay roles, we performed a test where two Consumers subscribe to the GPS sensing services of a Producer and a Storage, respectively. This test is useful to evaluate the computational cost of both Storages and Relays since such a cost is only related with the rate at which Storages or Relays send data to Consumers. Therefore, it is not necessary to perform two separate tests to evaluate both types of roles.

In the test performed, the Storage role was assigned to the last node entering the network. This Storage receives the GPS data sensed by the Producer every 60 seconds and sends such data to the Consumer subscribed to it at the same rate. Results in Figure 3.34 show how the CPU utilization in the Storage is slightly higher than the in the Consumer but significantly lower than in the Producer. In addition, the CPU utilization of both Producers and Consumers in the case of having one Producer and two Consumers increases slightly when we add one Storage. These results show the usefulness of including Storages or Relays when we have two Consumers and one of them cannot receive the information from the Producer properly.

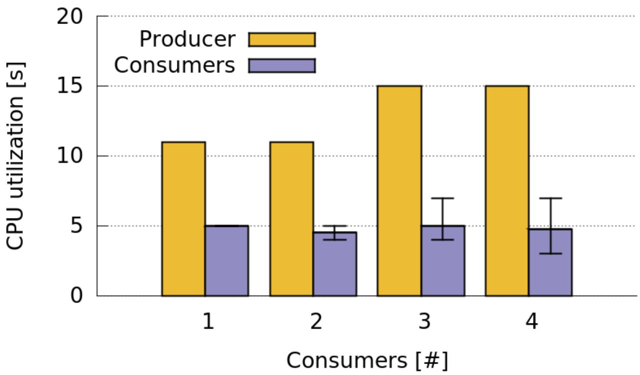


Figure 3.33: CPU utilization of Producers and Consumers when sharing GPS data periodically (low data transmission rate)

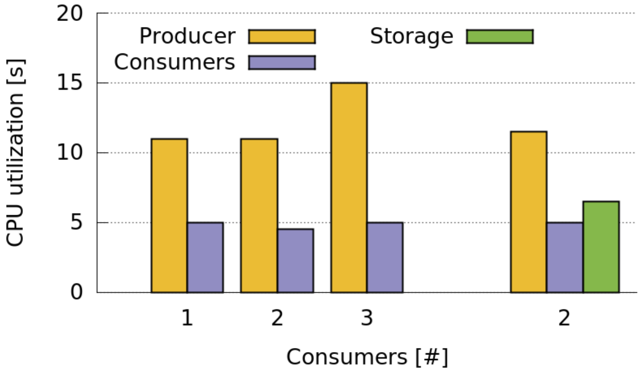


Figure 3.34: CPU utilization of Producers, Consumers and Storages when sharing GPS data periodically with two Consumers

3.4 Proposed Improvements to the MASU Framework

From the simulations results, we observed that the Consensus and Election actions were the most costly in terms of number of messages sent through the network. Considering these facts, several improvements can be introduced in the *MASU* framework to reduce the costs involved in these types control actions. The aim of these improvements is to reduce the frequency at which Role Selection and Activation processes take place.

To that end, we propose two possible enhancements of the framework:

(i)Assignation of Backup Manager by the Manager: The failure of the Manager role could also be mitigated by the existence of a Backup Manager role. Such a role can be directly assigned by the Manager since it already has the information of all the participating devices. This Backup Manager can be the second-best Manager candidate as calculated by the leader election algorithm. The existence of this backup Manager could reduce the number of Role selection and Activation processes required every time the Manager fails. These processes would only take place if both, Manager and Backup Manager fail.

(ii)Restart the Role Selection and Activation Process in the Control

Tier only if the Producers fails: By taking this measure we could reduce the number of Role Selection and Activation messages in those cases where the Manager fails but the Producers previously assigned by it are working properly. In this case, it would be possible to successfully finish the collaborative sensing activity despite the fact that the Manager is not active anymore.

3.5 Conclusions

In this chapter we discussed the design of a framework for pervasive monitoring using smartphones and other sensor-enabled devices. The proposed framework preserves the autonomy of the devices and considers various parameters, such as the mobility of the user, the underlying communication infrastructure and the hardware characteristics of the devices involved. The design of the framework includes the definition of different roles that can be played by a group of devices that are performing collaborative sensing activities. We also presented a description of the protocols of interaction between such roles and the tolerance mechanisms of the framework for role failure, poor hardware performance or network dynamism.

We conducted several tests to explore the feasibility of performing collaborative sensing activities using the proposed framework as well as the costs involved. These tests included a number of simulations as well as an experimental evaluation of a prototype of the framework.

The simulations were used to evaluate the Control Tier of the framework. The simulation results demonstrated that the social nature of human interaction can benefit the performance of the framework since people's mobility patterns that reflect this social nature contribute to high availability of the information sensed by smartphone users. In addition, the simulations helped us to evaluate the costs involved in collaborative sensing in terms of network utilization. We also showed how Mobile Ad hoc Networks (MANETs) provide an interesting communication support that provides higher network connectivity due to their multi-hop features. Consequently, we demonstrated that MANETs can also contribute to the accessibility of the information sensed. Nevertheless, the simulations also revealed that MANETs have a slightly higher cost in terms of number of control messages but a considerably higher cost in terms of and data messages due to the unicast nature of the communication as well as due to the higher node connectivity. These facts could derive in scalability problems of the framework when using MANETs as communication support.

Using the prototype, we evaluated the Sensing Tier of the framework. We showed the benefits of using the framework to perform collaborative sensing in terms of energy savings and social welfare in comparison to pure phone sensing, achieving a 43% energy savings for the overall system (Section 3.3.4.3). We also evaluated the costs associated with the use of the framework for collaborative sensing in terms of hardware resources of the participating devices. This evaluation considered some device heterogeneity since we used smartphone and tablets with diverse hardware specifications.

Results from both types of evaluation methods provided empirical evidence on the usefulness of the proposed framework. These results provided valuable insights about the benefits of the proposed framework to support pervasive sensing in terms of resource optimization as well as about its limitations and associated costs.

Chapter 4

An Autonomous Communication Support

4.1 Introduction

One of the main requirements for pervasive monitoring solutions that aim to be implemented in a life-long and dynamic learning context, is the capability to ensure system autonomy. This is particularly challenging in uncertain communication scenarios where the students move from one place to another and therefore, there can be areas where the communication infrastructure is limited or does not pre-exist.

The concept of *Mobile Ad hoc Network (MANET)* has become an interesting contribution to solve communication problems on loosely coupled activities, carried out in several mobile collaboration scenarios [165]. In those contexts, the applications do not usually rely on a fixed infrastructure communication system, such as antennas or access points. A MANET creates a communication mesh to exchange messages among participating devices. Those devices are free to move, change connection status and even support autonomous tasks.

A MANET is an attractive low-cost alternative to provide networking capability in areas where there is no pre-existing communication support or when there is some communication infrastructure but its coverage or capacity is limited [14]. Moreover, MANETs can be used as a backup network to extend the main fixed network infrastructure [49, 50, 14] if it is not available or it fails. Furthermore, these types of networks have the capacity of dealing with mobility conditions, providing a feasible means to support the interaction of mobile users in non-traditional contexts like the ones envisioned by the new learning paradigms.

These non-traditional contexts can include interactions with IoT devices, such as networked printers, shared displays and other smart systems embedded in objects of the learning environment [52, 240]. In that line, although the use of other infrastructures is also possible, MANETs can facilitate the integration of different types of IoT devices and the detection of devices available in the environment [27].

Considering the fact that the new learning paradigms put great emphasis on social interactions and collaboration activities, other non-traditional contexts can include face-to-face spontaneous interactions among people. In that sense, MANETs can exploit the social behaviour of people and the opportunistic interactions that take place due to their mobility patterns, to provide temporal network connectivity [229, 19]. Hence, the advantages of MANETs related to social interactions have a twofold perspective: (i) they benefit from the temporal and spatial dependencies of the interactions among people to connect the devices carried by them and create temporal network infrastructures and (ii) they provide network connectivity to support those interactions in scenarios where there is no other suitable network infrastructure available. Therefore, MANETs can provide an autonomous and pervasive network infrastructure that takes advantage from and supports social interactions in dynamic learning scenarios, where the students (carrying a smartphone or other mobile device) perform loosely-coupled activities (that include both individual work and on-demand collaboration) in uncertain communication contexts.

Considering all the features and capabilities of Mobile Ad hoc Networks and the importance of collaboration and social interactions in earning, we envision a scenario where smartphones or other mobile devices carried by students can interact dynamically between them and with other nearby devices and IoT objects using these types of networks. This would allow complex collaborative sensing activities as well as dynamic feedback provision across diverse devices (e.g, in smartphones, laptops, shared displays, etc.). In addition, from the evaluation of the pervasive sensing framework proposed in Chapter 3, we provided evidence that suggest that MANETs are suitable communication supports to perform mobile collaborative sensing activities between different sensing devices. As a result, we propose the use of MANETs, in combination with other fixed infrastructures, to provide an autonomous communication network to support pervasive monitoring of mobile students and appropriate awareness provision, regardless of their physical location.

However, in order to design solutions for pervasive monitoring that are able to work over MANETs, we must take into account the capabilities and limitations of this communication infrastructure, some of which were already introduced in Chapter 3. Knowing these issues will help us to conceive applications able to support the interactions of mobile users in real-world scenarios. For example, the monitoring and awareness mechanisms to be embedded into the application must be selected by considering the stability and bandwidth of the communication link supporting them. For example, awareness mechanisms based on image contents could be inappropriate when the images are transferred through the network and the available bandwidth is narrow. Otherwise, we would be giving the user an awareness service without the required performance and responsiveness. A poor communication performance typically affects the coordination and collaboration services required for pervasive monitoring (e.g., the coordination required for collaborative sensing). These services also affect other services that are available for the users (i.e. awareness), and therefore it also impacts on the usaaebility of the application.

The main focus of this chapter is to understand the potentialities and limitations of Mobile Ad hoc Networks, providing empirical evidence on the viability of using these types of networks to support pervasive sensing and awareness provision in dynamic learning scenarios. Therefore, an experimental study was performed considering diverse collaborative interactions that can take place in such scenarios.

Once explored the usefulness of MANETs to support pervasive monitoring, we proposed some recommendations to deal with the restrictions of these networks. In that line, we propose a mechanism to reduce the overhead produced by the routing protocol. This mechanism help increase the available communication throughput and reduce network congestion and energy consumption, which contributes to the network scalability.

Chapter Overview

This chapter explores how MANET networks can be used as an opportunistic communication support for mobile collaborative sensing activities between the students' devices and/or other devices in the proximity and also enable flexible feedback provision through the creation of a network of displays between devices available in the environment (e.g., students' laptops, shared displays, etc.). Therefore, we provide evidence of the viability of using MANET as a type of communication infrastructure that can support pervasive monitoring and awareness provision in dynamic learning contexts. We also propose solutions to deal with some of the limitations of these types of networks. More specifically, we propose a mechanism to address the limitations highlighted in Chapter 3 in relation to pervasive data sensing. The remainder of the chapter is organised as follows: in Section 4.2 we describe the experimental study performed to evaluate the viability of using MANET networks as communication support for pervasive monitoring. In this section we also present the results, the lessons learned and some recommendations to deal with the limitations observed from the study. We describe the mechanism proposed to improve the efficiency and scalability of MANETs in Section 4.3. We also present an evaluation of the potential benefits of the proposed mechanism as well as the particular behaviour of this mechanism for several scenarios. Finally, we present the conclusions in Section 4.4.

4.2 Study of the Viability of MANETs to Support Pervasive Monitoring

Software designers are typically unaware of several characteristics and limitations of the communication infrastructure to support coordination and collaboration services, as they are usually not easy to deduce or foresee. In [91] the authors call this situation "the iceberg effect", because it encourages designers to focus on the visible part of the product (i.e. the user interface) and forget important parts of the solution that usually are not easy to see (i.e. the communication and coordination mechanisms) but critical. Therefore, one of the problems that the "iceberg effect" brings for the development of solutions that involve pervasive sensing and awareness provision is the uncertainty about the suitability of the communication infrastructure to support collaborative processes and interactions among mobile devices in real-world scenarios. This fact would make it impossible to guarantee the usefulness of the pervasive monitoring application in terms of the response time perceived by an end user.

In the case of Mobile Ad hoc Networks, most research works intended to evaluate the suitability of these communication infrastructures perform studies based on network simulators [122, 20] due to the high cost and technological difficulty of setting up MANET testbeds [121, 114, 224, 122]. These types of studies try to predict the behaviour of a network, usually based on highly simplified scenarios [224] that rely on artificial mobility patterns as well as on idealized models of radio propagation and interferences. Therefore, such studies do not accurately reproduce the behaviour of the network in real scenarios [222, 174, 122, 181, 20] and only provide a glimpse on the suitability of the communication infrastructure to support a certain mobile activity. One example of this, is the gray-zones effect, which is not usually considered in standard simulation tools, such as the well-known *ns-2* [174]. In addition, studies based on simulators are useful mainly to assess the performance of a given algorithm. However, they can not predict if such an algorithm is actually going to achieve the expected performance in real-world devices [114] because they do not consider the limitations of a real software implementation and the real behaviour of the hardware components of the devices.

As a result, we claim that, in order to be able to make a distinction between what is an acceptable or unacceptable communication support for pervasive monitoring, experimental studies are required. To understand more in depth the capabilities and limitations of the communication support, these studies should consider real devices, network cards, wireless links, software stacks, rooms, etc.

This is precisely the main focus of the study presented in this section, to provide empirical evidence on the viability of using MANET networks to support the communication processes required for pervasive monitoring in dynamic learning scenarios. To that end, we conducted an experimental study in real settings and involving different types of interaction scenarios that are widely representative of dynamic, opportunistic, mobile and collaborative learning environments.

To assess the feasibility of using MANETs as communication support for pervasive monitoring, it is necessary to understand the communication requirements of such types of activities. Next section describes the basic requirements that must be fulfilled by any communication infrastructructure used to support pervasive monitoring activities.

4.2.1 Requirements of a Communication Infrastructure for Pervasive Monitoring

Pervasive monitoring solutions must consider several communication requirements in order to enable collaborative sensing interactions among mobile users as well as awareness provision. These requirements, which are briefly explained below, affect the usability of the mobile application implementing these solutions in terms of response time.

(i) Adequate network performance. A pervasive monitoring solution requires a stable and efficient network. Whenever we have opportunities for collaborative sensing (e.g., due to social interactions between mobile users), the communication link must be able not only to support it, but also to provide sufficient performance for the application to offer a suitable response time to the user (e.g., when providing awareness). Network performance problems are frequent as users move and the network topology changes, which affects the response time of the solution. The most critical variables to take into account to evaluate the current network performance are *latency* (i.e. time required to transport the information between two locations), *jitter* (i.e. the variance of the latency) and *throughput* (i.e. data transfer rate) [64]. Adequate network performance in wireless networks can be obtained by using efficient routing protocols.

(ii) Reliable links. Pervasive monitoring also requires communication reliability, which is related to the trustworthiness of the communication link to transfer data between two points. The network overload and the agility of the collaborative sensing process will partially depend on this issue. Unreliable networks affect negatively the throughput and therefore, also affects the awareness provision since users perceive a bad response time. In other words, the reliability of the network links also affects the usability of the pervasive monitoring solutions. The network variables that can be considered to diagnose the reliability of the communication link are *packet loss* and *ordering* [64]. The links reliability cannot be guaranteed in a mobile network. However, the use of routing protocols designed to deal with a dynamic topology make the links reliable.

(iii) Communication coverage. Although the interaction distance between two mobile users will depend on the type of activity they are performing, a one-hop communication threshold is typically not enough to support collaboration. This is also in line with the observations made in Chapter 3 about the distance in number of hops between Producers and Consumers of sensor data (Figure 3.26). Therefore, additional mechanisms are required to extend it [202].The maximum coverage distances that enable current wireless technology (i.e. 802.11b/n/ac), can be around 35-70 meters, if we consider indoor areas; however, in open areas such a distance can reach up to 140-250 meters. Therefore, a node belonging to a MANET network (e.g. a smartphone user) must be able to interact not only with other nodes that are located at one hop of distance but also with more distant nodes. A well-known solution to overcome this limitation is the appropriate use of routing protocols [202]. In that case, the network variable that can be used to diagnose the communication coverage is the *number of hops.*

(iv) Interoperability. Mobile users must be allowed to interact with anyone else on a casual or opportunistic way. As a consequence, their applications for pervasive sensing and awareness provision should offer interoperability of communication, data and services [166]. Typically this issue can be addressed using standardized communication protocols (e.g. IP over diverse radio link standards, and TCP or UDP transports), data formats (e.g. XML) and service representations (e.g. Web Services). The variable that can be used to diagnose the communication aspect of the interoperability is the *adherence* to the *standards* involved in the solution.

Although, to the best of our knowledge, there are no studies that explore specifically how the issues considered affect pervasive monitoring solutions, we can extrapolate conclusions from research works in similar fields. For example, several studies have been published on how some of these issues affect collaborative applications in stationary scenarios when they run over the Internet. For instance, a study presented in [86] shows that performance and usability of real-time distributed groupware applications depend on network variables such as latency, jitter, packet loss, bandwidth and type of traffic (UDP/TCP). Network delays due to latency and jitter have serious effects on the users, causing difficulties in coordination and foresighting [86]. In extreme situations they cause communication breakdowns; this typically occurs when the ***latency is higher than 300 ms*** [86, 225] or ***jitter is higher than 500 ms*** [86]. It has been also reported that insufficient bandwidth increases latency and packet loss [86]. Moreover, other studies have identified the bandwidth requirements to insure acceptable audio and video communications, which are summarized in [227]. Some of this requirements are shown in Table 4.1.

Table 4.1: Communication requirements for different audio and video qualities

	Quality	**Required Bandwidth**
Audio	Telephone	8 Kbps
	AM	31 Kbps
	FM	96 Kbps
	Music	128 Kbps
Video	Videophone	16 Kbps
	Videoconferencing	128-384 Kbps
	VHS	1 Mbps

Several researchers have also stated that usability of mobile applications depends on several variables, e.g. network reliability, throughput and latency [75, 139, 242]. We can, then, assume that *communication reliability* and *performance* play a key role on the usability of any type of mobile solution. However, it is not clear which are the acceptable thresholds of those variables for mobile end users. In this chapter, we present a study that provides insights that can help software designers improve the values of these two variables when using MANET networks in mobile collaboration scenarios. Such scenarios are appropriate for the context of this work since they adapt properly to the different situations where pervasive monitoring in dynamic learning contexts can occur. Particularly, to situations where is possible to establish collaborative sensing activities and flexible awareness provision between nearby devices.

Although this work is focused on pervasive monitoring and awareness supported by MANET networks, it is important to note that, as mentioned previously, there are also other ways to provide communication support in this context. For example, mixing nodes from a MANET network and remote nodes accessible through Internet. In that case we have to consider gateway nodes acting as bridge between these two worlds. To select a gateway between all the nodes available in a MANET we could use similar methods to the one described in [115].

In this study, we are also considering that all nodes are ready to actively participate in the management of the MANET as they are also willing to participate in any activity required to support pervasive monitoring (e.g., collaborative sensing).

Considering the previous requirements, we deployed an experimental testbed, using real software and hardware as well as realistic experimentation scenarios to provide empirical evidence on the viability of using MANET networks to support pervasive monitoring and to evaluate the performance and reliability of these types of networks in real-world settings. Next section, introduces the hypotheses of the empirical study conducted using such a testbed.

4.2.2 Hypotheses of the Study

The hypotheses for this study are based on preliminary results provided by other researchers in similar studies. These hypotheses are the following:

- ***Hypothesis 1*** – *The network bandwidth and reliability decrease when increasing the number of hops between the sender and the receiver nodes.* This hypothesis intends to establish a basis to analyse and make conclusions about the tests included in this study. Validating this hypothesis will help us to identify the maximum acceptable distance between two collaborating nodes in order to consider that the pervasive monitoring application is usable (in terms of performance) by end users.

- ***Hypothesis 2*** – *The network bandwidth and reliability decrease with a high mobility level of the nodes.* Considering the *hypothesis 1,* this hypothesis intends to demonstrate that the mobility of the nodes also affects the throughput between two collaborating nodes. Validating this hypothesis will help us estimate the degree of mobility that the users can have without seriously deteriorating the performance of the pervasive monitoring application.

- ***Hypothesis 3*** – *The network bandwidth and reliability decrease due to increasing interferences generated by mobile devices from other users.* This hypothesis intends to verify that interference produced by mobile devices affect the throughput between collaborating nodes, and also that such interference increases with the number of nodes participating in the MANET. Validating this hypothesis will help us to observe the effect of the density of users on the obtained throughput, and the performance as perceived by the end users.

- ***Hypothesis 4*** – *Routing protocols based on number of hops (such as BATMAN [163]) have better reliability and bandwidth than protocols based on statistics (such as OLSR [56]).* This hypothesis intends to demonstrate that routing protocols based on statistics are slower to react than those based on number of hops. Therefore, the first ones are able to provide better throughput to mobile users. As a consequence, pervasive monitoring applications that use the first type of protocols would have better usability in terms of performance perceived by end users.

- ***Hypothesis 5*** – *In MANET networks, UDP-based communication has better performance than TCP-based communication.* This hypothesis attempts to show that a connectionless communication is able to provide, in MANETs, additional throughput to mobile collaborative solutions. Demonstrating this hypothesis could provide software designers a tool to help them reduce the degradation of performance generated by the mobility of the user and the interferences from other users.

- ***Hypothesis 6*** – *Despite the limitations of MANETs, they can provide acceptable levels of performance in controlled conditions.* Validating this hypothesis is the main goal of the experimental study conducted. Consequently, all the previous hypotheses are directed towards understanding the particular conditions under which MANETs have an appropriate level of performance and reliability.

Next, we describe the testbed used to try to understand the influence of the MANET networking issues over the performance of pervasive monitoring solutions.

4.2.3 Description of the Experimental Testbed

All the tests done in this study used real implementations of MANET networks, using real hardware and software. However, since repeatability is difficult to achieve in real-world experiments that involve real users and real data transfer [114], the network traffic was pre-established to ensure the repeatability of the tests and to allow the comparability of the results obtained across different tests. Moreover, the tests included in the study considered a wide range of offered loads and therefore, there is a high probability that the data transfer needs of a particular real-world collaboration process could be within that range. This fact also helps to provide representativeness to the results of the tests.

On the other hand, several mobility patterns were used in this study. Such patterns adhere to typical stationary, partially mobile, and mobile collaboration processes encountered in real-life activities. In order to emulate these mobility patterns and to provide at the same time realism and repeatability, we asked real users to follow precise instructions about the direction and speed of their movements for the duration of the tests.

The tests conducted in each one of the settings of the study involved at least ten repetitions in order to obtain a representative number of samples for each one of the tests. Moreover, the variables or metrics evaluated were measured for at least one minute to be able to determine the accuracy of the results and isolate possible errors in the measurement process.

The physical environments used to perform all the tests were indoor spaces located at the Castelldefels School of Telecommunications and Aerospace Engineering, of the Universitat Politècnica de Catalunya (UPC), in Spain.

Next sections describe the experimentation scenarios involved in this study as well as the routing protocols, hardware and software used.

4.2.3.1 Experimentation Scenarios

In order to validate the hypotheses, our study considers four indoor experimentation scenarios: (i) stationary, (ii) partially mobile, (iii) mobile groups and (iv) mobile. We decided to use indoor scenarios because they present more important communication challenges than open areas. Typical indoor settings have important signal interference due to the presence of computing devices and access points in the area, and also signal degradation due to walls and doors. The experimentation scenarios considered in this study represent typical settings of mobile collaboration activities and take into account previous experience of researchers about the deployment of real-world MANET testbeds Such scenarios are briefly described below.

Stationary scenario: There was no mobility in this scenario and therefore, all the nodes remained static. In this scenario, five nodes were placed in different locations of the ground floor of one of the buildings of the *Castelldefels School of Telecommunications and Aerospace Engineering.* These laptops were placed at around 11 to 14 meters apart and we established communication processes between any pair of nodes independently of their distance. In addition, a packet filtering was used to force the network topology to work as a chain, which is the worst case that we can have in this scenario. Therefore, a 4-hops MANET was established. Figure 4.1 shows a floor plan with the locations of the nodes as well as the network topology configured in this scenario. As is illustrated by the figure, the stationary scenario allows monitoring and reproducing the multi-hop behaviour of the network, by transferring data between pair of nodes located at different distances in terms of communication hops. Therefore, it was used to validate *hypothesis 1.*

This scenario is representative of several mobile collaboration instances, e.g. in loosely-coupled work [186] where users are temporarily stationary when they decide to collaborate (i.e. attended collaboration). An example of these situations has been reported in [156], where the authors studied the mobile work in hospitals and identified an important number of collaboration meetings (i.e. stationary collaboration scenario) held by the medical staff. Similarly, [172] reports meetings held by construction inspectors in the field after an inspec-

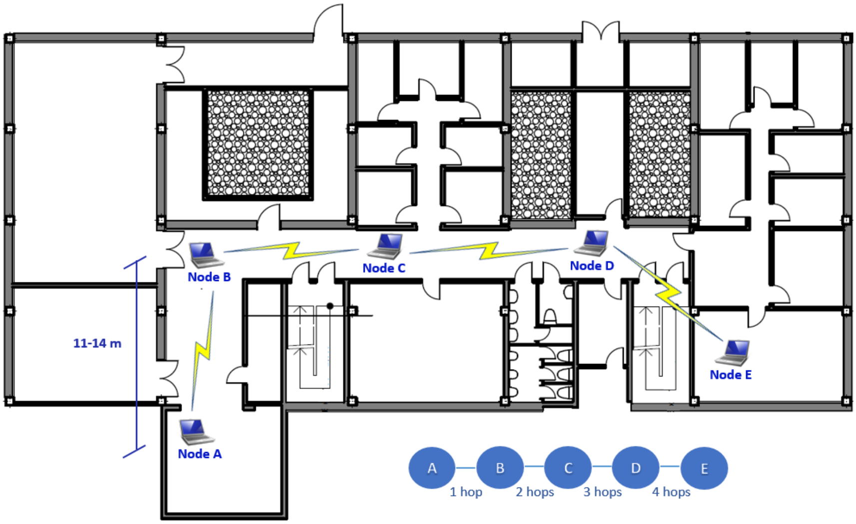


Figure 4.1: Stationary scenario

tion round. This scenario can also be representative of mobile collaboration mediated by access points (i.e. static nodes), which are temporarily deployed in the work area just to increase the coverage of the MANET network.

In a stationary collaboration scenario, mobile users are static while performing a collaborative activity. Typically, if mobile users need to see their devices' screens in order to collaborate, then they usually stop moving because the focus of their attention is now on the screens instead of on their steps. It seems to be a natural and involuntary reaction experienced by most collaborating mobile users, which leaves them static during such period.

Partially mobile scenario: This test scenario uses the same physical space, hardware and network topology than the stationary one. However, it introduces a mobile node that is continuously moving from the beginning to the end of the static network. This represents a scenario where a single person moves around while other people remain static working with their devices.

The movement of the mobile node was executed by a person carrying a laptop while moving at a stable velocity through a path drawn on the floor. The test began with the mobile node (i.e. *node M*) located close to *node A* (network ending point), and the data transfer is always done between the mobile user and *node E* (the other network ending point). Figure 4.2 depicts the partially mobile scenario, showing the path followed by the mobile user and the resulting network topology. Packet filtering was also used to force the communication between these nodes to always go through at least two hops. This scenario was used to validate *hypothesis 2*, because it made possible to isolate the effect produced by a single mobile user on the network.

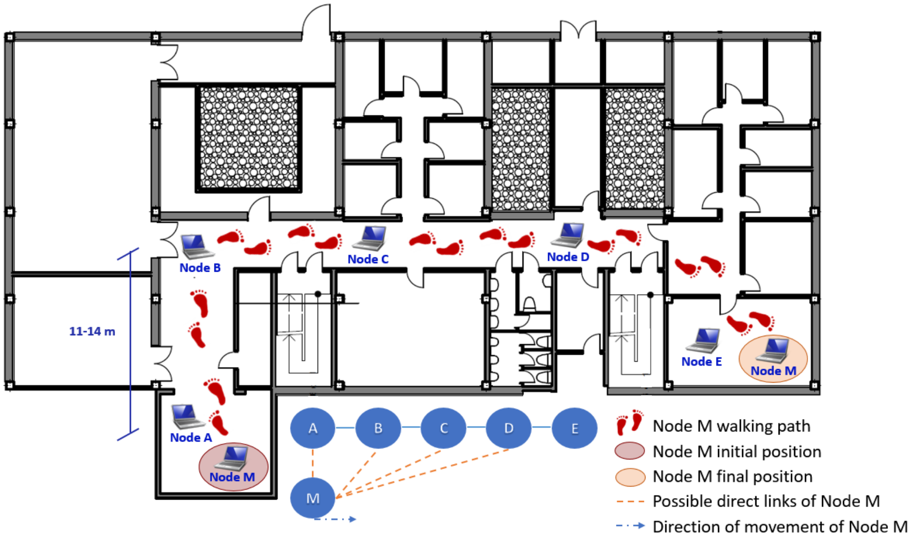


Figure 4.2: Partially mobile scenario

The partially mobile scenario can involve the use of access points as intermediaries to support the collaboration process (similar to the last collaboration situation described in the stationary scenario). This scenario is representative of *partially unattended collaboration activities*, where the mobile users interact with one or more mobile devices, but they do not necessarily interact with the persons that are using them. Examples of unattended collaboration interactions are activities that involve data synchronization as well as access, update and distribution of shared information. Users containing replicas of such information are unaware of this interaction process. In this scenario, the users that are triggering these actions are stationary while the rest of the participants keep moving. In [155] the authors present an interesting example of how partially unattended collaboration can be used to support the work of

Firefighter Incident Commanders during urban emergencies.

Mobile groups scenario: Typically, mobile users working in groups need to exchange information within their group or between groups. This situation was represented by the mobile groups scenario. In this scenario, we conducted the experiments in a laboratory of 146 m^2, which was free from walls and other obstacles in order to ensure the repeatability of the communication conditions across the different tests. For the tests, eight mobile nodes were arranged into two or three groups. The distance between the groups was around 8-10 meters. Figure 4.3 illustrates the two possible group arrangements considered.

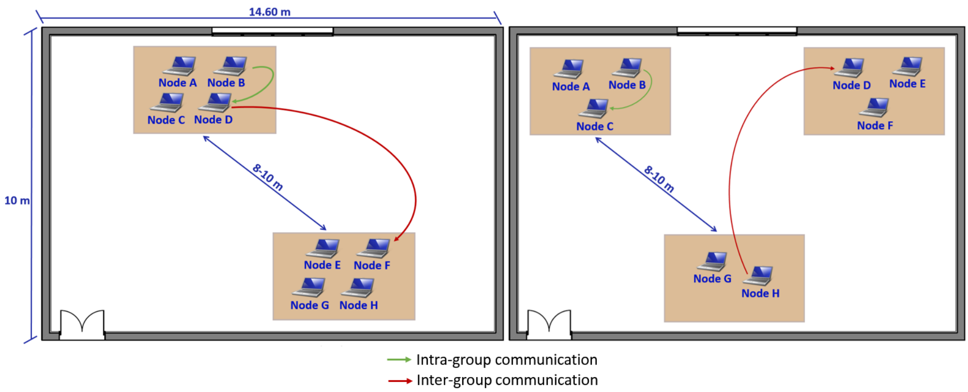


Figure 4.3: Mobile groups scenario

In the mobile groups scenario, there was no constraint on the number of hops used by the communication processes during the tests. Moreover, both intra-group and the inter-group communications were monitored. In the first case, mobile users interact just with their teammates, whereas in the second case, the communication is performed between members of different groups. The comparison of both types of communications was used to validate *hypothesis 3*.

Both collaboration settings (i.e. intra-group and inter-group) are present in real-world scenarios. For example, [165] reports unattended notifications that promote face-to-face collaboration instances among civil engineers and firefighters (i.e. inter-group interactions), who support urban search and rescue activities after a disaster. On the other hand, a study presented in [172] shows how unattended synchronization of a mobile shared workspace used by members of a construction inspection team (i.e. intra-group interactions) ease the inspection process and also the reporting of the results.

Mobile scenario: Mobile scenarios are representative of unattended collaboration instances involve users that are on the move while their devices are interacting between them in order to provide some collaboration services. The users are typically unaware of the interactions among the mobile devices. Unattended collaboration can be used to implement several awareness mechanisms, for example, to inform users about the location of other users or about the availability of shared resources.

The mobile scenario was implemented in the same physical environment than the previous scenario. In this scenario, a file is transmitted between two remote nodes that are situated in a mobility context. Seven nodes participate in this scenario, some of them remain static while others are on the move. The movement of the mobile nodes, which are represented as *"M*"* in Figure 4.4, produces disconnections and reconnections of the communication path between the sender and the receiver nodes. In order to imitate the movements of mobile users, a path was drawn on the floor and people carrying laptops walked over it at constant speed. Figure 4.4 represents the network topology of the mobile scenario. As shown in the figure, this scenario involves two different settings.

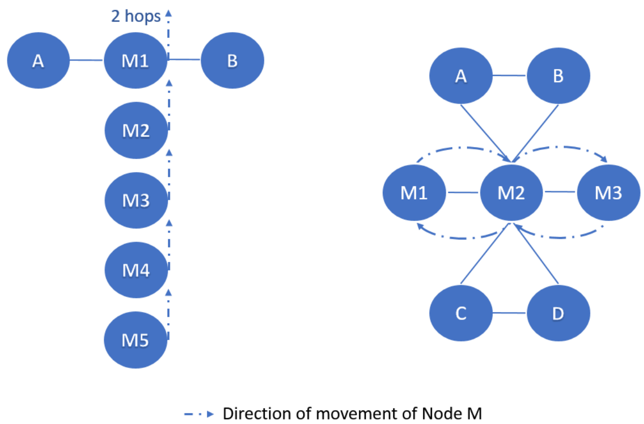


Figure 4.4: Mobile scenario

In the first setting, a file of 17 Mb is transmitted. The nodes acting as sender *(node A)* and receiver *(node B)* are static and the communication between these nodes go through two hops. Other five nodes move between these two nodes one after the other, creating active routes between them every 30 seconds. In this setting, there only one possible communication path available at a particular period of time and when such path is deactivated due to the mobility of the nodes, the communication is interrupted until a new path becomes available.

In the second setting, four nodes remain static while other three are mobile. A file of 5 MB was transferred between two of the static nodes (i.e. from A to D). In this setting, there are several possible communication paths and the communication between sender and receiver can go through two or more hops. In addition, during the tests the mobile nodes produce several changes in the topology of the MANET that make necessary that the routing protocol has to perform several consecutive recalculations of the communication paths.

The mobile scenario was useful to gain a further understanding of the effects of the mobility of the nodes on the network performance. Therefore, this scenario help us evaluate *hypothesis 2.*

The validation of *hypothesis 4* and *hypothesis 5* does not require specific settings; therefore, they can be evaluated in any of the experimental scenarios described previously.

Coordination mechanisms required by mobile collaborative applications were proposed by researchers in the field of *Computer-Supported Collaborative Work (CSCW)* several years ago, but more recently they have been redefined to deal with the changes in the work context produced by the mobility of the users and by unstable communication links [167]. These coordination services are frequently required by mobile applications that support diverse types of collaborative interactions in the three experimental scenarios presented previously. Such interactions can include the collaborative sensing and awareness provision between devices required for pervasive monitoring applications. Therefore, the results of the tests performed in the experimental scenarios can help designers to realize how to deal with issues related to the structural design of these types of applications.

4.2.3.2 Routing Protocols

The selection of the routing protocol has an important impact on the reliability and performance of the MANET network. Although there are several well-known routing protocols, e.g. *BATMAN* [163], *DSDV*[32], *DSR* [98], *TORA* [179] *AODV* [127] and *OLSR* [56], we wanted to include in this study the two most well-known strategies for routing on MANETs: distance vector and link state. This would allow us to have comparative results to understand the effects of the routing strategy on the performance of the network (i.e. throughput), which would also help us validate *hypothesis 4.* Therefore, we decided to use the protocol of each strategy type that displayed the best performance in previous studies. Thus, after reviewing the most widespread routing protocols and selected the two following:

Better Approach To Mobile Ad-hoc Networking (BATMAN) [163]. This is a proactive protocol that uses a distance vector approach to determine the best route between a sender and a receiver node. The routing metric used by this protocol is the number of hops used for the communication between these two nodes. For the tests, we used the *BATMANd* implementation (version 0.3) for *Linux,* available in [4].

Optimized Link State Routing Protocol (OLSR) [56]. This protocol is also proactive but it uses a link state approach to select the optimal route. The routing metric used by this protocol is *Expected Transmission Count (ETX)* [59], which is based on statistics about the quality of the communication link. For the tests we used the well-known *OLSRd* implementation of the OLSR protocol (version 0.5), available for *Linux* and *Windows,* available in [7] (newer releases available in [8]).

4.2.3.3 Metrics of Link Quality

The metrics used to evaluate the quality of the communication link during the tests were those relevant for pervasive monitoring solutions (as described in Section 4.2.1) as well as those designed to determine the performance of the MANETs protocols [63, 114]. The metrics provided by the traffic generator itself were also taken into account [221]. These metrics were divided into three groups, depending on the type of traffic used for measuring them:

- **ICMP traffic metrics:** to measure the Round-Trip Time (RTT).
- **UDP traffic metrics:** for throughput, packet loss and jitter.
- **TCP traffic metrics:** for throughput, handshake time, out of order packets and number of re-transmissions.

The UDP/TCP traffic was pre-established and generated using the Iperf tool [221] in order to ensure the repeatability of the experiments. The metrics were measured by conducting a 60 seconds test, on which UDP/TCP packets were transferred between a given source-destination pair. In case of UDP traffic, the data packets were generated at different bit rates. Consequently, several UDP traffic loads were offered to the network. By contrast, in the TCP experiments we tested the maximum achievable throughput; therefore, no fixed bit rates were specified.

The RTT was measured by conducting a 60 seconds test, on which ICMP packets were transferred between a source-destination pair, using the regular Ping service. Those experiments were carried out for packet sizes of 64 and 1024 bytes.

4.2.3.4 Hardware

The experiments conducted in all the experimentation scenarios were performed using eight HP NX6310 laptops with a processor *IBM Intel Core 2 T5500* of *1.66 GHz* and *1GB of RAM.* Such laptops had an internal *Intel PRO/Wireless 3945ABG* Network Connection card for *IEEE 802.11b/g* wireless connectivity. During the experiments, the wireless cards of the laptops were set to *channel 1* at the *802.11b/g* band, *1 dBm of transmission power* and deactivating the *RTC/CTS* (i.e. an optional mechanism that reduces chances of collisions between transmissions but introduces some overhead). This particular setup was selected taking into consideration the different configurations of other real-world implementations of MANETs, as described in

4.2.3.5 Testbed Supporting Software

All laptops were equipped with two operating systems: *Linux* (Ubuntu 8.04 Linux distribution with the 2.6.24-19-generic kernel) and *MS Windows XP.*

The traffic generators used in the experiments were both the *Iperf* (version 2.4) and the regular *Ping* service provided by the operating system.

As network traffic analysers we used *Wireshark* [11] and *Tcpdump* [9] (similar to Wireshark but with a command line interface). Moreover, following the recommendations provided by other MANET testbeds described in [114], a *MAC filter* was also used to classify packets on the MAC layer and force a multi-hop behaviour, avoiding direct communication between a pair of nodes.

A *LiveCD* was prepared, following the recommendations of [224], in order to avoid the human intervention as much as possible. This *LiveCD* contains a customized extension of the operating system that facilitates the testbed implementation, use and data gathering.

4.2.4 Empirical Results

This section presents the obtained results for the tests performed using the experimentation scenarios described previously. These results allow us to observe the range of values that can be found, for each key networking issue, in real implementations of MANET networks. Therefore, they can be useful to assess the type of coordination and collaboration mechanisms that can be implemented to support pervasive sensing and awareness in such scenarios. The experimental results also allow us to understand the degree of validity of the hypotheses stated.

4.2.4.1 Results of the Stationary Scenario

In the tests performed in this scenario, the independent variables were the *packets size* and the *number of hops* between the collaborating nodes. The dependent variables were the *received throughput* and the *RTT (Round-Trip Time),* which help predict the bandwidth of the network and indirectly, the performance of the pervasive monitoring application in such scenario. These variables were measured at the ending points of the communication path. Most tests were performed using an 802.11b network. However, for some tests we used the 802.11g standard in order to verify that the results obtained for both standards follow the same trend.

Figure 4.5 shows the results obtained for communication distances of 1, 3 and

4 hops between collaborating nodes, which is representative of diverse collaboration instances in other fields (e.g. hospital work and responses to urban emergencies). This scenario represents distances of 30-60 meters between collaborating devices in built areas, but these distances could be extended to 200-300 meters in open areas.

The variable observed in Figure 4.5 was RTT obtained when using the ping service. This figure represents the average of the results obtained for different tests. The *sample mean* (i.e. the arithmetic average of the observed values) of the worst test (based on relative dispersion of the test measures) is *12.13 ms* with a *Standard Error of the Mean (SEM)* of *0.25 ms*. The *margin of error of the mean (E)* is at the most *0.58 ms* for a confidence level of 95%. Therefore, we can conclude that the observations and conclusions based on this set of tests are valid.

As can be seen from this figure, the RTT increases with the number of hops required for the communication between nodes and also with the packet size. The behaviour of OLSR and BATMAN protocols were similar. This is not surprising because the scenario is static and therefore, the network is relatively stable, which makes both protocols able to work appropriately.

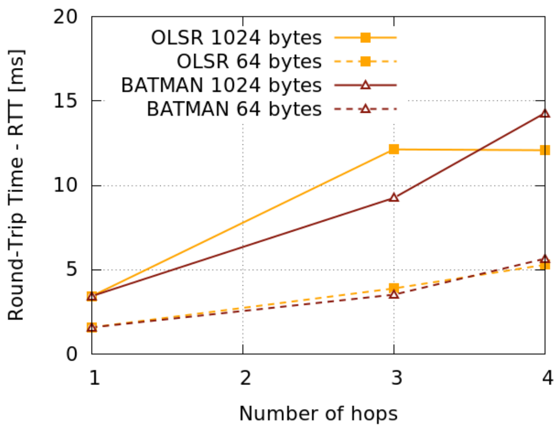


Figure 4.5: RTT obtained for different packet sizes and number of hops, considering BATMAN and OLSR protocols

Figure 4.6 shows the results of a set of tests conducted on the same setting, using the BATMAN protocol. In this case, the communication between source and destination nodes had to go through 1, 2 and 3 hops. For these tests, the MANET was configured to use the 802.11g standard instead of the 802.11b since we wanted to verify that the results are coherent regardless the technology used. These tests were performed in order to verify the trend of the results. This figure represents the average values of the results obtained for different tests. The *sample mean* of the worst test is 17.44 Mbps with a *SEM* of 0.34 Mbps. The *margin of error for the mean (E)* is at the most 0.79 Mbps for a confidence level of 95%. The results show the effect of the packet size and of the number of hops in the performance of the network. Thus, we can observe how the performance of the network, in terms of received throughput, degrades with smaller packet sizes and higher number of hops. This can be explained by the fact that the use of smaller packets involve higher overhead in headers, which make decrease the data throughput received.

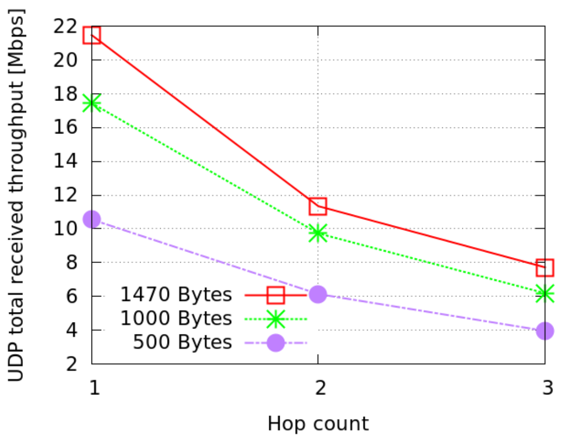


Figure 4.6: UDP throughput received for different packet sizes and number of hops, considering the BATMAN protocol in an 802.11g network

The figures that follow will present additional results in which we can observe how the network throughput decreases with the number of hops. Both figures compare the throughput received by the destination node when it is located at 1, 2 and 3 hops of distance from the source node.

Figure 4.7, depicts the throughput received by the destination node for different loads offered by the source node, when using UDP for transferring data.

In this figure, the *sample mean* of the worst test is 1658 Kbps with a *SEM* of 23.13 Kbps. The *margin of error for the mean (E)* is at the most 52.32 Kbps for a confidence level of 95%. In this figure, we can observe how the received throughput deviates from the ideal case for increasing offered loads and number of hops. Although, both routing protocols obtain similar results, OLSR obtains slightly higher throughput values than BATMAN for 4 hops communications.

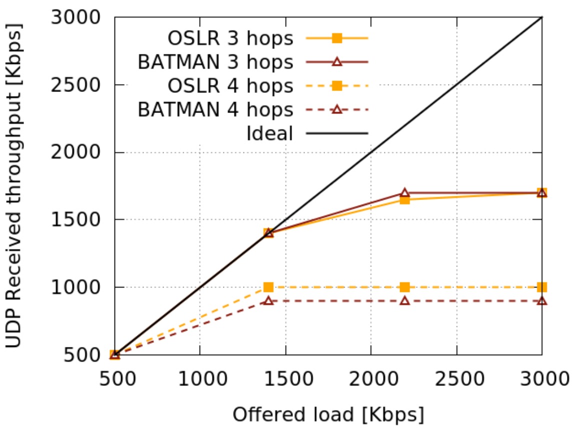


Figure 4.7: UDP throughput received for different offered loads and number of hops, considering BATMAN and OLSR protocols

Figure 4.8, represents the maximum throughput received by the destination node when the data transfer is performed using TCP. From the set of tests presented in this figure, the *sample mean* of the worst test is 4153 Kbps with a *SEM* of 106.9 Kbps. The *margin of error of the mean (E)* is at the most 106.87 Kbps for a confidence level of 95%. The results represented, show that the OLSR protocol achieve slightly higher throughput values than BATMAN for 3 and 4 hops communications.

The previous results show that the trend followed by the performance of the MANET network is independent of the transport protocol used (i.e. UDP and TCP). Therefore, for both types of traffic, the behaviour of OLSR and BATMAN was similar. In case of tests using TCP, the out-of-order packets, re-transmissions and handshake time values are zero or negligible numbers.

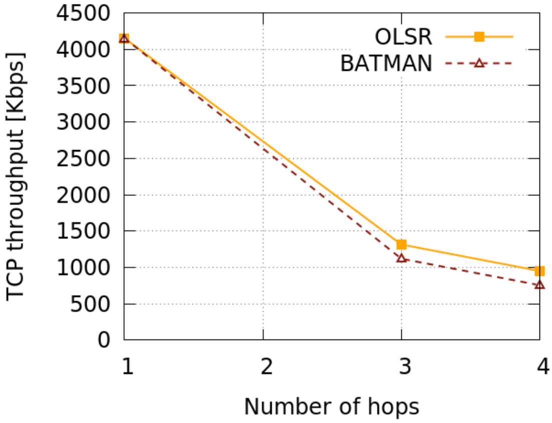


Figure 4.8: TCP throughput received for different number of hops, considering BATMAN and OLSR protocols

From the previous tests we can conclude that the received throughput was similar for both routing protocols but it decreases with the number of hops and with higher packet sizes. Since the influence produced by the number of hops was isolated in this experimentation scenario, we can claim that the obtained results are aligned with the statement of *hypothesis 1.*

4.2.4.2 Results of the Partially Mobile Scenario

This experimentation scenario included five static users and a mobile one. The obtained results for the tests performed in this scenario show that BATMAN has a better behaviour than OLSR for all the TCP metrics considered (Table 4.2). This results can be explained by the fact that OLSR uses the ETX metric for the selection of the routes, and that such a metric utilizes statistical information from probe packets (the 10 last ones) to compute its current value. Since the location of the mobile user is constantly changing, a recently computed best route becomes outdated very soon and the ETX metric does not react quickly because it has to wait for the probe packets to update its value. This slow adaptability of the OLSR protocol generates a significant number of out-of-order packets and require a high number of retransmissions.

Figure 4.9 shows the results of the same experimental scenario, when using

Table 4.2: Comparison of the TCP metrics for BATMAN and OLSR protocols

	BATMAN	**OLSR**
Received Throughput (kbps)	2110	2035
Number of out-of-order packets	0.05	2.25
Number of re-transmissions	0.00	296.75
Handshake time (ms)	0.00	0.04
RTT (ms)	6.59	7.37

UDP instead of TCP. In the tests represented in this figure, the *sample mean* of the worst test is 2525 Kbps with a *SEM* of 25.5 Kbps. The *margin of error of the mean (E)* is at the most 55.52 Kbps for a confidence level of 95%. We can observe that UDP is able to obtain a better throughput than TCP. Moreover, BATMAN showed a slightly better UDP throughput than OLSR for medium values of offered loads. This behaviour was reversed for higher loads. However, the difference in performance between both protocols is not statistically significant. On the other hand, this figure allows us to evaluate the degradation of the throughput received by the mobile device when it is on the move in comparison with when it is static. It clearly shows that the mobility of the users affects negatively the communication throughput. Then, these results support partially the statement of *hypothesis 2*.

To further study the effect of mobility in the performance of the MANET we compared the RTT of the communication for the static and the partially mobile scenarios. Figure 4.10 shows the results for the BATMAN protocol when the communication between source and destination nodes happens through 1, 2 and 3 hops. In the tests represented in this figure, the *sample mean* of the worst test is 24.71 ms with a *SEM* of 0.25 ms. The *margin of error of the mean (E)* is at the most 0.57 for a confidence level of 95%. These results show that the latency increases with the mobility of the users, which in turn reduces the network bandwidth (*hypothesis 2*). However, these results do not make possible to draw definite conclusions about the influence of the users' mobility on the communication reliability (second part of *hypothesis 2*).

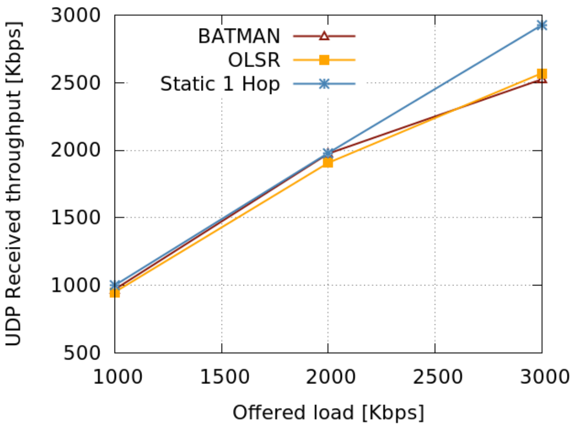


Figure 4.9: UDP received throughput in the partially mobile scenario for different offered loads, Considering BATMAN and OLSR protocols

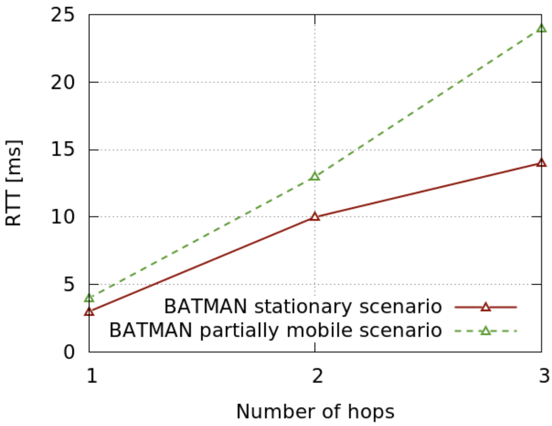


Figure 4.10: RTT obtained in the partially mobile scenario, considering the BATMAN protocol

4.2.4.3 Results of the Mobile Groups Scenario

This experimentation scenario had tests with two different arrangements of two and three groups of mobile users, respectively. Both, intra and inter-group communications were evaluated in this scenario.

Initially the mobile users were arranged into two groups of four nodes each and we evaluated the intra-group communication when only one data transmission process was taking place between a given pair of nodes.

Figure 4.11 shows the results of the UDP throughput considering this intra-group communication. In this case, both routing protocols showed a similar behaviour when the data transfer is between group members and the offered load is below 2000 Kbps. However, OLSR is able to obtain up to 500 Kbps more than BATMAN when the offered load is over 2000 Kbps. In this particular scenario, there were no relevant interferences between nodes because the communication was only performed among the four co-located members of each group. Due to the fact that the two groups were 8-10 meters apart from each other, the communication interferences of one group over the other were negligible since such interferences were received with lower strength than the communication signal received from members of the same group.

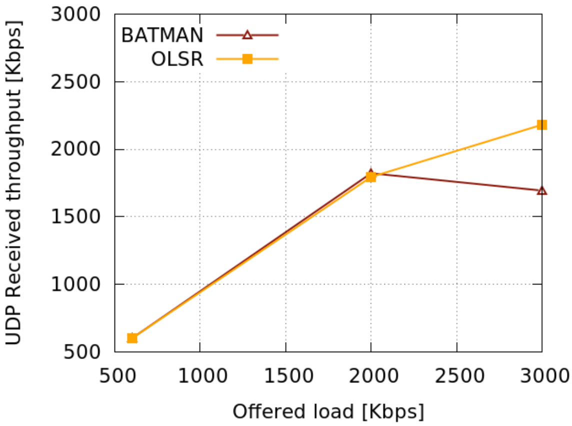


Figure 4.11: Intra-group communication involving mobile nodes

As we can observe in Figure 4.12, the network behaviour for inter-group communications differs from the previous interaction scenario. We now have a higher number of mobile nodes (i.e. 8 nodes) to consider when determining the communication path than in the previous scenario (i.e. 4 nodes). Therefore, routing protocols based on number of hops seem to achieve higher throughput than those based on statistics. These results show that, in this case, BATMAN performs better than OLSR for loads over 600 Kbps. In this setting

BATMAN is able to reach up to 800 Kbps of “extra” received throughput. This situation could be explained by the fact that to determine the best path between sender and receiver, BATMAN uses the hops count metric, whereas OLSR uses the ETX link quality metric. Therefore, OLSR frequently uses 2-hops routes instead of the faster 1-hop route used by BATMAN, which makes decrease the received throughput.

The selection of long routes by OLSR can be explained by the fact that, in this scenario, the communications between members of different groups generates interferences that degrade the link quality and generates losses. Therefore, OLSR chooses slower routes with smaller number of losses instead of faster routes that have more losses. On the other hand, the selection of longer routes by OLSR produces a higher occupation of the communication channel, degrading other concurrently active communication paths, which results in a lower received throughput.

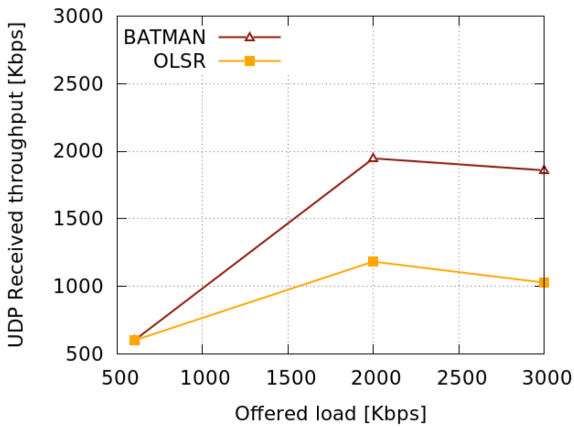


Figure 4.12: Inter-group communication involving mobile nodes

Table 4.3 shows additional results from the inter-group communications tests. In this case, we can observe how the network throughput decreases with an increasing number of transmitting nodes (one or two nodes transmitting per group). Therefore, the network performance is affected by the number of nodes that are transmitting concurrently. This fact could be an indicator that the communication interference increases with the number of transmitting nodes (hypothesis 3). This assumption is also supported by the fact that the percentage of packet loss as well as the jitter increase with the number of transmitting nodes. These results are aligned with the statement of *hypothesis 3*.

Table 4.3: Protocol comparison for inter-group communications

UDP Offered load (Kbps)	**2000**				**3000**			
Routing Protocol	**BATMAN**		**OLSR**		**BATMAN**		**OLSR**	
Number of Transmitting Nodes	1	2	1	2	1	2	1	2
Received Throughput (kbps)	2000	1620	1477	1327	2133	476	2737	369
Packet loss (%)	0	0	0.53	0.93	0.18	28.7	6.59	63
Jitter (ms)	1.86	16.5	1.62	5.45	136.6	1085	140.2	195.2
Number of out-of-order datagrams	0	1	0	0	6	1	125	38

These experiments were repeated using TCP as transport protocol instead of UDP. The trend of the results was consistent with that obtained for UDP. However, the throughput was lower than in such a case. This fact allow us to draw some preliminary conclusions: (i) the throughput obtained when using UDP seems to be higher than when using TCP in most mobile collaboration scenarios and (ii) OLSR is usually better than BATMAN when the communication is intra-group, but BATMAN has a better performance when the communication is inter-group.

We performed further tests in order to study more in depth the influence of the interferences on the communication throughput and the reliability of the network (*hypothesis 3*). We used BATMAN as routing protocol for these tests. A set of test was conducted with several offered loads and one node transmitting per group. Then, the tests were repeated but with two transmitting nodes per group. The results are presented in the following figures.

Figure 4.13 shows how the throughput decreases with the number of nodes transmitting concurrently, probably because of the interference produced by two simultaneous data transfer processes on two "long-distance" communication paths that are physically close. That is, due to the fact that the communication is inter-group, the received signal can be low due to the attenuation of the signal because of the distance between the groups. Consequently, two attenuated communications with similar signal strength can interfere on each other and also be more susceptible to other interferences and noise existing in the environment. In this case, the *sample mean* of the worst test is 1606 Kbps a *SEM* of 41.2 Kbps. The *margin of error of the mean (E)* is at the most 97.37 for a confidence level of 95%.

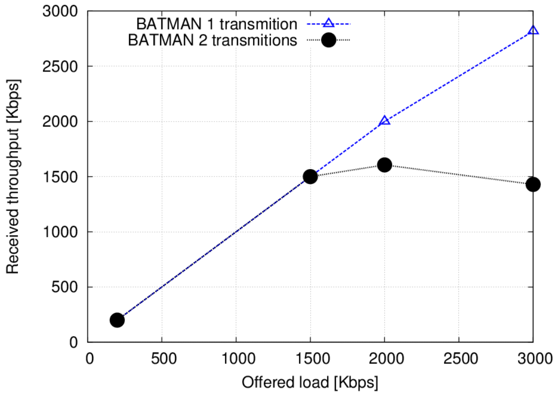


Figure 4.13: UDP throughput for different number of transmitting nodes

The results represented in Figure 4.14 also show how the network performance is affected by the number of concurrent transmission. We can observe how the network jitter increases with the number of transmitting nodes. Moreover, this figure clearly shows that the difference between one and two transmissions becomes highly relevant for offered loads higher than 2000 kbps. In these tests, the *sample mean* of the worst test is 389 ms with a *SEM* of 8.8 ms. The *margin of error of the mean (E)* is at the most 28.06 ms for a confidence level of 95%. However, the *margin of error (E)* after 400 ms of test, was 48 ms. Although there is a considerable variation in the measured values, we think that the previous conclusion about the effect of concurrent transmission on the network jitter remains valid.

We can infer from these figures that any communication instance between nodes that are located at a relatively long distance from each other will be affected by the interference produced by other mobile users with similar communication paths.

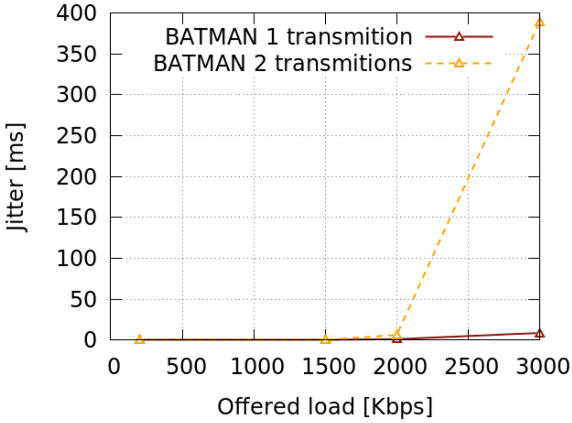


Figure 4.14: UDP jitter for different number of transmitting nodes

We conducted an additional set of tests involving three groups (i.e. two groups of three users each and one group of two users). In this case, each one of the groups had only one transmitting node and therefore, three concurrent transmissions were taking place. We compared these tests with the ones performed with the original group arrangement (i.e. two groups of four mobile users each) with one and two transmitting nodes per group, which means that two and four concurrent transmissions were taking place. Table 4.4 summarizes the results obtained for various key networking issues. We can observe in this table that the number of groups per se does not affect the results. The effect on the network performance and reliability is based on the number of simultaneous communication instances that involve mobile users that are not co-located (i.e. are not in close physical proximity) during the collaboration process. Therefore, we can conclude that a high number of concurrent transmissions of this type could lead to the degradation of the behaviour of the MANET network.

4.2.4.4 Results of the Mobile Scenario

In the first setting of this experimental scenario, when commutations between the interim mobile nodes occurs, the network seems to have pauses to reactivate the path through which it will send the packets of the communication process that is currently active. Figure 4.15 shows a sample of a network pause caused by the OLSR protocol, when the system is reacting to consecu-

Table 4.4: Network performance for different number of transmitting nodes

UDP Offered load (Kbps)	**2000**			**3000**		
Number of groups	2	2	3	2	2	3
Number of Transmitting Nodes	2	4	3	2	4	3
Received Throughput (kbps)	2000	1606	1822	2818	1429	1694
Jitter (ms)	1.21	6.36	4.56	8.81	389.43	30.37
Packet loss (%)	0	0.37	0	0.28	24.61	4.49
Out-of-order datagrams (%)	0.5	0.33	0.5	0.67	42.67	3.61

tive disconnections and reconnections (D/R) in the communication due to the mobility of the devices. In all the repetitions of the tests conducted in this setting, the OLSR protocol seems to have inactivity periods of about 13-15 seconds.

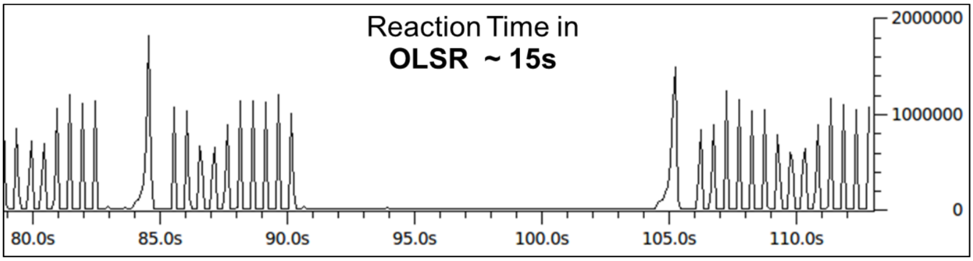


Figure 4.15: Reaction time of the OLSR protocol

The tests performed in the second setting of the mobile scenario, involved several D/R rates of the mobile nodes which, caused consecutive recalculations of the communication paths. A D/R rate of $\boldsymbol{t}$ seconds indicates that the mobile nodes involved in this scenario were consecutively joining and leaving the communication path every $\boldsymbol{t}$ seconds while the file was being transferred. Consequently, the network topology changed and the routing protocol had to try to self-adapt, reacting to the topology changes by updating the communication path.

The results of the tests showed that for D/R rates from 5 to 15 seconds, the data transfer failed in around a 30% of the tests. Higher D/R rates reduced the failure rate almost linearly. For D/R rates of 40 seconds the failure rate was 10%. Figure 4.16 shows the results obtained for D/R rates of 0, 5 and 10 seconds. This figure presents only the results obtained in those cases where the data transfer did not fail. These results show that the throughput obtained in this setting when all the nodes are static (D/R of 0 seconds) is higher than when some nodes move. Moreover, the throughput obtained is quite stable independently of the D/R rates caused by the mobility of the nodes.

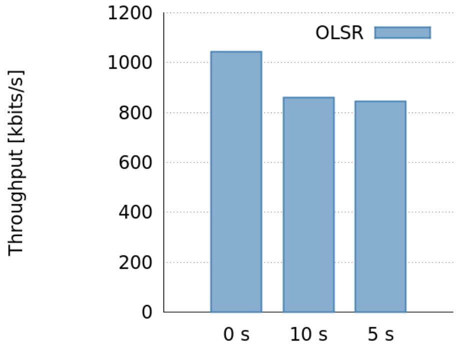


Figure 4.16: Throughput obtained in a mobile scenario with consecutive disconnections and reconnections

4.2.5 Lessons Learned

In this section we describe the most relevant lessons learned from the experimental evaluation performed in the mobile collaboration scenarios described previously. This information is relevant to understand the capabilities and limitations of a system in a real-world scenario to support sensing and awareness interactions between mobile collaborating devices. Such knowledge is extremely useful for the design of pervasive monitoring solutions.

Next, we detail the lessons learned, which help determine the particular settings that are required for specific conditions as well as the limitations of using MANETs as communication support.

(i) *The communication support in terms of network performance and reliability* *degrades when:*

a *The number of hops required to transport a message increases.* Evidence of this is the reduction in throughput and the increment in latency and packet loss. This circumstance affects the mobile collaborative interactions required for pervasive monitoring when the users are dispersed, e.g., on activities taking place in a large University Campus or when the students are located in different classrooms.

b *The mobility of users increases.* Typically, the latency increases and the throughput decreases because the routing protocols are not fast enough to react to the changes in the network topology and composition. In addition, very fast topology changes (i.e. disconnections and reconnections of nodes) produce failures in the data transmission. This situation affects the performance of pervasive monitoring applications that require interactions between devices in scenarios with high mobility; for example, when the students are changing classes in the hallways or doing team sports.

c *The simultaneous interactions in the same area increase.* Typically, the throughput decreases and the packet loss increase. Although the throughput in these scenarios is good enough to support collaboration between devices at moderate rates, some network demanding data transfer processes (e.g. when performing pervasive sensing that requires audio or video data, for example, to detect the presence of particular students within a classroom) or situations with many simultaneous interactions (e.g., many students attending a class in the same classroom) can degrade it. Then, the pervasive monitoring solution would be seriously affected.

(ii) *Adequate routing protocols running at each node are required to enable communication beyond the immediate neighbour nodes.* This means that to enable interactions between devices that are located at more than one hop of network distance a suitable routing protocol must be used. This would allow interactions between devices located, for example, in two different buildings. Otherwise such interactions are restricted to devices that are physically close (around 10-20 meters in built environments). Due to the fact that the behaviour of various routing protocols can be different for diverse situations, the designer of a pervasive monitoring solution that uses MANET as communication support must select an appropriate protocol that is suitable for the characteristics of the mobility patterns of the users as well as for the features of the physical scenario.

(iii) *The choice of transport protocols is must consider a trade-off between performance and reliability.* Typically, a connection-less transport protocol (e.g., UDP) provides a better throughput than a connection oriented one (e.g., TCP) but at the cost of a higher number of losses and disordered packets. Once the transport protocol is selected, it is possible to implement diverse mechanisms to deal with their particular limitations. For example, when using TCP, the introduction of redundant communication paths could help increase the communication throughput. If UDP is selected, some mechanisms could be implemented in both, the transport and the application layer in order to alleviate the limitations of this protocol. An interesting example of a mechanism implemented to improve the reliability of UDP in the transport layer is presented in [120].

4.2.6 Hypotheses Validation

A brief validity analysis of the hypotheses is presented below based on the results discussed in the previous sections.

- ***Hypothesis 1*** - *The network bandwidth and reliability decrease when increasing the number of hops between the sender and the receiver nodes.* We isolated the effect produced by the number of hops in the stationary work scenario. The results presented in Figure 4.7and Figure 4.8 show that the throughput decreases with the number of hops for both UDP and TCP transport protocols. Therefore, these results support hypothesis 1.

- ***Hypothesis 2*** - *The network bandwidth and reliability decrease with a higher mobility level of the nodes.* Considering the results of the tests in the four experimentation scenarios considered, we can confirm this hypothesis. Figure 4.9 and Figure 4.10 show the influence produced by a single mobile node, and the obtained results in terms of received throughput and latency are aligned with the hypothesis. Moreover, if we compare the results obtained considering the same number of transmitting nodes in partially mobile (Figure 4.9) and mobile groups scenarios (Figure 4.11 and Figure 4.12), it seems that the mobility of the users negatively affects the network throughput. In addition, the results of the mobile scenario confirmed that fast topological changes produces failures in data transmission processes.

- ***Hypothesis 3*** **-** *The network bandwidth and reliability decrease due to increasing interferences generated by mobile devices from other users.* Based on the results presented in Table 4.3 and Table 4.4 it seems highly probable that *hypothesis 3* is true.

- ***Hypothesis 4*** **-** *Routing protocols based on number of hops (such as BATMAN) have better reliability and bandwidth than protocols based on statistics (such as OLSR).* The experimental results indicate that this hypothesis might be false. These results allowed us to identify the behaviour of both routing protocols for each one of the scenarios studied. In the static and the partially mobile scenarios, both routing protocols have similar behaviour, which can be explained by the fact that in these scenarios the users are static or have low mobility and thus, the communication routes between them do not change much. By contrast, in the case the mobile groups scenario, the results depend on the physical location of the devices involved in the collaboration process. In this case, OLSR seems to have a slightly better performance than BATMAN if the users are grouped in a small area because most communication messages are delivered through just one hop of distance. However, in situations where collaborators are not co-located, BATMAN seems to be better than OLSR. A possible explanation to this is that OLSR uses the ETX metric to determine the best route to transmit messages and since such a metric depends on statistical values, it does not react as fast as required when the users are highly mobile.

- ***Hypothesis 5*** – *In MANET networks, UDP-based communication has better performance than TCP-based communication.* The results obtained for all the experimental scenarios show that the UDP communication degrades slower than the TCP communication. Comparing the results of the stationary scenario represented in Figure 4.7 and Figure 4.8, we can observe that for three and four hops the network throughput is higher when using UDP than when using TDP, as shown in Figure 4.17. Regarding the partially mobile scenario, if we compare the results of Table 4.2 and Figure 4.9 we can observe that UDP achieves a higher maximum throughput than TCP. Then, UDP achieves in average from 535 to 817 Kbps of extra throughput for OLSR and BATMAN protocols, respectively. Finally, the results obtained in the mobile groups scenario also confirm that the maximum throughput obtained with UDP is higher than with TCP (Table 4.3 and comments about TCP). These results suggest that our original hypothesis could be valid.

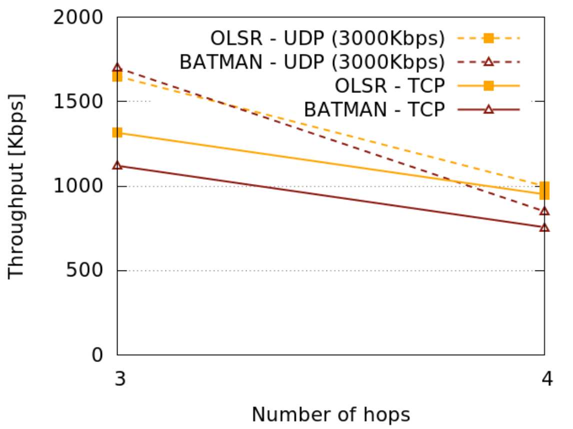


Figure 4.17: Comparison of the UDP and the TCP throughput in the Stationary scenario

- ***Hypothesis 6*** – *Despite the limitations of MANETs, they can provide acceptable levels of performance in controlled conditions.* In all the experimentation scenarios, we obtained latencies, jitter and throughput values of 25 ms, 6 ms and 1000 Kbps (if we perform some rate control; for example, using maximum offered loads of 2000 Kbps), respectively if we consider the worst cases in terms of mobility, number of hops, selected routing protocol and technology (i.e. 802.11b). These values can be considered as acceptable in terms of performance. In addition, if we select the appropriate transmission rates and protocols for the specific conditions of the scenario, we can improve such values. Therefore, we can confirm the validity of this hypothesis.

Once verified the viability of using MANETs as communication support for pervasive monitoring solutions, based on the lessons learned about such communication support, we propose several methods to improve their efficiency.

4.2.7 Recommendations for Dealing with the MANET Networking Issues

Next, based on the results of experimental evaluation as well as on conclusions drawn from developers of similar solutions, we present a list of recommendations to help MANET networks meet the requirements of a communication infrastructure for pervasive monitoring, as presented in Section 4.2.1. Such requirements can be addressed at two levels: (i) in the networking infrastructure that support the interactions among mobile devices, and (ii) in the pervasive monitoring application that supports collaborative sensing and awareness activities among mobile users. The recommendations presented below deal with most communication requirements at these two levels.

Dealing with the Communication Requirements in the Network Infrastructure

Following we present some recommendations to be implemented at the network level to deal with communication requirements of pervasive monitoring solutions:

a Data control. Compression is applied to the volume of data needed to represent information. It helps to increase the apparent throughput [64] and to reduce the number of packets required to perform an interaction between two mobile devices. Less packets on the network help reduce the packet loss, and therefore, to increase the communication reliability.

b Rate control. The goal is to ensure a minimal acceptable level of performance for the communication infrastructure. For this purpose, the network transmission should be decoupled from the events in the pervasive monitoring system and the transmission rates should be carefully regulated. Since MANETs have a limited bandwidth, which is shared among all the nodes that are transmitting simultaneously, the regulation of the transmission rate on each node could be a solution to avoid the collapse of the network when it is overloaded. These regulation mechanisms may also help to maintain an acceptable level of the quality of service offered. The consequence is that the response time perceived by the mobile users would be homogeneous, and thus we avoid having extremely slow or extremely fast nodes. Rate control mechanisms can be used to regulate the definition and assignation of sensing tasks performed by the Manager of a pervasive sensing activity. This would avoid that the data delivery rate imposed by the Manager could produce network congestion. An example of rate control mechanism can be found in [120], where the RTT is used as control rate metric to avoid network congestion.

c Standardized Protocols. Clearly the use of standardized protocols contributes to the communication interoperability. However, the interoperability required by pervasive monitoring systems also involves shared data and services between collaborating devices. In such case the recommendation is the same; i.e. using standardized data representations (e.g., XML or JSON) and services (e.g., web services, CoAP or RESTful APIs). For example, we could use web services to provide sensor data, as envisioned by [83]

d Routing. We can infer from the test results that routing protocols using the ETX metric to determine the best communication path can offer a best performance if the users are co-located or they have low mobility. Pervasive monitoring activities involving high mobility users should be supported by routing protocols based on number of hops, because they react quickly to changes in the network topology, and therefore, they can offer a good communication performance.

Dealing with the Communication Requirements at the Application Level

Regardless of the mechanisms used to deal with the communication requirements at the networking layer, we can also consider other solutions to help improve communication between end user pervasive monitoring applications. Such solutions are the following ones:

a Gossip propagation mechanisms. Sometimes two collaborators are unreachable because there is no direct link between them. Then, it is possible to deliver a gossip, which is a message that travels through the network during a certain time period looking for the destination user [166]. Typically, this message (if they are received by the destination) try to promote an encounter. For example, *"URGENT: try to be at the library after lunch".* Although this mechanism may not always succeed, it can contribute to improve the reachability of users in disperse scenarios with low interactivity between people or in situations in which only few people are together at the same time. These mechanisms could be use in pervasive monitoring solutions to provide awareness to the users or to facilitate the dissemination of the information sensed; for example, by propagating a gossip with the data sensed by a Producer in order to reach a Consumer subscribed to it but that is currently unavailable (this can be a supplementary mechanism to the services provided by Storages or Relays).

b Pushing notifications. If a user has a couple of unsuccessful attempts to interact with other devices, after a certain time period, this user may no longer be trying to reach such device. However, if the system notifies the user when the device becomes active or reachable again, then, it facilitates collaborative interactions with the device. Notification mechanisms must be autonomous, proactive and non-invasive to reduce the impact on the users. Such mechanism can be used in pervasive monitoring applications that require interactions with specific devices (e.g., a shared display) or collaboration between particular groups of users.

c Adaptive user interfaces. Pervasive monitoring applications that dynamically change their interaction paradigm by implementing adaptive user interfaces [48] can better accommodate to changing network conditions. Thus, these applications can deliver a limited or extended level of service to the end-user depending on the network conditions. For example, the awareness provision method can change from high to low quality video, to audio only or to a simple text message, according to the network conditions. This type of self-adaptation mechanism allows pervasive monitoring applications to adapt gracefully, reducing the impact of the network dynamics on end-users.

d Revealing network problems. This can be implemented as an awareness component that inform users about networking problems. Thus, users can take some actions to try to solve or mitigate the problem. For example, when a mobile user becomes isolated, the awareness mechanism can inform him about that fact. Therefore, the user can change his location so that his pervasive monitoring application could interact with the mobile devices of other users.

4.3 The OLSRp: Mechanism to Improve the Efficiency of MANETs

In addition to the previous recommendations, we propose a mechanism to address some of the limitations of MANETs. Particularly, we propose a mechanism to improve (at least partially) the limited bandwidth of these types of networks. According to the simulation study performed in Chapter 3, MANET networks increase the availability of nodes participating in a pervasive sensing activity. However, this benefit comes at the cost of a high number of routing messages and sensor data messages from active devices, which make reduce the available throughput. For this reason, we propose a mechanism to reduce the messages of the routing protocol in order to alleviate this situation and increase the free bandwidth availability. This mechanism also help increase the efficiency of the MANET by reducing the network collisions as well as the resource consumption of the devices that are participating in a pervasive monitoring activity. The increased bandwidth and efficiency provided by this mechanism can also contribute to the scalability of real-world pervasive monitoring solutions. Following we describe the details of the mechanism proposed.

Our proposal is based on the Optimized Link State Routing (OLSR) [56] since the MANET working group from the Internet Engineering Task Force (IETF) has proposed this protocol as a standard link state proactive routing protocol for MANETS. In a link state routing protocol, a node periodically broadcasts the list of its neighbours through the network. Consequently, when operating normally, every network node has information about the neighbours of all the other nodes. Therefore, an algorithm can compute the whole network topology, and thus have all the routes and the shortest path to every destination. Proactive protocols maintain updated lists of destinations and their routes regardless of the data transference needs.

Typically, link state proactive protocols allow lower latencies when sending data through the network because an optimized data path to the destination is already known. However, this comes at the cost of having to periodically flood the network with the routing information so that all the network nodes can have this information. When the number of nodes is large the amount of routing information to be sent is too high so that it can overload the network. In this situation the system does not scale. Therefore, disseminating the routing information in a way that reduce the overhead generated is essential to ensure that a routing protocol of this type scales.

The overhead generated by sending the routing information follows the DQ principle [33], where Q stands for Queries and D for Data size. When applied to routing protocols, Q corresponds to the number of routing information packets that are sent to the network and D is the size in bytes of these packets. A system is perfectly scalable if DxQ remains constant when the number of nodes increases. However, in a MANET network, when the number of nodes increases, typically the DxQ coefficient also increases. Consequently, several mechanisms have been described to make routing protocols more scalable by reducing Q, D or both [95, 104]. For instance, the FSR protocol decreases Q, sending the entire link state information only to neighbours instead of flooding it throughout the network [95]. Another example is the OLSR protocol with Multipoint Relays (MPRs), which manages to reduce the number of "superfluous" broadcast packet retransmissions (thus decreasing Q) as well as the size of the link state update packets (thus decreasing D) [95]. The TBRPF protocol also decreases D by sending "differential" messages periodically, which are only send by a node to report the changes in its neighbours of the [95]. Finally, the HOLSR routing scheme decreases Q and D by proposing a dynamic clustering mechanism so that the OLSR protocol can increase scalability.

The mechanism proposed in this chapter, called OLSRp, targets scalability by reducing Q. Unlike the mechanisms described previously, which try to reduce Q by defining a hierarchy of nodes with different roles where only some of them send routing information to the network, in OLSRp, all the nodes have the same role, which simplifies network management. Moreover, in all the other mechanisms, the nodes involved in disseminating routing information always send such information, even when the network topology remains unchanged, whereas OLSRp only disseminates routing information, contained in the TC control messages, if the network topology changes.

Although, originally conceived for OLSR, the OLSRp mechanism could be adapted to be used with other protocols that need to deal with periodic transmission of control messages. Therefore, the OLSRp can be used to increase the scalability of any link state proactive routing algorithm.

If the proposed mechanism is implemented in a MANET, all the nodes responsible for disseminating the routing information would have a very simple software predictor. Then, if a message that is to be sent contains the same routing information that has just been posted in a previous message (i.e. if the network topology remains unchanged), the message would not be sent. If a node does not receive the packet with the expected routing information, it assumes that the routing tables have not changed and does not recalculate the paths, saving computational and energy resources.

It is important to notice that our mechanism is independent of the OLSR configuration (emission intervals of the HELLO and TC control messages). That means that it does not modify the number of TC messages that are processed but instead it reduces the amount of TC messages transmitted through the network. The messages that are not transmitted are predicted by the expected receiving node. Consequently, the proposed mechanism is able to dynamically self-adapt to network changes (it behaves exactly like OLSR only if network changes occur).

To evaluate the potential benefits of the OLSRp mechanism, we analysed the degree to which the OLSR protocol sends repeated control packets as well as the associated energy consumption of the nodes.

Figure 4.18 shows clearly (for different node densities) that the traffic generated by the OLSR protocol grows exponentially with the number of nodes. The following sections will show that a significant volume of this traffic contains redundant information.

Figure 4.19 shows that the energy consumption of the system increases with

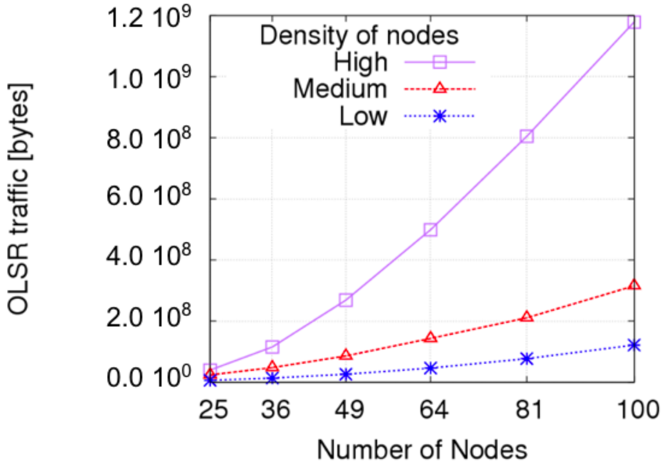


Figure 4.18: OLSR traffic for increasing number of nodes

the number of nodes. As we observed in Figure 4.18, an increasing number of nodes produces an exponential increment in the OLSR traffic. Moreover, due to the fact that the energy consumption of the Wi-Fi system is positively correlated with the network traffic [70] and that, in the scenario considered in both figures, there was no additional data traffic introduced to the network, we can claim that the energy consumed by the OLSR protocol is a very significant part of the overall energy consumption of the system. Moreover, a study of the energy consumption of several routing protocols described in [54] shows that OLSR is one of the most energy-intensive consumers. Consequently, we can conclude that the energy consumption values shown in Figure 4.19 are mainly caused by the traffic of the OLSR protocol and therefore, that the energy consumed by OLSR traffic increases with the number of nodes.

Based on the previous observations, the OLSRp mechanism has two main advantages:

(i) *Reduces network collisions* because it reduces the routing traffic by sending only non-redundant routing control information.

(ii) *Reduces the CPU processing time and energy consumption* because fewer

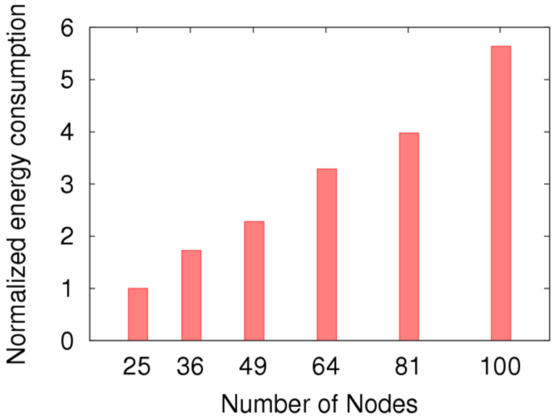


Figure 4.19: Energy consumption versus number of nodes

routing control packets are sent and received.

In order to fully understand the performance of the OLSRp, first we need to know a few characteristics of the OLSR protocol in which OLSRp is based. Consequently, next section briefly explains the basic operation of OLSR, specifying only aspects that are relevant for the OLSRp mechanism.

4.3.1 The OLSR protocol

The OLSR [56] protocol is a well-known proactive routing protocol for mobile ad hoc networks. It is an optimization of the Link State algorithm. The nodes in an OLSR network periodically exchange routing information to maintain a map of the network topology. The Multipoint Relays (MPRs) are the network nodes selected for propagating the topology information. The use of MPRs reduces the number and size of the messages to be flooded during the routing update process.

In OLSR, there are two types of control messages: HELLO and Topology Control (TC).

HELLO messages allow each network node to discover its neighbours and to obtain information about the state of its communication links to them. In an OLSR network, every node periodically broadcasts HELLO messages to all its one-hop neighbours. By sending a HELLO message, a node identifies itself and reports its list of neighbours.

When an MPR receives HELLO messages, it records the list of nodes that have selected it as one of their MPRs (i.e. the Advertised Neighbour Set). Then, this MPR (MPR originator) generates a TC message in which it announces its selectors. This routing update message is relayed by other MPRs throughout the entire network, allowing every remote node to discover the links between each one of the MPRs and its selectors (note that the non-MPR nodes will receive and process the message but will not retransmit it). Through this selective flooding mechanism, all the MPRs existing in the network retransmit and flood the whole network with TC messages.

Figure 4.20 shows the OLSR protocol operating in MANET with two MPRs. Every node periodically transmits HELLO messages to its one-hop neighbours and the nodes selected as MPRs are responsible for retransmitting the TC messages containing the topology information.

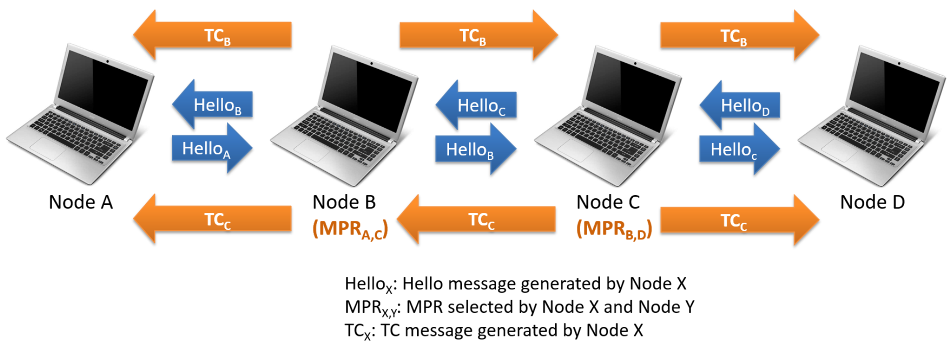


Figure 4.20: MPR mechanism and control messages in OLSR

In MANET networks that use OLSR, each node maintains a routing table containing the information that it receives periodically in the TC messages. The nodes use this information to calculate the shortest path to other nodes. In other words, a given node calculates the shortest path to another node using the topology map that it creates by means of the TC messages that it receives periodically. The routing tables of all the nodes are updated every time a change in any of the network links is detected.

Due to the fact that the proposed OLSRp mechanism is based on the prediction of the TC control messages, we perform an exploratory evaluation of the proportion of the control messages of the OLSR protocol that correspond to TC messages, considering several degrees of node density. The results of this evaluation are presented in Figure 4.21 This figure shows that when the distance between network nodes increases (i.e. the node density decreases), the percentage of TC messages also increases. Consequently, the percentage of TC messages is very significant for network topologies with low node density. These results combined with the exponential growth trend of the OLSR traffic (shown in Figure 4.18) confirm that the TC messages are an important part of the protocol traffic.

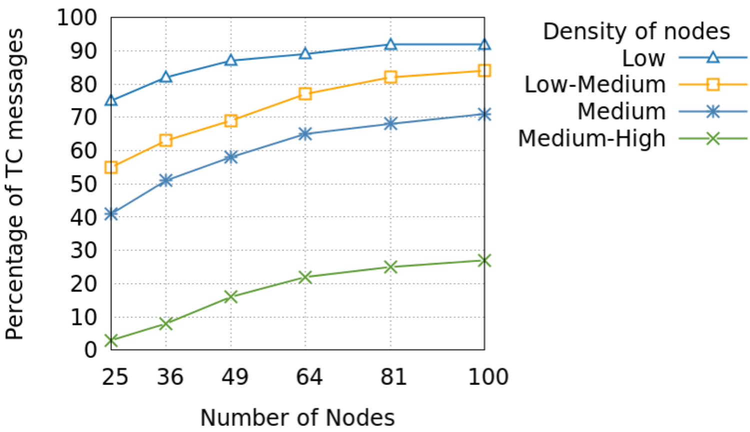


Figure 4.21: Ratio of OLSR control messages corresponding with TC messages

A particular field of the TC message that is very significant for prediction mechanism proposed is the Advertised Neighbour Sequence Number (ANSN). This field is a sequence number that only increases its value if the Advertised Neighbour Set associated with a given MPR changes. Thus, every time the Advertised Neighbour Set of an MPR changes (i.e. when new nodes appear or existing nodes disappear), the MPR increases the ANSN value of its TC message. When a node receives a TC message from an originator MPR, it can use this sequence number to determine whether or not the information about the advertised neighbours of this MPR is more recent than the information that the node already had. This mechanism allows a node to verify if the information that it received in the latest TC message is not valid, that is, if it had already received a message with a higher ANSN value from the same originator MPR.

Next section, explains more in depth the OLSRp mechanism proposed.

4.3.2 Description of the OLSRp Mechanism

The purpose of implementing the OLSRp mechanism is predicting the control information of the OLSR routing protocol contained in the TC messages. OLSRp is a predictor designed to be placed in every node of an OLSR MANET network to prevent the MPRs from transmitting duplicated TC packets throughout the network. The operation of the OLSRp mechanism is the following:

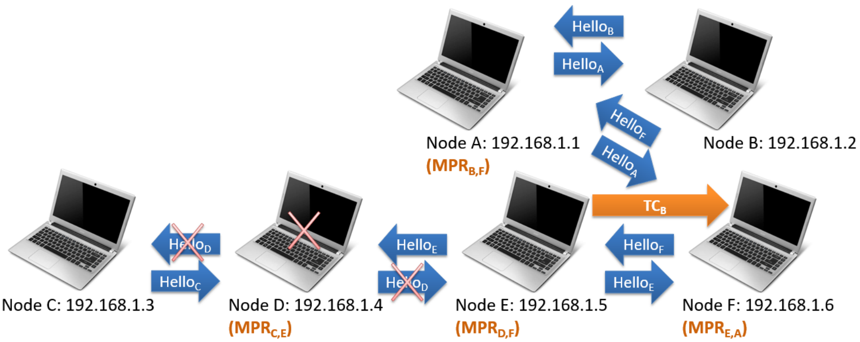
A given MPR executes the OLSRp when it has a new TC message to transmit. The OLSRp launches a last-value predictor, which means that the result of every prediction is always the last TC message generated by the MPR. Immediately after a prediction is made, the OLSRp compares the result of such a prediction with the new TC message generated by the MPR. If both, the predicted TC and the new TC message are the same, the MPR does not transmit the new TC message. Due to the fact that the OLSRp mechanism is installed in every network node and because all the nodes have the same last-value predictor, all the other nodes will also calculate the same TC message as predicted by the original MPR. By making this prediction, we are able to reuse previous TC messages, preventing the transmission of duplicated messages and thus, reducing the network traffic, which also contributes to the reduction of the network congestion.

The OLSRp is 100% accurate because the prediction results are always correct (i.e. all the nodes expecting a given TC message will always predict the same TC message, corresponding to the last received one) and when OLSRp cannot make a prediction, a new TC message will be transmitted (i.e. working exactly as OLSR). However, it could be argued that although the proposed OLSRp is based on the certainty of its predictions, it does not take into account the fact that the originator MPR may not be working properly. In this case, the network nodes will not receive a new TC message not because it was the same than the previous one, but because the MPR originator failed. In order to deal with this issue, the OLSRp uses the reception of the HELLO messages generated periodically for the network nodes as a validation method. Therefore, if a MPR implementing the OLSRp system does not receive a HELLO message from a given node, it will be aware that the node is inactive and that the topology has changed. Consequently, the OLSRp will deactivate the predictor and will send the actual TC message.

The use of OLSRp implies that every node has to keep a table containing information about any other node existing in the network. Each entry of the table contains specific information about each network node. The information contained is the following:

- The node's IP address.
- A list of MPRs that announce the node in the TC message. This list includes the IP address of the MPR (i.e. the originator address (OA)) and the current state of the node, which is either active (A) or inactive (I). The state of a given node will be determined depending on whether or not the MPR has received HELLO messages from the node.
- A predictor state indicator for MPR nodes (On or Off). This item will be activated for a particular MPR when at least one of the other MPRs existing in the network that contains information about this particular MPR activates its state; that is, when the MPRs that generate the TC messages in which the specific MPR is announced, have received HELLO messages from the announced MPR. However, when the node is inactive in all the announcing TC messages, the predictor state indicator will be deactivated and the new TC message generated will be sent throughout the network.

Figure 4.22 shows the execution of the OLSRp predictor in a network of six nodes where four of them were selected as MPRs. The figure shows the OLSRp table of node E. From the HELLO and TC messages that this node had received previously it detects that the MPRs A and F are active and it starts the corresponding predictors. However, when such MPR do not receive the $HELLO_D$ message from node D (because this node went inactive), it deactivates the predictor of node D, generates a new TC message and send it throughout the network. Then, when node F receives the new TC message generated by Node E it will deactivate the predictors of both node D and node E and retransmit the message. The retransmission of the new TC message will continue so that all the network nodes that receive it (i.e. Node A and Node B) will deactivate the predictors of nodes D and E.



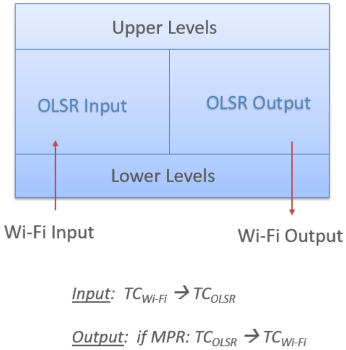
Hello$_X$: Hello message generated by Node X
MPR$_{X,Y}$: MPR selected by Node X and Node Y
TC$_X$: TC message generated by Node X

Node	OA$_{Node1}$ / State$_{Node1}$	OA$_{Node2}$ / State$_{Node2}$	...	Predictor State
192.168.1.1	192.168.1.6/A			On
192.168.1.2	192.168.1.1/A			-
192.168.1.3	?			-
192.168.1.4	192.168.1.5/I			Off
192.168.1.6	192.168.1.5/A	192.168.1.1/A		On

Figure 4.22: OLSRp mechanism

OLSRp can be easily integrated with systems that use OLSR since it does not modify the original implementation of this protocol. OLSRp can be implemented as a transparent layer that acts as intermediary between the OLSR protocol and the lower communication layers of the system. Figure 4.23 shows the interlayer communication of a node that is implementing the OLSRp system compared with that of a node that is only using the standard OLSR protocol. Although both approaches deal with exactly the same type of control traffic, the main difference between them is that they use different data sources as input for the OLSR layer. When the original OLSR protocol is used, all the information comes from what the node has received through its Wi-Fi interface, whereas when the OLSRp implementation is used, the information can be provided by both the Wi-Fi interface and the OLSRp layer.

The OLSRp has several advantages. The most obvious one is the reduction of the control traffic that is transmitted through the network and the consequent reduction in network congestion, packet collisions and losses. Another



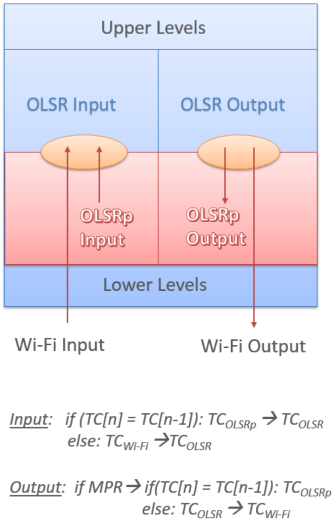


Figure 4.23: Inter-layer interactions in OLSR and OLSRp systems

interesting advantage is the reduction in the energy consumption and CPU utilization of the nodes involved in a communication process. All these benefits lead to an increment in the network's lifetime and also have a positive impact on its performance and scalability.

On the other hand, implementing the OLSRp mechanism introduces some minimal additional costs. Each node executing the OLSRp has to maintain a table whose dimensions depend on the number of MPRs existing in the network. In addition, the OLSRp consumes processing time of the node's CPU. However, OLSRp considerably reduces the overall cost involved in the transmission/reception (it is known that wireless transmission usually consumes more energy than processing tasks [160, 28, 212]) and packing/unpacking processes. Therefore, the energy and processing costs involved in the regular transmission of control messages of the OLSR protocol are considerably higher than the additional costs introduced by the implementation of the OLSRp mechanism. To illustrate the reduction in the consumption of the network resources caused by the introduction of the OLSRp mechanism, we performed several simulations of 300 seconds that consider different number of TC messages transmitted through the network. Figure 4.24 shows normalized values of the resource consumption of a node for different emission intervals of the

TC messages. We can clearly observe how the CPU utilization and energy consumption of the network decreases when less TC messages are transmitted by the node.

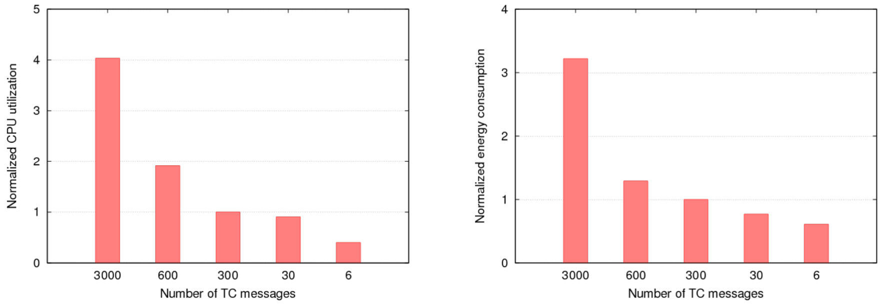


Figure 4.24: Resource consumption per node versus TC emission interval

4.3.3 Experimental evaluation and Implications

Next, we present the experimental setup and the results of a set of simulations performed to analyse the potentialities of the OLSRp mechanism under diverse conditions.

4.3.3.1 Experimental Setup

For the simulation we used the *ns-2* and *ns-3* [6] simulators since these tools allow us to model several network scenarios and to collect statistics through the generation of PCAP files. Such simulation tools facilitate the definition of network topologies, the configuration of wireless network interfaces and the specification of the mobility patterns of the nodes.

We considered a variable number of Nodes, *N,* and an initial node distribution in a grid of *N* rows and *N* columns. In this grid the nodes were initially placed at a distance of *D* meters (delta distance) between them, producing a square terrain of *((N-1)xD)x((N-1)xD)* meters. If we consider a diverse range of values for *N* and *D,* all possible combinations of number of nodes and node density can be evaluated. In our case, we considered five different values for the delta distance. That means that we have, for a fixed number of nodes, five different levels of node density (low, low-medium, medium, medium-high and high), considering that the size of the terrain in which the nodes are deployed changes according to the value of *D*. Figure 4.25 depicts the initial grid distribution and the physical area of the different scenarios considered in our simulations.

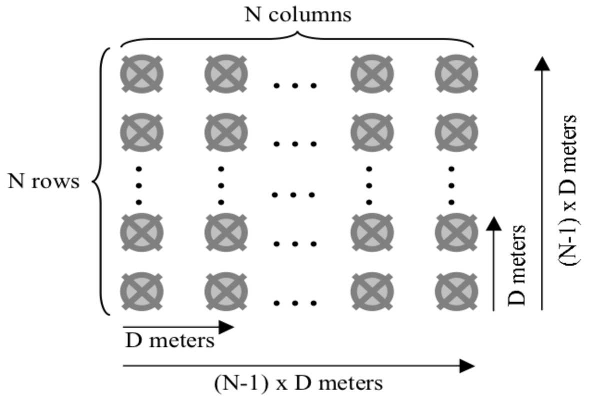


Figure 4.25: Grid distribution of the nodes in the simulations

In the simulators each node was equipped with an 802.11b Wireless Network Interface Card operating at 2.4 GHz with a transmission rate of 1 Mbps and a coverage range of 500 meters. We also considered a Wi-Fi channel with two different propagation models: the *TwoRayGround* for ns-2 and the *YansWifiChannel* for ns-3.

Regarding the OLSR protocol, we used emission interval values of 2 and 5 seconds for HELLO and TC messages respectively.

In reference to the mobility model of the nodes, all the simulations begin with a static (non-mobile) scenario and immediately use the *Random Direction* mobility model [22]. This model considers that the nodes move following random directions and that they reach the edge of the simulation area before changing their direction. Therefore, when a node gets to the boundary, it pauses and then selects a new direction and speed. We have five different simulation scenarios according to the speed of the network nodes. This speed is fixed for the whole duration of the simulation and we considered five different values: 0.1 m/s (baby crawling speed), 1 m/s (walking speed), 5 m/s (running speed) and 10 m/s (car speed within a residential area). We also fixed the pause time of the nodes when they get to a boundary to zero, because we wanted that the nodes were moving continuously.

It is important to take into account that the speed values considered in this evaluation were selected taking into account the type of pervasive monitoring activities for learning purposes that would require the use of a MANET network (instead of a fixed network infrastructure). These activities typically involve a student carrying a smartphone, which does not implicate high speeds.

Finally, we generated application traffic that consists of several UDP packets transmitted every second, each of which is 100 bytes long. We also configured half of the nodes to send UDP packets and the other half to receive such packets.

4.3.3.2 Analysis of Repetition of the Control Information

In order to evaluate all the potentialities of our proposal, it is necessary to assess the degree of repetition of the TC control messages generated by the OLSR protocol in diverse scenarios. Therefore, in this section we quantify the amount of TC message repetitions produced by the OLSR protocol. We analyse this issue by considering the variables that we have already mentioned: mobility, density and number of nodes. In addition, we discuss the implications of the results obtained in terms of the usefulness and the limitations of our proposal.

To quantify the number of duplicated TC messages we consider whether or not the last message received by a node is equal to the preceding one. Therefore, in order to calculate the percentage of repetition of the overall network every node observes the TC messages received and quantifies the repeated ones. To quantify the number of repetitions of a given TC message, we focus on the ANSN field of the TC. If the value of this field in the current TC message matches the value observed in the previous message, we consider that both messages are duplicated. Moreover, we distinguish between TC messages created by different originator nodes. This fact implies that every network node has to store the ANSN value of the last TC message received from every originator in order to quantify repetition.

In static scenarios, where all the nodes are always active, the results were as expected and the network topology remains stable. Therefore, we can state that in such scenarios a 100% of TC messages are repeated. By contrast, in mobile scenarios the percentage of message repetition observed varies according to the particular characteristics of the scenario. Figure 4.26 shows the results. This figure depicts the percentage of TC message repetition for four different speeds (0.1 m/s, 1 m/s, 5 m/s and 10 m/s), considering diverse number and density of nodes. From the information represented in these figures, we can make the following observations:

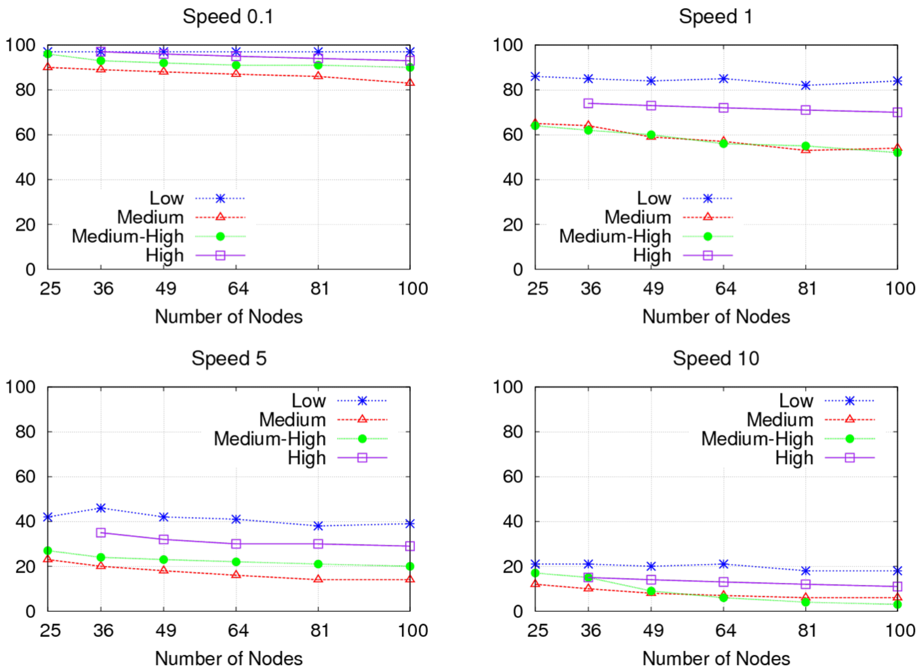


Figure 4.26: Percentage of TC message repetition

The number of nodes does not significantly affect the percentage of repetition. If we fix the speed and the density of nodes, the percentage of repetition decreases very slightly when the number of nodes increases. Overall, we can claim that this percentage is very stable and remains almost unchanged. This result is extremely interesting in terms of scalability because the performance of the OLSRp mechanism would be similar when applied to diverse scenarios, independently of the number of nodes. Therefore, the control traffic reduction achieved by this mechanism can compensate the higher amounts of data traffic generated in networks with a large number of nodes in comparison with the lower amounts of data traffic generated in networks with a small number of nodes.

The percentage of repetition is dramatically affected by the mobility of the nodes. We can observe that the percentage of repetition varies considerably for different node speeds. For example, it can reach a maximum of 98% for speeds of 0.1 m/s, whereas this value decreases up to 20% for 10 m/s, as represented in Figure 4.27. This can be explained by the fact that TC messages are generated every 5 seconds, which means that when the speed increases, the probability of having topological changes during such a period of time also increases. Therefore, a high number of non-repeated TC messages will be generated.

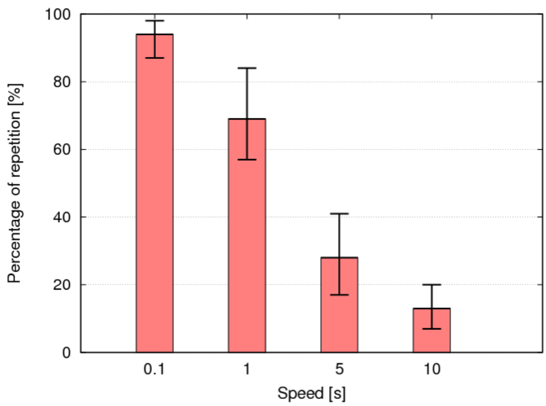


Figure 4.27: Effect of mobility on the percentage of TC message repetition

The percentage of repetition is still significant even with high node speeds. The results indicate that the percentage of repetition remains high even in mobile scenarios where the nodes move at high speed (from 5% to 20% for speeds of 10 m/s). This result is interesting because, as explained previously, the number of TC messages generated in the network increases exponentially with the number of nodes (see Figure 4.18). Therefore, even with low percentages of repetition, the control traffic sent to the network can be significantly reduced, especially in scenarios with a high number of nodes. Consequently, the OLSRp provides a cost-effective mechanism to alleviate the network congestion produced by the generation of replicated TC messages.

The density of nodes affects the percentage of repetition. From the four graphs shown in the figure it is clear that for different degrees of node density, the percentage of TC messages repetition varies. This variation seems to be higher for medium speed values. Nevertheless, for such speed values, the percentage of repetition is still above 10% and its maximum variation for different node density values is around a 30%. Therefore, we can claim that although the density of nodes affects the performance of the OLSRp mechanism, it does not limit its usefulness. According to the figure, the percentage of repetition is lower for medium values of node density than for high and low values. This can be explained by the fact that high node densities imply that not many topological changes occur because a high number of nodes always have direct communication links between them. Similarly, low node densities imply a low number of direct links between nodes, which makes that topology changes only affect a low number of nodes. By contrast, medium node densities increases the probability that topology changes affect a high number of nodes.

4.3.3.3 OLSR and OLSRp Performance Comparison

To conclude with the evaluation of the OLSRp, in this section we present some results that compare the behaviour of the OLSRp and the standard OLSR protocol.

Figure 4.28 shows that the OLSR protocol always sends through the network a 100% of the TC messages generated by the MPRs, independently of the occurrence of topological changes. On the other hand, OLSRp achieves a significant reduction in the number of TC messages that are sent, even at high node speeds. This reduction is between a 10 to 20% for high speeds (10 m/s) and between 60 to 80% for low speeds (1 m/s).

Finally, we proved that the reduction in the number of TC messages sent does not affect the performance of the routing protocol. This is shown in Figure 4.29. We can observe that both the original OLSR implementation and the proposed OLSRp achieve the same percentage of received ICMP traffic.

In conclusion, the analysis of the control information repetition of OLSR and the performance comparison of OLSR and OLSRp offers sufficient evidence of the usefulness of our proposal in diverse scenarios. We observed that the nodes speed is the factor that has a more relevant influence in the potential

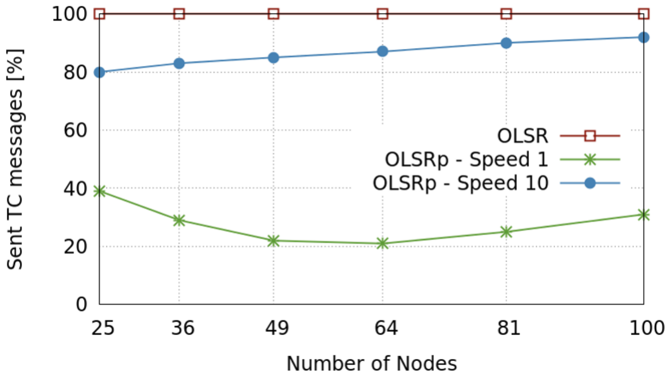


Figure 4.28: Percentage of TC messages sent

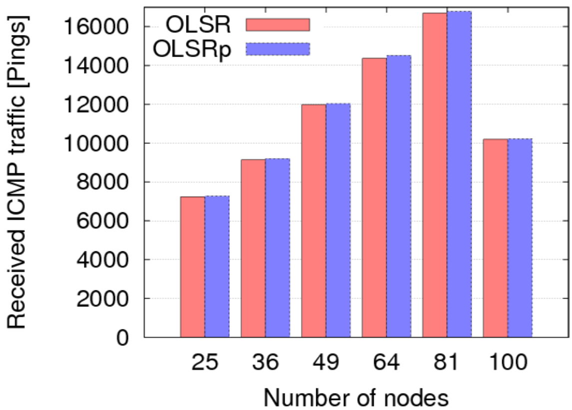


Figure 4.29: ICMP traffic received

usefulness of the OLSRp mechanism. However, we discussed how even in high speed scenarios, the percentage of control information repetition is still significant. In addition, the performance of the OLSR protocol is not affected by the introduction of the OLSRp mechanism. Therefore, this support our argument that the OLSRp mechanism can be applied to improve the efficiency and scalability of MANET networks, regardless of the particular conditions of the application scenarios.

4.4 Conclusions

In this chapter we presented a study that explores the feasibility of using MANET networks as communication support for pervasive monitoring applications. We showed through an experimental evaluation performed on a realistic physical environment with real users and devices that these types of networks can effectively support collaborative interactions between mobile devices to enable pervasive sensing and dynamic feedback provision. This statement can be supported due to the fact that the obtained latency, jitter and throughput values are above the thresholds that are considered satisfactory [86, 225, 227] to avoid communication breakdowns and insure acceptable audio and video communications (this was proved with the validation of *hypothesis 6*). In addition, if we select the appropriate transmission rates and protocols for the specific conditions of the scenario, we can improve such values. Through a number of tests performed in diverse mobile scenarios we also analysed several networking issues of MANET networks, determining how they influence the performance of pervasive monitoring solutions in various interaction scenarios. Our last contribution related with this feasibility study, was the identification of some limitations of MANETs in terms of performance and reliability and provided suggestions on how to improve them.

As a different contribution regarding the viability of using MANETs to support pervasive monitoring, we proposed a novel approach to improve the efficiency of these types of networks by reducing the amount of information produced by the routing protocol. Such approach provides a transparent, cost-effective and energy-aware mechanism to predict the control packets of the routing protocol that contain information about the changes in the network topology. Therefore, this mechanism can offer considerable reductions in the energy and computing costs of the mobile devices as well as in the network traffic without compromising the accuracy of the network topology information generated by the routing protocol.

The potential usefulness of the proposed mechanism was evaluated considering various parameters such as speed, density and number of nodes. We showed through several simulation tests that this mechanism can be applied to diverse scenarios regardless of the value of these parameters. We also observed that the OLSRp achieves a reduction in the number of TC messages sent through the network of up to a 90% in low mobility scenarios and up to a 20% in high mobility scenarios. Moreover, the performance of the protocol in terms of received traffic was not affected by this reduction. Therefore, the proposed approach can be applied to improve the efficiency and scalability of MANET networks when supporting pervasive monitoring solutions, regardless of the particular conditions of the application scenarios.

Chapter **5**

A Flexible Awareness Mechanism

5.1 Introduction

Some studies emphasise the importance that the interaction patterns and social network structures have in the development of collaborative activities and in people performance. For example, in [162] the authors conclude that Wikipedia editors who had extensive and cohesive interpersonal relationships before starting to work on an article, were the most efficient and their articles had the highest quality. Similarly, results from the study presented in [15] show that scholars who present repeated co-authorship relationships and that are connected to many different scholars have a better citation-based performance than those who have less connections and single co-authorships with many different scholars. Another interesting study in the area of sport [82] explores the relationship between patterns of interactions and team performance. It suggests that high level of interactions between soccer players (i.e. passing rate) improves team performance.

Therefore, our question is: *what makes the learning process effective?* The traditional idea is that if lectures and information resources have good quality, then the learning process of a student should be satisfactory [71]. By contrast, studies like the presented above and the appearance of new learning paradigms [206, 51, 244], which advocate that learning should be highly situational, collaborative, informal and pervasive in order to be successful, suggests that there are also many factors and stimuli from the students' context and social interactions that contribute to the learning experience in addition to the formal lecture and the pre-established learning environment [71].

On the other hand, due to the fact that the provision of feedback information can be used as an awareness mechanism that allows students to improve their behaviour [207], if we can quantify some of the factors that influence the effectiveness and quality of particular learning processes and provide feedback to make students aware of these stimuli, this can produce a change in their behaviour that benefit such learning processes. Therefore, by making students aware of their prior and/or current behaviour regarding their activities, social interactions and communication patterns through targeted and personalised feedback we could promote better learning practices, create improved learning experiences and positively impact in the performance of students.

For this reason, the ultimate purpose of the pervasive monitoring system proposed in this thesis (presented in Chapter 1) is to deliver feedback to students and lecturers about particular features of existing activities, practices and behaviour patterns that can influence the learning experience and its outcomes. However, the diversity of contexts and situations involved in modern learning environments, such as collaborative processes, social interactions, informal situations, contextualized learning activities outside pre-established learning contexts or practice-based learning in real workplaces, make it very challenging the design of appropriate awareness solutions to meet the requirements of both the specific learning activities or processes that these solutions are intended to support as well as the particular environment in which they will be deployed.

In order to develop a comprehensive pervasive monitoring system that can be used for the quantification of diverse kinds of factors (e.g., motivational, task-related, social, etc.) that can influence a learning process as well as for a timely and dynamic provision of awareness information about such factors, in Chapter 3 and Chapter 4 we provided solutions to deal with the data collection and communication prerequisites, required to deal with the quantification tasks.

In this chapter, we address the problem of providing appropriate awareness solutions that could be suitable for the diversity of activities and environments that can be encountered in today's pervasive learning contexts.

Due to the fact that smartphones are mobile and pervasive devices that can offer diverse feedback capabilities such as their displays and their acoustic and haptic features, they provide an interesting method for the provision of awareness across diverse learning contexts. Moreover, since smartphones have network interfaces that allow connectivity with other networked devices available in the environment and particularly, with shared displays, they can facilitate the use of such devices to provide awareness to the users. This is why, this chapter explores the use of smartphones to provide a flexible awareness mechanism to allow the provision of dynamic feedback in pervasive learning environments. Consequently, two awareness mechanisms proposed are based on the use of smartphones for the provision of feedback. The first mechanism uses the smartphone's local screen as ***awareness display*** and the second one takes advantage of their connectivity features to allow the use of remote displays available in the environment (i.e. situated micro-displays). Both mechanisms were considered in order to provide flexible awareness solutions that could be easily adapted to support specific learning activities in diverse environments.

The focus of the chapter is on two particular use cases that describe the designs and functionalities of the two proposed awareness mechanisms to provide feedback information in specific learning contexts. The first use case considers a collaborative learning context, where several past and present behavioural factors are considered to have influence in the current collaborative learning process. For this context, we propose delivering feedback through an awareness mechanism that helps provide personal and social awareness on the historic collaborative learning behaviour of the students. Such a mechanism is intended to offer feedback in a dynamic and holistic way by displaying awareness information about the behaviour of the students in their smartphone's screens. In the second use case, the awareness mechanism was designed for a context where students need awareness about spatially distributed tasks that are part of a particular learning activity. In this context, the students have to perform multiple tasks that involve interaction with diverse objects and/or people. In this case, we propose delivering real-time in-situ feedback through an awareness mechanism that provides task-centric information by means of a network of situated micro-displays. As will be explained in more detail in this chapter, these situated micro-displays are a special type of shared display that provides a method for embedding awareness information into a physical environment.

Chapter Overview

This chapter introduces two types of ***smartphone-triggered awareness mechanisms*** designed to allow a flexible and dynamic provision of personalised feedback in diverse learning contexts. In Section 5.2 we describe the design and evaluation of an awareness mechanism for the provision of feedback about behavioural factors that affect collaborative learning. This section also describes and evaluates a prototype of the proposed mechanism and its implementation in a collaborative mobile learning application, using a user study and a case study. In Section 5.3 we present an awareness mechanism based on situated micro-displays that allows delivering task-centric feedback in dynamic learning activities that include a certain number of spatially distributed tasks. Furthermore, we describe a user study performed to assess how the spatial distribution of these micro-displays impacts on the behaviour of the students. Finally, we present conclusions in Section 5.4.

5.2 The Behaviour Awareness Mechanism

The findings of previous research studies highlight that: (i) the effectiveness of a student team is determined by a combination of cognitive, social and motivational processes, and (ii) collaboration should not only be assessed by the quality of its outcomes or achievements [216, 73, 123]. Moreover, although social interaction has been identified as a key element that influences the quality of collaborative learning [119], there are still various social interaction areas that are unexplored in the context of Computer-Supported Collaborative Learning (CSCL) [216].

Most researchers agree that the provision of feedback information is crucial to improve social interactions and collaboration processes [152]. In that line, awareness has been considered as an extremely valuable feature of collaborative systems [21] that affects motivation [238] and group coordination [123] and therefore the quality of any collaboration process or interpersonal interaction.

Consequently, some interesting studies in Computer Supported Collaborative Learning (CSCL) have been prompted by the need of providing appropriate awareness support to promote active learning and coordinate students' activities [123, 73].

Considering the importance of social interactions in the quality of collaboration and performance of student teams, in this section we propose a visual feedback mechanism to support CSCL applications aimed at providing feedback that encourage reflection and promote social interactions among students. This awareness mechanism, named *Behaviour Awareness Mechanism (BAM),* helps provide personal and social awareness on the collaborative learning behaviour patterns of the students, delivering feedback in a direct, dynamic and holistic fashion. The *BAM* provides awareness of the students' collaborative behaviour as well as individual and cognitive elements (e.g., motivation, performance, social presence, connectedness, participation, etc.) that affect collaborative learning. To the best of our knowledge, this type of awareness provision method has not been previously explored in CSCL. We also believe that this mechanism can positively impact the quality of collaboration in several other application areas. Hence, it can be embedded in several types of collaborative applications such as, software development frameworks for managing product development, team building activities in companies, project management teams, etc.

Next, we describe the design of the *BAM* and the evaluation of a proof-of-concept prototype designed to be embedded in a mobile collaborative learning application.

5.2.1 Design of the Behaviour Awareness Mechanism

The main goal of the proposed *Behaviour Awareness Mechanism (BAM)* is to provide feedback about the students' collaborative learning behaviour and encourage social interactions among them. To achieve such a goal, we took into account the design criteria detailed below.

5.2.1.1 Design Considerations

As highlighted in [216], many educational teams are "ad hoc". That is, most collaborative learning teams only exist during specific tasks or courses, because they were only established for that particular purpose. For that reason, the provision of awareness to support collaborative learning is frequently focused on a specific activity or project. Therefore, the supporting application provides only the feedback that is relevant within that particular context. Nevertheless, personal behavioural patterns or individual experiences in previous collaborative tasks are usually transferred to collaboration events in the future [216], and they influence new group interactions and outcomes. To a large degree, we based the design of the feedback mechanism on such an assumption. Thus, we took into account collaborative and individual experiences of the students, as they are clear indicators of their future behaviour. Our aim is to make students aware of their previous and current behaviour, and based on that, make recommendations (e.g., actions that they could take) to help them improve their collaboration attitude and learning practices.

There is sufficient evidence in the literature supporting the fact that there is an intrinsic relationship between the individual, social, motivational and cognitive aspects involved in collaborative learning [80, 216, 73, 123], and that such a relationship also determines the effectiveness of a team. Consequently, our proposed *BAM* takes a holistic approach and provides awareness of each one of these aspects.

Furthermore, many research studies focus on specific collaboration tools and activities [152, 123, 238, 39] and provide indirect feedback about underlying aspects of the collaborative behaviour extracted from how the users have interacted among them using these tools. The objective usually is to make the user reflect on their previous actions and promote collaboration through higher engagement with a particular collaboration tool [238]. By contrast, we decided to use direct feedback, specifying concrete collaboration aspects that should be improved, not limiting it to a specific activity or to the use of a particular supporting application.

Regarding strategies for providing awareness information, the literature presents several alternatives; some of them are based on automatic data capture and others require a conscious user feedback [38]. Our proposal followed a mixed approach to generate the awareness information, and therefore it considers both implicit (i.e. awareness information is generated automatically) and explicit (i.e. requires user intervention) feedback of the users. Hence, our design requires for the mobile application that embeds the *BAM* to include metrics collected automatically in an unobtrusive way (e.g., from application logs, smartphone-based sensing, etc.) and also information gathered from the user feedback (e.g., ratings, self-assessments, questionnaires, etc.). This helps us provide awareness about a wider range of aspects, integrating multiple data sources and including both qualitative and quantitative measures of the learning experiences.

We have also identified in the literature three different kinds of awareness that are essential for supporting effective collaborative learning, and therefore they are included in our proposed *BAM*: ***behavioural, cognitive*** and ***social*** awareness [30]. We have also considered the ***motivational*** awareness as a forth awareness type to be included because it usually has high relevance in collaboration processes [216, 238, 150]. Hence, the *BAM* intends to contribute to the development of CSCL systems, providing a comprehensive awareness method that considers the following features:

- ***Integral awareness:*** offering behavioural, cognitive, social and motivational information of the users.
- ***Aggregated information:*** providing representations of the historic collaborative and learning behaviour of the users, regardless of the collaborative process or activity being supported. Thus, it is possible to identify behaviour patterns of the users.
- ***Mixed feedback:*** including a combination of implicit and explicit feedback.
- ***Dynamic information:*** providing real-time awareness information that indicates the current behaviour of the students.
- ***Multiple data sources:*** representing information from several data sources such as questionnaires, self-reports, software logs and information collected automatically through the sensors of mobile devices carried by students (e.g., smartphones, tablets, laptops, etc).
- ***Explicit feedback:*** providing synthesized and direct awareness information that indicates what needs to be improved in the collaboration or learning process.

5.2.1.2 Components of the Behaviour Awareness Mechanism

The proposed awareness mechanism has the following components: the *Personal Awareness Component* and the *Social Awareness Component.* The design of these components is based on two main ideas: (i) any awareness mechanism must provide an understanding of the activities of others as a context for the activities of the individual [21], and (ii) the feedback provision in CSCL must ensure that the students are able to relate their current state of learning and performance with specific targets or standards [168]. Next we describe these components in detail.

Personal Awareness Component

The *Personal Awareness Component (PAC)* provides awareness of the collaborative patterns of a specific student, and it represents several features of the students' behaviour. This component of the awareness mechanism provides feedback on aspects related to the way in which the students interact within different teams (e.g., participation, coordination, etc.), personal features of these students that affect their collaboration and learning (e.g., motivation, satisfaction, individual performance, etc.) and characteristics of the student's social interactions (e.g., social presence, connectedness, etc.). Hence, the *PAC* is a simple visual representation of collaboration processes and outcomes, and motivational, cognitive and social aspects. On the other hand, the *PAC* also allows the students to compare their own behaviour with the behaviour of their peers, which provides students with an understanding of the activities and behaviour of others.

The collaborative behaviour features that should be represented in the *PAC* were determined based on previous research work about quality assessment of computer-supported collaboration processes [150, 13, 108, 131]. We found seven basic dimensions related to the effectiveness of collaboration, and classified them according to the awareness types provided by the *BAM.* Nevertheless, for the sake of simplicity and to facilitate the visual representation of the *PAC,* we condensed such dimensions into five types, because we considered that some of them were strongly related to each other. Consequently, the resulting five dimensions correspond to the features of the students' collaborative behaviour represented in the *PAC* component: ***communication, coordination, motivation, performance*** and ***satisfaction.*** Table 5.1, summarizes the relationship between the types of awareness considered in the proposal, the collaboration dimensions found in the literature, the collaborative behaviour features and the metrics that can be used to assign a value to these collaborative features.

Table 5.1: Awareness types and collaborative behaviour features

Awareness types	Collaboration dimension	Collaborative behaviour feature	Metrics
Behavioural: Informs about learners' activities	Communication	Communication	Based on knowledge and information exchange as well as on collaboration flow
	Joint information processing		
	Coordination	Coordination	Presence of roles, planning activities, time management and reciprocal interactions
	Interpersonal relationship		
Cognitive: Determines how well the student's output meets the expected values	Performance	Performance	Scoring of both individual and group outcomes (achievements)
Social: Determines the functioning of the group, as perceived by the collaborators	Satisfaction	Satisfaction	Measurement of the students satisfaction about both, the collaboration process and outcomes
Motivational: Represents the awareness of the student motivation	Motivation	Motivation	Motivation

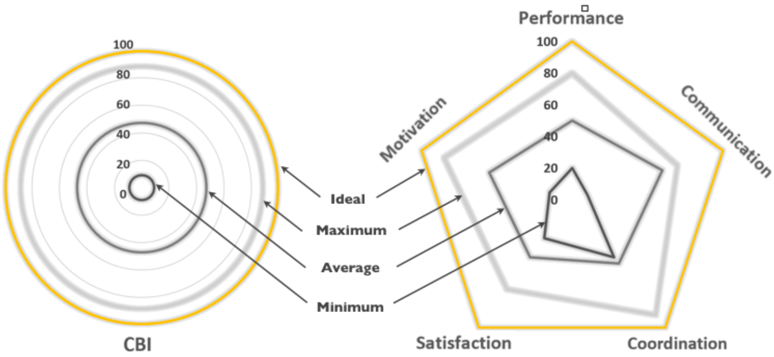
In order to represent the five features of the students' collaborative behaviour, we divided the *PAC* visualizations into two subcomponents. The first one, the *PAC-CBI,* shown in Figure 5.1(a), displays an overview of the collaborative learning behaviour by combining the collaborative features through a global rating scheme, defined by the *Collaborative Behaviour Index (CBI).* This index is calculated as the average of the features represented (or *CBI* elements), and therefore it provides a representation of the overall collaborative behaviour of a student. Once the *PAC-CBI* is displayed, the user can have more information through the visualization of the second subcomponent, the *PAC-Features,* depicted in Figure 5.1(b). This subcomponent shows specific details about each collaborative feature included in the previous subcomponent.

As we can observe in Figure 5.1(a), the *PAC-CBI* subcomponent is represented with a coloured circle, whose size corresponds to the *CBI* value within a normalized scale from 0 to 100. The four concentric circles in the figure represent the theoretical ideal, the normalized minimum, average and maximum values of the *CBI* for the overall group of students considered in the representation. This allows us to provide awareness of the behaviour of a student in comparison to the behaviour of his peers.

Figure 5.1(b) shows the *PAC-Features* subcomponent, represented using a radar diagram. Thus, each feature of the students' collaborative behaviour is depicted as a vertex of a coloured pentagon. The pentagon size corresponds to the normalized value of the features. Similar to the *PAC-CBI,* we depict four concentric pentagons; one regular and the other three of variable size and shape. The regular pentagon represents the theoretical ideal value that the students are expected to reach for all the behaviour features. This theoretical ideal value will be defined by lecturers according to specific targets that ideally they expect that students could achieve. The pentagons of variable size represent the normalized minimum, average and maximum values of the features for the overall group of students. This enables a student to compare, for each feature, his own performance to the one of his peers.

Notice that both the *PAC-CBI* and the *PAC-Features* visualizations represent the behaviour of a specific student, to whom the feedback is displayed as colour-filled shape (a circle and a pentagon, respectively). Moreover, the visualization of additional blank shapes, which represent ideal as well as minimum, average and maximum values, provides such a student with an understanding of his current state with regards to his learning behaviour in relationship with both specific targets (i.e. ideal) and the state of other fellow students (i.e. minimum, average and maximum values obtained within a particular group)

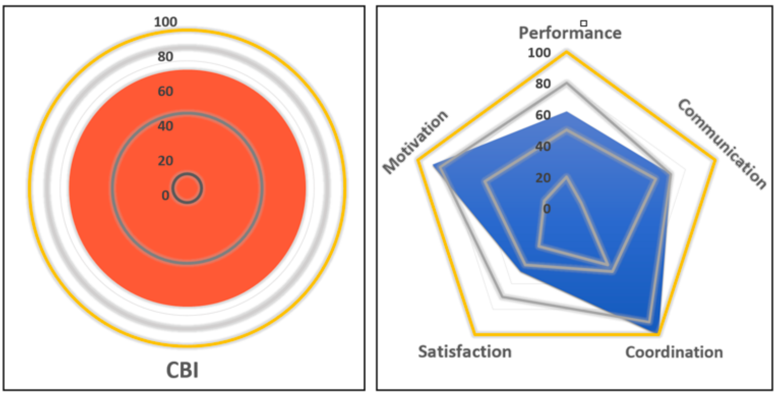
Considering the previous design, Figure 5.2 shows an example of the visual representation of a student behaviour as displayed in the *Personal Awareness Component.* As we can observe, it is composed by the *CBI* index, i.e. the *PAC-CBI* subcomponent, shown in Figure 5.2(a), as a measure of the overall



(a) PAC-CBI (b) PAC-Features

Figure 5.1: Design of the the CBI and the collaboration features

collaborative behaviour, and also a detail of the five previously explained collaborative dimensions, i.e. the *PAC-Features* subcomponent, represented in Figure 5.2(b).



(a) PAC-CBI (b) PAC-Features

Figure 5.2: Sample representations of the Personal Awareness Component

Social Awareness Component

The *Social Awareness Component (SAC)* provides social awareness and proposes possible suitable collaborators (i.e., other students) to the user. In order to identify potential collaborators, we use the Multi-Dimensional Scaling (MDS) method to represent students as points in a 2D space [40]. By performing MDS, the values of the five collaboration features (5D space) of the *CBI* can be mapped into a point in a 2D space, in such a way that distances between points are preserved. Thus, we can represent, in the *SAC,* two students that have similar behaviour as two points located at a short distance from each other. However, it could happen that students having similar *CBI,* could also have very dissimilar values of the several collaboration features that compose this index. In that case, the MDS also allows us to represent such students as two distant points in the *SAC;* therefore, these students will not be suggested as potential collaborators.

Moreover, we defined two different criteria to propose collaborators, depicted as the ***"highly recommended collaborators"*** and the ***"other recommended collaborators"*** areas of the *SAC,* respectively. The former includes at least one potential collaborator that is located at the closest MDS distance from the represented student, and the latter area includes the previous one and it has a range that covers at least a 20% of the closest potential collaborators. This percentage was decided on the basis of the Pareto's principle or 80-20 rule [88], which states that "80% of all effects result from 20% of all causes". Accordingly, we considered that 20% of all possible collaborators can produce the most significant impact in the collaboration process. Figure 5.3 shows the design proposed for the visualization of the *SAC* component as displayed for a particular student.

This method for suggesting collaborators is based on the correlation between values of the *CBI* components for several students. Hence, we only propose collaborators with similar behaviour. That is, only students who have similar values in the same collaboration features will be encouraged to collaborate. Two alternative methods for providing this feedback are the following: (i) suggesting as possible collaborators only those students who have complementary behaviour or skills, and (ii) proposing collaborators with both similar and complementary behaviour.

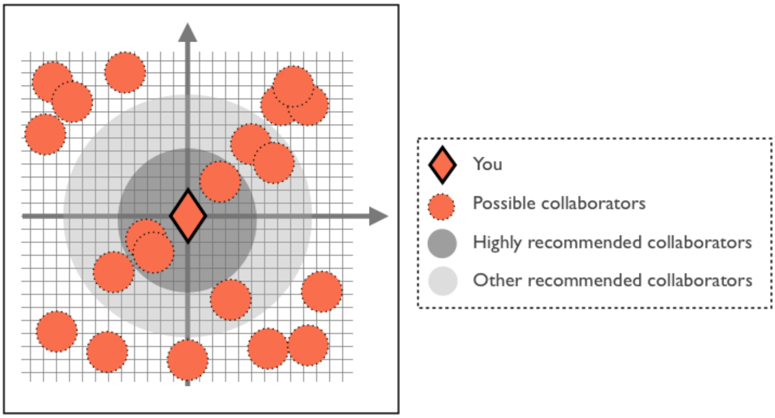


Figure 5.3: Design of the Social Awareness Component

Figure 5.4 shows examples of SAC representations, using these alternative methods. Figure 5.4(a) represents the feedback provided to a student, where only those possible collaborators with complementary behaviour are proposed. Thus, those students who have high values of certain behaviour features will be suggested as potential collaborators of other students who have small values in such features and vice versa. By contrast, Figure 5.4(b) corresponds to the visual representation displayed to a student, where other students with similar or complementary behaviour are suggested as collaborators. As we can observe in both figures, we represent possible collaborators using two different colours, depending on whether we recommend them because they have similar or complementary behaviour to the student that is receiving the feedback.

All the methods proposed to recommend collaborators have the purpose of promoting collaboration among students, helping them to improve their own behaviour and their learning experience. However, determining which method is the most appropriate to fulfil such a purpose is beyond of the scope of this work.

5.2.2 Evaluation of the BAM Prototype

In order to evaluate the usefulness of the proposed awareness mechanism, we developed a proof-of-concept prototype and embedded it in the *Moodle* learning platform used by the *Universitat Politècnica de Catalunya (UPC)*, in

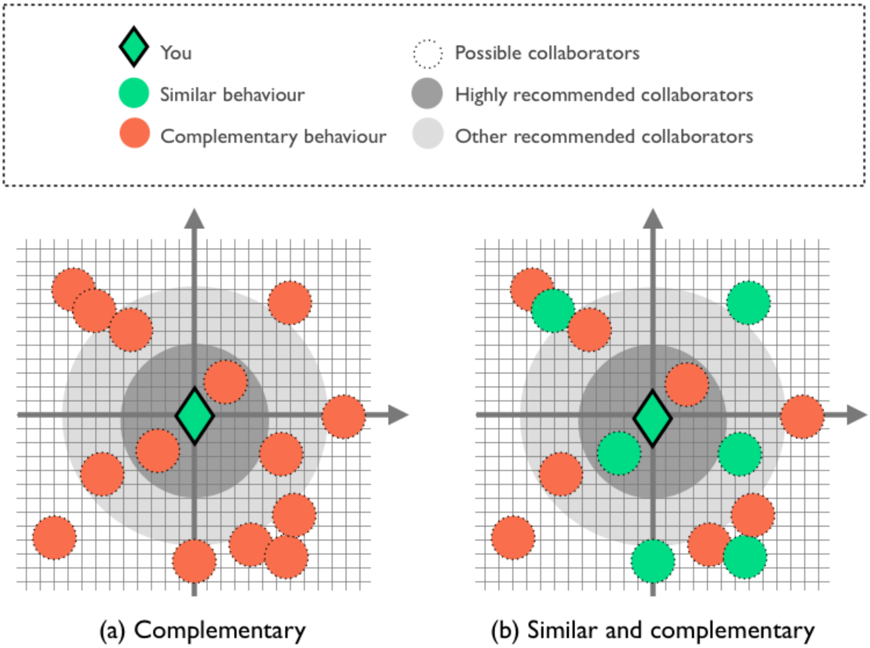


Figure 5.4: Alternative design of the Social Awareness Component

Spain, to support undergraduate courses. Therefore, this platform allowed us to provide feedback visualizations to students, including both the *PAC* and *SAC* components. The *Moodle* platform was also used to collect the answers of the students concerning the evaluation tasks and questionnaires. Next sections present the evaluation methodology and the obtained results.

5.2.2.1 Evaluation Methodology

The evaluation process involved a user study conducted with real students and the collaborative learning environment that these students use every day to support their learning activities. Twenty four students were recruited; all of them were third year students enrolled in the course *"Design of Applications and Services (DSA)"* delivered at the *Castelldefels School of Telecommunications and Aerospace Engineering, of the UPC.* We also used a real data set from students of the DSA course to create the visualizations presented to the participants of the study.

The dataset included information from the students' activities and opinions while working within the formal learning environment as well as outside the classroom in an informal and unplanned way. The data sources used to gather the information included surveys and log files. The surveys investigated the students' feelings, opinions and behaviour during the course (both inside and outside the classroom). On the other hand, the log files, collected from the learning supporting platform, had information about the students' activities and performance while working in the course project.

The visualizations used in the study consisted of three different figures, corresponding to the *PAC-CBI, PAC-Features* and the *SAC* components of our awareness mechanism.

In order to evaluate the fitness of the awareness proposal for the intended application, we asked participants to complete three tasks; one for each visualization type. Consequently, for each representation the students had to perform a classification task, indicating whether those figures represented "poor", "average" or "good" student performance, or if some students represented in the *SAC* were "highly recommended", "recommended" or "not recommended" as collaborators. For simplicity, we named the classification tasks according to the rating levels that they represent as *"good", "medium"* or *"bad".*

In addition to the classification tasks, we asked participants to answer several questions to assess the usability of the three components of the *BAM.* These questions were taken from the *Usability Perception Scale (UPscale)* [110] and the *Post-Study System Usability Questionnaire (PSSUQ)* [130]. Both tools were adapted to suit the purposes of our study and formatted in a 5-point Likert scale (i.e. a scale commonly used in psychological studies to represent people's attitudes or opinions about a specific topic). The resulting usability questionnaires included questions designed to evaluate attributes of the visualizations, such as ease of interpretation, learnability, usefulness, relevance and intention of use.

5.2.2.2 Evaluation Results

The prototype evaluation considered the analysis of the perceived usefulness of the feedback model, and also its suitability to be used as part of the awareness support of collaborative learning applications. The next sections present and discuss the obtained results.

On the one hand, the results from the classification tasks were useful to provide insights on how suitable the proposed awareness mechanism is to classify different learning behavioural patterns and suggest possible collaborators. Figure 5.5 shows the results of the classification tasks for the three elements of the *BAM,* which compose the visual representations of our proposal. As we can observe, there is a high rate of correct answers (94.91% in average) for the three elements in all the rating levels considered (i.e. good, medium and bad), which supports the suitability of our feedback proposal.

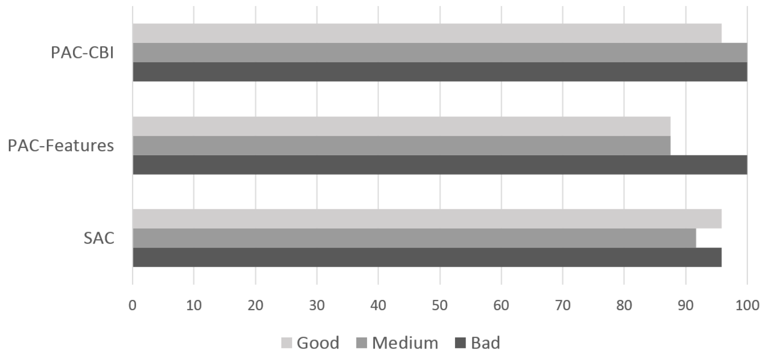


Figure 5.5: Results of the classification tasks

On the other hand, results from the usability questionnaires helped us evaluate the students' perceived satisfaction concerning the information quality and its representation. We also evaluated the usefulness and comprehensibility of the feedback. Figure 5.6 shows the results obtained from the *UPscale* that suggest very positive participants' perceptions about the usability (70.42% in average) and engagement (65.69% in average) of the three kinds of visualizations.

Similarly, the results from the *PSSUQ* questionnaire, depicted in Figure 5.7, indicate a high rate of participants' satisfaction (76.31% in average) for such visualizations. Considering both usability questionnaires, it is important to notice that the results revealed the highest satisfaction with the representation provided by the *SAC* component, followed by the *PAC-Features* and the *PAC-CBI* respectively. This means that the *SAC* awareness component was the representation with the highest score in this evaluation.

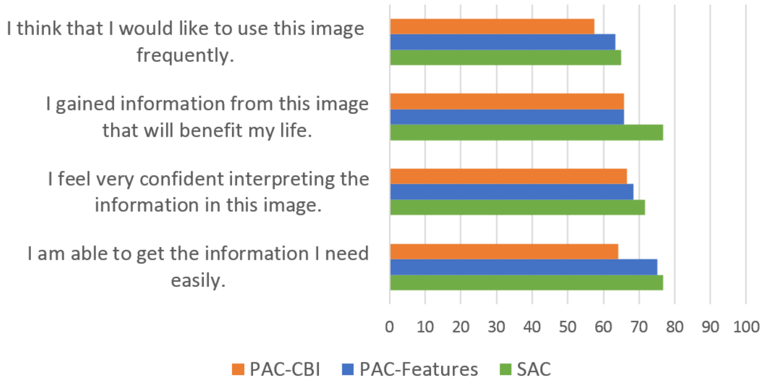


Figure 5.6: Results of the UPscale questionnaire for the BAM

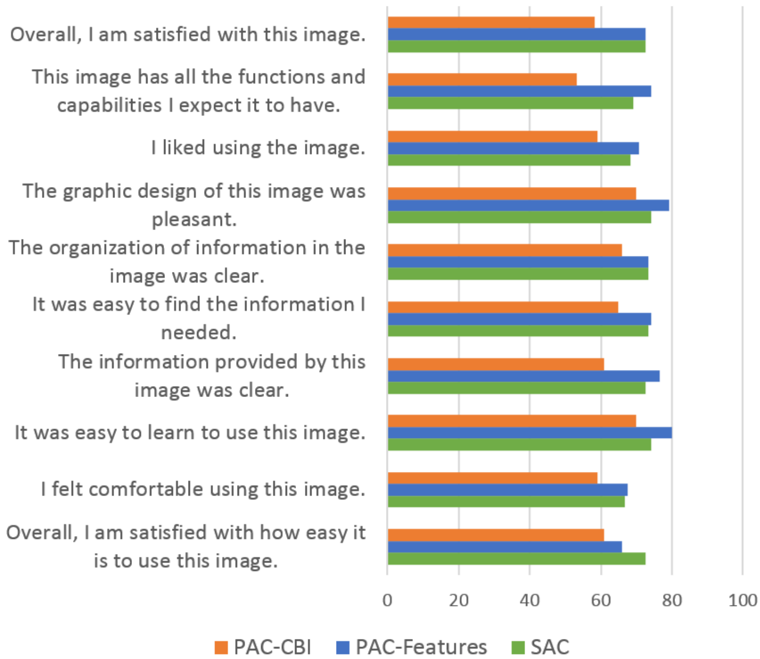


Figure 5.7: Results of the PSSUQ questionnaire for the BAM

5.2.3 Case study

The awareness mechanism proposed in this paper can be integrated into collaborative learning applications in order to provide visual awareness about the collaborative learning behaviour of the users. As a proof-of-concept of such an integration, in this section we present a case study that describes an imagined situation where the proposed awareness mechanism is used in a real-life learning scenario. This case study describes the implementation of a mobile collaborative application that combines information from different types of data sources, and displays a dynamic and explicit feedback to users using the *Behaviour Awareness Mechanism.*

5.2.3.1 Data sources

In order to generate the information required to provide awareness, the pervasive sensing framework described in Chapter 3 was used to collect data traces about the students' behaviour during an academic semester. The traces correspond to data captured about the participants in the previously mentioned *DSA* course, and they contain information about the students' actions while working in teams in a software development project. More specifically, we gathered data from the following sources:

- *Moodle* platform. In order to collect information about the students' performance, communication and coordination, we used the Moodle regular services. Examples of data traces collected through this mechanism are the number of tasks completed in time, number of forum messages posted by the students, number of group tasks submitted in time, and the individual and group grades.

- *Trello* web-based project management application. We used software logs from this tool to generate information related to the coordination among the team members, such as activity planning, collaboration flow, group interaction and group hierarchy. Examples of traces from this source are the number of tasks assigned, updated or finished on time by each member.

- *Online surveys* to collect communication, satisfaction and motivation information. We recorded the students' answers to a number of questionnaires, including questions about the collaboration with peers and the learning experience.

- *GitHub* web-based version control system. Logs from this software helped us obtain data about certain aspects related to the team coordination and performance. Examples of the collected information are the coding frequency and the number of pull request and open issues of the team members.

In order to calculate the five collaborative behaviour features considered in this study, we used different combinations of data traces from different sources. Hence, each feature is calculated using specific traces, normalizing (from 0 to 100) the measurements that each trace provides, assigning weights as multiplying factors depending on the number of traces, and aggregating the resulting values. This process can be summarized through the following equation:

$$Feature_x = \sum_{n=1}^{\#ofdatatraces} \alpha_n * Trace_n \tag{5.1}$$

In this equation, $Feature_x$ represents the collaborative feature to be calculated, $\boldsymbol{n}$ is the number of data traces used, α_n corresponds to the multiplying factors, and $Trace_n$ is the measurement from the particular data trace normalized from 0 to 100.

From the previous equation and for the considered feature, we obtain a value within the range $0 - 100$. As an example, let us consider that we use three data traces to calculate the "Performance" collaborative feature of a specific student. Such traces include individual and group grades of *Moodle* assignments and also the coding frequency as calculated by *GitHub*. In this case, the resulting equation for performance would be the following:

$$\begin{gathered} Performance = 0.4 * (Moodle_individual_grades)+ \\ 0.4 * (Moodle_group_grades) + 0.2 * (GitHub_coding_frequency) \end{gathered} \tag{5.2}$$

We must take into account that the measurements from each data trace can lay within any possible range of values; therefore we must normalize the values of such metrics. For example, the *"GitHub coding frequency"* indicates the number of items added by a particular student to the software project repository. We can normalize the *GitHub coding frequency,* assigning the values of 0 and 100 respectively to the theoretical maximum and minimum number of expected additions for a specific time period. Thus, 0 and 100 correspond to coding frequencies of 1 and 5 additions per week respectively. Also, notice that in this case we assigned different weights to the multiplying factors, giving more importance to some measurements than to others. However, determining the weight that should be given to each metric is not part of this research work.

5.2.3.2 Sample visualizations

Using the information gathered from the previous sources, the application classifies the data according to the five collaborative features and combines it appropriately in order to compute a value for each feature (within a normalized scale from 0 to 100). In addition, the *CBI* index is calculated as the average of the features.

Finally, based in the features and *CBI* values of a specific student and his peers, the application performs various MDS operations to represent, with a short distance, the students that have similar behaviour. Figure 5.8 depicts an example of the visual representations of the students' collaborative behaviour, provided by the *Behaviour Awareness Mechanism,* as shown in the students' smartphones.

5.3 The Task-Centric Awareness Mechanism

Advances in wireless communication, sensor networks, ubiquitous computing and particularly in Internet of Things (IoT) technologies, have made possible the interaction between people and numerous devices that are interconnected and physically distributed in the environment [223, 94]. These advances have promoted the evolution of single-monitor setups towards multi-display environments [27, 106], where it is possible to have displays embedded in a physical environment and also in everyday objects. In these environments, diverse sensors and displays (or other actuators) are embedded seamlessly in order to capture information about people's actions when interacting with diverse devices and objects and also to provide feedback information that is meaningful

Figure 5.8: Interface of the Behaviour Awareness Mechanism

to the user [183].

Several studies on workplaces have shown how instrumented environments and everyday artefacts support people cognition and collaboration [170, 101, 188]. In addition, researchers have emphasized the need to deliver task-centric information in dynamic workplaces, such as hospitals [25] or industrial plants [92], as well as in educational contexts [90, 16] as a way to support activities that are taking place in such environments. To deal with this issue, *situated information systems* [236] can offer an interesting alternative to provide information from the physical environment to help people accomplish a particular activity.

Based on the previous ideas, some interesting studies in the area of education, have shown how physical environments enriched with sensors, intelligent objects and displays can be used to provide awareness about the actions, status and progress of the students' activities by delivering situated, task-centric and relevant feedback [96, 203, 18].

Typically, these types of systems rely on the use of mobile devices and large displays to provide task-centric information [145, 208]. However, some research works [111, 232] advocate for the use of micro-displays to provide situated information and offer activity-specific guidance and feedback.

The *Task-Centric Awareness Mechanism (TAM)* proposed in this section is based on the use of a network of situated micro-displays, shown in Figure 5.9. These types of displays are small-size, mobile and adaptive (i.e. they change their appearance and content dynamically to adapt to the current activity. They can also be easily replaced or moved from one location to another. Situated micro-displays are a special kind of shared display that is integrated in the environment and linked to physical entities –such as objects and people–. They also provide simple and highly visual representations of human activities that are situated in place and time, providing awareness about the presence of a specific activity at a specific place, at a specific time. Therefore, the awareness mechanism proposed uses micro-displays to provide task-centric information, indicating when, where and how (i.e. which physical entities are involved) some tasks can or should take place. This awareness mechanism can be compared to signs and traffic signals: the word Exit or the iconic picture of a green figure indicate the meaning (the presence of an emergency exit), while the location of these signs indicates the location of the actual exit. Similarly, the colour of a traffic light conveys information about whether to stop or go, whereas the position of this sign conveys information about where to stop.

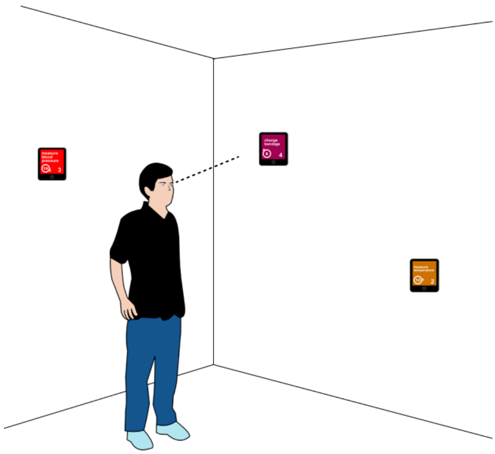


Figure 5.9: Micro-display network scenario

Notice that situated micro-displays can interact with smartphones carried by students allowing a smooth information interchange between them by creating a Mobile Ad hoc Network [27]. Other possible ways to address this issue is to use solutions based on RFID [109] or NFC [133] technologies. This interaction between these two different types of devices makes possible to develop an awareness mechanism that takes advantage of all the pervasive sensing services provided by the framework described in Chapter 3 to deliver high quality awareness information.

We envision the potential benefits of the proposed mechanism to provide task-centric awareness information to mobile students in highly dynamic learning contexts through situated micro-displays. This mechanism can be used to create simulated practise-based learning [213] environments, where students achieve specific learning objectives by performing a particular activity while interacting with tools, objects or elements of the physical environment that simulate a particular context of a real-world work practice. Some possible applications could be: (i) laboratory modules in undergraduate courses; e.g., electronic instrumentation lab sessions that involve practical training in measurement and instrumentation, which require the use of electrical components and actual laboratory instruments such as oscilloscope, function generator and multimeter, (ii) hands-on training courses; e.g., cooking courses that entail the use of specialized kitchen equipment and utensils such as deep fryers, ovens, steamers, food thermometers, slicers or blowtorches, (iii) task-based language learning [200] classes that require the completion of activities that involve interaction with objects and (iv) collaborative learning activities that entail complex structuring through Collaborative learning Flow Patterns (CLFP) that depend on the configuration of the physical space and on the distribution of the students in such a space as well as of the resources, objects, equipment or devices located within it [90, 145].

In the following sections we present the design of the *TAM mechanism* and the evaluation of a prototype of this mechanism that explores its effects in the students' awareness and performance.

5.3.1 Design of the Task-Centric Awareness Mechanism

The proposed *Task-Centric Awareness Mechanism (TAM)* uses situated micro-display to provide activity-specific guidance and feedback to mobile students. For the design of the visual representations that will be shown in this special type of display we followed the guidelines proposed in [111].

A network of these micro-displays, deployed in a learning context, enables the provision of awareness about contextual cues related to the physical environment to help students perform learning activities that require the completion of a number of tasks that are spatially dispersed in such an environment. The contextual cues (i.e. awareness information) represented in the displays describe the necessity or possibility for action in a given location or involving a specific object. They also provide feedback by showing the result or execution state of preceding actions, and presenting a possible next action.

In the *TAM,* these contextual cues have different properties that can be represented according to the particular activity patterns that can take place in a structured learning environments (i.e. environments specially designed and organized, where the arrangements of elements such as objects, furniture or equipment within them has been carefully planned). Therefore, the properties of the awareness information are represented in the *TAM* using particular combination of colours, shapes, texts and numbers. These properties are the following:

- ***Identity:*** identifies the entities -people or objects- that are required for a particular task.
- ***Relationship:*** establishes a relationship between a given entity and the current task.
- ***Type:*** indicates the type of awareness information that is being provided; e.g., if it requires an action or is just providing feedback.

Let us consider an example of how these properties can be represented according to particular activity patterns. If we consider a structured laboratory space equipped with various types of electronic instruments, where a group of students have to perform several measurements in electronic circuits (such measurements are the particular activity patterns that take place in this environment), the contextual properties defined previously can be represented as depicted in Figure 5.10. This figure shows that numbers are used to represent the identity of students and measurement devices (e.g., number “3” identifies the voltmeter, whereas number “2” identifies a particular student). Shapes are used to represent relationships between the current activity and a given electronic instrument (e.g., the presence of a circle shows that the instrument must be used for the activity and if an arrow is displayed, it would mean that instrument is available, working properly and ready to be used. Finally, different colours represent the type of awareness information that is being displayed (e.g., violet for action and green for feedback).

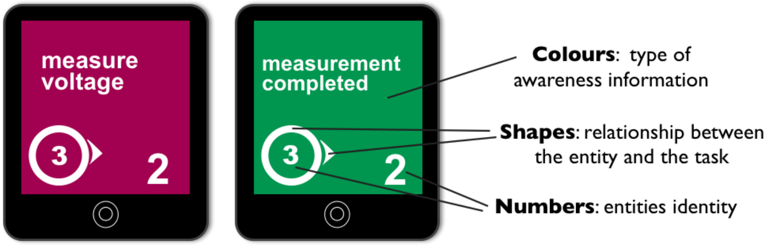
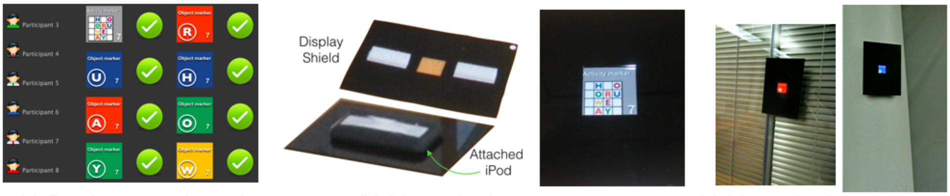


Figure 5.10: Sample design of the Task-Centred Awareness Mechanism

For our prototype of the Task-Centric Awareness Mechanism, we used shielded mobile devices of varying size as the placeholders (i.e. micro-display) of the visual representations of the contextual cues of the learning activity. Figure 5.11(b), and Figure 5.11(c) show two different form factors of micro-displays, which are used to provide activity-related information. The former is used to provide an overview of the activity in context, and the latter is used to present object-specific information pertaining to a task at hand. Each of these types of micro-displays runs a tiny client application (*Ajax-Comet*) that shows visual representations of the activity-related information. All the micro-displays are connected to a central display server in a *RESTful* way following multitenancy principles (i.e. in the server there is only one instance of each representation and such representation can be displayed in multiple micro-displays). Therefore, the activity information shown in the micro-displays is stored in the central display server, which pushes the appropriate information to a specific micro-display in a contextual fashion. Although we did not implement actual context recognition in our prototype, this pushing mechanism enabled us to dynamically display and update the information in the micro-displays appropriately. For instance, when a student arrives to the main entrance of the room where the activity is taking place, a micro-display located at the entrance automatically provides him an overview of the whole activity.

The micro-displays network was implemented connecting several computing devices through Wi-Fi, using an Apple's Airport Express base station. Particularly, as shown in Figure 5.11(a), a MacBook laptop was used to run the server and allowed us to manage the control panel of the system. Moreover, as shown in Figure 5.11(b), nine iPods touch, which perform the function of *object-marker* micro-displays, provide object-related information, and one Apple's iPad, which acts as the main *activity-marker* micro-display, shows the activity overview. We covered part of these devices' screen with black acrylic plastic in order to create the effect of having displays of small size screens, as shown in Figure 5.11(b) and Figure 5.11(c). The *activity-marker* micro-display had a screen size of 7 x 7 cm (i.e. the acrylic plastic window), whereas the *object-markers* had a window of 3 x 3 cm.



(a) Display control panel (b) Micro-display prototype (c) Micro-display in operation

Figure 5.11: Micro-display network prototype

5.3.2 Evaluation of the TAM Prototype

As stated in [111], the use of multiple micro-displays also raises a number of questions regarding their spatial placement and distribution. For instance, where and how the displays should be deployed in a physical environment to optimize the information support? By increasing the number of displays we can show the information in a fine-grained and situated fashion. However, having to process information from multiple displays causes fragmentation of the users' attention, which is known as *divided attention.* Furthermore, too much and/or not-so-relevant information demands higher cognition and could lead to *information overload,* jeopardizing its assimilation by the end-users. In that sense, it is necessary to identify the trade-off between the quality of the information provided by the micro-displays and the fragmentation of the users' attention, which can lead to *information overload.* Then, it is critical to understand the impact of the distribution granularity and placement alternatives of situated micro-displays on the effectiveness of the awareness provision mechanism.

Considering these facts, for the evaluation of the *TAM* prototype we conducted a user study that explores the impact of the spatial distribution of situated micro-displays on the students' awareness. Particularly, we want to understand whether and under what circumstances the use of situated micro-displays is useful to support spatially distributed learning activities and also how such circumstances affect the students' satisfaction and performance.

5.3.2.1 User Study Design

In this subsection we present a detailed description of the user study design and the methods adopted to conduct it.

Tasks

The activities that the participants of the study had to complete involved a number of spatially distributed simple tasks. We decided to use simulated activities instead of real-world learning activities due to the fact that our research is a proof-of-concept focused on the use of micro-displays to build a task-centric awareness mechanism to support mobile students, independently of the specific learning domain or activity where this mechanism will be applied. For the completion of these activities, little information processing was required to understand the information displayed and to carry out a single task. However, we added some complexity to the activities as a whole due to the fact that the information about many different tasks was displayed at the same time. The use simple activities allowed us to isolate the aspect of the use of situated micro-displays that we wanted to study. Therefore, because we were interested in evaluating the impact of the spatial placement of the micro-displays on the students' awareness, these types of activities allowed to avoid that the results of the study were affected by the complexity of the activities. Specifically, the activities selected for the study were several puzzles that the participants had to solve using the awareness information shown in the micro-displays. In order to do that, they had to pick up the correct objects –among the objects distributed around the room– and place them in the correct positions on a grid. The tasks selected for this study have the following properties:

1. Physical: The tasks involve physical movement and involve tangible

interaction with objects.

2. Spatially distributed: Participants have to move from one place to another to complete the tasks.

3. Goal oriented: All the tasks have a common final goal (i.e. to complete the activity successfully).

4. Non-sequential: The interdependency among tasks is minimal.

Accordingly, we selected this particular puzzle activity from the nine categories of manual tasks referenced in [205], however we adapted it to assess the quality of non-sequentially and spatial distribution of situated micro-displays.

The *independent variable* of the user study is the number of micro-displays. For this reason, each participant was always exposed to the same type of activity, but we varied the distribution granularity of the micro-displays between the different experimental conditions of the study (i.e. each one of the particular circumstances under which we want to test participants). By doing so, we maintained the complexity level of the tasks that the participants had to perform, so that the activity itself did not influence the study results. In order to avoid learning effects that can lead to the improvement on the performance of the users, for each condition of the study we altered the pattern of the activity and the objects involved on it, as a way to make the activity look like a completely different one. Accordingly, each experimental condition had a different activity pattern, as well as a specific number of micro-displays.

The visualizations designed for the study are shown in Figure 5.12. These representations provide awareness about: (i) the actions required from the participants in order to complete each activity, (ii) the position and state of the objects involved in such actions and (iii) the result of the actions (i.e. feedback indicating if the actions associated with a given task have been performed correctly or incorrectly). Figure 5.12(a) shows the main micro-display (activity-marker), which was placed on top of a table located at the main entrance of the room and next to the grid were the participants had to drop the objects collected. This micro-display shows the activity overview and indicates the position of the grid where each specific object must be placed. Moreover, other micro-displays (object-markers), shown in Figure (5.12(b), were distributed across the room to help participants select only the objects related with their current activity. These object-markers only display information about each particular object instead of about the activity as a whole.

Figure 5.12: Design of the visual representations of the activities

Procedure

The user study involved several students that had to move around a physical space to complete a given activity using the awareness information displayed in the micro-displays. We varied the distribution and density of micro-displays presented to the participants, generating different work conditions. The placement of situated micro-displays followed the guidelines given in [111] and the study involved three experimental scenarios.

The first scenario considers that the students only have one micro-display (activity-marker) located in an *activity-centric* fashion (i.e. at the main area where the activity is taking place) and it shows information about the activity as a whole. The second and third scenarios represent the *space-centric* and the *entity-centric* distribution respectively. The *space-centric* distribution considers micro-displays placed in a space shared by multiple entities (people or objects) and the *entity-centric* distribution involves a micro-display embedded in every entity.

To understand better the previous placement alternatives, let us consider a learning activity where medical students have to perform several treatment and care tasks with patients. Such tasks involve the use of medical equipment with several patients located in a big room. Figure 5.13 shows an example of an activity involving a patient and a blood pressure monitor. Considering this scenario, in an *activity-centric* placement, represented in Figure 5.13(a), the micro-display can be placed next to the patient's bed if we assume that this activity will be conducted while the patient is in bed. In the *space-centric* placement shown in Figure 5.13(b), the micro-display can be placed in an easily observable location of the physical space, such as the wall between two patients' beds. Finally, in the entity-centric placement represented in Figure 5.13(c), the micro-displays can be attached to the medical student, to the patient and to the blood pressure monitor, so that they can provide a finer detail of information and require less information updates to their more situated nature.

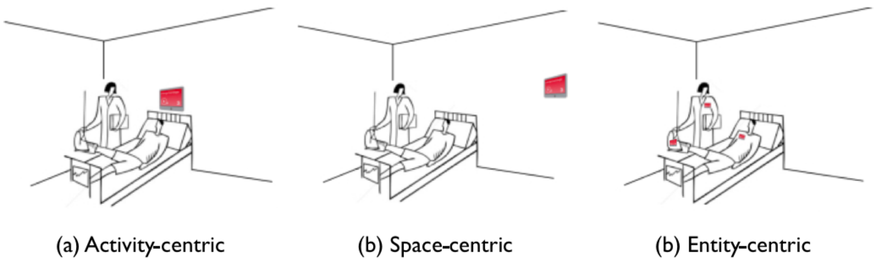


Figure 5.13: Placement posibilities of situated micro-displays

In our user study, in case of *space-centric* and *entity-centric* distributions, in addition to the activity-marker, we introduced 3 and 9 extra micro-displays respectively, which were used as object-markers. These object-markers show information about the objects involved in the main activity. In the *space-centric* scenario, we placed 3 micro-displays at different locations of the physical space where the several objects involved in the activity were placed. For the *entity-centric* scenario, due to the fact that the activities of the study entail interactions with 9 different objects, we placed the micro-displays very close to the location of these objects. We decided to use this specific number of micro-displays due to hardware restrictions –wireless connectivity– and also to make the study conveniently manageable and not tiring for the participants. Summarizing, the three experimental scenarios involved 1, 4 and 10 micro-displays respectively.

Physical Setup

The space where the study took place was a conference room of 20.4 m^2 approximately. Figure 5.14 shows, on a floor plan, the physical setup used in the *entity-centric* scenario. In this case, the distance between micro-displays was about 1.5 m.

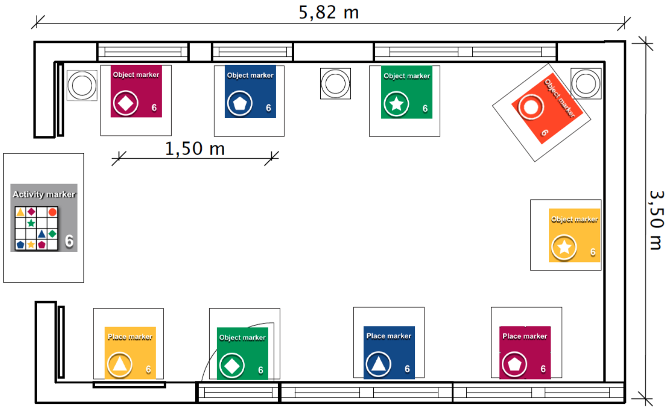


Figure 5.14: Floor Plan showing the physical setup

It is important to notice that across the different scenarios of the study, the spatial distribution of the micro-displays in the room was maintained, independently of the number of devices. Particularly, the maximum distance (in metres) between the farthest pair of micro-displays was the same for all scenarios and experimental conditions. Thus, we intended to assure that the different configurations of the various scenarios did not determine or affect the results of this study. The activity took place mainly on a tall table placed at the main entrance of the room. There we placed the main micro-display with the activity overview (to represent the *activity-centric* placement of situated micro-displays). We also placed across the room the different objects involved in the study activities. Other objects and activities were intentionally introduced in the room to simulate a scenario where the same physical space can be shared between several activities and entities. The walls of the room were partially covered with *Velcro*® material in order to be able to place and remove the micro-displays when needed, according to the characteristic of the particular experimental condition.

Participants

The participants in this study were 14 students from *Lancaster University,* who were recruited through posters and mailing lists. We did not involve participants with a particular profile or groups with special characteristics, because the study was not intended for a specific domain. Prior to perform the study, we asked participants to provide demographic data. There were 9 male and 5 female, aged 21 to 27 (average of 24.3). The study took approximately one and a half hour per participant. After finishing the study, the participants were paid £10 for their time.

Method

Participants took part in the experiment individually. They began the study being told about the study purpose and with a brief training session. We used A/V equipment to record the experiments and the people interviews for later analysis. As we mentioned previously, there was no context recognition per se so the user study was performed as a *Wizard of Oz experiment* (i.e. the participants believed that the system was autonomous but it was actually being controlled by a human) [143]. The study followed a *within-subjects design* [2], where each participant is exposed to the same experimental condition, experiencing the three different scenarios considered. In addition, we used a *Balanced Latin Square* [2] (i.e. each particular experimental condition appears before and after another condition an equal number of times, considering all the participants) for counterbalancing to mitigate potential learning effects. We also ensured that two participants completed each row in the Latin Square. The conditions of the study entailed the completion of 3 different activity patterns composed by 9 tasks each, which corresponds to the number of objects the users had to interact with to complete the activity. Following the completion of each condition, we asked each participant to answer several subjective questions taken from the *IBM Computer Usability Satisfaction Questionnaires* [129] and the *NASA Task Load Index* [89]. We also asked them additional questions for further evaluation of *divided attention* (i.e. using multiple sources of information instead of a single one in order to perform multiple tasks that require attention) and *information overload* (i.e. "receiving too much information") [68] issues. Furthermore, after the whole experimentation process, each participant answered the questions of a final *semi-structured interview* aimed at gathering additional feedback about the best distribution arrangement of micro-displays.

5.3.2.2 Evaluation Results

While participants were performing the different scenarios we observed and recorded their behaviour and reactions to have a log of quantitative data for later analysis. Moreover, we obtained qualitative data from participants through questionnaires and semi-structured interviews. In this section, we present and discuss the results obtained for this quantitative and qualitative data from five perspectives: task performance, fragmentation of attention, information overload and participant's satisfaction.

Completion Time and Errors

In [107] the author presents the use of the reaction time to measure the division of attention and also the accuracy and speed of an action as a measure of the spare cognitive capacity. Similarly, we use completion time and errors as indicators of the appearance of *divided attention* and *information overload* respectively as well as metrics of *performance.*

We computed the activity's ***completion time*** as the time elapsed from the moment the participants first looked at the main micro-display and the moment just after they placed the last piece of the puzzle in the right position of the grid. Results showed that a higher number of micro-displays can help decrease the activities' completion time. Figure 5.15 shows the average time that took the participants to complete the activities of each one of the scenarios of the study (i.e. *activity-centric, space-centric* and *entity centric* with 1, 4 and 10 micro-displays respectively). The difference between the fastest (using 10 micro-displays) and slowest performance (using 1 micro-display) was 8.67 seconds (7.9%). In addition, the dispersion of the completion time values is smaller for scenarios with a higher number of micro-displays.

Errors were classified into two types: completion and location errors. *Completion errors* are those occurred during the completion of the puzzle, e.g. placing a wrong object in the grid, having some objects missing, etc. The number of these errors was very small and we did not observe a direct correlation between the number of micro-displays and this kind of error. However, in the scenario

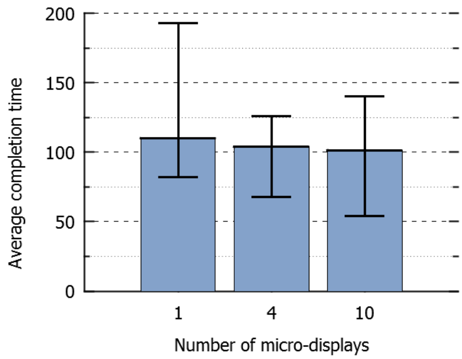


Figure 5.15: Completion time

with the highest number of micro-displays (i.e. *activity-centric*), the completion errors were 50% smaller than in the scenario with the lowest number of micro-displays (i.e. *entity-centric*). *Location errors* were counted when the participant picked the wrong objects from the different room locations. Location errors are a good metric of performance and efficiency, especially when the tasks are physically dispersed.

A high number of location errors imply that the individuals have to walk longer distances to complete the activity and, as a result, the effort and time required is higher. Figure 5.16 shows that the mean and maximum values of the location errors have a negative correlation with the number of micro-displays. The experiments performed in the *activity-centric* scenario (i.e. 1 micro-display) had a significantly higher average error rate (57.1%) than in the *entity-centric* one (i.e. 10 micro-displays).

Simultaneous Tasks and Iteration Steps

We used both simultaneous tasks and iteration steps as metrics to try to understand the effect of *divided attention* and *information overload* on the participants while performing the activities of the user study.

During the study we observed a strong relationship between the overall satisfaction of the participants and the number of simultaneous physical tasks they engaged with to complete a given activity. The participants' satisfaction also had a negative correlation with the number of iteration steps that they had

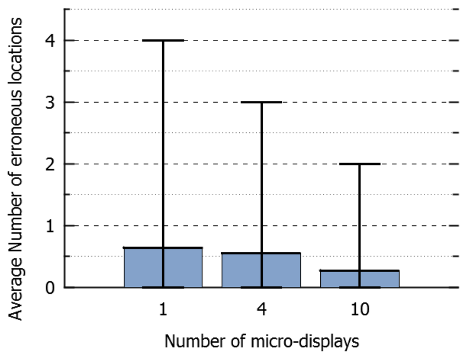


Figure 5.16: Location errors

to perform for completing the activity.

We computed the number of ***simultaneous tasks*** performed by participants, counting the maximum number of objects that they picked in the routes followed for completing the activity. Figure 5.17 shows the number of simultaneous tasks (minimum, maximum and average) performed by the participants. These results indicate a direct correlation between the average values of this variable and the micro-displays density. When we have nine *object-marker* micro-displays, the number of simultaneous tasks is 43.3% higher (in average) than when we only have the main *activity-marker* micro-display.

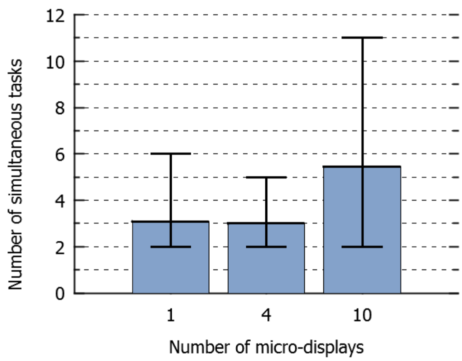


Figure 5.17: Simultaneous tasks

The ***iteration steps*** were defined as the number of stages that participants needed to complete the activity (i.e. the number of rounds around the room). Figure 5.18 shows the results of the iteration steps for the three scenarios of the user study. The results show a negative correlation between the number of micro-displays and the number of iteration steps required for the completion of the activities. There is a difference of 33.3% between the average values obtained in *activity-centric* and the *entity-centric* scenario. The same tendency is followed by the maximum and minimum values.

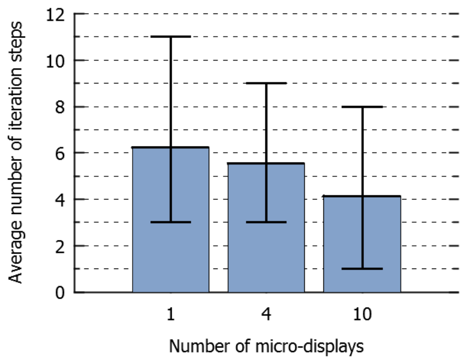


Figure 5.18: Iteration steps

Context Switches

A *context switch* happens when the participant's view switches from the main activity micro-display to any other point. Accordingly, we computed the number of eye movements of the participants. The results indicate that, in the scenario with the smallest number of micro-displays (i.e. *activity-centric*), students required a higher number of switches to accomplish the tasks. The results are depicted in Figure 5.19. The average context switches in the *activity-centric* scenario were 32.5% higher than in the *entity-centric* scenario. The maximum and minimum values of context switches also have this tendency.

It seems reasonable to think that *entity-centric* micro-displays introduce maximum *fragmentation of attention* (or *divided attention*) in comparison to *activity-centric* placement because the information is dispersed across a higher number of micro-displays, which could demand more context switches. However, these results confirm that a higher density of micro-displays actually reduces the context switching because the information is presented in a more situated fashion.

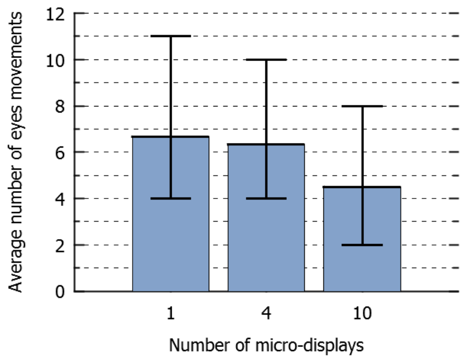


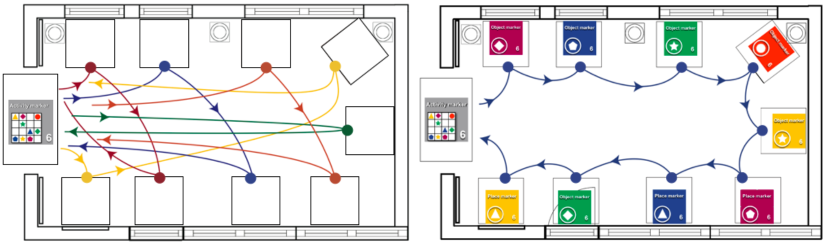
Figure 5.19: Context switches

Therefore, we cannot claim that having a higher number of micro-displays increases the *fragmentation of attention.*

Participants' Behaviour

Another interesting observation about the participants' behaviour while completing the activities is related to the physical path that they followed. We observed that there was an important difference in the number and shape of the routes that the participants followed for collecting the objects around the room. Figure 5.20 depicts two examples of the movement pattern of the participants to complete the activities of the study. Such movement patterns can be used as a metric of performance because they have influence on the physical effort required for the tasks, and therefore they also have an effect in the efficiency of the participants.

Figure 5.20(a) shows a sample result for the scenario with only the main *activity-marker* micro-display, whereas Figure 5.20(b) shows the result when the participants also had 9 additional *object-marker* micro-displays. Analysing these paths, we observe that a high number of micro-displays help reduce the number of rounds around the room required to complete the activities of the study. Therefore, we can claim that increasing the number of micro-displays results in a more efficient use of the physical space. We can also confirm the participants' impressions that a higher physical effort was needed when the number of micro-displays was small.



(a) Only the main micro-display (b) 10 micro-display

Figure 5.20: Examples of the movement patterns of the participants

Subjective feedback

After each experimental condition of the study, participants were asked about task demand, frustration level, perceived performance and needed effort using the *NASA Task Load Index* questionnaire. Figure 5.21 shows the results normalized to a 5 points scale from very low to very high. It shows that the condition with the highest number of micro-displays (i.e. *entity-centric*) was significantly better than the one with only one *activity-centric* micro-display with regard to the demand and effort required to complete the task. Nevertheless, they are more similar in terms of perceived performance and frustration level.

These results show that, according to the participants' feedback, completing the tasks without any *object-marker* micro-display required higher mental, physical and temporal demand, which resulted in a higher frustration level and lower perceived performance. For this reason, the effort needed for participants to accomplish their level of performance was higher in such a case than when they had *object-marker* micro-displays available.

In the post-condition interview, participants had also to express their agreement to several statements of the *IBM After-Scenario Questionnaire (ASQ)* and *Post-Study System Usability Questionnaire (PSSUQ)* using a 5 points scale from strongly disagree to strongly agree. A summary of the results is presented in Figure 5.22 and Figure 5.23.

Figure 5.22 shows that, in case of *entity-centric* scenarios, participants were more satisfied with their performance and the effort required to complete the

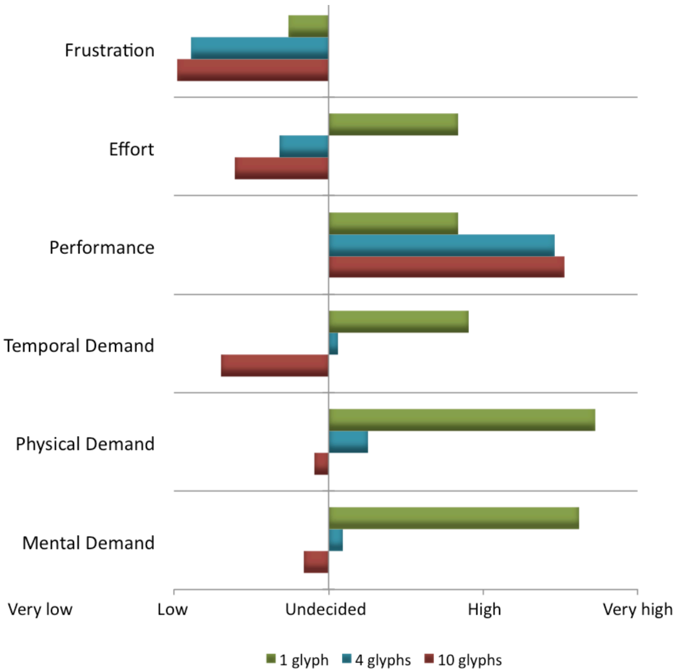


Figure 5.21: Task Load Index

tasks and especially, with the information support provided. The participants' opinions about the usability of the *TAM* are also shown in Figure 5.23.

In general, the conditions of the study with higher number of micro-displays gained better results than the one with only one micro-display. The participants felt that it was easier and faster to use as many micro-displays as objects. The scenario with the highest micro-display granularity (i.e. *entity-centric*) appealed to the majority of participants resulting in the most effective, enjoyable and effortless support. Participant 11, for example, indicated a low level of satisfaction when completing the activities without any *object-marker* micro-display, stating *"I had to do all by myself! The smaller screens were helpful in the previous tasks and I used to them a lot"*. Similarly, participant 12 indicated that if he would have had more displays, the task had been easier and faster, he also said that *"Having lots of displays is really good"*.

The results also showed that the participants think that the information pro-

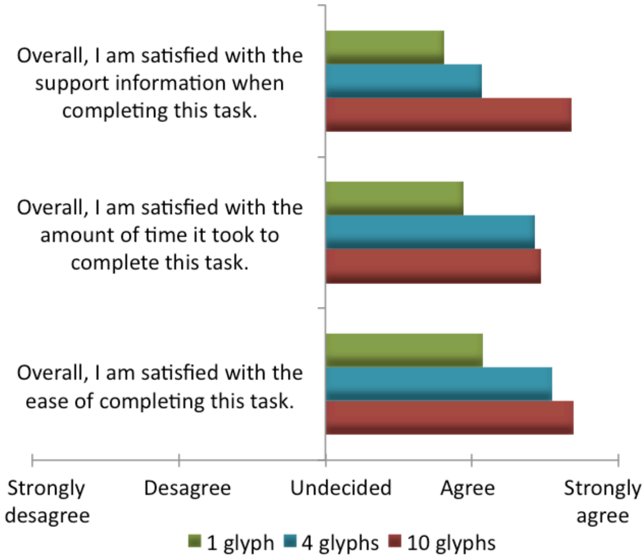


Figure 5.22: Results of the ASQ questionnaire for the TAM

vided with a high number of micro-displays was effective, clear and easy to find and understand. We consistently observed that the overall subjective response to the increment of the number of micro-displays was positive even when many participants already felt that they were able to complete the activities relying on their own capacity and with the only support of the *activity-marker* micro-display. However, most participants agreed that if the activity they had to perform were more complex, they would have preferred to have the support of a system with the highest micro-display granularity. For example, when asked how many micro-displays he would prefer to have, participant 2 answered *"As many as objects or a few less because I'd leave some room to think by myself"*. But when asked whether he would like to have situated micro-displays to support him in some real-world learning activities, he said *"If the activity is complex I'd trust completely in the system"*. Asked the same question, participant 13, said, *"Sure! Them make you organize and prioritize your work"*.

In addition to the *ASQ* and *PSSUQ* questionnaires, we conducted a *semi-structured interview* to ask participants some additional questions to evaluate some *attention management* (i.e. focused attention versus *divided attention*)

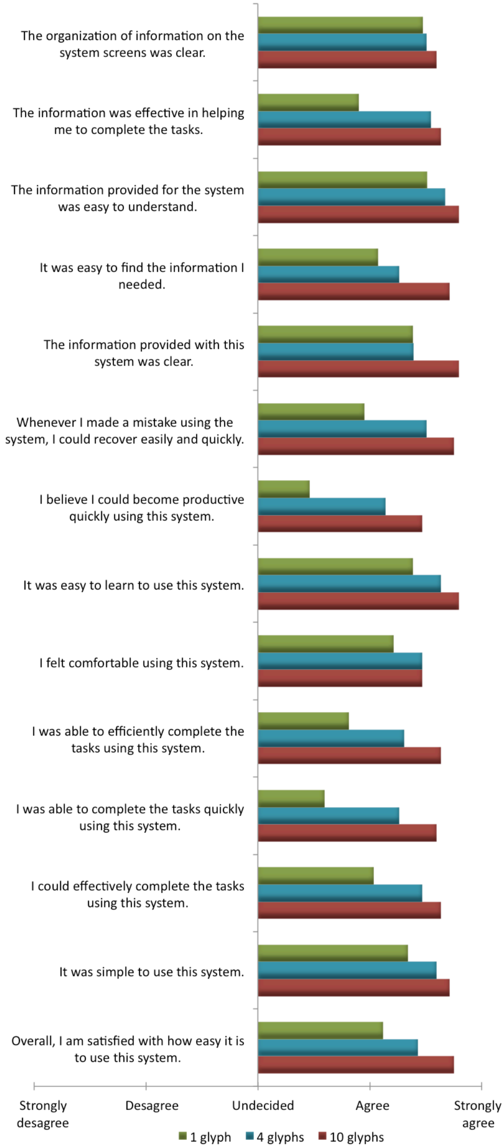


Figure 5.23: Results of the PSSUQ questionnaire for the TAM

and *information overload* issues. Our aim was to assess whether or not the fact of improving the quality of the information by increasing the number of micro-displays introduces *fragmentation of attention* (i.e. *divided attention*) and/or *information overload.*

Based on a study presented in [161], we used some metrics and indicators of *information overload*, such as recall and emergent and implicit poles, by asking participants some specific questions after finishing each experimental condition. Such questions required that the participants provided the following types of information: (i) descriptions of specific aspects of the information presented in the micro-displays, such as the colour of the screen or the shapes displayed and (ii) evaluations of how those aspects were different between displays, such as differences in colour between different groups of displays. The ability of participants to recall specific details of the information displayed was significantly good as well as their ability to highlight similarities and differences between the information provided in different displays. Hence, we did not observe signs of *information overload.*

On the other hand, all the participants said that they looked at the micro-displays one at a time, so that we could not find any evidence of the fact that a high number of micro-displays caused *fragmentation of attention.* In addition to this, although most participants claimed that the information provided for all the experimental conditions of the study was enough to meet the information requirements of the activity, they were more satisfied with the information provided by the highest number of micro-displays. Moreover, none of the participants felt, for any of the conditions, that they had received more information than what they could consistently handle. If we relate these observations with the results presented previously in Figure 5.19, where the context switches do not correlate with the number of micro-displays, we can therefore claim that there is not a direct relationship between the number of micro-displays and the participants' *attention management.* As a consequence, we can also affirm that having a high number of micro-displays did not produce a feeling of *information overload* on the participants.

5.3.3 Implications: Design Insights

Next, we summarize some design insights drawn from the results of our study. These insights allow designers to make informed decisions when developing task-centric awareness systems based on situated micro-displays.

Increasing the density of micro-displays improves activity performance and information support

The results indicate that an *entity-centric* distribution of the micro-displays helps boost user experience and has a positive impact on the activity performance and the quality of the information support. Both, quantitative and qualitative data showed that the perceived performance as well as the actual activity performance and increases with the number of micro-displays. Measurements of completion time, location errors, iteration steps and number of simultaneous tasks confirmed that the best performance is achieved when there are as many micro-displays as the number of objects involved in the activity. Furthermore, the participants' feedback reveals that most of them prefer to have a high density of micro-displays, because the information provided by them becomes clear and easy to find. This indicates that the quality of the supporting information increases with the micro-displays granularity.

Situated micro-displays require focused attention

During the interviews, the participants mentioned that they looked at the micro-displays one at a time. Thus, although we initially expected that situated micro-displays with an *entity-centric* placement would require *divided attention,* we found that instead, they required focused attention. Previous researchers have found that the performance of an individual when completing a task correlates positively with the amount of information that he receives; however, if the information provided is too much, his performance rapidly decline [68]. For this reason, we hypothesized that increasing the number of situated micro-display would improve activity performance but up to certain point, due to the fragmentation of the users' attention. Nevertheless, our findings revealed that micro-displays require focused attention and a higher density of them help reduce context switching, because the information is presented in a more situated fashion. The fastest completion times obtained during the experiments also confirm this finding. We cannot unequivocally assert these claims due to the limited number of participants and micro-displays involved in the experiments. Therefore, it would be necessary to perform more longitudinal studies in order to confirm statistically these observations.

Spatial distribution does not affect information processing capacity

According to the quantitative results and the participants' feedback, it seems that the spatial distribution of the information does not cause *information overload*. Moreover, the results confirmed that the quality of the provided information and the users' satisfaction increases with the density of micro-displays. Consequently, we can claim that an *entity-centric* placement of situated micro-displays, when the entities and task involved in the activity are spatially dispersed, does not affect the capacity of the users to successfully process the information. In fact, from the metrics of *information overload* used in the user study we could conclude that the participants did not show signs of *information overload* in any of the three scenarios considered.

Situated micro-displays can be used for structured activity route

As already expected and confirmed by the study results and the observation of behaviour of the participants, there are certain learning applications that could benefit from the use of situated micro-displays that are distributed in an *entity-centric* fashion; for instance, any type of application that involves a structured activity route. In other words, we can deploy the micro-displays in the physical environment where a learning activity is taking place in a way that the students are led to follow a specific path to complete the activity. Therefore, if the micro-displays are placed one after another in a structured fashion, there is a high possibility that the students follow a controlled activity route. An additional benefit is that if the deployment of the micro-displays is carefully planned, we could use more efficiently the physical space, improving the user experience and the physical effort required to complete the activity.

5.3.4 Design Guidelines

The presented results allow us to provide several design guidelines, which can support the design of pervasive monitoring solutions to display *task-centric* information in situated micro-displays. It is important to follow a user centric approach when deploying a situated micro-display network that supports mobile students while performing spatially distributed tasks. Thus, the designer improves the chances that the implementation of the pervasive monitoring system fits with the practices and awareness provision needs of the specific learning environment or activity.

Entity-centric distribution. *Entity-centric* placement of situated micro-displays seems to be the best alternative to guide spatially distributed learning activities. For this reason, micro-displays should be fully integrated in the learning environment and linked to the physical entities that are relevant for the activities.

Micro-display density. The scenario with the highest density of micro-displays was perceived as providing the most effective, enjoyable and effortless support for the students that participated in the study. Therefore, we recommend embedding as much micro-displays as possible in tools, resources and objects used by the students during a learning activity.

Trade-off between structured deployment of micro-displays and users' autonomy. We can use situated micro-displays to determine the physical movement patterns of the mobile students at the learning environment (e.g., classroom, laboratory, countryside, etc.). By taking away part of the control of the activity from the student, is possible to make a more effective use of the physical space and reduce the effort required for the completion of the learning activities. However, we cannot ensure that it would necessarily improve, for any type of learning activity, the students' efficiency and performance. Hence, the deployment of micro-displays should reach a delicate balance between regulating the learning flow patterns and preserving the autonomy and decision-making capacity of the students.

Context-based customisation. It is important to consider the learning context for the deployment of awareness solutions based on micro-displays. This context should consider the characteristics of both the learning activities and the environment in which they will be performed. Therefore, some factors such as screen size, visual design and the kind and amount of information to be provided by the micro-displays should be adapted accordingly.

5.4 Conclusions

In this chapter, we described and evaluated two awareness mechanisms that show how smartphone can be used as a flexible awareness tool in diverse learning contexts.

The first mechanism, the *Behaviour Awareness Mechanism (BAM)* was proposed as a method to provide visual feedback that supports collaborative learning by promoting reflection and encouraging social interactions. This mechanism differs from other proposals found in the literature (Section 2.5.1) mainly in two different aspects: (i) they typically focus on a particular type of awareness, such as individual contributions, conflict or peer feedback, whereas our proposal includes a wider range of sources for feedback, providing both subjective and objective information, (ii) their methods of feedback provision are restricted to particular contexts; i.e. most studies provide awareness only within the context of a specific collaborative activity, and they are linked to a particular collaborative application. By contrast, the *BAM* is intended to be used across different CSCL systems and contexts, and thus, it provides dynamic as well as lifelong feedback to the users.

In order to determine the usability and usefulness of the *BAM*, we conducted a proof-of-concept user study in an undergraduate course at the *Universitat Politècnica de Catalunya (UPC),* Spain. This evaluation included a case study considering a group of students working collaboratively during a software development project and using a mobile collaborative application that implements the proposed awareness mechanism.

The evaluation results indicate that the proposed awareness mechanism is useful to provide aggregate feedback about the students' behaviour and performance in educational contexts. They also show that this mechanism represents properly the different collaborative learning behavioural patterns of the students as well as the suggestions of potential suitable collaborators for them. Moreover, these findings suggests that the proposed awareness mechanism could help researchers and developers of CSCL applications to provide dynamic, direct and holistic awareness on the learning patterns and collaborative behaviour of the users. Although the *BAM* was initially proposed to support undergraduate courses and to use the smartphone's local screen directly as *awareness displays*, our findings suggests that it could also be suitable to be used in other types of collaborative activities and using other display technologies. The second awareness mechanism, the *Task-Centric Awareness Mechanism (TAM)*, is based on the use of situated micro-displays to present real-time, in-situ, and task-related awareness information to support complex, dynamic and spatially distributed learning activities. This focus differs from previous work, presented in Section 2.5.2, because the concept behind this research work is novel. Situated micro-displays are not peripheral or public displays. They have different qualities and their intended applications (i.e spatially distributed, complex and dynamic tasks that involve interaction with physical objects) are also distinct from the presented in the research studies reviewed (such as social interaction or collaborative work). In addition, our work is specifically centred on attention management issues related to the spatial distribution of ubiquitous, distributed displays, which are used to support demanding real-world learning activities.

We provided a proof-of-concept on the usability of situated-microdisplays, by developing a prototype of the *TAM*. We also performed a user study that explores the students' experiences with regards to the spatial distribution of micro-displays. We analysed the effect that the distribution granularity of micro-displays has on task performance as well as on the students' awareness, attention and satisfaction. The results provide clear evidence of the advantages of having a high density of situated micro-displays embedded in the learning environment. Some of these advantages are the improvement in activity completion time, the reduction of the errors, the improvement of the efficiency in the use of the physical space and a higher user satisfaction.

The results also indicate that the use of the *TAM* to support spatially distributed fluid tasks, which are part of a complex and dynamic activity, can boost user experience and have a positive impact in the performance of the students while completing such an activity. The results of the user study also helped us to gain further insights about the design implications of performing activities in environments with a high number of micro-displays. This fact, allowed us to provide some design guidelines that can help designers of pervasive monitoring solutions that will be deployed through situated micro-displays.

Chapter 6

Conclusions and Future Work

In this thesis, we investigated on the development of pervasive monitoring systems for heterogeneous and dynamic learning environments. More specifically, we focused on technological solutions to support the data collection, communication and awareness provision processes involved. In this chapter, we provide a brief overview of this work. It is organized as follows: Section 6.1 provides an abstract of our research, including the main findings and contributions. A summary of all the specific contributions of this dissertation is listed in Section 6.2. Some of the limitations of our work are presented in Section 6.3. Finally, Section 6.4 proposes some recommendations for future work.

6.1 Research Summary and Conclusions

This dissertation is inspired by the ubiquitous nature and sensor richness of modern smartphones and their application to the educational field. It explores the potentialities of using these devices as essential elements of the *pervasive monitoring system* proposed in this thesis. This system was envisioned to capture complex aspects about the activities that take place in today's dynamic learning environments. These aspects include individual and social factors about the student's behaviour, activities and performance that affect the learning experience. The main goal is to provide meaningful feedback to help students and lecturers to be aware of these factors and their effects on the learning process and its outcomes, enabling them to can take the necessary actions.

The literature review presented in Chapter 2 led us to the conclusion that the use of pervasive monitoring solutions in educational contexts have not been sufficiently explored. From this review, we identified three main demands: (i) there is a clear need to investigate in behaviour monitoring in learning contexts, providing a wider perspective on the topic and comprehensive solutions that consider technological, design and human factors, (ii) there is a lack of appropriate technological supports for both sensing and awareness provision, considering the complexity of contexts where learning processes can take place, and (iii) there is a need of clear approaches for modelling these systems and help developers envision their capabilities at design time. Therefore, despite the advances in sensing, communication and awareness solutions that could be used for pervasive monitoring in dynamic learning contexts, there are a number of aspects that still unexplored.

First, regarding the data collection from sensors, although a number of platforms, algorithms and applications have been developed to support and improve collaborative sensing interactions between diverse types of devices, it is not clear the sensing model that these platforms implement and the range of scenarios in which they can provide a solution. For this reason, it is necessary the development of generalizable and reusable solutions that could be applied to the diversity of devices, contexts and applications considered in today's heterogeneous learning activities. This is the objective of the *pervasive sensing framework* presented in Chapter 3.

Second, despite the advances in wireless communication technologies and the increasing availability of cellular and open-access Wi-Fi networks, there is a gap where *Mobile Ad hoc Networks (MANETs)* can provide an interesting communication alternative. These types of networks can be used as a complement to other fixed communication infrastructures to extend their capacity or coverage or as a low cost alternative when they are not available. Considering this, we proposed the use of *MANETs* to support pervasive monitoring. However, the particular features of these networks in terms of limited bandwidth and unreliability, make it necessary to assess the viability of using *MANETs* to support pervasive monitoring. Furthermore, due to the fact there is a limited number of real-world studies that assess the performance of *MANETs* and also that the credibility and reliability of simulation-based studies have been questioned [181, 122], there is a need for experimental studies that provide reliable insights on the suitability of these networks. The viability study presented in Chapter 4 closes the gap between simulations and real-world implementations of MANETs.

Third, the review of the related work on awareness provision showed that there is a need of designing flexible awareness methods that could be adapted to the diversity of environments and contexts where learning processes can take place. It was also relevant the lack of solutions that include a wider range of information sources for the *provision of awareness* and that can adapt to diverse contexts and applications. This fact has motivated the design of the *awareness mechanism* described in Chapter 5.

Consequently, the proposed pervasive monitoring system has three main research components. First, the description of a *generalized framework for pervasive sensing*. Second, the evaluation, through a real-world deployment, of the suitability of *Mobile Ad hoc Networks* as communication support for pervasive monitoring. Third, the design of two *awareness mechanisms* to allow flexible provision of information and feedback. Next, we describe briefly each one of these components.

The *Mobile Autonomous Sensing Unit (MASU) framework*, presented in Chapter 3 is a reusable design solution that offers a conceptual model to manage the distribution of collaborative sensing tasks among a group of devices (including smartphones, IoT devices, smart objects and other sensors available in the environment) in a context-aware and energy-efficient way. This framework considers changes in the context of the devices (e.g., battery level, processor load, ad hoc networking issues, etc.), the user (e.g., opportunities to collaborate) and the sensing activity (e.g., requirements and resources available at any given time) to determine the best arrangement for the allocation of sensing tasks among the participating devices. Even though, we developed this framework, envisioning its application in educational contexts, the level of abstraction of its design make it possible to use it as a general-purpose data collection solution for pervasive monitoring systems. The evaluation of this framework provided evidence on the usefulness and benefits to support pervasive sensing in terms of resource optimization, achieving up to 43% energy savings for the overall group of collaborating devices (Section 3.3.4.3)

The viability study described in Chapter 4 showed that *Mobile Ad hoc Networks* can effectively provide communication support for collaborative monitoring interactions between mobile devices. This study was based on a real-world *MANET* deployment that uses real hardware, software implementations and wireless channels. Results showed the suitability of *MANETs* to support pervasive monitoring, achieving acceptable levels of performance in terms of latency, jitter and throughput (Section 4.2.6). In addition, the *OLSRp prediction mechanism* was designed to increase the efficiency and scalability of these types of networks by reducing the control traffic produced by a particular type of routing message. This mechanism proved to be useful in reducing the network traffic and increasing the battery lifetime of the devices. The reduction in the control traffic was from 10% up to 80%, and the energy savings where from 20% up to 90%, both depending on the degree of mobility of the nodes. The findings of the viability study are applicable to collaborative applications intended to be deployed over *MANETs*. The *OLSRp* can also be used to increase scalability of other routing protocols that need to deal with the interchange of periodic control messages.

Finally, in Chapter 5 we described two *awareness mechanisms* that rely on the use of smartphones as flexible devices that can be used directly as awareness displays or to enable interaction with other remote displays available in the environment. The first mechanism, the *Behaviour Awareness Mechanism (BAM)*, was designed to provide visual feedback that supports collaborative learning by promoting reflection and encouraging social interactions. The *BAM* is intended to be used across different Computer-Supported Collaborative Learning (CSCL) systems and contexts, providing dynamic and lifelong feedback to the users. The second *awareness mechanism*, the *Task-Centric Awareness Mechanism (TAM)*, is based on the use of situated micro-displays to provide real-time, in-situ, and task-related awareness. The *TAM* supports dynamic and spatially distributed learning activities that require interaction with the entities (e.g., people, objects, furniture, etc.) that are within a physical space. Due to the generic features of the *BAM* mechanism, in addition to collaborative learning applications, it can be embedded in several other types of collaborative applications that require quantification and provision of awareness of a number of individual and group level variables that affect collaborative processes. Some examples include software development frameworks for managing product development, team building activities in companies, project management teams, etc.

We can conclude that, although the pervasive monitoring system proposed in this thesis was initially conceived for educational contexts, most parts of the research components proposed can be reused for similar monitoring solutions in other contexts.

6.2 Overview of Contributions

The contributions to the field of pervasive monitoring in dynamic learning contexts derived from the research work reported in this thesis can be divided into three basic groups: (i) contributions to the data collection (ii) contributions to the communication support and (iii) contributions to the awareness delivery. Following, we summarize the main components of these three sets of contributions.

6.2.1 Contributions to the Data Collection

An essential part of the research work presented is the definition of a *pervasive sensing framework* that allows to increase the quality of the data captured and optimize the use of resources. The contributions of this specific aspect of our research are the following:

C1. The description of the pervasive sensing framework, including its services, components and interaction protocols.

C2. The development of a prototype of the framework.

C3. An empirical evaluation of the framework that provides evidence on the usefulness and benefits of the proposed framework in terms of resource consumption as well as about its limitations and associated costs.

C4. A proposal of improvements to reduce the operating costs of the framework.

6.2.2 Contributions to the Communication Support

Concerning the communication support, this thesis proposes the use of *Mobile Ad hoc Networks* as an alternative communication infrastructure for pervasive monitoring. The specific contributions of this research component include: **C5**. An experimental study with real devices and networks on a realistic physical environment showing how *MANET* infrastructures can effectively support pervasive monitoring.

C6. An analysis of several networking issues of *MANETs*, identifying the limits of these networks in terms of performance and reliability and determining how they influence the usability of pervasive monitoring applications.

C7. A list of recommendations for the development of applications over *MANET* networks to help them meet the communication requirements for pervasive monitoring.

C8. The development and evaluation of a method to increase the efficiency of *MANETs* in terms of scalability, bandwidth availability, network collisions and resource consumption.

6.2.3 Contributions to the Awareness Delivery

We also propose several methods to deliver awareness information to the users of pervasive monitoring applications. The particular contributions of this aspect of our research are the following:

C9. The design of two *awareness mechanisms* to provide targeted and personalised feedback to students in diverse learning contexts.

C10. The implementation and evaluation of prototypes of the proposed *awareness mechanisms*.

C11. Design guidelines to support the development of awareness solutions to present the monitored information in two different types of displays.

C12. The description of use cases and user studies that show examples of applications of the proposed mechanisms and suggest that these mechanisms can produce changes in behaviour and contribute to improve the performance and experience the students.

In addition to the previous contributions, one indicator of the relevance of the research work presented in this thesis as well as its impact on future research work, is a number of scientific papers that have been published in seven international conferences and two journals. Tabla6.1 shows all the contributions presented above and their associated papers from the list of the core publications of this thesis.

Table 6.1: Contributions and associated publications

Contributions	**Publications**
C1, C2, C3, C4	Published in CC1 and CC2
C5, C6, C7	Published in CC6, CC7, CJ1 and CJ2
C8	Published in CC5
C9, C10, C11, C12	Published in CC3 and CC4

6.3 Limitations

The aim of this dissertation was to propose and develop a set of solutions to allow developers to build pervasive monitoring solutions that are suitable to be used in modern learning contexts. Our main focus was on the use of collaborative sensing techniques for data collection, *Mobile Ad hoc Networks* for communication, and smartphone-triggered solutions for awareness. For this reason, all the research and development effort was centred on reaching the objectives related to those specific aspects. Therefore, although, the objectives of this thesis have been successfully achieved, as any proposal, it also has a number of limitations. The main limitations identified are the following:

The *pervasive sensing framework* proposed in this thesis is not meant to provide a complete collaborative sensing solution or a final product. Our objective for the definition of this framework was to offer a generalized and adaptable solution that provides guidance for the implementation of a number of interesting solutions or applications. Therefore, to build pervasive monitoring applications, developers can easily reuse our solution, which facilitates the design phase and reduces the development costs.

Regarding the solutions proposed for the data collection and communication elements of our system, the evaluation methods used to assess the viability and performance also had some restrictions. Although we used a combination of simulations and prototypes to try to overcome the particular limitations of using either of these methods in isolation, there are still a number of aspects that could not be evaluated in a comprehensive way. On the one hand, simulations are based on models and simplifications of real-world conditions, which rely on artificial mobility patterns and idealized models of radio propagation and interferences. Moreover, they do not consider heterogeneity of devices, the limitations of real software implementations or the real behaviour of hardware components. On the other hand, real-world experiments also have some restrictions. Although the evaluation of prototypes or real deployments include realism and heterogeneity, the number of devices that can be use is limited. Furthermore, both data traffic and mobility patterns are modelled in order to emulate the behaviour of real users. However, they cannot accurately capture all the possible effects of the users' behaviour and their interactions with the devices. Therefore, the results from real-world experiments are useful to validate the usefulness and viability of these solutions. However, it would be necessary to perform further experiments considering real-life activities in order to be able to accurately evaluate the performance of the prototypes under real conditions.

Concerning the evaluation of the prototypes of the proposed *awareness mechanisms*, although they were evaluated with real users and in real-world learning environments, there are also a number of limitations that should be considered. The most important, and existing in the evaluation of both the *BAM* and the *TAM* prototypes, is the fact that the number of participants of the user studies was limited, which makes difficult to generalize the applicability of the results. Another limitation encountered in the evaluation of the *TAM* was the fact that the study conditions were controlled. The main reason for this was to ensure the repeatability of the experiments to be able to compare and contrast the performance and behaviour of the students, isolating the independent variable of the study (i.e. the number of micro-displays). Therefore, the experimental tasks do not fully reflect existing learning practices, which reduces the degree of realism of the study. Longitudinal field user studies that involve real-life learning activities would be necessary to assess accurately the impact of the proposed *awareness mechanism* on the students.

6.4 Future Research Directions

Considering the limitations of the solutions proposed in this dissertation, a number of important considerations for future work were identified, relating to both evaluation methodology and design. Next, we present a list of recommendations considering these aspects.

An evident future line of research can involve the implementation of the *MASU* framework as a smartphone application. This would involve the specification of the particular decision making policies that would be applied for the selection and activation of sensing roles. For instance, determining which specific hardware capabilities of the devices would be use the selection of roles as well as the particular thresholds that would trigger changes in the assignation of roles (i.e. fault tolerance mechanism). Other examples are the selection of appropriate algorithms for the selection of the manager of the collaborative sensing activity (i.e. leader election) or to determine if collaborative sensing is beneficial for the devices or if they should work autonomously (i.e. cost function) In reference to the evaluation methods, if we consider the data sensing and communication components of this thesis, an important next step is to explore how instrumental are the data traffic, application usage and mobility patterns of the users in the performance of the proposed monitoring system. Therefore, future works can focus on real-life experiments, involving the use of the developed prototypes in real learning activities.

Regarding the *OLSRp prediction mechanism*, future studies can investigate how to extend and adapt this work to similar routing protocols. Furthermore, it would be interesting to study the adaptability of this mechanism to heterogeneous scenarios in which some nodes use the *OLSRp* mechanism while other nodes use the standard OLSR protocol. More sophisticated prediction techniques can be also investigated to try to improve the results in high mobility scenarios.

Regarding the awareness provision component of this research, there is a need of additional case studies in order to further evaluate the suitability of the proposed approach in different educational and organizational contexts.

Based on the *BAM* mechanism, future research can investigate on how the provision of awareness information (about collaborative learning patterns) that this mechanism offers may affect the behaviour of the students and their collaboration dynamics. Another research direction can be the development of relevant and specific metrics to quantify the different features of the collaborative learning behaviour that are included in the *BAM*. The design of the *BAM* can also be improved and extended to include, for example, additional visualization modules that show details of how each one of the features represented have been measured (e.g., if the *Coordination* feature includes metrics from email interchanges, project management applications, etc.) and weighted (e.g., if email interchange only contributes to a 10% of the value of such a feature). Finally, an important area of future research can be centred on identifying the different types of data that can be captured using smartphones (and from the *e-Learning environment*), and how they can be used to quantify the collaborative features of the *BAM*. For instance, assessing whether or not is actually possible to measure the quality of collaborative processes and of individual contributions to the group work.

Regarding the *TAM* mechanism, future studies should consider performing longitudinal field studies that consider diverse types of real-world learning environments and activities. These studies can be useful to help generalise the results of the controlled laboratory user studies to particular environments. This would allow to study the impact of the *TAM* on the development of activities, the performance of students and the dynamics of the different types of interactions between students and other entities of the physical space. This fact could lead to the appearance of novel learning practices as well as to new evaluation methods based on the monitoring of such interactions.

Bibliography

[1] Google cloud messaging for android — android developers. http://developer.android.com/google/gcm/index.html. (Accessed on 15 October 2015).

[2] Within-subjects vs. between-subjects designs: Which to use? http://www.yorku.ca/mack/RN-Counterbalancing.html. (Accessed on April 2015).

[3] The alljoyn framework. https://allseenalliance.org/developers/learn/. (Accessed on 5 July 2015).

[4] B.A.T.M.A.N. http://www.open-mesh.org/projects/open-mesh/wiki/Download. (Accessed on 12 October 2015).

[5] CoAP – constrained application protocol overview. http://coap.technology/. (Accessed on 18 May 2015).

[6] Ns-3 network simulator. http://www.nsnam.org/. (Accessed on 12 Juny 2015).

[7] OLSR. http://www.olsr.org/mediawiki/index.php/Olsrd, . (Accessed on 12 October 2015).

[8] OLSR2. http://www.olsr.org/mediawiki/index.php/Olsrd2, . (Accessed on 12 October 2015).

[9] Tcpdump. https://www.wireshark.org/. (Accessed on 12 October 2015).

[10] Unity. http://www.unity3d.com. (Accessed on 15 October 2015).

[11] Wireshark. `https://www.wireshark.org/`. (Accessed on 12 October 2015).

[12] In *Trends in Applied Intelligent Systems*, volume 6096 of *LNCS*. 2010.

[13] Two make a network: Using graphs to assess the quality of collaboration of dyads. In *Collaboration and Technology*, volume 8658 of *LNCS*, pages 53–66. 2014. doi: 10.1007/978-3-319-10166-8_5.

[14] Z. H. Abbas. *Energy Efficiency in Hybrid Mobile and Wireless Networks*. PhD thesis, 2012.

[15] A. Abbasi, J. Altmann, and L. Hossain. Identifying the effects of co-authorship networks on the performance of scholars: A correlation and regression analysis of performance measures and social network analysis measures. *Journal of Informetrics*, 5(4):594–607, 2011. doi: 10.1016/j.joi.2011.05.007.

[16] G. D. Abowd. Classroom 2000: An experiment with the instrumentation of a living educational environment. *IBM systems journal*, 38(4):508–530, 1999. doi: 10.1147/sj.384.0508.

[17] N. Aharony, W. Pan, C. Ip, I. Khayal, and A. Pentland. Social fmri: Investigating and shaping social mechanisms in the real world. *Pervasive and Mobile Computing*, 7(6):643–659, 2011. doi: 10.1016/j.pmcj.2011.09.004.

[18] H. S. Alavi and P. Dillenbourg. An ambient awareness tool for supporting supervised collaborative problem solving. *Learning Technologies, IEEE Transactions on*, 5(3):264–274, 2012. doi: 10.1109/TLT.2012.7.

[19] R. G. Aldunate, G. E. Larson, M. Nussbaum, S. F. Ochoa, and O. A. Herrera. Understanding the role of mobile ad hoc networks in non-traditional contexts. In *Mobile and Wireless Communication Networks*, volume 211 of *IFIP*, pages 199–215. 2006. doi: 10.1007/978-0-387-34736-3_15.

[20] C. Ameixieira, A. Cardote, F. Neves, R. Meireles, S. Sargento, L. Coelho, J. Afonso, B. Areias, E. Mota, R. Costa, et al. Harbornet: A real-world testbed for vehicular networks. *Communications Magazine, IEEE*, 52(9):108–114, 2014. doi: 10.1109/MCOM.2014.6894460.

[21] P. Antunes, V. Herskovic, S. F. Ochoa, and J. A. Pino. Reviewing the quality of awareness support in collaborative applications. *Journal of Systems and Software*, 89:146–169, 2014. doi: 10.1016/j.jss.2013.11.1078.

[22] N. Aschenbruck, R. Ernst, E. Gerhards-Padilla, and M. Schwamborn. Bonnmotion: A mobility scenario generation and analysis tool. In *Proceedings of Simulation Tools and Techniques(SIMUTools)*, pages 51:1–51:10, 2010. doi: 10.4108/ICST.SIMUTOOLS2010.8684.

[23] L. Atallah and G.-Z. Yang. The use of pervasive sensing for behaviour profiling—a survey. *Pervasive and Mobile Computing*, 5(5):447–464, 2009. doi: 10.1016/j.pmcj.2009.06.009.

[24] R. Balan, Y. Lee, T. K. Wee, and A. Misra. The challenge of continuous mobile context sensing. In *Proceedings of Communication Systems and Networks (COMSNETS)*, pages 1–8, 2014. doi: 10.1109/COMSNETS.2014.6734869.

[25] J. Bardram. A novel approach for creating activity-aware applications in a hospital environment. In *Human-Computer Interaction – INTERACT 2009*, volume 5727 of *LNCS*, pages 731–744. 2009. doi: 10.1007/978-3-642-03658-3_78.

[26] P. Bellavista, A. Corradi, M. Fanelli, and L. Foschini. A survey of context data distribution for mobile ubiquitous systems. *ACM Computing Surveys*, 44(4):24:1–24:45, 2012. doi: 10.1145/2333112.2333119.

[27] C. Berkhoff, S. F. Ochoa, J. A. Pino, J. Favela, J. Oliveira, and L. A. Guerrero. Clairvoyance: A framework to integrate shared displays and mobile computing devices. *Future Generation Computer Systems*, 34:190–200, 2014. doi: 10.1016/j.future.2013.10.013.

[28] R. S. Bhadoria, G. S. Tomar, and S. Kang. Proficient energy consumption aware model in wireless sensor network. *International Journal of Multimedia and Ubiquitous Engineering*, 9(5):27–36. doi: 10.14257/ijmue.2014.9.5.03.

[29] S. Biswas, J. Bicket, E. Wong, R. Musaloiu-E, A. Bhartia, and D. Aguayo. Large-scale measurements of wireless network behavior. In *Proceedings of Special Interest Group on Data Communication (SIGCOMM)*, pages 153–165, 2015. doi: 10.1145/2785956.2787489.

[30] D. Bodemer and J. Dehler. Group awareness in cscl environments. *Computers in Human Behavior*, 27(3):1043–1045, 2011. doi: 10.1016/j.chb.2010.07.014.

[31] D. Börner, M. Kalz, and M. Specht. Beyond the channel: A literature review on ambient displays for learning. *Computers & Education*, 60(1):426–435, 2013. doi: 10.1016/j.compedu.2012.06.010.

[32] A. Boukerche, S. K. Das, and A. Fabbri. Analysis of a randomized congestion control scheme with {DSDV} routing in ad hoc wireless networks. *Journal of Parallel and Distributed Computing*, 61(7):967–995, 2001. doi: 10.1006/jpdc.2000.1723.

[33] E. A. Brewer. Lessons from giant-scale services. *IEEE Internet Computing*, 5(4):46–55, 2001. doi: 10.1109/4236.939450.

[34] H. Brignull and Y. Rogers. Enticing people to interact with large public displays in public spaces. In *INTERACT*, volume 3, pages 17–24, 2003.

[35] C. Brown, C. Efstratiou, I. Leontiadis, D. Quercia, and C. Mascolo. Tracking serendipitous interactions: How individual cultures shape the office. In *Computer supported cooperative work & social computing (CSCW)*, pages 1072–1081, 2014. doi: 10.1145/2531602.2531641.

[36] C. Brown, C. Efstratiou, I. Leontiadis, D. Quercia, C. Mascolo, J. Scott, and P. Key. The architecture of innovation: Tracking face-to-face interactions with ubicomp technologies. In *Pervasive and Ubiquitous Computing (UbiComp)*, pages 811–822, 2014. doi: 10.1145/2632048.2632056.

[37] R. Bruno, M. Conti, and E. Gregori. Mesh networks: commodity multihop ad hoc networks. *IEEE Communications Magazine*, 43(3):123–131, 2005. doi: 10.1109/MCOM.2005.1404606.

[38] J. Buder. Group awareness tools for learning: Current and future directions. *Computers in Human Behavior*, 27(3):1114–1117, 2011. doi: 10.1016/j.chb.2010.07.012.

[39] J. Buder and D. Bodemer. Supporting controversial cscl discussions with augmented group awareness tools. *International Journal of Computer-Supported Collaborative Learning*, 3(2):123–139, 2008. doi: doi:10.1007/s11412-008-9037-5.

[40] A. Buja, D. F. Swayne, M. L. Littman, N. Dean, H. Hofmann, and L. Chen. Data visualization with multidimensional scaling. *Journal of Computational and Graphical Statistics*, 17(2):444–472, 2008. doi: 10.1198/106186008X318440.

[41] J. Burke, D. Estrin, M. Hansen, A. Parker, N. Ramanathan, S. Reddy, and M. Srivastava. Participatory sensing. In *Workshop on World-Sensor-Web (WSW): Mobile Device Centric Sensor Networks and Applications*, 2006.

[42] D. Buszko, W.-H. D. Lee, and A. S. Helal. Decentralized ad-hoc groupware api and framework for mobile collaboration. In *SIGGROUP Conference on Supporting Group Work*, pages 5–14, 2001. doi: 10.1145/500286.500291.

[43] C. T. Calafate, M. P. Malumbres, and P. Manzoni. Performance of h. 264 compressed video streams over 802.11 b based manets. In *Distributed Computing Systems Workshops*, pages 776–781, 2004. doi: 10.1109/ICDCSW.2004.1284121.

[44] T. Camp, J. Boleng, and V. Davies. A survey of mobility models for ad hoc network research. *Wireless Communications and Mobile Computing*, 2(5):483–502, 2002. doi: 10.1002/wcm.72.

[45] A. T. Campbell, S. B. Eisenman, N. D. Lane, E. Miluzzo, R. Peterson, H. Lu, X. Zheng, M. Musolesi, K. Fodor, G.-S. Ahn, et al. The rise of people-centric sensing. *Internet Computing, IEEE*, 12(4):12–21, 2008. doi: 10.1109/MIC.2008.90.

[46] P. Carreño, F. J. Gutierrez, S. F. Ochoa, and G. Fortino. Supporting personal security using participatory sensing. *Concurrency and Computation: Practice and Experience*, 2014. doi: 10.1002/cpe.3450.

[47] I. Casas, C. Collazos, L. A. Guerrero, C. Leiva, S. Ochoa, and J. Puente. Addressing computer-supported collaborative learning in the classroom: Experiences in engineering education. *Procedia-Social and Behavioral Sciences*, 2(2):2685–2688, 2010. doi: 10.1016/j.sbspro.2010.03.396.

[48] E. Castillejo, A. Almeida, and D. López-de Ipiña. User, context and device modeling for adaptive user interface systems. In *Ubiquitous*

Computing and Ambient Intelligence. Context-Awareness and Context-Driven Interaction, volume 8276 of *LNCS*, pages 94–101. 2013. doi: 10.1007/978-3-319-03176-7_13.

[49] R.-S. Chang, W.-Y. Chen, and Y.-F. Wen. Hybrid wireless network protocols. *IEEE Transactions on Vehicular Technology*, 52(4):1099–1109, 2003. doi: 10.1109/TVT.2002.807126.

[50] H.-C. Chao and C.-Y. Huang. Micro-mobility mechanism for smooth handoffs in an integrated ad-hoc and cellular ipv6 network under high-speed movement. *IEEE Transactions on Vehicular Technology*, 52(6): 1576–1593, 2003. doi: 10.1109/TVT.2003.819450.

[51] H.-C. Cheng and W.-W. Liao. Situated learning: Legitimate peripheral participation. In *Proceedings of Human-Computer Interaction (CHI)*, 2011.

[52] H.-C. Cheng and W.-W. Liao. Establishing an lifelong learning environment using iot and learning analytics. In *Proceedings of Advanced Communication Technology (ICACT)*, pages 1178–1183, 2012.

[53] K.-W. Chin, J. Judge, A. Williams, and R. Kermode. Implementation experience with manet routing protocols. *ACM SIGCOMM Computer Communication Review*, 32(5):49–59, 2002. doi: 10.1145/774749.774758.

[54] J.-M. Choi and Y.-B. Ko. A performance evaluation for ad hoc routing protocols in realistic military scenarios. In *Proceedings of Cellular and Intelligent Communications (CIC)*, 2004.

[55] Y. Chon, N. D. Lane, F. Li, H. Cha, and F. Zhao. Automatically characterizing places with opportunistic crowdsensing using smartphones. In *Proceedings of Ubiquitous Computing (UbiComp)*, pages 481–490, 2012. doi: 10.1145/2370216.2370288.

[56] T. Clausen and P. Jacquet. Optimized link state routing protocol (olsr). Technical report, 2003.

[57] D. Davcev and A. Karadimce. Model for interactive, collaborative and multimedia mobile learning environment. In *Advances in Mobile Computing & Multimedia*, page 585, 2013. doi: 10.1145/2536853.2536913.

[58] S. Dawson, A. Bakharia, and E. Heathcote. Snapp: Realising the affordances of real-time sna within networked learning environments. In *Proceedings of Networked Learning (NLC)*, pages 125–133, 2010.

[59] D. S. J. De Couto, D. Aguayo, J. Bicket, and R. Morris. A high-throughput path metric for multi-hop wireless routing. In *Proceedings of Mobile Computing and Networking (MobiCom)*, pages 134–146, 2003. doi: 10.1145/938985.939000.

[60] H. de F Santos, L. H. Santana, D. S. Martins, W. L. De Souza, A. F. do Prado, and M. Biajiz. A ubiquitous computing environment for medical education. In *Symposium Applied computing (SAC)*, pages 1395–1399, 2008.

[61] A. A. de Freitas and A. K. Dey. The group context framework: An extensible toolkit for opportunistic grouping and collaboration. In *Proceedings of Computer Supported Cooperative Work & Social Computing (CSCW)*, pages 1602–1611, 2015. doi: 10.1145/2675133.2675205.

[62] A. Y. Ding. Collaborative communication and sensing for mobile systems. In *Doctoral Colloquium of Embedded Network Sensor Systems (SenSys)*, 2013.

[63] R. Draves, J. Padhye, and B. Zill. Comparison of routing metrics for static multi-hop wireless networks. *SIGCOMM Computer Communication Review*, 34(4):133–144, 2004. doi: 10.1145/1030194.1015483.

[64] J. Dyck. A survey of application-layer networking techniques for real-time distributed groupware. Technical Report HCI-TR-06-06, 2006.

[65] N. Eagle and A. (Sandy) Pentland. Reality mining: sensing complex social systems. *Personal and Ubiquitous Computing*, 10(4):255–268, 2006. doi: 10.1007/s00779-005-0046-3.

[66] C. Efstratiou, I. Leontiadis, M. Picone, K. Rachuri, C. Mascolo, and J. Crowcroft. Sense and sensibility in a pervasive world. In *Pervasive Computing*, volume 7319 of *LNCS*, pages 406–424. 2012. doi: 10.1007/978-3-642-31205-2_25.

[67] C. A. Ellis, S. J. Gibbs, and G. Rein. Groupware: some issues and experiences. *Communications of the ACM*, 34(1):39–58, 1991. doi: 10.1145/99977.99987.

[68] M. J. Eppler and J. Mengis. The concept of information overload: A review of literature from organization science, accounting, marketing, mis, and related disciplines. *The information society*, 20(5):325–344, 2004. doi: 10.1080/01972240490507974.

[69] Z. Feng, Y. Zhu, Q. Zhang, L. M. Ni, and A. V. Vasilakos. Trac: Truthful auction for location-aware collaborative sensing in mobile crowdsourcing. In *INFOCOM*, pages 1231–1239, 2014. doi: 10.1109/INFOCOM.2014.6848055.

[70] A. Filipovic and A. Datta. Building blocks of energy and cost efficient wireless sensor networks. In *Wireless Sensor Networks*, volume 2920 of *LNCS*, pages 218–233. 2004. doi: 10.1007/978-3-540-24606-0_15.

[71] L. D. Fink. *Creating significant learning experiences: An integrated approach to designing college courses*. John Wiley & Sons, 2013.

[72] G. Fortino, S. Galzarano, R. Gravina, and W. Li. A framework for collaborative computing and multi-sensor data fusion in body sensor networks. *Information Fusion*, 22:50–70, 2015. doi: 10.1016/j.inffus.2014.03.005.

[73] J. Fransen, P. A. Kirschner, and G. Erkens. Mediating team effectiveness in the context of collaborative learning: The importance of team and task awareness. *Computers in Human Behavior*, 27(3):1103–1113, 2011. doi: 10.1016/j.chb.2010.05.017.

[74] A. Fuller, P. McFarlane, and D. Saffioti. Distributed, collaborative learning environments using ad hoc networks. In *Advanced Learning Technologies (ICALT)*, pages 705–707, 2004. doi: 10.1109/ICALT.2004.1357629.

[75] R. Gafni. Usability issues in mobile-wireless information systems. *Issues in Informing Science and Information Technology*, 6:755–769, 2009.

[76] R. Ganti, F. Ye, and H. Lei. Mobile crowdsensing: current state and future challenges. *IEEE Communications Magazine*, 49(11):32–39, 2011. doi: 10.1109/MCOM.2011.6069707.

[77] Ó. García, R. S. Alonso, D. I. Tapia, and J. M. Corchado. Evaluating zigbee protocol to design cafla: A framework to develop location-based learning activities. In *International Workshop on Evidence-Based Technology Enhanced Learning*, pages 125–132, 2012. doi: 10.1007/978-3-642-28801-2_15.

[78] P. Georgiev, N. D. Lane, K. K. Rachuri, and C. Mascolo. Dsp. ear: Leveraging co-processor support for continuous audio sensing on smartphones. In *Embedded Network Sensor Systems (SenSys)*, pages 295–309, 2014. doi: 10.1145/2668332.2668349.

[79] S. Greenberg and M. Rounding. The notification collage: posting information to public and personal displays. In *Human factors in computing systems (CHI)*, pages 514–521, 2001. doi: 10.1145/365024.365339.

[80] C. L. Gress, M. Fior, A. F. Hadwin, and P. H. Winne. Measurement and assessment in computer-supported collaborative learning. *Computers in Human Behavior*, 26(5):806–814, 2010. doi: 10.1016/j.chb.2007.05.012.

[81] J. Grudin. Partitioning digital worlds: focal and peripheral awareness in multiple monitor use. In *Human factors in computing systems (CHI)*, pages 458–465, 2001. doi: 10.1145/365024.365312.

[82] T. U. Grund. Network structure and team performance: The case of english premier league soccer teams. *Social Networks*, 34(4):682–690, 2012. doi: 10.1016/j.socnet.2012.08.004.

[83] D. Guinard, V. Trifa, S. Karnouskos, P. Spiess, and D. Savio. Interacting with the soa-based internet of things: Discovery, query, selection, and on-demand provisioning of web services. *IEEE Transactions on Services Computing*, 3(3):223–235, 2010. doi: 10.1109/TSC.2010.3.

[84] B. Guo, Z. Yu, X. Zhou, and D. Zhang. From participatory sensing to mobile crowd sensing. In *Workshops of Pervasive Computing and Communications (PERCOM)*, pages 593–598, 2014.

[85] B. Guo, Z. Wang, Z. Yu, Y. Wang, N. Y. Yen, R. Huang, and X. Zhou. Mobile crowd sensing and computing: The review of an emerging human-powered sensing paradigm. *ACM Computing Surveys (CSUR)*, 48(1):7, 2015. doi: 10.1145/2794400.

[86] C. Gutwin. The effects of network delays on group work in real-time groupware. In *Proceedings of European Conference on Computer Supported Cooperative Work (ECSCW)*, pages 299–318, 2001. doi: 10.1007/0-306-48019-0_16.

[87] L. Hallnäs and J. Redström. Slow technology–designing for reflection. *Personal and ubiquitous computing*, 5(3):201–212, 2001. doi: 10.1007/PL00000019.

[88] M. Hardy. Pareto's law. *The Mathematical Intelligencer*, 32(3):38–43, 2010. doi: 10.1007/s00283-010-9159-2.

[89] S. G. Hart and L. E. Staveland. Development of nasa-tlx (task load index): Results of empirical and theoretical research. *Advances in psychology*, 52:139–183, 1988. doi: 10.1016/S0166-4115(08)62386-9.

[90] D. Hernández-Leo, R. Nieves, E. Arroyo, A. Rosales, J. Melero, and J. Blat. Sos: Orchestrating collaborative activities across digital and physical spaces using wearable signaling devices. *Journal of Universal Computer Science*, 18(15):2165–2186, 2012. doi: 10.3217/jucs-018-15-2165.

[91] V. Herskovic, S. F. Ochoa, J. A. Pino, and H. A. Neyem. The iceberg effect: Behind the user interface of mobile collaborative systems. *Journal of Universal Computer Science*, 17(2):183–201, 2011. doi: 10.3217/jucs-017-02-0183.

[92] C. Heyer. Investigations of ubicomp in the oil and gas industry. In *Ubiquitous computing (UbiComp*, pages 61–64, 2010. doi: 10.1145/1864349.1864360.

[93] C. Hochleitner, C. Graf, D. Unger, and M. Tscheligi. Making devices trustworthy: Security and trust feedback in the internet of things. In *Workshop on Security and Privacy in Spontaneous Interaction and Mobile Phone Use (IWSSI/SPMU)*, 2012.

[94] S. Hodges, S. Taylor, N. Villar, J. Scott, D. Bial, and P. T. Fischer. Prototyping connected devices for the internet of things. *Computer*, 46(2):26–34, 2013. doi: 10.1109/MC.2012.394.

[95] X. Hong, K. Xu, and M. Gerla. Scalable routing protocols for mobile ad hoc networks. *IEEE Network*, 16(4):11–21, 2002. doi: 10.1109/MNET.2002.1020231.

[96] C. J. Hooper, A. Preston, M. Balaam, P. Seedhouse, D. Jackson, C. Pham, C. Ladha, K. Ladha, T. Plötz, and P. Olivier. The french kitchen: task-based learning in an instrumented kitchen. In *Ubiquitous Computing (UbiComp)*, pages 193–202, 2012. doi: 10.1145/2370216.2370246.

[97] S. A. Hoseini-Tabatabaei, A. Gluhak, and R. Tafazolli. A survey on smartphone-based systems for opportunistic user context recognition. *ACM Computing Surveys (CSUR)*, 45(3):27, 2013. doi: 10.1145/2480741.2480744.

[98] Y.-C. Hu and D. Johnson. Design and demonstration of live audio and video over multihop wireless ad hoc networks. In *Proceedings of Military Communications (MILCOM)*, volume 2, pages 1211–1216, 2002. doi: 10.1109/MILCOM.2002.1179651.

[99] E. M. Huang and E. D. Mynatt. Semi-public displays for small, co-located groups. In *Human factors in computing systems (CHI)*, pages 49–56, 2003. doi: 10.1145/642611.642622.

[100] D. R. Hutchings, G. Smith, B. Meyers, M. Czerwinski, and G. Robertson. Display space usage and window management operation comparisons between single monitor and multiple monitor users. In *Advanced visual interfaces (AVI)*, pages 32–39, 2004. doi: 10.1145/989863.989867.

[101] E. Hutchins. *Cognition in the Wild.* MIT press, 1995.

[102] K. Inkpen, K. Hawkey, M. Kellar, R. Mandryk, K. Parker, D. Reilly, S. Scott, and T. Whalen. Exploring display factors that influence co-located collaboration: angle, size, number, and user arrangement. In *HCI international*, 2005.

[103] S. S. Intille. Change blind information display for ubiquitous computing environments. In G. Borriello and L. Holmquist, editors, *UbiComp 2002: Ubiquitous Computing*, volume 2498 of *LNCS*, pages 91–106. 2002. doi: 10.1007/3-540-45809-3_7.

[104] A. Iwata, C.-C. Chiang, G. Pei, M. Gerla, and T.-W. Chen. Scalable routing strategies for ad hoc wireless networks. *IEEE Journal on Selected Areas in Communications*, 17(8):1369–1379, 1999. doi: 10.1109/49.779920.

[105] N. Jafarinaimi, J. Forlizzi, A. Hurst, and J. Zimmerman. Breakaway: an ambient display designed to change human behavior. In *Human factors in computing systems (CHI)*, pages 1945–1948, 2005. doi: 10.1145/1056808.1057063.

[106] Y. Jin, C. T. Dang, C. Prehofer, and E. André. A multi-display system for deploying and controlling home automation. In *Interactive Tabletops and Surfaces (ITS)*, pages 399–402, 2014. doi: 10.1145/2669485.2669553.

[107] D. Kahneman. *Attention and effort.* Englewood Cliffs, NJ: Prentice-Hall., 1973.

[108] G. Kahrimanis, A. Meier, I.-A. Chounta, E. Voyiatzaki, H. Spada, N. Rummel, and N. Avouris. Assessing collaboration quality in synchronous cscl problem-solving activities: Adaptation and empirical evaluation of a rating scheme. In *Learning in the Synergy of Multiple Disciplines*, volume 5794 of *LNCS*, pages 267–272. 2009. doi: 10.1007/978-3-642-04636-0_25.

[109] D. Karali. Integration of rfid and cellular technologies. wireless internet for the mobile enterprise consortium (winmec). Technical Report UCLA-WINMEC-2004-205-RFID-M2M, 2004.

[110] B. Karlin and R. Ford. The usability perception scale (upscale): A measure for evaluating feedback displays. In *Design, User Experience, and Usability. Design Philosophy, Methods, and Tools*, volume 8012 of *LNCS*, pages 312–321. 2013. doi: 10.1007/978-3-642-39229-0_34.

[111] F. Kawsar, J. Vermeulen, K. Smith, K. Luyten, and G. Kortuem. Exploring the design space for situated glyphs to support dynamic work environments. In *Pervasive Computing*, volume 6696 of *LNCS*, pages 70–78. 2011. doi: 10.1007/978-3-642-21726-5_5.

[112] M. Keally, G. Zhou, G. Xing, and J. Wu. Remora: Sensing resource sharing among smartphone-based body sensor networks. In *Proceedings*

of Quality of Service (IWQoS), pages 1–10, 2013. doi: 10.1109/IWQoS.2013.6550261.

[113] A. A. Khan, M. H. Rehmani, and Y. Saleem. Neighbor discovery in traditional wireless networks and cognitive radio networks: Basics, taxonomy, challenges and future research directions. *Journal of Network and Computer Applications*, 52:173–190, 2015. doi: 10.1016/j.jnca.2015.03.003.

[114] W. Kiess and M. Mauve. A survey on real-world implementations of mobile ad-hoc networks. *Ad Hoc Networks*, 5(3):324–339, 2007. doi: 10.1016/j.adhoc.2005.12.003.

[115] M. Kim, Y. Jung, and K. Chae. Adaptive data mining approach for flow redirection in multihomed mobile router. *International Journal of Information Technology & Decision Making*, 9(05):737–758, 2010. doi: 10.1142/S0219622010004081.

[116] T. Kim, A. Chang, L. Holland, and A. S. Pentland. Meeting mediator: enhancing group collaborationusing sociometric feedback. In *Computer supported cooperative work (CSCW)*, pages 457–466, 2008. doi: 10.1145/1460563.1460636.

[117] R. E. Kraut and L. A. Streeter. Coordination in software development. *Communications of the ACM*, 38(3):69–81, 1995. doi: 10.1145/203330.203345.

[118] R. E. Kraut, R. S. Fish, R. W. Root, and B. L. Chalfonte. Snapp: Realising the affordances of real-time sna within networked learning environments. In *Proceedings of Human reactions to technology: Claremont symposium on applied social psychology*, pages 145–199, 1990.

[119] K. Kreijns, P. A. Kirschner, and W. Jochems. Identifying the pitfalls for social interaction in computer-supported collaborative learning environments: a review of the research. *Computers in human behavior*, 19(3):335–353, 2003. doi: 10.1016/S0747-5632(02)00057-2.

[120] M. Kuehlewind, G. Hazel, S. Shalunov, and J. Iyengar. Low extra delay background transport (ledbat). Technical report, 2012.

[121] E. Kulla, R. Ozaki, A. Uejima, H. Shimada, K. Katayama, and N. Nishihara. Real world emergency scenario using manet in indoor environment:

Experimental data. In *Complex, Intelligent, and Software Intensive Systems (CISIS)*, pages 336–341, 2015. doi: 10.1109/CISIS.2015.49.

[122] S. Kurkowski, T. Camp, and M. Colagrosso. Manet simulation studies: the incredibles. *ACM SIGMOBILE Mobile Computing and Communications Review*, 9(4):50–61, 2005. doi: 10.1145/1096166.1096174.

[123] K. Kwon, R.-Y. Hong, and J. M. Laffey. The educational impact of metacognitive group coordination in computer-supported collaborative learning. *Computers in Human Behavior*, 29(4):1271–1281, 2013. doi: 10.1016/j.chb.2013.01.003.

[124] N. Lambropoulos, X. Faulkner, and F. Culwin. Supporting social awareness in collaborative e-learning. *British Journal of Educational Technology*, 43(2):295–306, 2012. doi: 10.1111/j.1467-8535.2011.01184.x.

[125] N. D. Lane, M. Mohammod, M. Lin, X. Yang, H. Lu, S. Ali, A. Doryab, E. Berke, T. Choudhury, and A. Campbell. Bewell: A smartphone application to monitor, model and promote wellbeing. In *Pervasive computing technologies for healthcare*, pages 23–26, 2011.

[126] K. Lee, S. Hong, S. J. Kim, I. Rhee, and S. Chong. Slaw: A new mobility model for human walks. In *Proceedings of INFOCOM*, pages 855–863, 2009. doi: 10.1109/INFCOM.2009.5061995.

[127] S.-J. Lee, E. M. Belding-Royer, and C. E. Perkins. Ad hoc on-demand distance-vector routing scalability. *SIGMOBILE Mobile Computing and Communications Review*, 6(3):94–95, 2002. doi: 10.1145/581291.581306.

[128] Y. Lee, Y. Ju, C. Min, S. Kang, I. Hwang, and J. Song. Comon: Cooperative ambience monitoring platform with continuity and benefit awareness. In *Proceedings of Mobile Systems, Applications, and Services (MobiSys)*, pages 43–56, 2012. doi: 10.1145/2307636.2307641.

[129] J. R. Lewis. Ibm computer usability satisfaction questionnaires: psychometric evaluation and instructions for use. *International Journal of Human-Computer Interaction*, 7(1):57–78, 1995. doi: 10.1080/10447319509526110.

[130] J. R. Lewis. Psychometric evaluation of the pssuq using data from five years of usability studies. *International Journal of Human-Computer Interaction*, 14(3-4):463–488, 2002. doi: 10.1080/10447318.2002.9669130.

[131] C. Lin, C. Standing, and Y.-C. Liu. A model to develop effective virtual teams. *Decision Support Systems*, 45(4):1031–1045, 2008. doi: 10.1016/j.dss.2008.04.002.

[132] R. Loomba, L. Shi, B. Jennings, R. Friedman, J. Kennedy, and J. Butler. Information aggregation for collaborative sensing in mobile cloud computing. In *Mobile Cloud Computing, Services, and Engineering (MobileCloud)*, pages 149–158, 2014. doi: 10.1109/MobileCloud.2014.23.

[133] D. López-de Ipiña, I. Díaz-de Sarralde, and J. G. Zubía. An ambient assisted living platform integrating rfid data-on-tag care annotations and twitter. *J. UCS*, 16(12):1521–1538, 2010. doi: 10.3217/jucs-016-12-1521.

[134] H. Lu, W. Pan, N. D. Lane, T. Choudhury, and A. T. Campbell. Soundsense: scalable sound sensing for people-centric applications on mobile phones. In *Mobile systems, applications, and services (MobiSys)*, pages 165–178, 2009. doi: 10.1145/1555816.1555834.

[135] H. Lu, A. Bernheim Brush, B. Priyantha, A. K. Karlson, and J. Liu. Speakersense: Energy efficient unobtrusive speaker identification on mobile phones. In *Pervasive Computing*, volume 6696 of *LNCS*, pages 188–205. 2011. doi: 10.1007/978-3-642-21726-5_12.

[136] X. Lu, D. Li, B. Xu, W. Chen, and Z. Ding. Minimum cost collaborative sensing network with mobile phones. In *Proceedings of Communications (ICC)*, pages 1816–1820, 2013. doi: 10.1109/ICC.2013.6654784.

[137] X. Lu, Y. Zhu, D. Li, B. Xu, W. Chen, and Z. Ding. Minimum payment collaborative sensing network using mobile phones. *Wireless Networks*, 20(7):1859–1872, 2014. doi: 10.1007/s11276-014-0715-0.

[138] P. Lubkowski, M. Hauge, L. Landmark, C. Barz, and P. Sevenich. On improving connectivity and network efficiency in a heterogeneous military environment. In *Proceedings of Military Communications and Information Systems (ICMCIS)*, pages 1–9, 2015. doi: 10.1109/ICMCIS.2015.7158702.

[139] O. Lundahl. *Usability of mobile applications for near field communication*. PhD thesis, 2009.

[140] C. Luo and M. C. Chan. Socialweaver: Collaborative inference of human conversation networks using smartphones. In *Proceedings of Embedded Networked Sensor Systems (SenSys)*, pages 20:1–20:14, 2013. doi: 10.1145/2517351.2517353.

[141] A. Madan and A. S. Pentland. Vibefones: Socially aware mobile phones. In *Wearable Computers*, pages 109–112, 2006. doi: 10.1109/ISWC.2006.286352.

[142] A. Madan, M. Cebrian, S. Moturu, K. Farrahi, and S. Pentland. Sensing the "health state" of a community. *IEEE Pervasive Computing*, 11(4): 36–45, 2012. doi: 10.1109/MPRV.2011.79.

[143] K. Mäkelä, E.-P. Salonen, M. Turunen, J. Hakulinen, and R. Raisamo. Conducting a wizard of oz experiment on a ubiquitous computing system doorman. In *Workshop on Information Presentation and Natural Multimodal Dialogue*, pages 115–119, 2001.

[144] D. Maltz, J. Broch, and D. Johnson. Quantitative lessons from a full-scale multi-hop wireless ad hoc network testbed. In *Wireless Communications and Networking Conference (WCNC)*, volume 3, pages 992–997, 2000.

[145] K. Manathunga, D. Hernández-Leo, J. Caicedo, J. Ibarra, F. Martinez-Pabon, and G. Ramirez-Gonzalez. Collaborative learning orchestration using smart displays and personal devices. In *Design for Teaching and Learning in a Networked World*, volume 9307 of *LNCS*, pages 596–600. 2015. doi: 10.1007/978-3-319-24258-3_67.

[146] R. L. Mandryk, M. E. Rodgers, and K. M. Inkpen. Sticky widgets: pseudo-haptic widget enhancements for multi-monitor displays. In *Human Factors in Computing Systems (CHI)*, pages 1621–1624, 2005. doi: 10.1145/1056808.1056981.

[147] R. Martinez-Maldonado, Y. Dimitriadis, A. Martinez-Monés, J. Kay, and K. Yacef. Capturing and analyzing verbal and physical collaborative learning interactions at an enriched interactive tabletop. *Inter-*

national Journal of Computer-Supported Collaborative Learning, 8(4): 455–485, 2013. doi: 10.1007/s11412-013-9184-1.

[148] S. Masum, A. Ali, and M.-y. Bhuiyan. Asynchronous leader election in mobile ad hoc networks. In *Proceedings of Advanced Information Networking and Applications (AINA)*, volume 2, page 5, 2006. doi: 10.1109/AINA.2006.106.

[149] T. Matthews, A. K. Dey, J. Mankoff, S. Carter, and T. Rattenbury. A toolkit for managing user attention in peripheral displays. In *User interface software and technology*, pages 247–256, 2004. doi: 10.1145/1029632.1029676.

[150] A. Meier, H. Spada, and N. Rummel. A rating scheme for assessing the quality of computer-supported collaboration processes. *International Journal of Computer-Supported Collaborative Learning*, 2(1):63–86, 2007. doi: 10.1007/s11412-006-9005-x.

[151] J. Melero, D. Hernández-Leo, J. Sun, P. Santos, and J. Blat. How was the activity? a visualization support for a case of location-based learning design. *British Journal of Educational Technology*, 46(2):317–329, 2015. doi: 10.1111/bjet.12238.

[152] M. Miller and A. Hadwin. Scripting and awareness tools for regulating collaborative learning: Changing the landscape of support in cscl. *Computers in Human Behavior*, 52:573—588, 2015. doi: 10.1016/j.chb.2015.01.050.

[153] E. Miluzzo. *Smartphone sensing.* PhD thesis, Dartmounth College Hanover, New Hampshire, 2011.

[154] E. Miluzzo, N. D. Lane, K. Fodor, R. Peterson, H. Lu, M. Musolesi, S. B. Eisenman, X. Zheng, and A. T. Campbell. Sensing meets mobile social networks: The design, implementation and evaluation of the cenceme application. In *Proceedings of Embedded Network Sensor Systems (SenSys)*, pages 337–350, 2008. doi: 10.1145/1460412.1460445.

[155] A. Monares, S. F. Ochoa, J. A. Pino, V. Herskovic, J. Rodriguez-Covili, and A. Neyem. Mobile computing in urban emergency situations: Improving the support to firefighters in the field. *Expert Systems with Applications*, 38(2):1255–1267, 2011. doi: 10.1016/j.eswa.2010.05.018.

[156] E. B. Moran, M. Tentori, V. M. Gonzalez, J. Favela, and A. I. Martinez-Garcia. Mobility in hospital work: towards a pervasive computing hospital environment. *International Journal of Electronic Healthcare*, 3(1): 72–89, 2006. doi: 10.1504/IJEH.2007.011481.

[157] A. Moreno, R. van Delden, R. Poppe, and D. Reidsma. Socially aware interactive playgrounds. *Pervasive Computing, IEEE*, 12(3):40–47, 2013. doi: 10.1109/MPRV.2013.40.

[158] S. Mukherjee, S. Pal, P. Choudhury, and S. Nandi. Challenges of establishing a collaborative learning environment using manet. In *Business and Information Management (ICBIM)*, pages 23–26, 2014. doi: 10.1109/ICBIM.2014.6970922.

[159] M. Müller, N. Otero, A. Alissandrakis, and M. Milrad. Increasing user engagement with distributed public displays through the awareness of peer interactions. In *Pervasive Displays*, pages 23–29, 2015. doi: 10.1145/2757710.2757740.

[160] K. Musaazi, T. Bulega, and S. Lubega. Energy efficient data caching in wireless sensor networks: A case of precision agriculture. In *e-Infrastructure and e-Services for Developing Countries*, volume 147 of *LNICST*, pages 154–163. 2015. doi: 10.1007/978-3-319-16886-9_16.

[161] J. Müller, D. Wilmsmann, J. Exeler, M. Buzeck, A. Schmidt, T. Jay, and A. Krüger. Display blindness: The effect of expectations on attention towards digital signage. In *Pervasive Computing*, volume 5538 of *LNCS*, pages 1–8. Springer Berlin Heidelberg, 2009. doi: 10.1007/978-3-642-01516-8_1. URL `http://dx.doi.org/10.1007/978-3-642-01516-8_1`.

[162] K. Nemoto, P. Gloor, and R. Laubacher. Social capital increases efficiency of collaboration among wikipedia editors. In *Proceedings of Conference on Hypertext and Hypermedia (HT)*, pages 231–240, 2011.

[163] A. Neumann, C. Aichele, M. Lindner, and S. Wunderlich. Better approach to mobile ad-hoc networking (batman). Technical report, 2008.

[164] A. Neyem, S. F. Ochoa, and J. A. Pino. Designing mobile shared workspaces for loosely coupled workgroups. In *Groupware: Design, Im-*

plementation, and Use, volume 4715 of *LNCS*, pages 173–190. 2007. doi: 10.1007/978-3-540-74812-0_14.

[165] A. Neyem, S. F. Ochoa, and J. A. Pino. Integrating service-oriented mobile units to support collaboration in ad-hoc scenarios. *Journal of Universal Computer Science*, 14(1):88–122, 2008. doi: 10.3217/jucs-014-01-0088.

[166] A. Neyem, S. F. Ochoa, and J. A. Pino. Coordination patterns to support mobile collaboration. In *Groupware: Design, Implementation, and Use*, volume 5411 of *LNCS*, pages 248–265. 2008. doi: 10.1007/978-3-540-92831-7_21.

[167] A. Neyem, S. F. Ochoa, and J. A. Pino. A patterns system to coordinate mobile collaborative applications. *Group Decision and Negotiation*, 20 (5):563–592, 2011. doi: 10.1007/s10726-011-9258-2.

[168] D. J. Nicol and D. Macfarlane-Dick. Formative assessment and self-regulated learning: A model and seven principles of good feedback practice. *Studies in higher education*, 31(2):199–218, 2006. doi: 10.1080/03075070600572090.

[169] S. Nikoletseas, M. Rapti, T. P. Raptis, and K. Veroutis. Decentralizing and adding portability to an iot test-bed through smartphones. In *Proceedings of Distributed Computing in Sensor Systems (DCOSS)*, pages 281–286, 2014. doi: 10.1109/DCOSS.2014.39.

[170] D. Norman. Cognitive artifacts. *Designing interaction: Psychology at the human-computer interface*, pages 17–38, 1991.

[171] S. F. Ochoa and R. Santos. Human-centric wireless sensor networks to improve information availability during urban search and rescue activities. *Information Fusion*, 22:71–84, 2015. doi: 10.1016/j.inffus.2013.05.009.

[172] S. F. Ochoa, G. Bravo, J. A. Pino, and J. Rodríguez-Covili. Coordinating loosely-coupled work in construction inspection activities. *Group Decision and Negotiation*, 20(1):39–56, 2011. doi: 10.1007/s10726-010-9203-9.

[173] S. F. Ochoa, A. Monares, N. Ochoa, R. Hervas, and J. Bravo. Understanding the interaction support for mobile work in an emergency room. In *Human-Computer Interaction. Applications and Services*, volume 8512 of *LNCS*, pages 312–322. 2014. doi: 10.1007/978-3-319-07227-2_30.

[174] T. Oda, Y. Liu, K. Matsuo, S. Sakamoto, M. Ikeda, and L. Barolli. Experimental results of a centos-based ad-hoc network testbed considering los scenario. In *Innovative Mobile and Internet Services in Ubiquitous Computing (IMIS)*, pages 9–14, 2015. doi: 10.1109/IMIS.2015.6.

[175] D. Olguín and A. Pentland. Assessing group performance from collective behavior. In *Proceedings of Computer-Supported Cooperative Work and Social Computing (CSCW)*, volume 10, 2010.

[176] D. O. Olguın, P. A. Gloor, and A. S. Pentland. Capturing individual and group behavior with wearable sensors. In *Symposium on human behavior modeling*, volume 9, 2009. doi: 10.4108/ICST.PERVASIVEHEALTH2009.6033.

[177] D. O. Olguín, B. N. Waber, T. Kim, A. Mohan, K. Ara, and A. Pentland. Sensible organizations: Technology and methodology for automatically measuring organizational behavior. *Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on*, 39(1):43–55, 2009. doi: 10.1109/TSMCB.2008.2006638.

[178] D. Olguín Olguín. *Sociometric badges: wearable technology for measuring human behavior*. PhD thesis, Massachusetts Institute of Technology, 2007.

[179] V. D. Park and M. S. Corson. A highly adaptive distributed routing algorithm for mobile wireless networks. In *Proceedings of the INFOCOM*, pages 1405–1413, 1997. doi: doi:10.1109/INFCOM.1997.631180.

[180] E. Paulos and E. Goodman. The familiar stranger: anxiety, comfort, and play in public places. In *Human factors in computing systems (CHI)*, pages 223–230, 2004. doi: 10.1145/985692.985721.

[181] K. Pawlikowski, H.-D. Jeong, and J.-S. Lee. On credibility of simulation studies of telecommunication networks. *Communications Magazine, IEEE*, 40(1):132–139, 2002. doi: 10.1109/35.978060.

[182] A. Pentland. The new science of building great teams. *Harvard Business Review*, 90(4):60–69, 2012.

[183] C. Perera, A. Zaslavsky, P. Christen, and D. Georgakopoulos. Context aware computing for the internet of things: A survey. *Communications Surveys & Tutorials, IEEE*, 16(1):414–454, 2014. doi: 10.1109/SURV.2013.042313.00197.

[184] M. J. Perry and K. O'Hara. Display-based activity in the workplace. In *INTERACT*, 2003.

[185] C. Phielix, F. J. Prins, P. A. Kirschner, G. Erkens, and J. Jaspers. Group awareness of social and cognitive performance in a cscl environment: Effects of a peer feedback and reflection tool. *Computers in Human Behavior*, 27(3):1087–1102, 2011. doi: 10.1016/j.chb.2010.06.024.

[186] D. Pinelle and C. Gutwin. A groupware design framework for loosely coupled workgroups. In *Proceedings of European Conference on Computer Supported Cooperative Work (ECSCW)*, pages 65–82, 2005. doi: 10.1007/1-4020-4023-7_4.

[187] I. Podnar Zarko, A. Antonic, and K. Pripužic. Publish/subscribe middleware for energy-efficient mobile crowdsensing. In *Proceedings of Pervasive and Ubiquitous Computing (UbiComp) Adjunct Publication*, pages 1099–1110, 2013. doi: 10.1145/2494091.2499577.

[188] S. Poslad. *Ubiquitous computing: smart devices, environments and interactions*. John Wiley & Sons, 2011.

[189] D. Quercia and L. Capra. Friendsensing: recommending friends using mobile phones. In *Recommender systems (RecSys)*, pages 273–276. ACM, 2009. doi: 10.1145/1639714.1639766.

[190] K. K. Rachuri and K. K. Rachuri. Smartphones based social sensing: Adaptive sampling, sensing and computation offloading, 2012.

[191] K. K. Rachuri, M. Musolesi, C. Mascolo, P. J. Rentfrow, C. Longworth, and A. Aucinas. Emotionsense: a mobile phones based adaptive platform for experimental social psychology research. In *Ubiquitous computing (UbiComp)*, pages 281–290, 2010. doi: 10.1145/1864349.1864393.

[192] K. K. Rachuri, C. Mascolo, M. Musolesi, and P. J. Rentfrow. Sociablesense: exploring the trade-offs of adaptive sampling and computation offloading for social sensing. In *Mobile computing and networking (MobiCom)*, pages 73–84, 2011. doi: 10.1145/2030613.2030623.

[193] K. K. Rachuri, C. Efstratiou, I. Leontiadis, C. Mascolo, and P. J. Rentfrow. Smartphone sensing offloading for efficiently supporting social sensing applications. *Pervasive and Mobile Computing*, 10:3–21, 2014. doi: 10.1016/j.pmcj.2013.10.005.

[194] A. Razaque, K. Elleithy, and N. Salama. Novel framework for mobile collaborative learning (mcl) to substantiate pedagogical activities. *arXiv preprint arXiv:1210.2023*, 2012.

[195] R. Reagans, E. Zuckerman, and B. McEvily. How to make the team: Social networks vs. demography as criteria for designing effective teams. *Administrative Science Quarterly*, 49(1):101–133, 2004. doi: 10.2307/4131457.

[196] F. Rebecchi, M. Dias de Amorim, V. Conan, A. Passarella, R. Bruno, and M. Conti. Data offloading techniques in cellular networks: A survey. *IEEE Communications Surveys & Tutorials*, 17(2):580–603, 2015. doi: 10.1109/COMST.2014.2369742.

[197] C. Reffay and T. Chanier. How social network analysis can help to measure cohesion in collaborative distance-learning. In *Designing for Change in Networked Learning Environments*, volume 2 of *Computer-Supported Collaborative Learning*, pages 343–352. 2003. doi: 10.1007/978-94-017-0195-2_42.

[198] D. Reilly. Not in karlsplatz anymore: Navigating cities together. In *Workshop on Ubicomp in the Urban Frontier*, 2004.

[199] M. Ringel. When one isn't enough: an analysis of virtual desktop usage strategies and their implications for design. In *Human factors in computing systems (CHI)*, pages 762–763, 2003. doi: 10.1145/765891.765976.

[200] P. Robinson. Task-based language learning: A review of issues. *Language Learning*, 61(s1):1–36, 2011. doi: 10.1111/j.1467-9922.2011.00641.x.

[201] M. J. Rodríguez-Triana, A. Martínez-Monés, J. I. Asensio-Perez, and Y. Dimitriadis. A monitoring-aware learning design process: Pilot studies in authentic cscl scenarios. *Computing & Informatics*, 34(3), 2015.

[202] J. Rodríguez-Covili, S. F. Ochoa, and J. A. Pino. High level {MANET} protocol: Enhancing the communication support for mobile collaborative work. *Journal of Network and Computer Applications*, 35(1):145–155, 2012. doi: 10.1016/j.jnca.2011.02.006.

[203] Y. Rogers, S. Price, G. Fitzpatrick, R. Fleck, E. Harris, H. Smith, C. Randell, H. Muller, C. O'Malley, D. Stanton, et al. Ambient wood: designing new forms of digital augmentation for learning outdoors. In *Interaction design and children: building a community (IDC)*, pages 3–10, 2004. doi: 10.1145/1017833.1017834.

[204] H. Rogge and E. Baccelli. Packet sequence number based directional airtime metric for olsrv2. `https://tools.ietf.org/html/draft-rogge-baccelli-olsrv2-ett-metric`, 2014.

[205] S. Rosenthal, S. K. Kane, J. O. Wobbrock, and D. Avrahami. Augmenting on-screen instructions with micro-projected guides: when it works, and when it fails. In *Ubiquitous computing (UbiComp)*, pages 203–212, 2010. doi: 10.1145/1864349.1864391.

[206] J. W. Schell and R. S. Black. Situated learning: An inductive case study of a collaborative learning experience. *Journal of STEM Teacher Education*, 34(4):5–28, 1997.

[207] J. Schneider, D. Börner, P. van Rosmalen, and M. Specht. Augmenting the senses: A review on sensor-based learning support. *Sensors*, 15(2): 4097–4133, 2015. doi: 10.3390/s150204097.

[208] S. D. Scott, F. Sasangohar, and M. Cummings. Investigating supervisory-level activity awareness displays for command and control operations. *(HSIS)*, 2009.

[209] S. Sendra, M. Garcia, C. Turro, and J. Lloret. People mobility behaviour study in a university campus using wlans. In *Mobile Ubiquitous Computing, Systems, Services and Technologies (UBICOMM)*, pages 124–129, 2009. doi: 10.1109/UBICOMM.2009.32.

[210] C. Shang, M. Zhou, and C. Chen. Cellphone data and applications. *International Journal of Intelligent Control and Systems*, 19(1):35–45, 2014.

[211] R. Sharpe, H. Beetham, and S. De Freitas. *Rethinking learning for a digital age: How learners are shaping their own experiences*. Routledge, 2010.

[212] P. Skocir, H. Maracic, M. Kusek, and G. Jezic. Data filtering in context-aware multi-agent system for machine-to-machine communication. In *Agent and Multi-Agent Systems: Technologies and Applications*, volume 38 of *Smart Innovation, Systems and Technologies*, pages 41–51. 2015. doi: 10.1007/978-3-319-19728-9_4.

[213] D. L. Soule and A. C. Edmondson. Situated knowledge and learning in dispersed teams. *British journal of management*, 13:S17–S34, 2002.

[214] V. Srinivasan, S. Moghaddam, A. Mukherji, K. Rachuri, C. Xu, and E. Tapia. Mobileminer: Mining your frequent behavior patterns on your phone. In *Ubiquitous computing (UbiComp)*, 2014.

[215] O. Storz, A. Friday, and N. Davies. Supporting content scheduling on situated public displays. *Computers & Graphics*, 30(5):681–691, 2006. doi: 10.1016/j.cag.2006.07.002.

[216] J.-W. Strijbos. Assessment of (computer-supported) collaborative learning. *Learning Technologies, IEEE Transactions on*, 4(1):59–73, 2011. doi: 10.1109/TLT.2010.37.

[217] C. M. Stuetzer, T. Koehler, K. M. Carley, and G. Thiem. “brokering” behavior in collaborative learning systems. *Procedia - Social and Behavioral Sciences*, 100:94–107, 2013. doi: 10.1016/j.sbspro.2013.10.702.

[218] M. B. Syson, M. R. E. Estuar, and K. T. See. Abkd: Multimodal mobile language game for collaborative learning of chinese hanzi and japanese kanji characters. In *Web Intelligence and Intelligent Agent Technology-Volume 03*, pages 311–315, 2012. doi: 10.1109/WI-IAT.2012.65.

[219] K. P. Tang, P. Keyani, J. Fogarty, and J. I. Hong. Putting people in their place: an anonymous and privacy-sensitive approach to collecting sensed

data in location-based applications. In *Human Factors in computing systems (CHI)*, pages 93–102, 2006. doi: 10.1145/1124772.1124788.

[220] M. Tentori and J. Favela. Activity-aware computing for healthcare. *Pervasive Computing, IEEE*, 7(2):51–57, 2008. doi: 10.1109/MPRV.2008.24.

[221] A. Tirumala, F. Qin, J. Dugan, J. Ferguson, and K. Gibbs. Iperf: The tcp/udp bandwidth measurement tool. `https://iperf.fr/`. (Accessed on 12 October 2015).

[222] J. Toutouh and E. Alba. Light commodity devices for building vehicular ad hoc networks: An experimental study. *Ad Hoc Networks*, 37:499–511, 2016. doi: 10.1016/j.adhoc.2015.09.013.

[223] L. Trappeniers, M. A. Feki, F. Kawsar, and M. Boussard. The internet of things: the next technological revolution. *Computer*, 46(2):0024–25, 2013. doi: 10.1109/MC.2013.63.

[224] C. Tschudin, P. Gunningberg, H. Lundgren, and E. Nordström. Lessons from experimental manet research. *Ad Hoc Networks*, 3(2):221–233, 2005. doi: 10.1016/j.adhoc.2004.07.007.

[225] I. Vaghi, C. Greenhalgh, and S. Benford. Coping with inconsistency due to network delays in collaborative virtual environments. In *Proceedings of Virtual Reality Software and Technology (VRST)*, pages 42–49, 1999. doi: 10.1145/323663.323670.

[226] R. Valdivia, M. Nussbaum, and S. F. Ochoa. Modeling a collaborative answer negotiation activity using ims-based learning design. *Education, IEEE Transactions on*, 52(3):375–384, 2009. doi: 10.1109/TE.2008.930089.

[227] A. Vasiliou and A. A. Economides. Mobile collaborative learning using multicast manets. *International Journal of Mobile Communications*, 5 (4):423–444, 2007. doi: 10.1504/IJMC.2007.012789.

[228] A. Vasiliou and A. A. Economides. Manet-based outdoor collaborative learning. In *Interactive Mobile and Computer Aided Learning (IMCL)*, pages 16–18, 2008.

[229] N. Vastardis and K. Yang. An enhanced community-based mobility model for distributed mobile social networks. *Journal of Ambient Intelligence and Humanized Computing*, 5(1):65–75, 2014. doi: 10.1007/s12652-012-0118-y.

[230] S. Vasudevan, J. Kurose, and D. Towsley. Design and analysis of a leader election algorithm for mobile ad hoc networks. In *Proceedings of Network Protocols (ICNP)*, pages 350–360, 2004. doi: 10.1109/ICNP.2004.1348124.

[231] S. Vasudevan, M. Adler, D. Goeckel, and D. Towsley. Efficient algorithms for neighbor discovery in wireless networks. *IEEE/ACM Transactions on Networking*, 21(1):69–83, 2013. doi: 10.1109/TNET.2012.2189892.

[232] J. Vermeulen, F. Kawsar, A. L. Simeone, G. Kortuem, K. Luyten, and K. Coninx. Informing the design of situated glyphs for a care facility. In *Visual Languages and Human-Centric Computing (VL/HCC)*, pages 89–96, 2012. doi: 10.1109/VLHCC.2012.6344490.

[233] C. Ververidis and G. Polyzos. Service discovery for mobile ad hoc networks: a survey of issues and techniques. *IEEE Communications Surveys Tutorials*, 10(3):30–45, 2008. doi: 10.1109/COMST.2008.4625803.

[234] E. Vollset and P. Ezhilchelvan. Design and performance-study of crash-tolerant protocols for broadcasting and reaching consensus in manets. In *Proceedings of Reliable Distributed Systems (SRDS)*, pages 166–175, 2005. doi: 10.1109/RELDIS.2005.15.

[235] B. N. Waber, D. Olguin Olguin, T. Kim, and A. Pentland. Productivity through coffee breaks: changing social networks by changing break structure. *Available at SSRN 1586375*, 2010. doi: 10.2139/ssrn.1586375.

[236] V. Waller. Information systems 'in the wild': supporting activity in the world. *Behaviour & Information Technology*, 28(6):577–588, 2009. doi: 10.1080/01449290903188971.

[237] R. Wang, L. Zhang, K. Xiao, R. Sun, and L. Cui. Easisee: Real-time vehicle classification and counting via low-cost collaborative sensing. *Intelligent Transportation Systems, IEEE Transactions on*, 15(1):414–424, 2014. doi: 10.1109/TITS.2013.2281760.

[238] K. Wu, J. Vassileva, X. Sun, and J. Fang. Motivating wiki-based collaborative learning by increasing awareness of task conflict: A design science approach. In *Collaboration and Technology*, volume 8658 of *LNCS*, pages 365–380. 2014. doi: 10.1007/978-3-319-10166-8_33.

[239] W. Wu, J. Cao, J. Yang, and M. Raynal. Design and performance evaluation of efficient consensus protocols for mobile ad hoc networks. *IEEE Transactions on Computers*, 56(8):1055–1070, 2007. doi: 10.1109/TC.2007.1053.

[240] R. Xue, L. Wang, and J. Chen. Using the iot to construct ubiquitous learning environment. In *Proceedings of Mechanic Automation and Control Engineering (MACE)*, pages 7878–7880, 2011.

[241] Y. S. Yilmaz, B. I. Aydin, and M. Demirbas. Google cloud messaging (gcm): An evaluation. In *Proceedings of Global Communications Conference (GLOBECOM)*, pages 2807–2812, 2014.

[242] D. Zhang and B. Adipat. Challenges, methodologies, and issues in the usability testing of mobile applications. *International Journal of Human-Computer Interaction*, 18(3):293–308, 2005. doi: 10.1207/s15327590ijhc1803_3.

[243] G. Zurita, N. Baloian, and F. Baytelman. A collaborative face-to-face design support system based on sketching and gesturing. *Advanced Engineering Informatics*, 22(3):340–349, 2008. doi: 10.1016/j.aei.2007.09.003.

[244] G. Zurita, N. Baloian, and J. Frez. Using the cloud to develop applications supporting geo-collaborative situated learning. *Future Generation Computer Systems*, 34:124–137, 2014. doi: 10.1016/j.future.2013.10.007.