Ph.D. Dissertation

International Doctoral School in Information

and Communication Technology

DISI – University of Trento

Study and Analysis of Socio-behavioural Dynamics for Decision Support Systems in Smart Buildings

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To my colleagues of the ELEDIA Research Center.

To my mom, the most important teacher of my life.

Abstract:

This thesis deals with the energy saving in smart building with focus on the impact of the user behaviour on the energy consumption. The problem of human behaviour modelling has been widely studied in the state of the art, but it is still an open problem in the field of smart building since the stochastic nature of the behaviour is difficult to be accurately represented by numerical tools. An interdisciplinary approach is proposed in order to identify the suitable user features from the psychological and social point of view and to integrate such a representation into a DSS for appliance scheduling and energy cost reduction. The proposed method has exploited location-based features of the users in order to represent their habits and needs and to compute the schedules that maximize the user acceptance toward an “energy-aware” behaviour. The obtained results point out a reduction of the peak-to-average ratio higher than 40% also considering the user constraints imposed by their presence into the building.

Keywords:

Smart building, energy saving, decision support system, behaviour modelling, behaviour change program.

Published Journal Papers:

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F. Viani, N. Anselmi, M. Donelli, P. Garofalo, G. Gottardi, G. Oliveri, L. Poli, A. Polo, P. Rocca, M. Salucci, L. Tenuti, and A. Massa, “On the role of information in inversion and synthesis – challenges, tools, and trends," *2015 IEEE Mediterranean Microwave Symposium* (MMS’2015) (no. 978-1-4673-7602-0/15/$31.00©2015 IEEE), Lecce, Italy, pp. 1-4, November 30 – December 2, 2015.

Thesis Outline

The thesis is organized as follows: In Chapter 2, the influence of user behavior on the energy consumption in smart building is introduced. Then, Chapter 3 presents the user features selected to represent the user behavior. The results of the performance analysis are also discussed in Chapter 3. Finally, some conclusions are drawn in Chapter 4.

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Abbreviations:

ACEEE	American Council for an Energy-Efficient Economy
DNAs	Drivers-Needs-Actions-System
DR	Demand Response
DSS	Decision Support System
GPS	Global Positioning System
GT	Game Theory
HVAC	Heating, Ventilation and Air Conditioning
ICT	Information and Communication Technologies
IEEE	Institute of Electrical and Electronic Engineers
PAR	Peak-to-Average Ratio
PHEV	Plug-in Hybrid Electric Vehicle
RSS	Received Signal Strength
TPB	Theory of Planned Behavior
VBN	Value Belief Norm
WiFi	WIreless FIdelity
WSN	Wireless Sensor Network

1. INTRODUCTION

Over the last years, the smart building has become one of the most challenging issues in today's framework of smart cities and communities. Many factors impact on the development of a smart building and one of the most unexplored is the understanding of the users' behavior that has direct consequences on the energy consumptions.

Understanding the users' behavior is fundamental for the design of smart buildings and in particular for the adaptive control and calibration of the energy-hungry plants of the building like the heating, ventilation, and air conditioning (HVAC) system or the lighting system that are regulated according to the user needs and habits. The problem of user behavior understanding and modelling has been addressed with different approaches in the state of the art and from different disciplines. However, the occupants' behavior in smart buildings has to be more deeply investigated since it influences how and how much the energy is consumed to ensure high comfort standards and environmental quality [36][37].

The human behavior has to be considered starting from the very beginning of the smart building design. In this framework, ergonomics approaches with focus on the user impact on the energy consumption have been considered in the state of the art. The first category of approaches has investigated the reaction of occupants to the comfort conditions in the building and has proposed solutions to encourage the occupants to self-regulate the properties of the indoor environment. The user responsibility of the comfort control became an effective mean to increase the satisfaction of the users, but on the other hand reduced the building efficiency. Consequently, a second category of approaches arose to focus the attention on the practical understanding of the occupants' behavior during everyday life and to increase the awareness of occupants about the positive and negative impacts of their behavior on the energy efficiency of the building. The basic idea is to make the users responsible of the building systems management and provide feedback about the consequences of their actions to stimulate virtuous behavior [49].

Starting from these considerations, further research is required to investigate the behavioral models and the behavioral changing programs based on psychological and behavioral aspects of the users in order to identify the key-features of the behavior that mostly impact on the efficient management of the building. Even if the user behaviour is one of the most important parameters influencing the building's performance, the extent to which users affect the energy consumption is largely unknown. The scientific approaches to this topic often remain limited to partial and simple aspects of the user–building interaction. Moreover, the proposed solutions rarely consider an integrated multi-disciplinary approach, by integrating the physical and social sciences [72], which is fundamental for the proper fusion of the engineering aspects of the building design with the social and psychological basics of human understanding [100].

In this context, the main objective of this thesis is twofold: (*i*) to analyze the characteristics of the user behavior that affect the energy efficiency of buildings, modelling presence, absence, and activities in the rooms, and (*ii*) to optimize the daily profiles of energy demand suggesting the user actions with focus on the usage of the household appliances.

The modelling of the user behavior through few and representative key-features as well as the behavior changing strategies are fundamental for the design of decision support systems (DSSs) that implement a user-centric approach for energy efficiency through the suggestion of the energetically virtuous actions.

2. INFLUENCE OF USER BEHAVIOUR ON ENERGY EFFICIENT BUILDINGS

2.1 SMART BUILDING DESIGN AND HUMAN BEHAVIOR

A smart building delivers services to the occupants at the lowest cost and environmental impact over the building lifecycle. Information technologies are used during operation to connect a variety of building subsystems so that they can share information to optimize the total energy saving performance. Modern buildings contain complex mechanical devices, sophisticated control systems and a suite of features to improve the safety, comfort and productivity of occupants.

However, the building efficiency degrades without the intelligent interaction and involvement of the users, and such an involvement is often modeled in a simplistic way by designers and device manufacturers. The buildings are designed to perform on the basis of standard rules and schemes, defined under controlled conditions and predefined assumptions about the occupants behaviors. In fact, the designers take into account during the construction phase of the building a "standard" interaction of the occupants with the building and a "standard" behavior of consumers. They slightly consider that the user could behave in many different ways far from the standard rules. For these reason, it is inevitable that the energy consumptions are different from the expectation.

In this sense, the state of the art presented in [57][58][59] stated that building occupants' behavior and their activities are among the most important factors that determine relevant fluctuations in actual energy consumption respect to the planned one. The use of simplified methods to quantify the impacts of occupants' behavior on the building energy performance has significantly contributed to the accurate simulation of the building model and the improvement of the management as well as the prediction of the power consumption. For example, the simplification of the occupant's behavior has been addressed in [60] through a stochastic modelling of the user actions.

However, the integration of qualitative approaches and behaviour models driven by data is even more important to support the design and operation of low-energy buildings taking in consideration the real effects of the occupants and not only a statistical or simplified version. Therefore, it is important to introduce the human factors, that includes some variables that are not observable such as the influence of the people in the some contest, norms, attitudes related to energy, motivation, trust, concerns regarding the environmental, in a building's design to better understand how the buildings actually works and how the users are involved with building and control strategy [49][73].

A common limiting factor of the existing approaches for human behavior modelling is that the occupants are processed at the same level of the other technical factors of the building. In this regard, the ergonomics discipline pays attention on the user-driven perspective of the smart building design. Such a discipline considers that humans are linked in many different ways to a dynamic environment, including physical and psychological relationship with the building.

It has to be underlined that the human behaviour can be defined as a collection of factors, activities, and preferences that in most of the cases do not fit the predefined models since the occupants tend to follow the easiest and quickest option, not always compliant with the energy saving best practices. As a consequence, the building that has been designed assuming standard occupant profiles operates with performance far from the expected targets. K. Kant [38] has identified some important aspects of smart intelligent infrastructures to keep in mind, in order to understand human behavior in relation to the resource use:

1. demand Shaping;

2. user Compliance;

3. social Influence;

4. behavior Shifting.

The first aspect refers to some non-coercive mechanisms, such as the demand sensitive pricing and provide appropriate feedback that influence the use of resources. The demand sensitive pricing is actually a mechanism that does not have long-term influences if used without further mechanisms, as well as provide feedback that sometimes cause the opposite effect. This means again, that users are influenced by many factors at the same moment and different people can be effected by different things. The second aspect, refers to possibility to extent the compliance of customer with monitoring the user behavior. The problem in this case is that the people may not feel comfortable, knowing that it is being monitored and that does not allow to create customized systems to reduce the energy consumption. The third relevant aspect are the social influence that guide the human behaviors in form of imitation and conformance or on the opposite. It is difficult to create a general model by measuring this aspect and furthermore, compliance does not necessarily imply a reduction in consumption: if around me the users consume more, social influence may lead to increase my own consumption. The last aspect is the behavior shifting over the time in the use of the resources. This aspect is really difficult to predict and understand, since it depends from many human behavior issues not so clear until now.

The need of a realistic and effective modelling of the users' behaviour is rather acknowledged and this thesis aims to propose an approach that estimates the occupants' behaviour as an adaptive model based on the real presence and location of the users throughout the building.

2.2 USER BEHAVIOUR MODELS

From a psychological point of view, many theories have dealt with various aspects of the human behavior, some of them can be considered in the analysis of intelligent buildings. Therefore, the "intelligent buildings" are places among the "objects" that cooperate in order to provide an optimal service to the user through a more comfortable and efficient life conditions. From a technological point of view, intelligent buildings have solved many problems in the last 30 years, but the issue of user behavior, the possibility of modifying it to make it more efficient needs to be investigated in depth.

Given the increasingly urgent need to use energy more efficiently, to reduce energy waste, and to make optimal use of the building plants, the investigation of behavioural models plays a fundamental role since a "smart building" cannot exist without "smart users". It is not possible to create optimal conditions for any occupant because different users apply different strategies even in identical situations. According to the "social practice theory", considered more in detail below, the habits of humans derive from a variety of interconnected elements (e.g., mental and physical activities, norms, ideas, use of technology, etc.) that form the daily actions of people [3][4][5].

Such actions can be driven by leveraging on exogenous factors like information about products energy consumption, product prices, or people attitudes and values. Typically, the actions are considered linked to the behaviours through cause-effect relationships with the assumption that the users take rational decisions, or that the behaviours are a consequence of user attitudes [97][98].

In order to introduce some behavioral theories, it is important to underline the concept of "learning". Learning means a change in human behavior that depends on the interaction with the environment and is the result of human experiences that create new configurations of response to external stimuli. The stimuli are all those interactions that are perceived by the body that lives in interaction with the environment.

The relationship between the organism and the environment depends on a third variable that is the context. The context is the set of events that are the background to a specific situation [96].

From the beginning of the ‘900, psychologists began to affirm that the explicit behavior of the individuals is the only aspect that can be scientifically studied and analyzed within psychology, using the stimulus (i.e., the environment) and the response (i.e., the behavior) method introduced for the first time by the psychologist John Watson [1] as “behaviorism”. The behaviorism has expanded the vision of psychology, that is no longer limited to the study of consciousness, as occurred until the early 20th century, but is focused on the *observable behavior* with the main goal to predict and control the behavior.

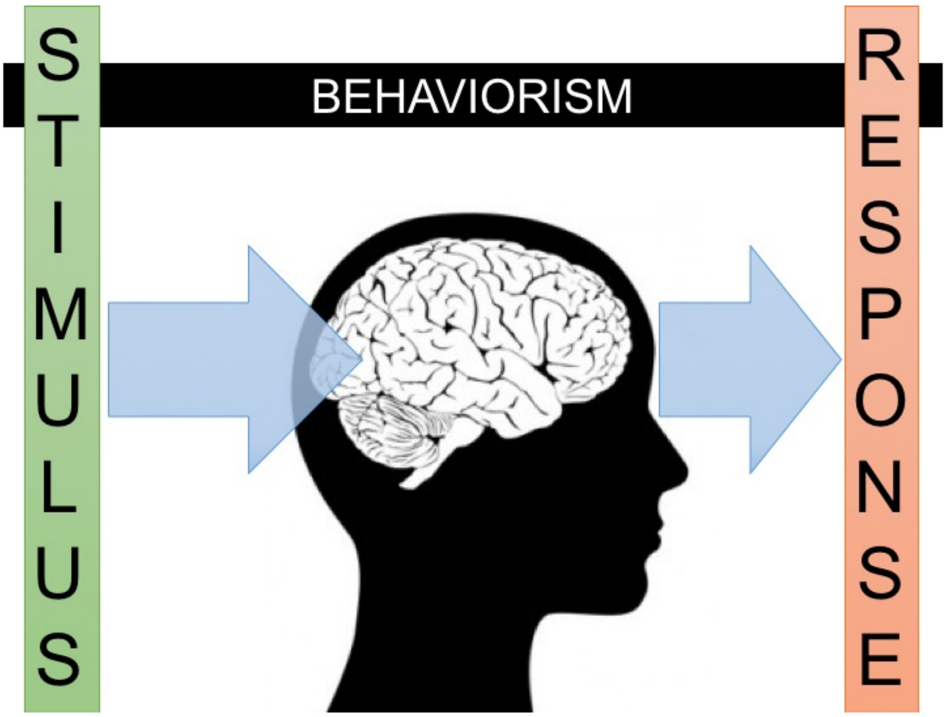

Figure 1. Behaviorism approach and the “stimulus and response method”.

Although the behavioral vision can be considered revolutionary and has changed the vision of psychology, it has some limitations. For example, as shown in Figure 1, the external stimuli are considered the only driving force of behavior and the symbolic world is not considered. According to this viewpoint, the human mind is only a system that provides answers to external stimuli.

Successively, with the birth of Neo-Behaviorism the human mind has taken a more active role in exploring the environment and elaborating the acquired knowledge. This means that the interaction between the individual and the environment also depends on the "intervening variables", such as the psychological conditions, the cognitive map, and the expectations, as shown in Figure 2.

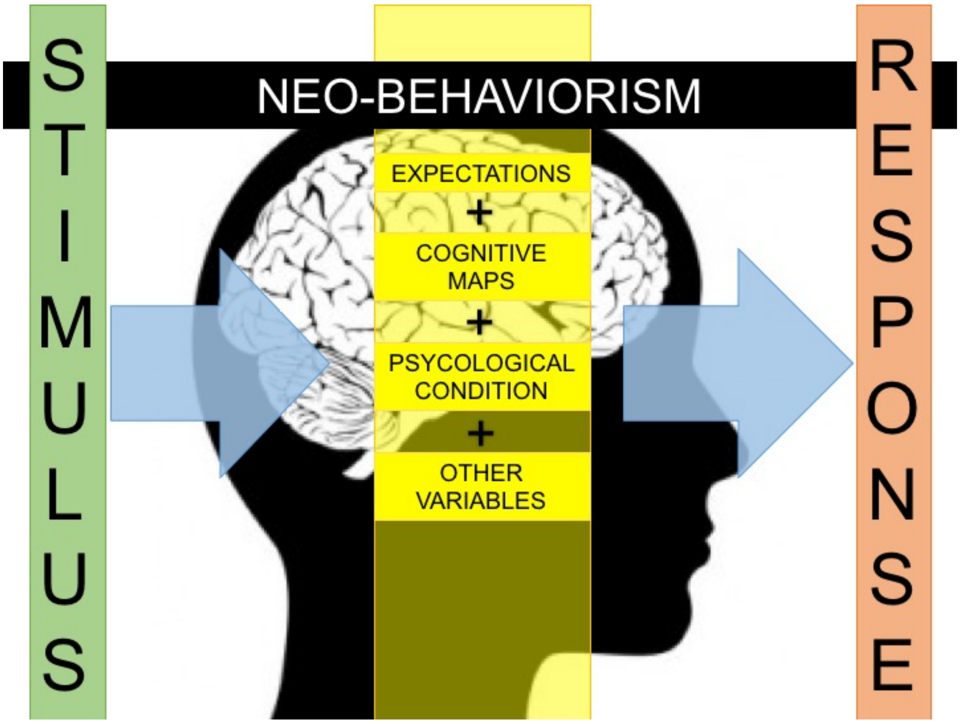

Figure 2. Neo-Behaviorism approach and the "Intervening variables" in the interaction stimulus and response.

The birth of the Neo-Behaviorism in social psychology has allowed to expand the concept of stimulus and response introduced by behaviorism, creating the basis of social learning theory and the development of the term "*modelling*" more investigated from the Cognitivism, introduced by the psychologist Ulric Neisser in the '70 and reviewed in more recent years by Albert Bandura. The *modelling* identifies a learning process that is activated when the behavior of an individual changes according to the behavior of another individual who acts as a model. People learn by observing behavioral patterns, but the representation of behavioral models is challenging given the complexity linked also to the interaction between individuals and the environment. Such interaction is difficult to be represented and predicted because on one hand humans influence the environment where they live, on the other hand they are influenced by the environment itself [2].

The comparative feedback represents another example of behaviour modelling with reference to the energy domain [106]. The comparative feedback exploits the energy past usage to model the future behaviour of users and to estimate the potential energy saving. Such a model also represents a persuasive tool that can be used to stimulate virtuous energy behaviour. An example of comparative feedback model is represented by the energy audit. In this case, a detailed report about the energy usage is provided also pointing out the potential savings that can be achieved changing the consumption patterns, for example modifying the appliance schedule respect to the past actions and habits of the users.

As defined by neo-behaviorism, the behavior processes information through the mind, which is seen as an intermediate element between behavior and the cerebral activity. The information coming from outside is processed returning the output in the form of knowledge representation. More in detail, the human behavior is the result of the information processing passing through a set of mental processes that are not scientifically recognizable, as shown in Figure 3.

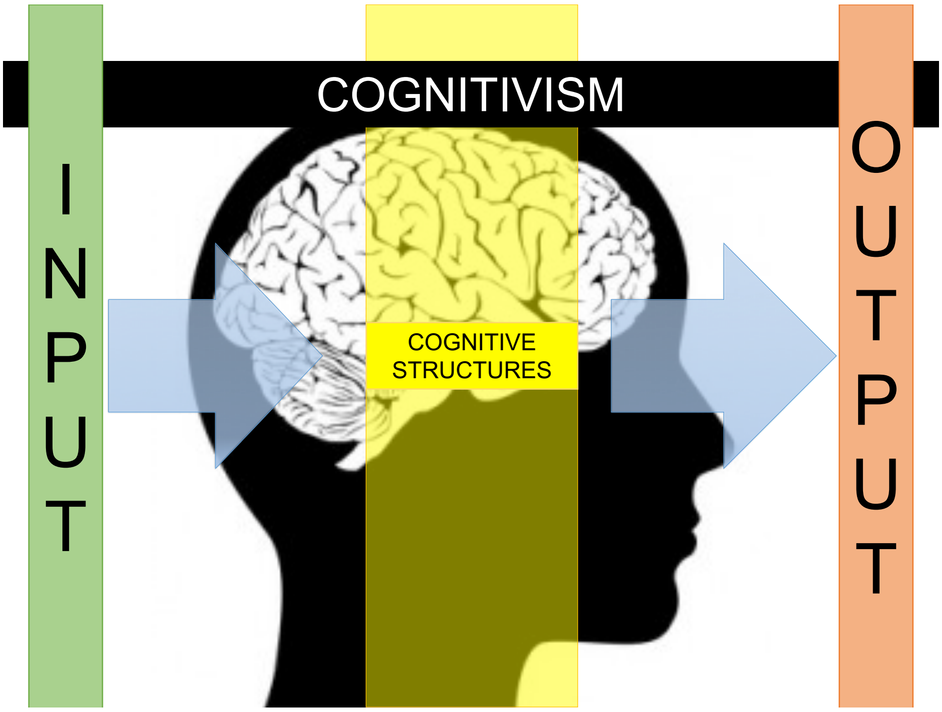

Figure 3. Cognitivism approach and the “Cognitive Structures” in the interaction stimulus and response.

According to Bandura, the behavior of the users is influenced mainly by the expectations that one has respect to the abilities [96]. Many psychological theories have been addressed during the years in order to better understand the human behavior related to the energy consumption.

For example, the behavioral research has identified in the past years some reasons of such complexities that make consumers not following the energy saving advices. It is indeed true that energy consumption could be reduced by following few simple rules (for example, switching off the lights) and modifying some daily behavior [41][42]. Therefore, it would be appropriate to create behavioral programs to change these attitudes. Toward this end, it is fundamental to understand how psychological, contextual, and social factors are correlated, directly or indirectly, with the energy-efficient behaviour, and to clarify how to change the reasons that prevent consumers from modifying their own behavior.

Numerous researches have shown that the user's behavior depends not only on economic reasons, but in particular on numerous psychological, social, environmental and physical stimuli that push the user to seek a condition of comfort within the environments in which they live and work. Figure 4 reported in [110] shows schematically the role of user behavior on the use of energy resources in smart buildings.

The main attention has been directed towards technological improvements, while ignoring the human dimension. Nowadays, the knowledge of the influence of occupant behavior on building system design and energy retrofit is insufficient. This limited understanding of occupant behavior lead to inaccurate estimation of building energy performance and building energy simulations. Figure 4 shows how occupant behavior impacts on building operation with effects on the usage and costs of energy. Both short-term and long-term effects on occupant behavior are triggered by this process through multiple factors including psychological, physiological and economic factors (short-therm) and confer and culture factors (long-term). Therefore, occupant behavior and building performance are highly coupled, with multiple feedback loops.

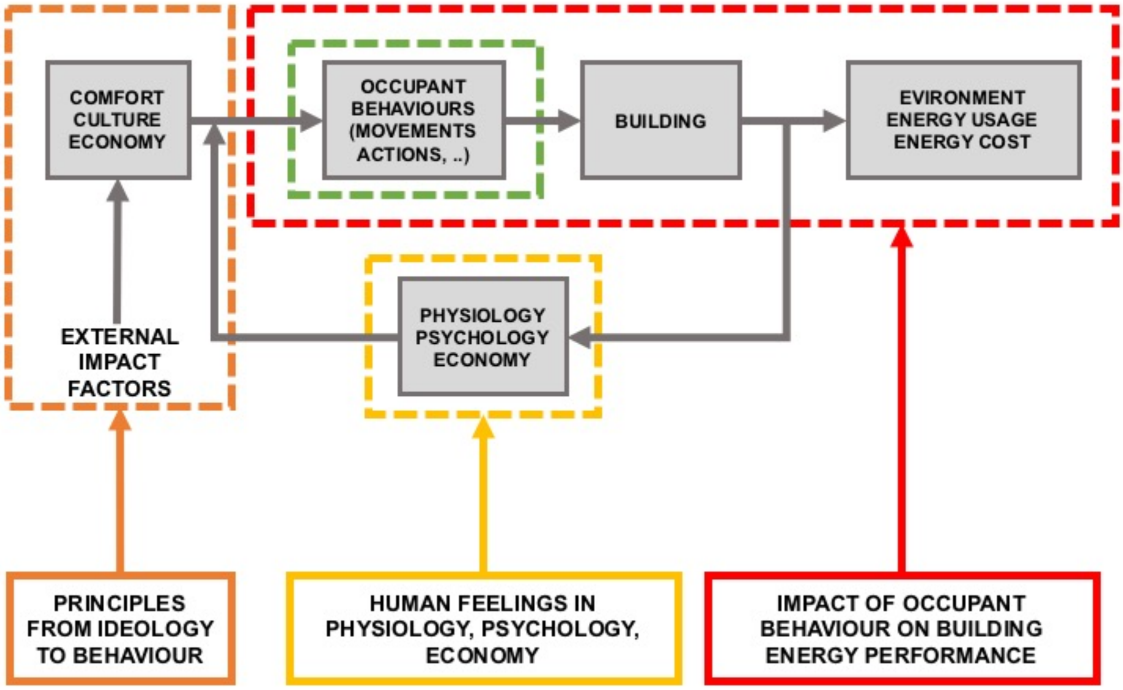

Figure 4. Modelling of user behaviors in smart buildings context.

In order to integrate the occupant behaviour into the analysis of the building performance, the numerical modelling of the aforementioned features of the behaviour is required. A model is by definition a description or a simplification of the reality. Accordingly, a model of the occupants' behaviour can be considered an approximation of actual, measured, and surveyed behavior.

Some examples of behavioural models and theories available in the state of the art are summarized in the following sub-sections. Moreover, a summary of the main advantages and drawbacks of the illustrated models is pictorially reported in Table 2.

2.2.1 THORGERSEN AND GRONHOJ MODEL

Thorgersen e Gronhoj [61] investigated that energy consumption in residential buildings, and in particular within families, strictly depends on motivational and structural elements determined by the family habits. The behaviour among the family members impact on the effort spent by the individuals to reduce power consumptions because higher the confidence of the individual on that behaviour and higher the success rate. Other elements affecting the behaviour are the expectations and the value given by the user to that action, also in terms of quality of the results obtained by other users who applied that behaviour.
The authors in [61] underlined most of the key-concepts of the socio-cognitive theory formulated by Bandura [65]. This theory has pointed out the main factors that influence each other and that determine the uniqueness of the humans. The relations among such factors are schematically represented in Figure 5, in the so-called "mutual triadic determinism".

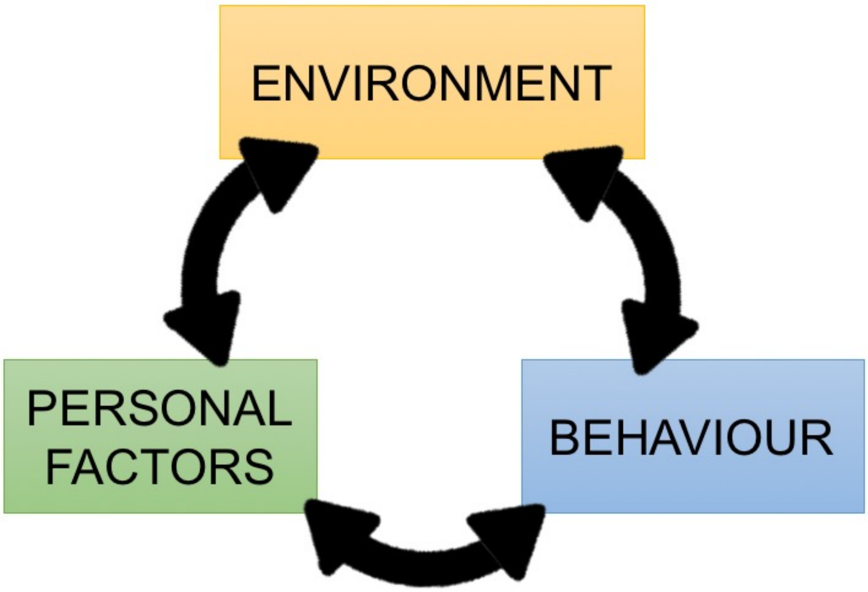

Figure 5. Mutual triadic determinism.

Such a representation points out that the human personality derives from the complex interactions among the physical and social environment, the cognitive and affective systems, and the individual behaviour. Each factor applies a causal influence on the others leading to mutual correlations that change with the variability of the context. Accordingly, the human actions act both as stimulus and feedback of the unique personality.

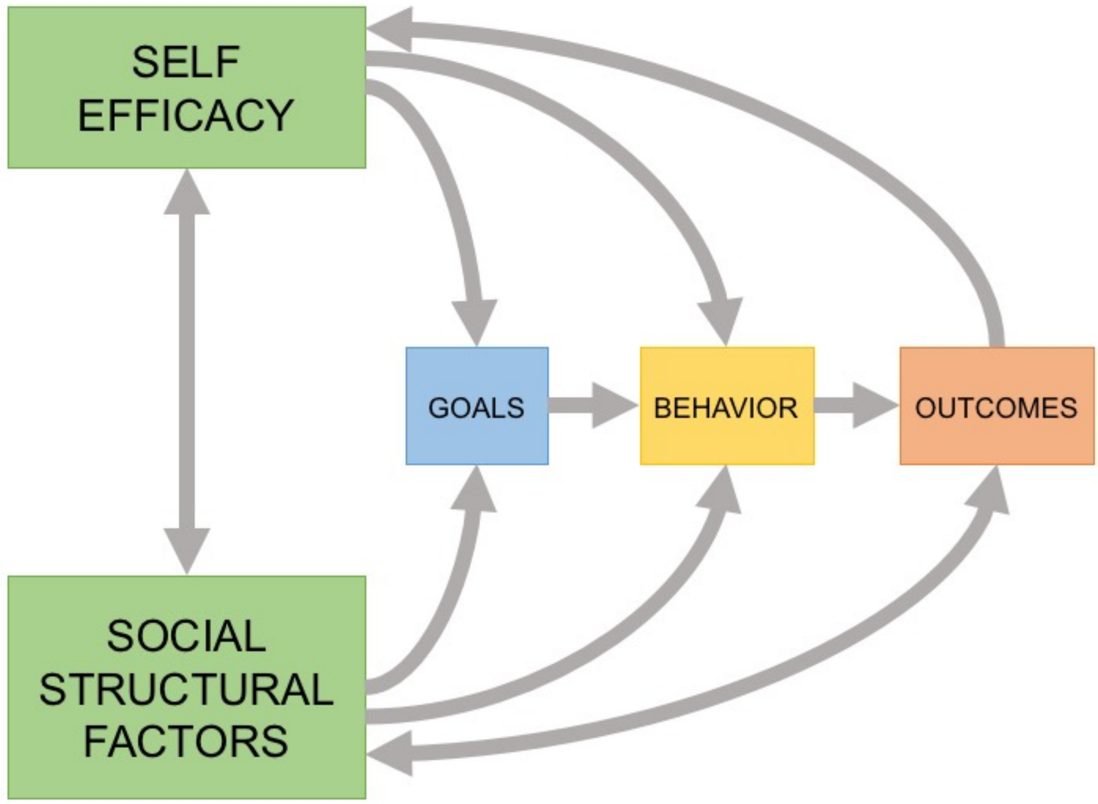

Figure 6. Thorgersen and Gronhoj model.

In Figure 6, the individuals learn from the obtained outcomes updating continuously the expectations and the perception of the self-efficacy. In this sense, Thorgersen e Gronhoj [61] have underlined that the behaviour can be modified providing more environmental enablers and modifying the expectations toward the desired actions [62][63][64].

2.2.2. Energy Culture Framework

The so-called "Energy culture framework" [76][77] has been developed by a group of multi-disciplinary researchers to model how and why the same individuals present a specific energy behaviour and also why changing such behaviour is a difficult task. The proposed framework has been developed including the main disciplines of economy, sociology, physics, law, and psychology in order to merge all the key-features of heterogeneous theories in a unique model. The basic idea is that the energy behaviour is determined by the interactions among norms (i.e., what a user consider correct), material culture (i.e., technologies and infrastructures), and energy practices (i.e., how they use energy). Moreover, the framework considers that external influences can modify the customer behaviour (e.g., the energy cost is an external influence). The final aim of the framework is to create *energy cultures* that are categories of behaviours, used as models to construct behaviour changing programs.

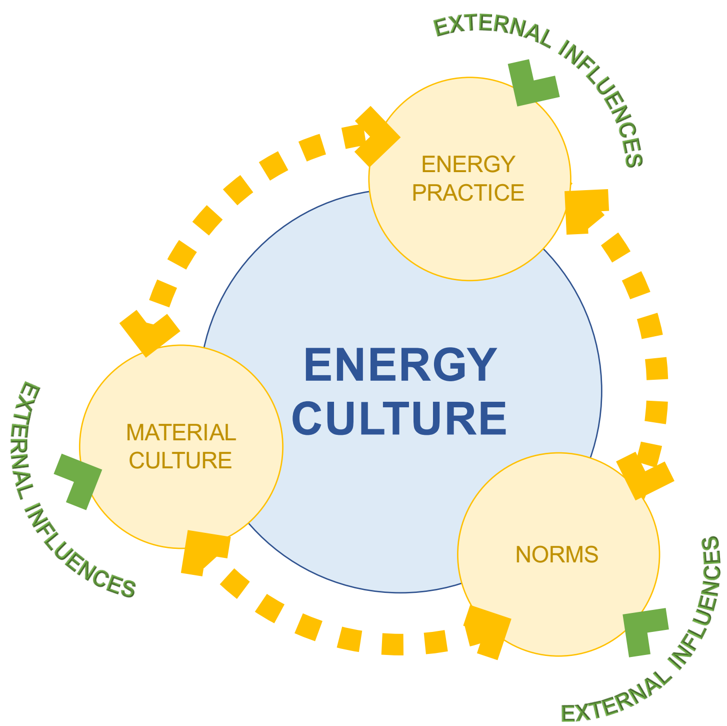

Figure 7. Energy culture framework.

2.2.3 Drivers-Needs-Actions-System Framework

The Drivers Needs Actions (DNA) System Framework [85] was introduced by Turner and Hong [86] with the purpose to create a common language regarding the modelling and the simulation of the occupant behavior related with the building. The framework states that there are four components of the user behavior, that consider the environment of the building but also the cognitive processes of the occupants, that has an impact on the building energy use.

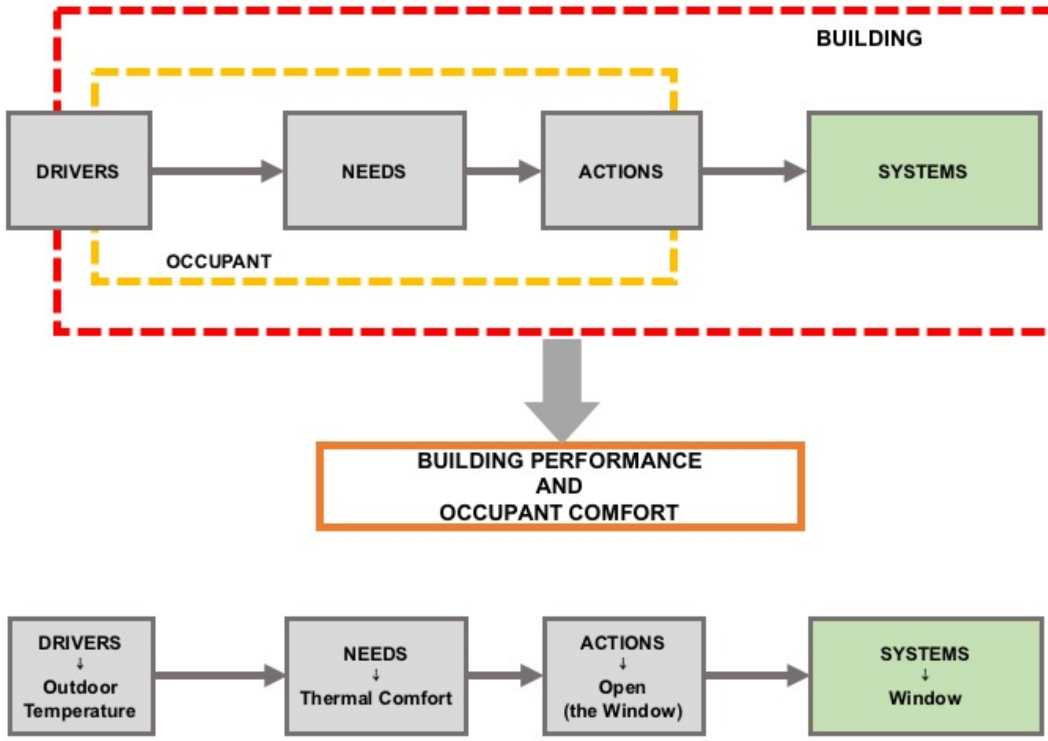

Figure 8. The DNAs framework.

As shown in Figure 8 the four components of the DNAs framework are:

- *drivers* that are the environmental factors leading the occupants to meet their needs;
- *needs*, which represent the physical and non-physical needs to be met by the internal sphere of the occupant, to ensure satisfaction with the environment;

- *actions* that are the interactions undertaken by the occupant with the system to achieve environmental comfort;
- *systems* which allow the occupant to satisfy theirs needs interacting with the mechanisms within the building

The stochastic nature of humans makes it difficult to describe and predict energy behavior and there is a lack of standardized models in literature. The purpose of this framework is to incorporate more accurate models of behaviour in order to better clarify (*i*) the behavioral factors that affect the performance of the building from the energy point of view, (*ii*) the energy saving that can be potentially achieved with an *energy-improved* occupant behavior in buildings, and (*iii*) the design of a robust scenario where innovative technologies and retrofit methods are adopted.

2.2.4 Theory of Planned Behavior and Value Belief Norm Theories

The Theory of Planned Behavior (TPB) and the Value Belief Norm (VBN) are two important theories used in the last decades to explain users' behavior change in the energy saving application field [45][46]. The TPB suggests that behaviors are based on individual's intentions that are determined by a combination of psychological constructs as subjective norms, attitudes towards a specific behavior, and the perceived control of this behavior [47]. This theory takes into account the attitudes of consumers, the social norms and behavioral control in order to reduce energy consumption. Furthermore, the theory states that people will avoid environmentally harmful behaviours if they are aware about potential penalties, and on the contrary they will follow environmentally beneficial behaviour if a reward is expected.

The VBN theory [48] postulates that the human behavior consists in a chain of psychological factors, where the values define beliefs, beliefs define norms, and finally norms define behaviours. The theory states that pro-environmental actions by users occur in response to personal moral norms and that in the involved individuals believe that environmental conditions can cause threats to others and that their actions could avoid such negative consequences [48].

2.2.5 Social practice theory

The social practice theory is one of the most used theories in the field of energy and aims to explain why people do not always act in accordance with their attitudes, creating a gap between the expected behavior and real behavior. This gap has been attributed to individual differences, contextual influences, temporal discrepancy, as well as to the methodologies used to measure attitudes compared to the behavior [46]. In fact, this theory can be correlated with energy use and consumption because energy supply and energy demand can be seen as the reproduction of complex social human practices, and daily life is a set of activities that determine and create people's behavior [53]. Moreover, energy can be defined as an ingredient of the social practices. For this reason, it is important to focus on individual or group behavior in order to understand and influence the energy demand. The energy is used to realize social practices and the understanding of social practice changing enables also the understanding of trends and models in energy demand [40]. On this matter, Hughes [40] underlined that electricity systems were built to redefine daily practices so that electricity becomes mandatory for certain practices. Therefore, it is possible to affirm that energy consumption patterns are based on the typology of the technological systems available in the building and on the specific practices of individuals or groups.

Social practice theory is based on the idea that the attention should not be paid only to individual behavior, but mainly to social practice with focus on the relations with other individuals and with the surrounding context. In order to change the social practices in favor of energy-efficient behaviors, it should be understood what determines social practices and how the technology contributes to their evolution.

Shove et al. [101] proposed a conceptual framework, starting from the definition of Social Practice Theory of Reckwitz [53], in which he postulated the idea that social practice are composed, as shown in Figure 9, from 3 elements: meanings, materials and competences. The first component includes symbolic meanings, aspirations and ideas, the second include tools, hardware, human body and objects, finally the third component include the practical knowledge of the practice, and the skills to execute those practice. The principal concept is that the individuals are the vehicle of a social practice, that is an entities made of material arrangements, know how, rules and affective structures.

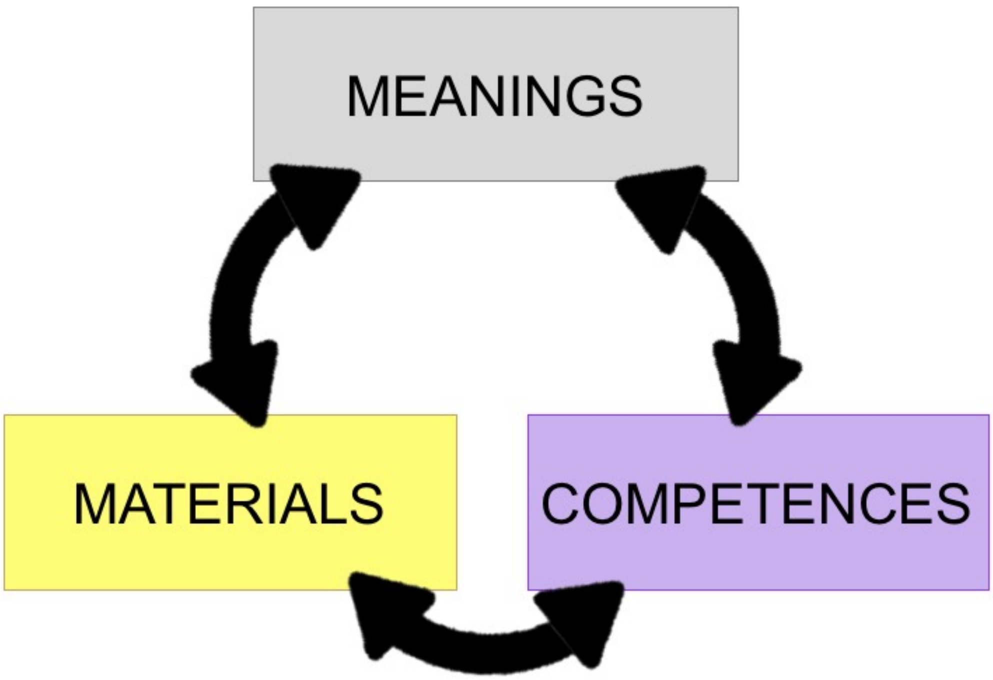

Figure 9. Elements of a social practice.

For example, [103] suggested three types of possible interventions for sustainable energy. They suggest that policies informed by practices can either aim to re-elaborate the practices by modifying the elements that compose them; replace existing practices with new practices, change the way interconnected practices are interconnected [102].

The social practice theory provides a realistic perspective of behaviour change and highlights the problems faced in changing behavior. Behaviour changing requires more than the removal of contextual “barriers” since the organization of whole everyday life is involved [46].

2.2.6 “Action-based” Modelling

The behavior can be considered a structured set of actions performed by a human in a conscious or unconscious way. The actions are oriented towards the achievement of specific objectives and are influenced by the surrounding context of the building [2]. The influence generated between the building and the users is investigated by many disciplines such as social sciences, psychology, architecture, engineering. Accordingly, a lot of models in the state of the art have interpreted the user behaviour like a sequence of actions that affect somehow the status of the building. For example, a selected set of interactions user-building proposed in the state of the art and also reviewed in [3] is reported in Table 1. As it can be noticed, most of the authors represent the user behaviour as the practical interaction with building plants and/or structure, like the “use of appliance”, “use of ventilation”, “window opening”, “thermostat control”.

Author (s), year	Methodology	Building Type	Occupant Interactions	Influential parameter
Li et al. (2014) [87]	Field Observation, Data Analysis Using SPSS Statistical Software	Offices	Window opening	Climatic
Yu et al. (2015)[67]	Existing 2-year Survey Data, Data mining-based Methodology	Residential	Use of appliances	-

Simona D'Oca and Hong (2014) [66]	Combined Statistical Analysis (with two data-mining techniques: cluster analysis and association rules mining)	Offices	Window opening	-
Zhao et al. (2014)[88]	Experiment, Data Mining	Offices	Use of appliances	Climatic
Langevin et al. (2015) [78]	Longitudinal Case Study, Survey, Measurements, Human Tracking	Offices	Thermal Control	Personal
Jang and Kang (2016) [89]	Case Study, Survey, Gaussian Process Classification	Residential	Heating and Electricity consumption	-
Khosrowpour et al. (2016) [90]	Sensor-based Monitoring, Classification and Predictions	Commercial	Use of appliances	Personal
Fabi et al. (2013) [92]	Case study, Medium/Long-term Monitoring	Residential	Window opening	-
Ryu and Moon (2016) [91]	Experiment, Decision Tree and Hidden Markov Model	Building Integrated Control Test-bed	Electricity Consumption	Climatic

Table 1. Examples of “action-based” user behaviour modelling in the state of the art.

More in detail, among the selected examples, D’Oca *et al.* in [66] models the behaviour with the schedule of window opening assuming that general patterns of windows closing and opening can be identified with data mining techniques, such as clustering and association rules algorithms. The main goal is to discover typical users’ profiles in an office to identify specific behavioral patterns as (*i*) motivational, (*ii*) opening duration, (*iii*) interactivity, and (*iv*) window tilting angle position. The authors showed a set of relevant clusters that classify the windows opening habits, pointing out that the air temperature outside, the time of the day, and the occupancy presence are the principal drivers for windows opening. Furthermore, they find out that the drivers of windows closing are the air temperature inside and outside, the occupancy presence, and the time of the day. In fact, the temperature discomfort, the time of the day and the routine of the users impact with the users interaction with the windows.

Yu *et al.* in [67] models the behaviour with the schedule of appliance assuming that they are related to each other. The authors developed a data mining technique selecting a set of association rules existing between household appliances. In particular, the rules define that (*i*) video and light point out the possibility to be used at the same time, therefore the suggestion for energy saving is to watch video with the light off or with a shady light; (*ii*) The TV is often watched at the same time that the occupants use the computer. The recommendation is to optimize the use of one appliance for both the tasks; (*iii-iv*) the appliances in kitchen, the air conditioner, a medical machine, the dishwasher, the microwave oven, and the rice cooker show high correlated usage since the authors supposed that medical machine is used during cooking time with the air conditioning active. Moreover, dishwasher, rice cooker, and microwave oven were often used at the same time; (*v*) the last rules appoints out a strong association between the refrigerator and living room outlet since the refrigerator is connected to the living room outlet.
Furthermore, they investigated the association between the usage of household appliances and the environmental parameters discovering an association between outdoor air temperature and the reduction in the usage of appliances for cooking (e.g., higher temperature reduces the appetite of the occupants).
Another example presented by Langevin *et at.* in [78] has investigated the key-elements of a behaviour model starting from the occupant comfort measuring the local thermal environment in the proximity of each occupant.

The results have pointed out that certain behaviors are clearly related to changes in the thermal environment, but others are better described by non-thermal elements. The thermal sensation that is acceptable by an occupant has been considered a significant information to predict the thermal comfort and the corresponding behavior. This suggests that the individual thermal acceptability range is a representative information for the definition of the behavior model also pointing out the differences among the individuals. The measurement campaign performed by the authors has also suggested that a behavior hierarchy exists and that the daily sequence of such hierarchy in the considered air-conditioned environment gives the priority to the most immediate behavior, with minor attention to the most “virtuous”. It has also been found that the behaviors related to cold discomfort are chosen later than those behaviour caused by warm discomfort. The authors concluded that a representative behaviour model should satisfy the following requirements: (*i*) the behaviour should be represented at individual-level, (*ii*) a single modelling framework should include and accommodate multiple behaviours, (*iii*) at least 2 realistic constraints on the behaviour should be considered (e.g., appropriate clothing, limits on the conflicts among the comfort of different occupants), (*iv*) also non-thermal behaviour should be included like for example the use of lights for lighting comfort.

Even if many “action-based” models are available in the state of the art, occupant behavior is much more complex, stochastic, and diverse that a simple sequence of actions and interactions with building. An interdisciplinary viewpoint is mandatory to accurately model how humans behave. However, at a certain level, the arising complexity would be too high to the extent necessary to energy saving. In this regard, the behaviour model proposed in this thesis is based on the integration of location-based information as a *glue* between the actions of the users that can be recognized looking at the interactions with the building (e.g., usage of appliance, control of the HVAC systems, etc.). This interpretation of the human model will improve the understanding of the human impact on the building, since even only the estimation of the “passive” presence of the occupants (i.e., without specific actions) provides information to understand the behavior.

Model	Features		
	Flexibility	*Usability*	*Multi-disciplinarity*
Thorgersen and Gronhoj Model (Sect. 2.2.1)	☹	😐	☹
Energy Culture Framework (Sect. 2.2.2)	😐	☹	☺
DNAs Framework (Sect. 2.2.3)	☺	😐	😐
TPB and VBN (Sect. 2.2.4)	😐	😐	☹
Social Practice Theory (Sect. 2.2.5)	😐	☺	☺
Action-based Models (Sect. 2.2.6)	☺	😐	☺

Table 2. Advantages and drawbacks of main behaviour models in the state of the art.

2.3 BEHAVIOUR CHANGE PROGRAMS

The behavior change programs have been addressed in the state of the art to further reduce the energy consumption stimulating the target audience to behave in an “energy-virtuous” way. The performance of such programs are difficult to be assessed since the effects depend by many factors that usually change very slowly and with low persistence.

During the '70s, in parallel with the technological innovation, various solutions have been investigated to identify and promote virtuous behavior (both individual and social) with focus on the energy efficiency. A large number of energy efficiency programs have been developed by researchers but also by the utilities. Most of them considered the human behavior secondary to the adoption of smart technologies and devices, but nowadays it is well known that all the energy efficiency programs have to involve human activities and behaviour into the decision-making processes [43][44]. Accordingly, the behavior changing programs have increased recently putting the physical measures into the background and investigating the consumer behavior from the social science point of view, with focus on the relation between stimulus and human response that plays an important role on human decision-making during the interaction with technology [79].

For many years, the most common models for behavior change toward energy efficiency have been the *attitude-behavior* and the *rational-economic* models. The first typology of models assumes that users with already “positive” attitude toward energy saving would easily achieve high energy efficiency each time they have the opportunity. The second category of models is based on the common rule that users act rationally when they can save money with minor impact on their well-being [81].

The main consideration related to such models was that providing information and indication on how to achieve energy efficiency and the consequent financial benefits will determine a natural engaging of users in energy-efficient behavior. Accordingly, the most effective approach to stimulate behavior change was considered the mass information campaign. However, a review by the American Council for an Energy-Efficient Economy (ACEEE) in 2000, pointed out that this default approach often went unevaluated. The main cause of the failure was the assumption that “information given is information received” [82], which has proved to be simplistic respect to the real feedback of the users. Accordingly, it has been demonstrated that neither the *attitude-behavior* nor the *rational-economic* models adequately describe how behavior change happens. Even people that consider themselves “green” have rarely changed their behavior according to information campaigns focused on the environmental impact of energy waste [83]. Despite the big effort of governments, electric utilities, and non-profit organizations in the promotion of information campaigns, the well-known “efficiency gap” (i.e., the difference between the potential and the actual energy efficiency) persists because people do not change behavior as expected by the program designers [84].

People do not clearly understand how much energy they are using and how much they can reduce the efficiency gap by changing the daily behaviour or improving the awareness of power consumption through detailed measurements. Such awareness has been studied in the “feedback” literature to point out the relevance of feedback to make the energy consumption more visible and understandable. The first studies on feedback control started in the 1970s pointed out that communication through display monitors has measurable effects as a learning tool that allows energy users to teach themselves. For example, it has been demonstrated that a clear feedback has enabled users to learn how to control the fuel usage more effectively both in short-term (e.g., through instantaneous direct feedback like adaptive billing) and over a long-term period to ensure a sustained demand reduction thanks to a better understanding and control of the energy usage. Such studies on energy feedback have been carried out mainly by psychologists who considered the feedback as an intervention in the normal user behaviour to reinforce specific trends through rewards or punishment [109].

The learning process of feedback has been defined by researchers pointing out that interventions focus on the control of narrow target behaviours [104] or, on the opposite, on wide-ranging studies [105] saying that any type of feedback produce positive results under any conditions and with reference to any kind of population. However, as a common conclusion has been confirmed that the context is important for feedback management.

The general idea is to consider the contribution of feedback to the generation of a ”tacit knowledge” about the supply and usage of energy. The users receive information about their energy use, they act changing behaviour somehow and they gain understanding by interpreting the available feedback.

In [79], ACEEE delivered the first classification of the behavior-based programs, where the authors summarized a list of drivers that are psychological and social mechanics influencing the decision making. Such drivers (e.g., feedback, framing, commitment, social norms) can be used by the behavior change programs. The following categorization of behavior programs has been created by ACEEE:

- **Cognition**: unidirectional programs, which give information to consumers through traditional means of communication such as TV, emails, social media, or classroom lessons and courses in companies (e.g., general communication efforts, targeted communication efforts, social media, classroom education, training programs).
- **Calculus**: programs based on consumer economic decisions based on feedback, competing games, incentives, and home energy audits
- **Social Interaction**: programs based on social interactions that can be undertaken directly or through online services. This kind of programs relies on the deep basis of sociality. For example, social marketing, person-to person efforts, eco-teams, peer champions, online forums are among the existing categories.

Few years later in 2016 [80], ACEEE proposed a new categorization on the basis of more studies and results obtained in the field of behavior change programs. In particular, the main categories are:

- **Information-based programs**: these programs are based on the idea that changes occur by providing to the users the information regarding their energy consumption. Although there is evidence that the lack of knowledge influences the behavior, many other factors have to be considered. For example, information-based programs are also based on the mutual influence caused by the physical interactions between two or more users that lead to new "mixed" behaviors due to information exchange among users. Some examples of such programs are home energy reports, real-time feedback, audit programs.

- **Programs based on social interaction**: the energy behavior is affected by the interactions among users and in particular by the comparison with the others. The main programs based on social interaction are the competitions and games, where the games lead consumers to achieve higher goals by confronting each other, and the community-based programs that create ad-hoc behavioral change programs based on specific communities.
- **Education and training programs**: these approaches consider teaching as the main vehicle for behavioral change and include a set of elements of other programs. For example, the strategic energy management (SEM) programs are based on direct interaction with users to provide energy information, and training programs that teach the strategy to the community about how to reduce energy consumption.

Figure 10 shows the stages of behavioural change, summarized in [108] starting from the definition reported in the previous work, "Principles of Awareness-Raising" by Richard Sayers [107].

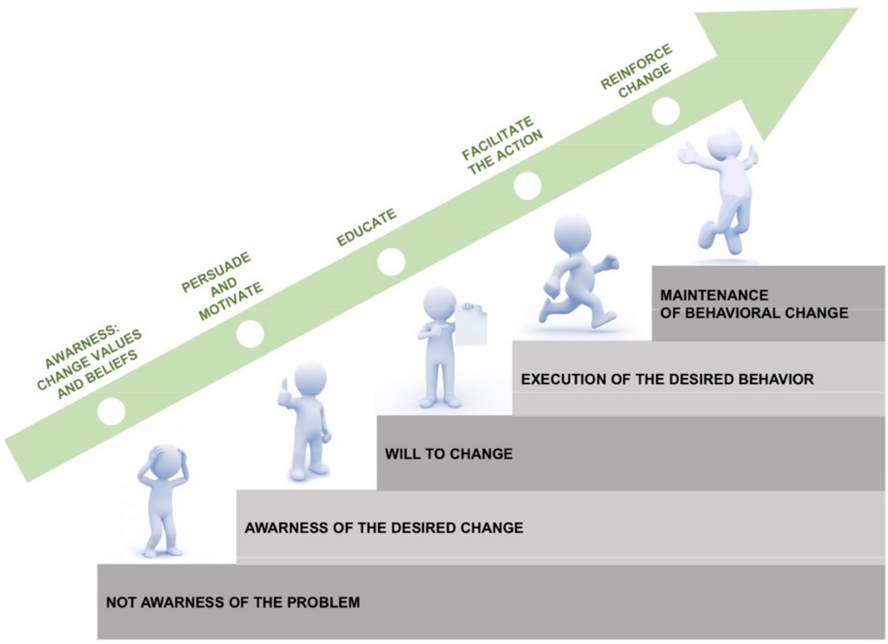

Figure 10. Stages of behavioral change.

The change from one status to the other of the behaviour change scale should be achieved through suggestions given in a slightly and creative way in order to modify the attitudes with a reduced impact on the user comfort and avoid impositions.

More recent works [55][69][70] have revealed that new typologies of programs are particularly influential on user behavior toward energy saving, like the programs based on *game* and on *eco-feedback*. The gamification has been proven to be an efficient way to model the behaviour of users, who are considered the players of a game applying strategies and actions that maximize a reward (e.g., the energy cost saving, or the reduction of the total consumption [56]). The actions are usually suggested by the program, often based on recommendation systems that observe the user behaviour (e.g., through energy usage monitoring) and learn the best strategy to modify the actual behaviour toward the optimized one that maximize the reward of each player [71]. Concerning the programs based on *eco-feedback*, the virtuous energy behaviors are promoted through "eco" feedback provided to the users pointing out their current consumptions with respect to the past ones and highlighting inefficiencies in order to identify how to improve.

Summarizing, the main recent programs have demonstrated that the occupant behavior needs to be directed towards a more efficient use of energy in order to effectively optimize the power consumption and the exploitation of the grid. However, the mutual influence among users, with the buildings, and with the environment cannot be described in a simplistic way due to the stochastic nature of the occupant behavior. Appropriate methodologies and techniques are required to describe the complex combination of actions, response to stimuli, and user strategies that are responsible for real energy performance of the building during its life [85]. Most of the behaviour-based efficiency programs have focused on the influence of the users on the building in order to integrate such influence in the numerical modelling of the building itself and improve the accuracy of the simulations. Better simulations enable more accurate design and control of the energy plants of the building. However, such approaches usually model an average human behaviour that represent a category of users, with less attention of the actions of single users and how these actions impact on the consumption.

This thesis is focused on the study of user actions in smart buildings scenarios with focus on the socio-behavioral dynamics that are useful to model the behaviour of single users into decision support tools. The system suggests daily actions to each user that lead to virtuous behavior from an energetic point of view considering how they behave daily and their main habits. Assuming the understanding of individual behaviour (e.g., how a user moves in the building and how/when the appliances are used) make feasible the creation of individual suggestions to improve the energy-habits of single users that are part of a community (e.g., at the building/district scale).

However, there are some obstacles that interfere in the suggestion of optimal programs customized on the profiles of single users. For example, top-down communications that are commonly used to promote actions are not sufficient. Moreover, the so-called "rebound effect" [94][45] often arise: technology allow the users to save energy, but given the energy savings, the users are motivated to use the devices more. Accordingly, technical improvements in the buildings can lead to behavioral changes, but it may happen that the occupants look to higher comfort and they finally the energy consumption are increased [54].

The goal of the solution proposed in this thesis is to avoid the aforementioned limitations of mono-directional communication (i.e., from the system to the user) integrating the user habits directly into the configuration of the system and the computation of the suggestion. This approach integrates a sort of "automatic feedback" that is virtually received by the users even if they do not directly cooperate with the decision support system thanks to the estimation of the users positions and movements that naturally occur during the user actions/interactions with the appliances.

2.4 USER BEHAVIOUR IN DECISION SUPPORT SYSTEMS

The term DSS dates back to before the invention of the computer and referred to paper documents and to the collection of practices based on experience. Hereafter, the development of the DSS has been extended to various scenarios and thanks to the support of advanced information and communication technologies (ICT), the development is today more and more innovative and allows to improve the activity of decision-makers [74]. Nowadays, the DSSs allow to quickly clarify the situation thanks to the numerous and heterogeneous data collected by means of ICT-based systems. A selection of important key features of a DSS includes [75]:

- assistance and improvement of human reasoning without replacing the final human control;
- adaptability to changes of the context thanks to the availability of new and updated information;
- combination of analytical models that provide synthetic information automatically collected from heterogeneous and distributed sources;
- high interactivity thanks to user-friendly interfaces.

A DSS provides suggestions regarding the actions to be carried out during certain circumstances, but does not act automatically. In fact, the human intervention is always expected by the system during the decision-making process. Therefore, with regard to the management of buildings, the DSS allows the reliable evaluation of comfort, costs, and performance based on the collected data in order to support the end-user in the energy management and to suggest energetically virtuous behaviors based on current and expected consumption. 0.

Among the solutions that consider the behavior of people in order to support their decisions, techniques based on game theory (GT) have been analyzed. Game theory studies the behavior of individuals in situations of strategic interaction compared to other rival subjects, aimed at maximizing the income of each participant [9]. The decisions of every individual who takes part in the strategic "game" can influence the results achieved by the other and/or vice-versa. Game theory is based on models that represent the real problem and defines the strategies that the players can apply according to the information on the energy consumptions that are available [11]-[13].

For example, DSSs have been proposed to support the demand response (DR), which is one of the most reliable solutions to manage the energy demand profile in a multiuser smart grid scenario. The integration of the consumer preferences in the load scheduling is a fundamental aspect to make DR programs acceptable by the users. State of the art methods [93][94] have solved the energy cost optimization problem considering the reduction of the user comfort due to the load scheduling suggested by the DSS. However, the standard approaches often under-estimate the users' needs. This thesis contributes improve the acceptability of the appliance scheduling taking in full consideration the users behaviour, which is modeled in terms of availability to change the consumption patterns. The GT-based approach has been integrated with the customers' constraints applied to the load shifting that can be optimized only within time windows defined according to daily habits of the users. The unknowns controlled by the DSS are the time instants when the monitored appliances are turned on. The main contribution of the proposed method is to incorporate the customers' constraints in the DSS flow toward a behavioral perspective of the user-centric grid.

3. USER FEATURES FOR BEHAVIOUR REPRESENTATION

A set of features representing the role of users in smart buildings has been selected for integration in DSS. The set of features includes the "location-based" characteristics, in particular those related to the presence, position, and movement of the users occupying the buildings, and the "energy-habits" characteristics relating to the daily energy habits of the users and their profiles of consumption.

This thesis focused on the analysis of the application scenarios in which the behavioral profiles of the users affect the energy consumption related to the building installations, considering the end user as a pro-active subject in the "energy chain" process. Among the scenarios and the behavioral models investigated, particular consideration has been given to the residential one where energy resources are shared by a large number of users. In this scenario, the users are supported in the management of their appliance in smart buildings, with the dual purpose of reducing the cost of energy consumption and at the same time limiting the impact of the suggestions on the user habits.

A frequent problem encountered with the generation of databases about the use of energy is the lack of connections between human behaviors and the energy consumption. The data are usually related to the energy consumed by household appliances, but they are not related to human activities and any detail about the related activities are known. The more accurate analysis of the human activities is important in order to correlate the actions with the consumption [34][35].

Toward this end, the aforementioned features (i.e., “location-based” and “energy-habits”) have been analyzed in the following sections in order to describe the technologies and the methods that enable the acquisition of the selected user information and the achievable performance. In particular, the estimation of the users position and movements by means of a wireless localization strategy is presented in Sect. 3.1. The mobile devices of the users (e.g., smartphone, wireless tags) are localized using the wireless networks that are deployed in the smart buildings, such as the residential WiFi that is widely diffused in most of private and public areas. In Sect. 3.2, the methodology based on game theory for the computation of the optimal consumption profiles suggested starting from the user needs and habits is presented.

3.1 LOCATION-BASED FEATURES

More and more location-based services are rapidly spreading thanks to the increased availability of localization technologies. Private and public end-users benefit from the rapid advances of both technological and methodological solutions that are making the position information ubiquitous. In such a framework, wireless communications play a key-role in the propagation and diffusion of the available information among the mobile entities of the network. Well-known localization technologies such as the global positioning system (GPS) have been integrated in commercial devices like smartphones and tablets. On the other hand, innovative technologies such as wireless sensor networks (WSNs) [7] allow one to collect a huge amount of heterogeneous data that can be exploited for localization purposes [27] and, more in general, to 'model' the complexity and the variability of the environment and its time-varying behavior. The possibility and ability to correlate such heterogeneous data with the position information of targets moving within the environment at hand enables innovative services for the 'management' of people and things. For example, position information can be exploited to control the light intensity of multiple lamps taking in consideration both the quality of the user experience and the energy saving as presented in [28]. In this work, the wireless sensor and actuator technology has been exploited to sense the environmental condition and the energy consumption as well as to control the lamp actuators for the autonomous light dimming also considering the presence of users throughout the controlled rooms.

More in general, the underlying idea of the wireless localization exploited for human behaviour understanding is that “the best position estimation is not the most accurate one, but one that provides the highest informative contribution respect to the context”. Knowing the real occupation of the spaces is obviously fundamental for regulating and managing the systems of a building and optimizing energy consumption accordingly. As discussed in Sect. 2, there are numerous state-of-the-art studies that estimate the patterns of presence and behavior typical for specific user typologies. These patterns are often static and representative of reference behaviours, but not of the real day-by-day use of the building.

In order to increase the accuracy in estimating and modelling user behaviour, technological solutions that can extract information on the presence of people have been considered starting from the real-time measurement of some parameters that characterize the environment under monitoring. Among these parameters, there are the information provided by wireless networks deployed in the buildings that can be exploited to localize wireless devices and understand where the users are located. In this case, it is assumed that the user is associated with a mobile device such as a smartphone or a tablet, as long as it is equipped with wireless technology such as WiFi connected to an existing wireless network [16]-[18].

Among the techniques that do not require dedicated hardware, there are those based on the Received Signal Strength (RSS) which indicates the power level of the wireless signal received by the device. There are several ways to implement location systems based on the Received Signal Strength Indicator (RSSI). The first family of techniques is based on fingerprinting and plans to map the spatial distribution of RSSI through a large number of detections. The value of RSSI acquired by the device in an unknown position is compared with the previously estimated spatial distribution to find the closest result and thus deduce the position of the target.

A second category of techniques is defined as "propagation-based" and is based on the estimation of wireless propagation in the monitored environment [16]. The information deduced from the signals like the attenuation is used to estimate the positions of the users. These techniques present a high complexity in the accurate modelling of wireless propagation, but they do not require time consuming data acquisition operations. For this reason, they are easily scalable and better adaptable in indoor environments that can change their characteristics over time, such as private apartments in residential scenario.

Among the techniques investigated for the estimation of the position of the users, a solution that exploits the characteristics of the WiFi wireless signal [16][26][27] has been selected. The required inputs are the positions of the wireless devices deployed in the environment (i.e., the WiFi access points) and the size of the monitored area (e.g., the apartment blueprint). The results provided by the localization technique are the positions of the WiFi devices moving throughout the rooms of the monitored building.

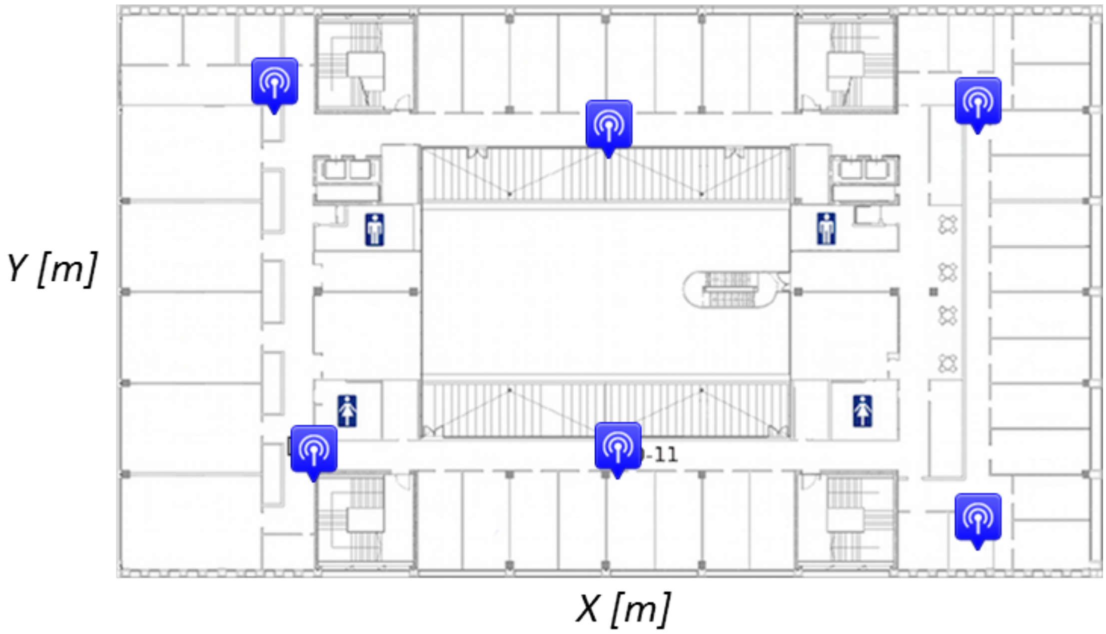

Figure 11. Wireless network deployed in the test site for the acquisition of the “location-based” features of the users.

The estimated positions can be used to infer the occupation of the rooms and consequently calibrate the management of the building's installations, such as the lighting system [28] or the air management system [29]. The selected localization technique presented in [16] has been validated within the laboratories of the University of Trento in order to assess the performance and verify the satisfaction of the application requirements. For example, the capability to recognize the room where the user is located is important from the point of view of the user-building interaction.

Figure 12. Graphical user interface of the wireless localization system providing the "location-based" features of the monitored users.

The methodology can be calibrated to operate by exploiting different wireless standards and platforms since the main requirement is to have access to the RSSI parameter, which is commonly provided by most of the commodity devices. Starting from this assumption, a preliminary validation can be carried out using the common WiFi network already deployed for connectivity purposes, and able to provide such information.

Figure 11 shows the blueprint of the area used for validation. The considered test site is representative of an indoor environment occupied by different types of objects and obstacles that make wireless propagation very complex for the purpose of localization.

Inside the test site of size X=80 [m] and Y=46 [m] are installed K=6 wireless access points (the blue icons shown in Figure 11) operating at the frequency f=2.4 [GHz] of the wireless standard *IEEE 802.11ac*, in known positions respect to the reference system and used as anchor nodes. The location of a stationary or moving device within the test site takes place using the RSSI values received from WiFi access points and processed in real time by the optimization methodology [6].

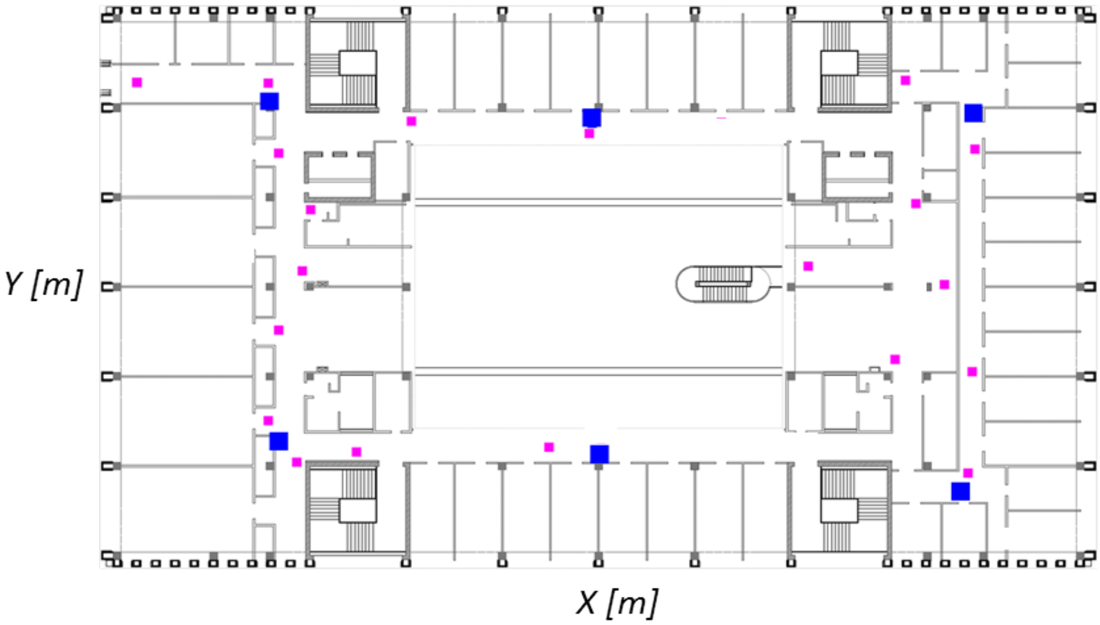

Figure 13. Test positions of the target within the monitored domain.

The wireless localization system provides the results through a graphical interface that is shown in Figure 12 for illustrative purposes. The position of the user is reported and updated in real-time on the blueprint of the test field. Concerning the computational load of the localization algorithm, the optimization procedure has been calibrated in order to ensure that the computational time is lower than the RSSI scan rate of the WiFi network. It has to be noticed that the scan of the RSSI takes about 1 [s] (i.e., the time required by the application installed on the mobile terminal to complete the scan of all the wireless APs) while the estimation of the target position takes less than 0.5 [s] using a standard computer (i.e., CPU Intel i5 with 8 GB RAM) as control unit. Toward this end, the termination strategy of the optimization algorithm has maximum number of iteration set to I=100. Accordingly, the computational load of the optimization algorithm satisfies the time constraints of the dynamic localization scenario. It has to be noticed that the number of localized targets impacts on the computational time since the position estimation of each target requires a standalone optimization. The localization of multiple targets has not been investigated in this thesis since it increases only the computational complexity without a direct impact on the localization accuracy. However, the investigation of the localization performance in presence of multiple targets will be considered among the future activities.

The performance of the localization method have been validated starting from a set of test positions, distributed within the area considered and shown in purple in Figure 13. In each of these positions, P = 50 measures of RSSI were acquired from anchor nodes that are in the wireless coverage range of the receiving device.

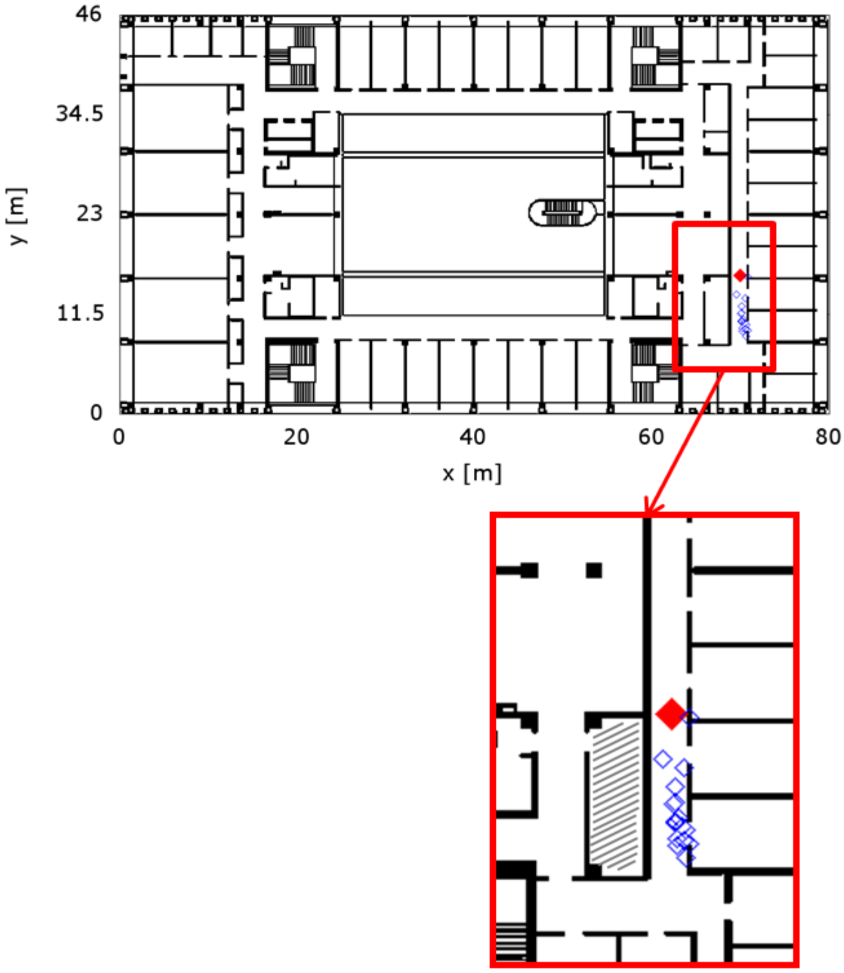

Figure 14. Comparison between the actual target position (red dot) and the positions estimated by the localization method (blue dots).

To evaluate the quality of the position estimates, the average Euclidean distance between the actual and the estimated positions has been considered as error metric:

$$\Delta_t = \frac{1}{P}\sum_{p=1}^{P}\sqrt{(x_t - \tilde{x}_t)^2 + (y_t - \tilde{y}_t)^2} \quad ; \qquad t = 0,...,T \tag{1}$$

where $\tilde{x}_t$ and $\tilde{y}_t$ are the coordinates estimated by the algorithm at the t-th target position.

An example of a comparison between the real position of the target and the positions estimated by the localization method is shown in Figure 14.

The obtained localization errors are shown in Figure 15. In order to provide an indication of the average performance of the localization method, the total average error has been calculated as

$$\overline{\Delta} = \frac{1}{T+1}\sum_{t=0}^{T}\Delta_t \tag{2}$$

that is equal to $\overline{\Delta} = 5.68$ [*m*].

The obtained results point out the ability to estimate the position of a wireless device in real time, using only the information on the quality of the wireless links.

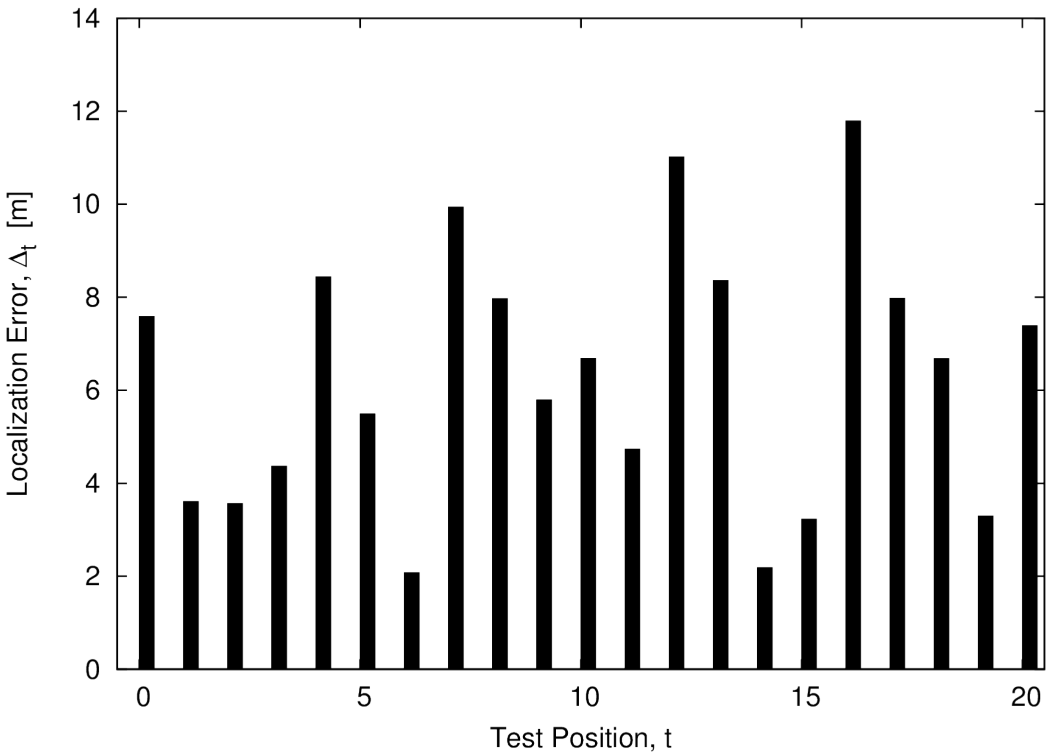

Figure 15. Localization error of the “location-based” features computation.

The high scalability and flexibility of this approach facilitate the application in different indoor scenarios characterized by geometric and electrical characteristics that are highly variable. The “location-based” features can be used to estimate the daily occupation of the monitored rooms by the users and to update accordingly the occupation patterns that are normally assumed “static” and predefined by the DSS in the state of the art. The ability to locate users in real time allows to improve energy savings and to promote good energy-habits [30].

Understanding the human presence and movements within the building helps to identify the user routines that are crucial in the coordination of domestic activities, and are also considered a valuable cognitive resource to ensure that human activities are carried out efficiently and comprehensively [32][33].

3.2 Daily Habits and Energy Profiles

The management of the energy demand by users of a smart building is a fundamental aspect for energy saving, obtained by balancing the loads with respect to the availability and the cost of the energy resources themselves. Different state-of-the-art strategies have been proposed to motivate users to be part of the energy management process [19]-[22].

In general, the main mechanisms of interaction with the user are aimed at reducing consumption or shifting it over time. The reduction can be obtained by stimulating virtuous behaviour in users for the reduction of waste. The shift is induced by suggesting the most appropriate time slots when using the loads (e.g., household appliances in a residential context) with the aim of reducing the absorption peaks, typically concentrated in the most likely times of use. The peak of absorption on the network translates into an increase in the cost of energy (in the case of energy cost models dependent on absorption). The 'reward' gained by the user for his involvement in the process translates into a reduction in the cost of energy. All players then share a common goal and "play" with the same rules. The rationale behind this interpretation is that the user must be aware that their actions affect the reward of the other players, and vice-versa. A change in the actions of user A may cause an increase in the cost of energy, which therefore falls on the benefit of the user B. Game theory defines a condition of equilibrium [19] as the condition in which no player has direct benefit in modifying his behaviour because any action would result in a worsening of the current situation. In the absence of external changes, this balance is a condition of stability.

Demand management methods can be classified as centralized or decentralized. In the first case, a central unit (often managed by the energy provider) calculates the optimal ways of using the appliances of users according to the information available on the network load profiles and the cost of energy.

In the second case, decentralized methods are applied locally by individual users and the results are shared to advertise their behaviour at the cluster level of users involved in the same process (e.g., on the building scale). The sharing of information can be detrimental in terms of privacy, but different practical solutions have been proposed to avoid this type of problem, for example by aggregating the profiles of multiple users. In both the categories of methods, the problem of managing loads in multi-user systems can be dealt with the principles of game theory. The players are the users of the building, the reward of the game is the economic savings related to the reduction of consumption, the actions that each player can play is to act on the profiles of appliance usage.

The proposed approach has been applied in multi-user scenarios for energy saving and in particular for the reduction of consumption peaks through an optimized schedule of the loads of each user. In general terms, most of the methods implement the calculation of the optimal consumption profile of each user following an iterative logic, as occurs in many multi-player games.

Each player in turn performs his action by evaluating the conditions of the other players and trying to follow his own strategy that leads him to maximize the reward provided by the game. The application of the strategy results in the execution of a method of optimizing the variables controllable by the player that can maximize the reward. For example, if the variables are the switching on and off times of the appliances, and the reward is the maximization of energy savings, the player will evaluate the optimal combination of their variables that guarantee the best result.

However, the goodness of the result does not depend solely on its own actions since the cost of energy depends on the aggregation of the absorptions of all the users involved in the game. This relationship then forces each player to consider the choices made by the other players and adjust their own accordingly. Assuming a rational behaviour of the players and the absence of changes from the outside (e.g., change of the energy cost function), the evolution of the game tends to a condition of equilibrium.

The results obtained showed that each user performed in turn the optimization of the consumption peak through the minimization of the peak-to-average ratio (PAR) calculated as the ratio between the maximum measured absorption and the total consumption within a predefined time window. The minimization takes place by acting on the variables controllable by the individual user that affect the time slots for the use of household appliances. The experimental tests were obtained using the energy consumption information made available by wireless devices able to measure in real time the interconnected loads (in this case incandescent lamps, to easily simulate different levels of absorption) [23]-[25].

The application of the load management method acting on the user behaviour for the reduction of the consumption peak led to a reduction of PAR greater than 25%.The presented results are obtained starting from a set of synthetic data that represent the energy consumption of household appliances used by several users in the residential area. The methodology suggests optimal time slots for each user to guarantee the minimization of consumption peaks and therefore of the cost of energy. Time slots are suggested starting from a set of preferences set by the users themselves in order to consider the user habits representative of the daily behaviour.

The energy resource is shared by several users, who decide the switching on and off schedule of the electrical devices. The consumptions of the devices are monitored by distributed power metering systems and the algorithms estimate the optimal energy consumption profile for each user. The overall objective is then to minimize the cost of energy used. Through a system of incentives based on the reduction of the cost of energy if the behavior is "virtuous". Every user is encouraged to cooperate according to the rules that are suggested. It can be shown how the solution to the general problem of energy cost reduction can be solved through a set of local problems of each individual user. This is equivalent to choose the optimal program for each user that finally will be the optimal trade-off for the global system.

The methodology uses the input dataset that is summarized in Table 3. The dataset considers 10 users and each user manages a variable number of household appliances up to a maximum of 20.

APPLIANCE	**USER**									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
PHEV	S	S	S	S		S	S	S	S	S
Slicer	S		S	S		S			S	
Dryer	S		S	S	S	S	S	S	S	S
Vacuum Cleaner	S	S	S		S	S	S	S	S	
Dehumidifier	S			S	S	S	S		S	S
Iron	S	S	S	S	S	S	S		S	S
Oven	S	S	S	S	S	S	S	S	S	S
Dishwasher	S	S	S	S	S	S	S	S	S	S
Washing Machine	S	S	S	S	S	S	S	S	S	S
Bread Machine	S	S	S	S	S	S	S		S	S
Microwave	S	S	S	S	S	S	S	S	S	S
Hairdryer	S	S	S		S	S		S	S	S
Sauna	S			S	S	S	S		S	S
Alarm Clock	N	N	N	N	N	N	N	N	N	N
Stereo	N		N	N	N	N	N	N	N	N
Air Conditioning	N	N	N		N	N	N		N	
Lighting	N	N	N	N	N	N	N	N	N	N
Freezer	N	N	N	N	N	N	N	N	N	N
Refrigerator	N	N	N	N	N	N	N	N	N	N

PC	N		N	N	N	N	N	N	N	N
TV	N	N	N	N	N	N	N	N	N	N

Table 3. List of shiftable (S) and non-shiftable (N) appliance of each user.

For each user, the Shiftable (S) and Non-shiftable (N) appliances are specified. Each Non-shiftable appliance is described by 24 values of hourly consumption in [KW], one for each hour of the day.

On the other hand, the Shiftable devices are described by the following parameters:

a) Start time of the band of possible use of the device.

b) End time of the band of possible use of the device.

c) Power consumed by the device [KW].

d) Hours of switching of the device.

e) Time to turn on the device set by the user.

The algorithm provides the following outputs:

- the initial consumption (original before the optimization) and final consumption (obtained with the execution of the methodology) of all users during a day. An example of the initial and final consumption is shown in Figure 16.
- the PAR calculated during the iterative optimization process, as shown in Figure 17.

The results have been computed with two optimization methods for the sake of comparison. In particular, the particle swarm optimization (PSO) [99] and a convex programming technique (CP) have been adopted. The CP-based solution has been taken from the state of the art presented in [20]. The validation aims also to point out the advantages and the drawbacks of the two different methods in the addressed test cases.

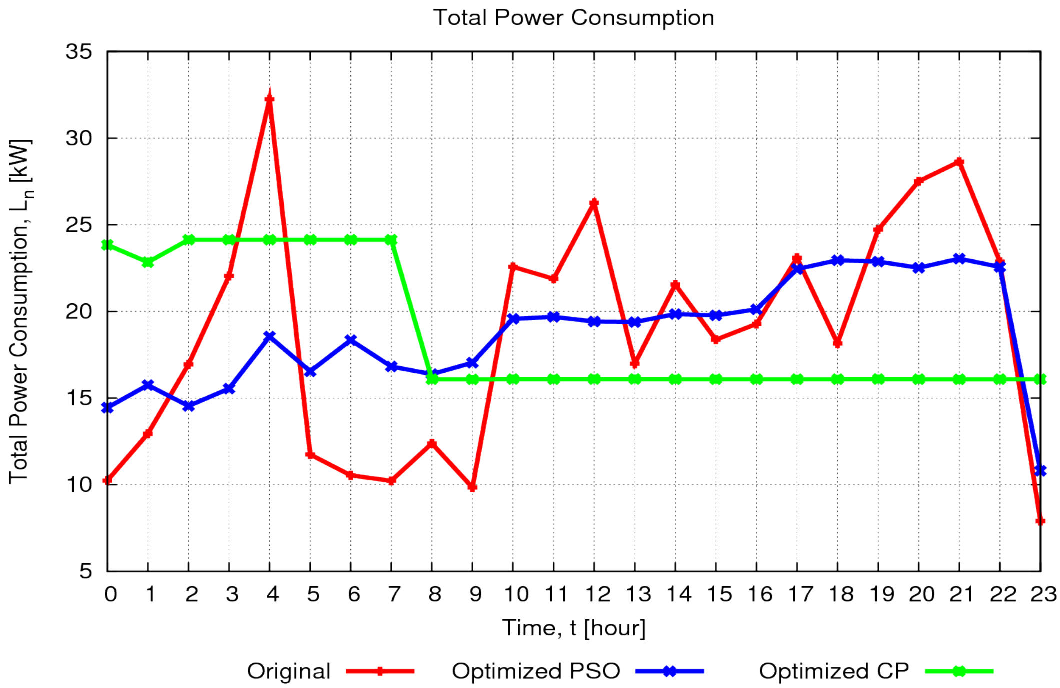

Figure 16. Comparison between original and optimized consumption profiles.

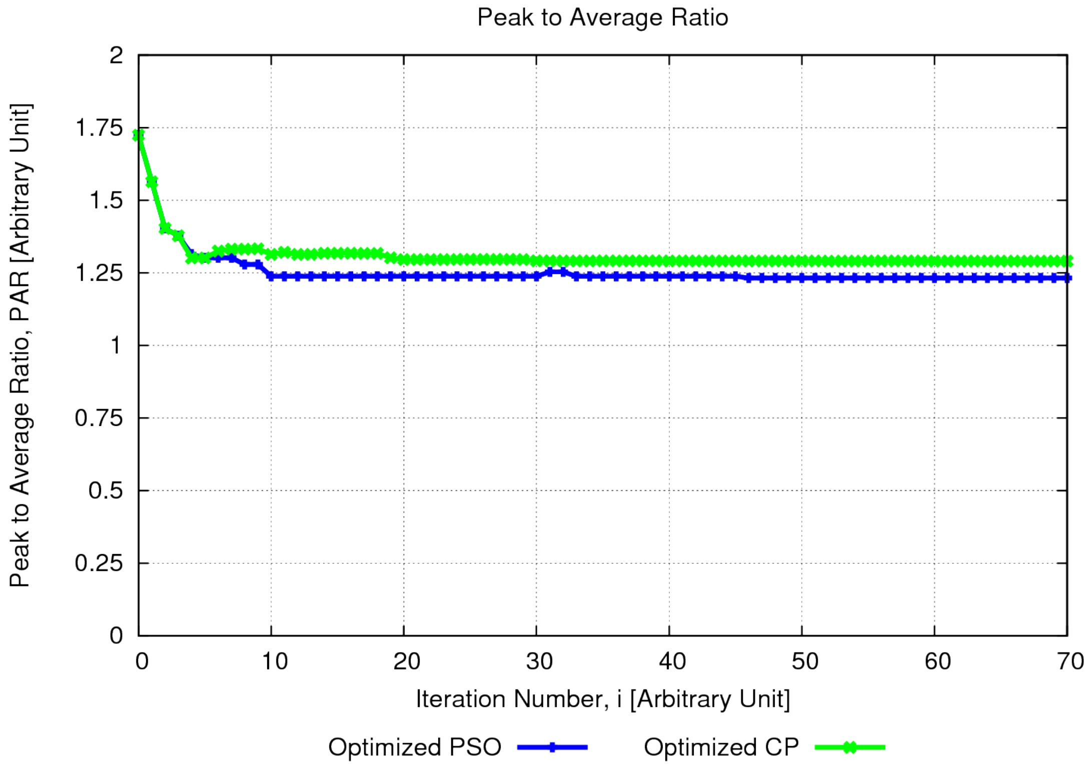

Figure 17. Evolution of PAR during the optimization process.

Minimizing the cost of the energy leads to a consequent reduction of the PAR as shown in Figure 17. The PAR reduction computed as the percentage reduction from the initial PAR to the final PAR using the dataset of Table 3 is reported in Table 4.

Initial PAR	1.72
Final PAR	1.23
PAR Reduction	28.53 [%]

Table 4. PAR Reduction achieved by the proposed method.

3.3 PERFORMANCE ANALYSIS VERSUS THE NUMBER OF USERS

The algorithm has been tested according to the variation in the number of users. In this case the number of 15 appliances has been set for each user and only the total number of users has been changed. The results of the optimization performed in presence of 2 users, 4 users, 6 users, 8 users, and 10 users are presented in the following sections.

3.3.1 TWO USERS

For the first case of analysis with N = 2 users, the users n = 1 and n = 2 listed in Table 3 have been considered. The number of household appliances have been selected randomly to totalize the default number (15 household appliances). The list of the selected household appliances is:

- user n=1: PHEV, vacuum cleaner, iron, oven, dishwasher, washing machine, hairdryer, radio alarm clock, stereo, air-conditioning, light, freezer, refrigerator, pc, tv;
- user n=2: PHEV, vacuum cleaner, iron, oven, dishwasher, washing machine, bread machine, microwave, hairdryer, clock radio, air conditioning, light, freezer, refrigerator, TV.

The results of the optimization are shown in Figure 18 and in Figure 19. It can be seen that optimal performance has been obtained by the method in this simplified configuration with a very small number of users.

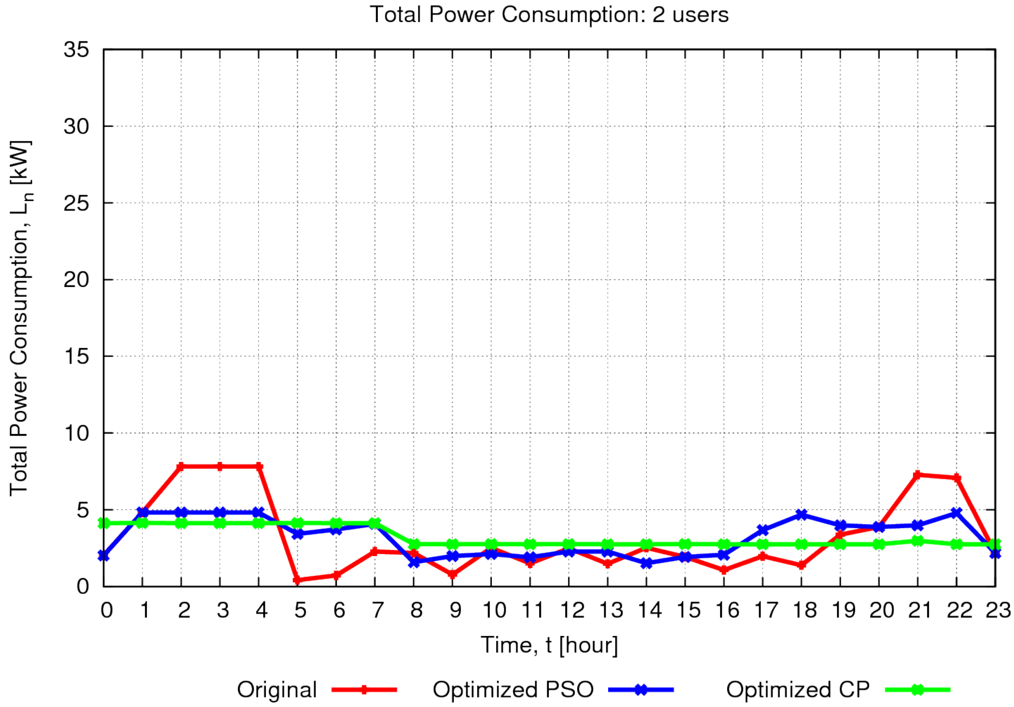

Figure 18. Comparison between the original and optimized consumption profiles with 2 users.

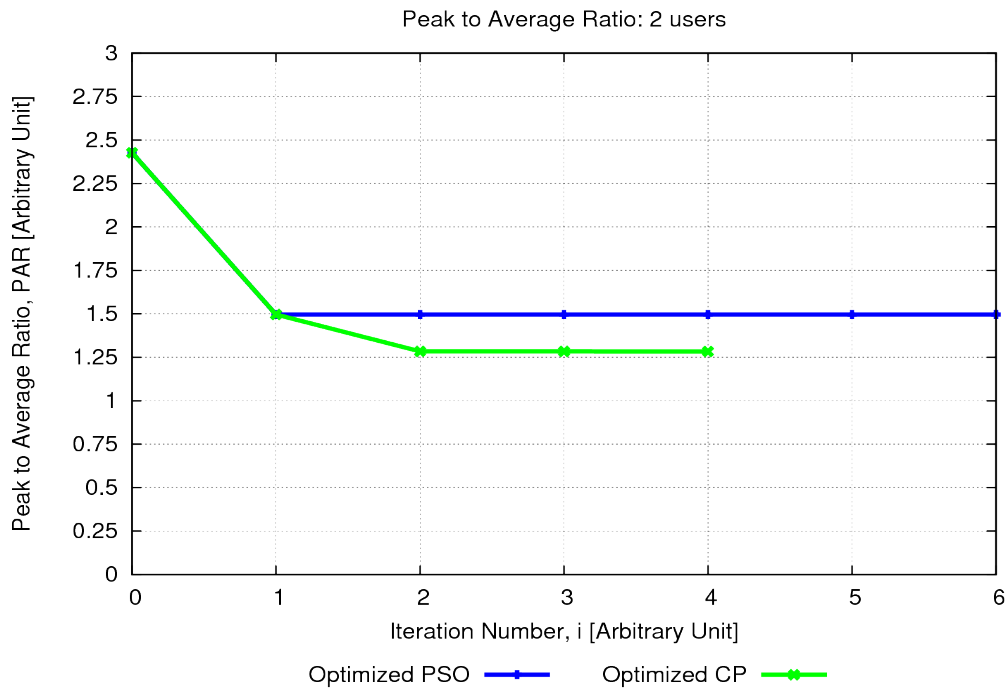

Figure 19. Evolution of PAR during the optimization process with 2 users.

3.3.2 Four Users

For the second case of analysis with N = 4 users, the users n = 1, n = 2, n = 3, n = 4 of Tab. 2 have been considered. Users n = 1 and n = 2 are associated with the household appliances of the previous case (N=2), while the users n = 3 and n = 4 to the following devices:

- user n=3: PHEV, slicer, dryer, vacuum cleaner, iron, oven, dishwasher, washing machine, bread machine, microwave, hair dryer, radio alarm clock, light, refrigerator, TV;
- user n=4: PHEV, slicer, dryer, vacuum cleaner, iron, oven, dishwasher, washing machine, radio alarm, stereo, light, freezer, refrigerator, pc, tv.

The results are shown in Figure 20 and Figure 21. The total consumption increases due to the higher number of users, but the PAR is lower than the case with N=2 because the algorithm has more degrees of freedom to find the optimal solution.

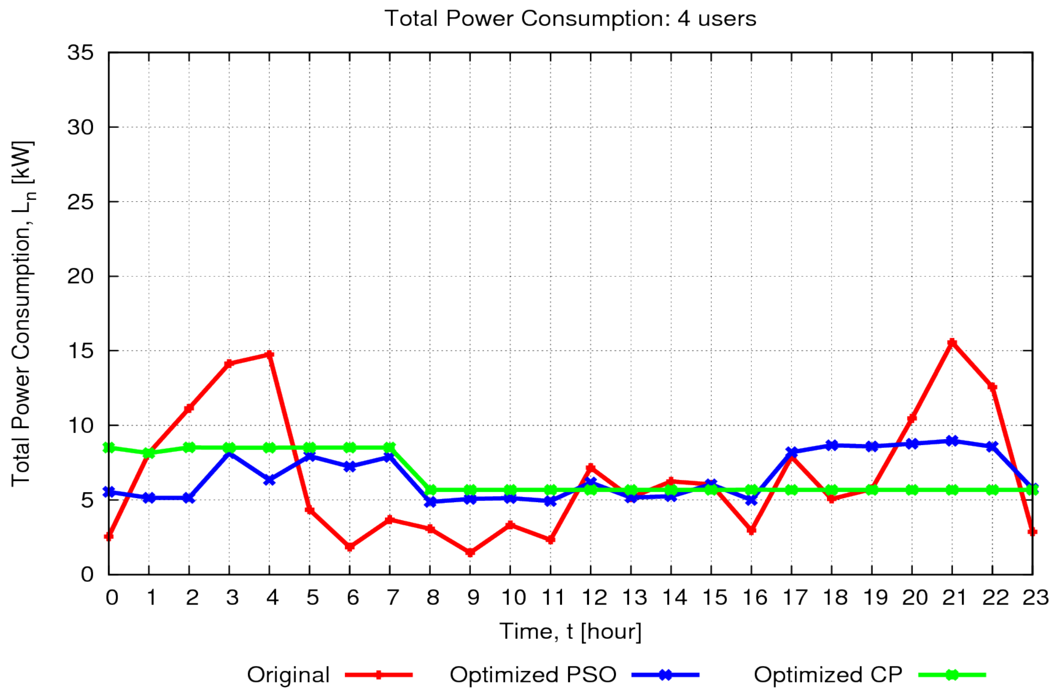

Figure 20. Comparison between the original and optimized consumption profiles with 4 users.

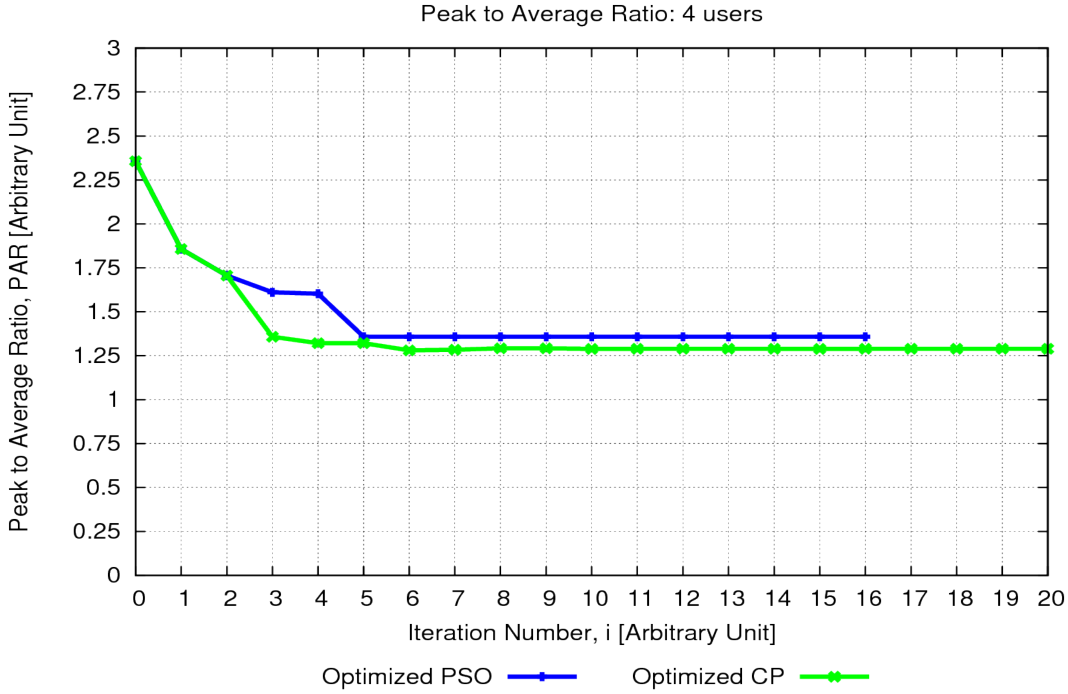

Figure 21. Evolution of PAR during the optimization process with 4 users.

3.3.3 Six Users

In the test case with N = 6, the users n = 1, n = 2, n = 3, n = 4, n = 5, n = 6 have been selected. The users n = 1, n = 2, n = 3, n = 4 are associated with the appliances of the previous case (N=4), while the users n = 5 and n = 6 to the following devices:

- user n=5: dryer, vacuum cleaner, dehumidifier, iron, oven, dishwasher, washing machine, bread machine, microwave, hair dryer, infrared sauna, light, freezer, refrigerator, TV;
- user n=6: vacuum cleaner, dehumidifier, iron, oven, dishwasher, washing machine, bread machine, clock radio, stereo, air conditioning, light, freezer, refrigerator, pc, tv.

The results shown in Figure 22 and Figure 23 point out the higher performance of the CP-based optimization compared to the PSO-based.

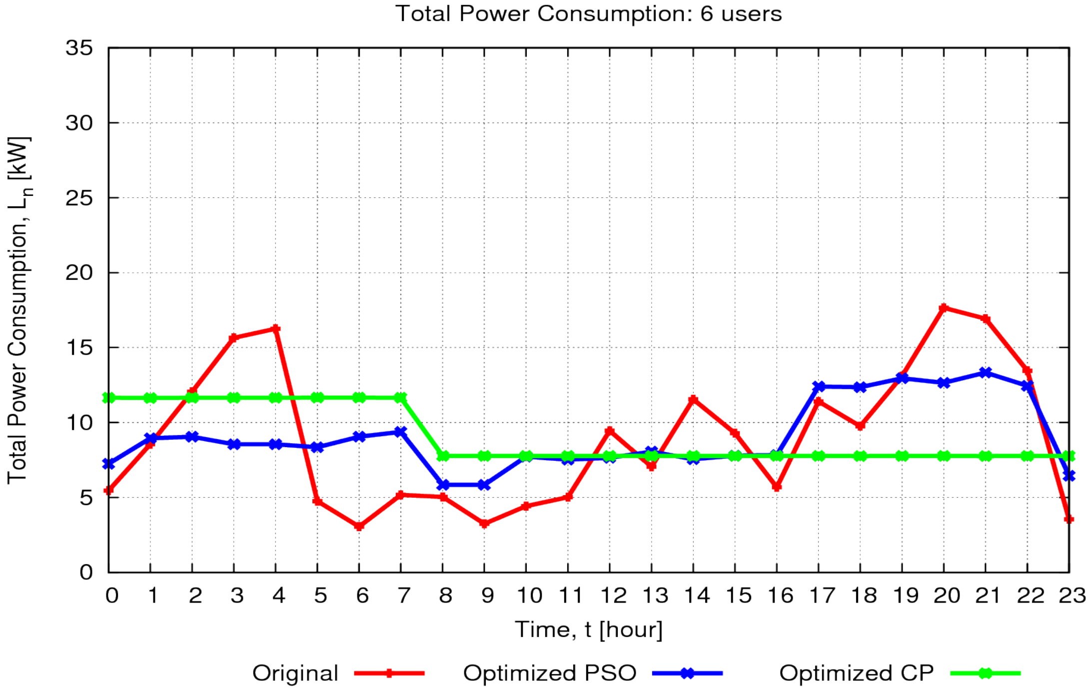

Figure 22. Comparison between the original and optimized consumption profiles with 6 users.

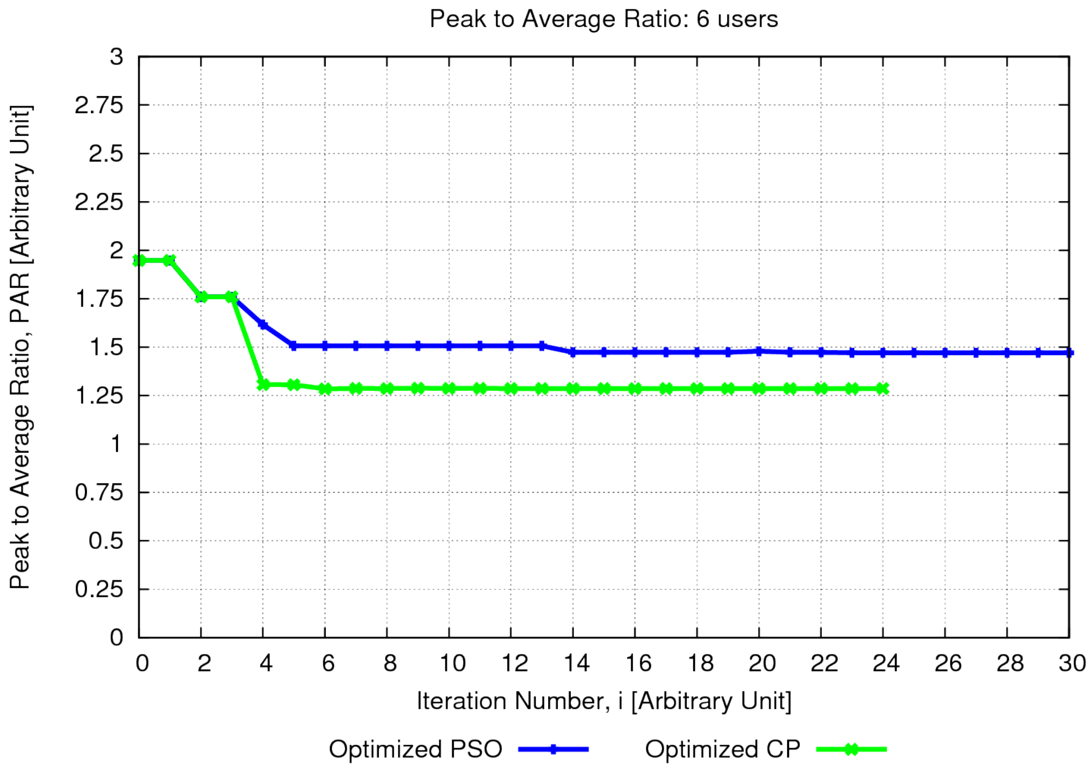

Figure 23. Evolution of PAR during the optimization process with 6 users.

3.3.4 Eight Users

In the analysis with N = 8 users, the users n = 1, n = 2, n = 3, n = 4, n = 5, n = 6, n = 7, n = 8 of Tab. 2 have been selected. The first 6 users are associated with home appliances as in the previous case (N=6), while users n = 7 and n = 8 to the following devices:

- user n=7: PHEV, dehumidifier, iron, oven, dishwasher, washing machine, bread machine, microwave, infrared sauna, air conditioning, light, freezer, refrigerator, pc, tv;
- user n=8: PHEV, dryer, vacuum cleaner, oven, dishwasher, washing machine, microwave, hair dryer, radio alarm clock, stereo, light, freezer, fridge, pc, tv.

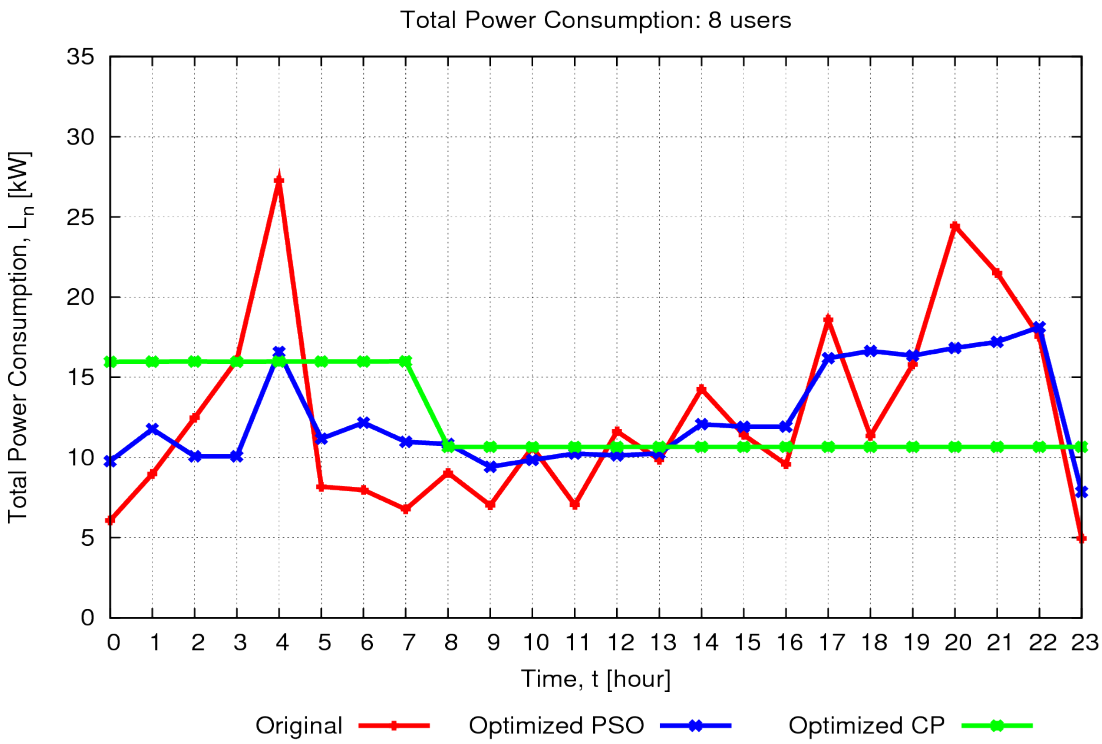

Figure 24. Comparison between the original and optimized consumption profiles with 8 users.

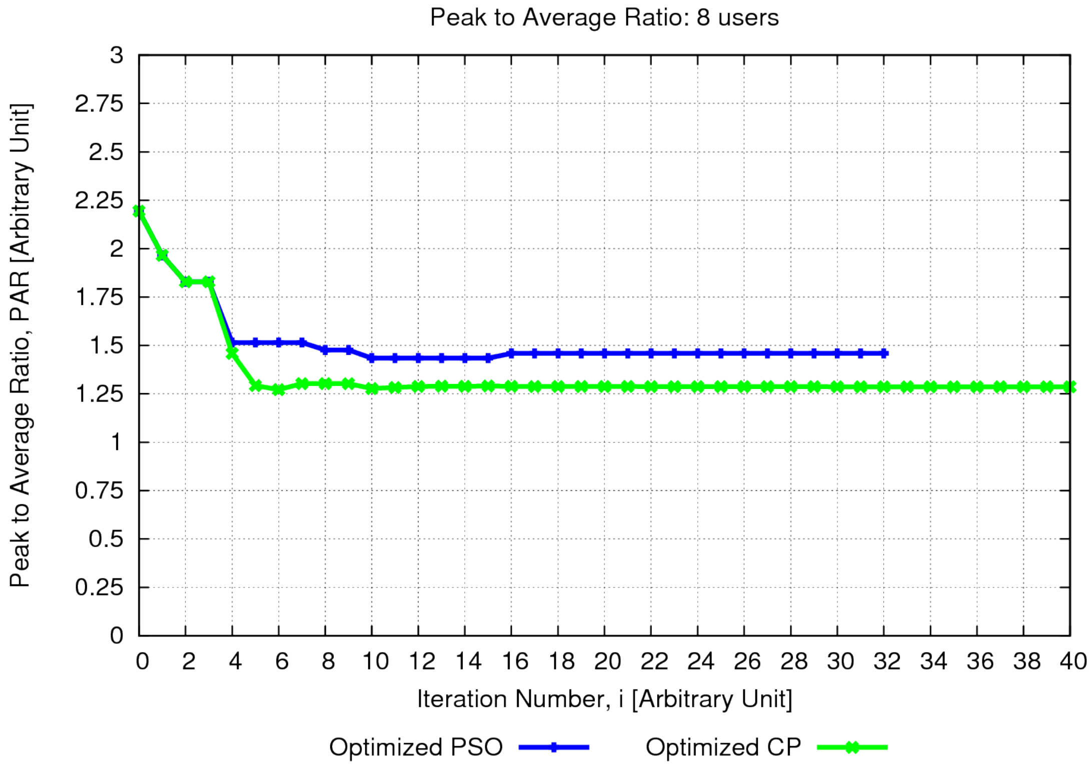

Figure 25. Evolution of PAR during the optimization process with 8 users.

The obtained performance shown in Figure 24 and Figure 25 point out lower PAR with the CP-based technique even if the PSO-based also achieves PAR values lower than 1.5.

3.3.5 Ten Users

The last test case with N=10 users considers all the users listed in Tab. 2. In particular, users n=1, n=2, n=3, n=4, n=5, n=6, n=7, n=8 are the same as in the previous case (N=8), while users n=9 and n=10 use the following appliances:

- user n=9: PHEV, dehumidifier, iron, oven, dishwasher, washing machine, hairdryer, clock radio, stereo, air conditioning, light, freezer, refrigerator, pc, tv;

- user n=10: PHEV, dryer, dehumidifier, iron, oven, dishwasher, washing machine, bread machine, microwave, hair dryer, infrared sauna, light, refrigerator, pc, tv.

Also in this last test case, the CP-based algorithm slightly outperforms the PSO-based optimization.

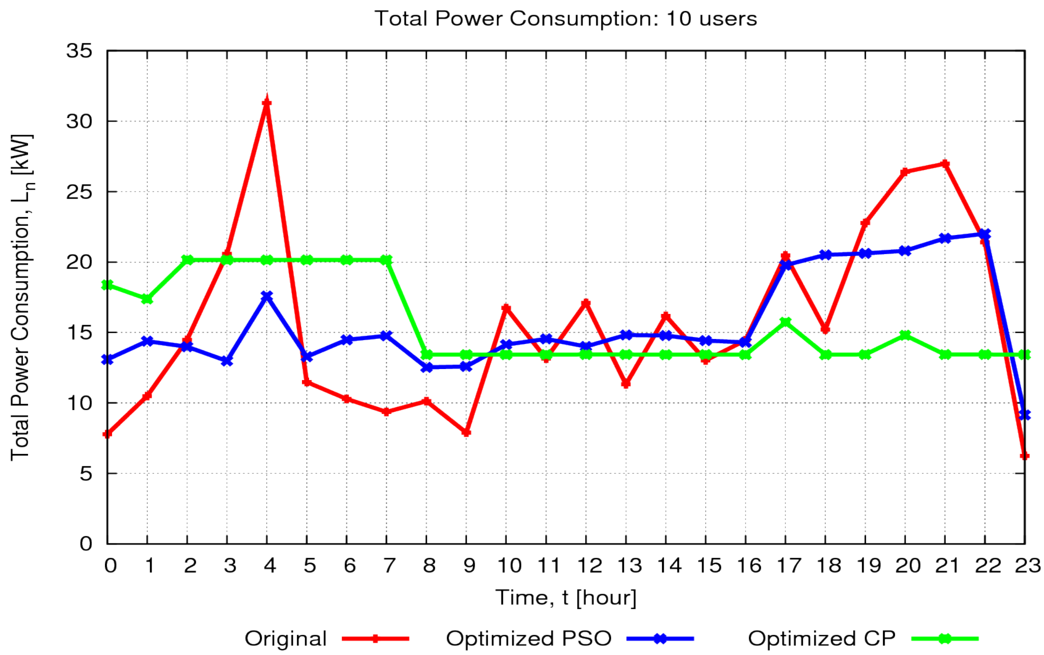

Figure 26. Comparison between the original and optimized consumption profiles with 10 users.

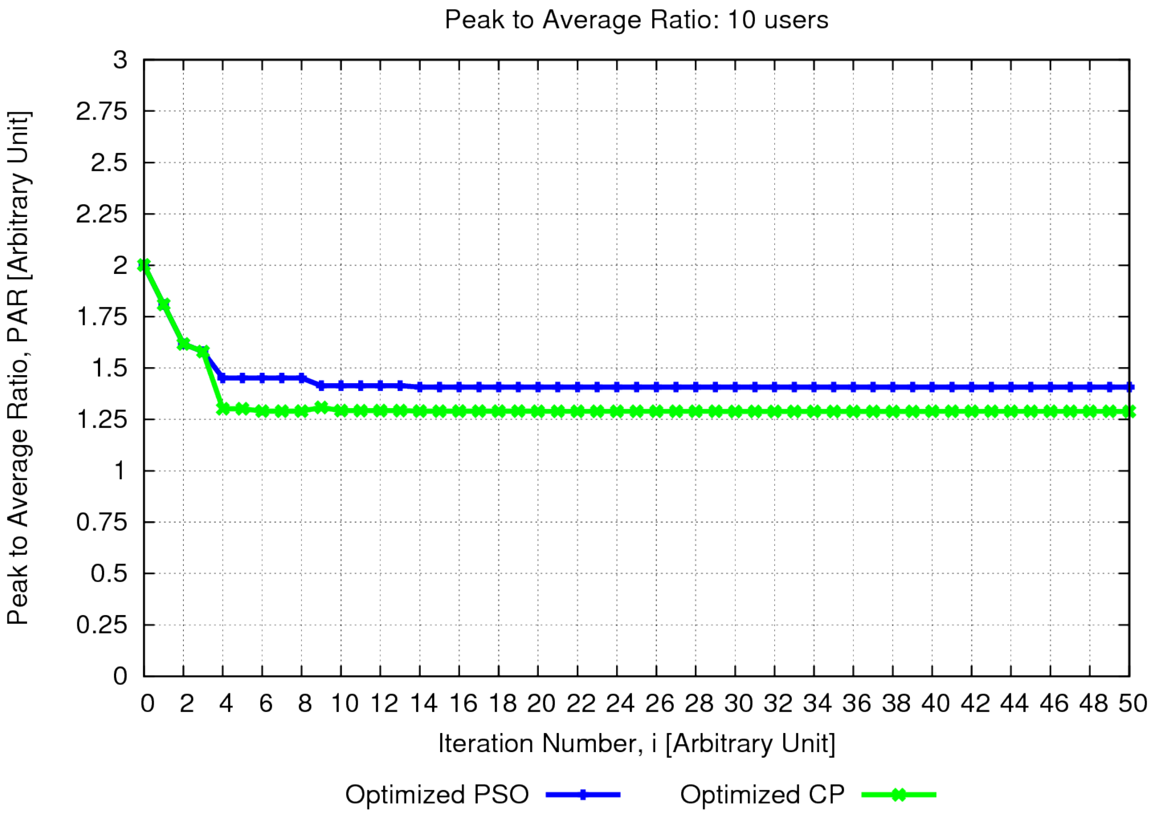

Figure 27. Evolution of PAR during the optimization process with 10 users.

The results shown in Figure 26 and Figure 27 point out good performance with PAR values lower than 1.5 regardless the optimization method.

3.3.6 PAR VS NUMBER OF USERS

Figure 28 compares the performance of the algorithm in terms of PAR reduction obtained with different number of users.

Figure 28. Optimized PAR obtained versus the number of users.

The results show that the PAR is minimized almost with the same performance changing the number of users. This behavior of the method is mainly due to the absence of constraints on the time slots in which the algorithm can distribute the shiftable appliances. This means that similar performance are achievable if the user behavior is not considered in the decision support. Accordingly, the following section aims at validating the DSS performance when constraints are imposed starting from the user needs and habits in the usage of appliances.

3.4 PERFORMANCE ANALYSIS VERSUS THE USER SCENARIOS

In this section, the analysis of the performance in the reduction of the energy cost through the PAR minimization is conducted by changing the user preferences on the admitted time slots where they want to use the appliance. In particular, the maximum number of users has been set to N=10 and the number of appliances has been set to 15. The considered test cases differ only in the boundaries of the possible time slots of appliance usage by each user. Three different configurations of user preferences in the form of time slots constraints have been considered, namely *Ideal*, *Real*, and *Complex*. The three configurations have a decreasing number of total hours useful for the usage of household appliances. These restrictions correspond to user preferences that are more and more stringent, and make more complex the solution to the optimization problem.

3.4.1 IDEAL SCENARIO

The first configuration is representative of a condition of ideality in which all loads can be allocated in each time slot of all the 24 hours of the day. This means that the users do not have preferences and any constraint is imposed. The used dataset is reported in Table 5 where the time slot for each household appliance is indicated.

APPLIANCE	**USER**									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
PHEV	0-23	0-23	0-23	0-23			0-23	0-23	0-23	0-23
Slicer			0-23	0-23						
Dryer			0-23	0-23	0-23			0-23		0-23
Vacuum Cleaner	0-23	0-23	0-23	0-23	0-23	0-23		0-23		

Dehumidifier					0-23	0-23	0-23		0-23	0-23
Iron		0-23	0-23	0-23	0-23	0-23	0-23		0-23	0-23
Oven	0-23	0-23	0-23	0-23	0-23	0-23	0-23	0-23	0-23	0-23
Dishwasher	0-23	0-23	0-23	0-23	0-23	0-23	0-23	0-23	0-23	0-23
Washing Machine	0-23	0-23	0-23	0-23	0-23	0-23	0-23	0-23	0-23	0-23
Bread Machine		0-23	0-23		0-23	0-23	0-23			0-23
Microwave		0-23	0-23		0-23		0-23	0-23		0-23
Hairdryer	0-23	0-23	0-23		0-23			0-23	0-23	0-23
Sauna	0-23				0-23		0-23			0-23
Alarm Clock	0-23	0-23	0-23	0-23		0-23		0-23	0-23	
Stereo	0-23			0-23		0-23		0-23	0-23	
Air Conditioning	0-23	0-23				0-23	0-23		0-23	
Lighting	0-23	0-23	0-23	0-23	0-23	0-23	0-23	0-23	0-23	0-23
Freezer	0-23	0-23		0-23	0-23	0-23	0-23	0-23	0-23	
Refrigerator	0-23	0-23	0-23	0-23	0-23	0-23	0-23	0-23	0-23	0-23
PC	0-23			0-23		0-23	0-23	0-23		0-23
TV	0-23	0-23	0-23	0-23	0-23	0-23	0-23	0-23		0-23

Table 5. Constraints on the time slots of appliance usage in the Ideal case.

3.4.2 REAL SCENARIO

The condition defined as *Real* imposes constraints on the time slots when using Shiftable loads. In order to implement the *Real* test case, time slots with an average maximum duration of 8-10 hours are fixed for each load. Also in this case, the synthetic dataset with 10 users and with 15 devices has been used. The dataset of the considered appliances with the relative time slots fixed by the users is reported in Table 6.

APPLIANCE	USER									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
PHEV	0-8	0-9	2-10	0-8			0-9	0-10	1-10	0-8
Slicer			11-20	12-20						
Dryer			0-8	14-22	15-23			14-23		0-9
Vacuum Cleaner	10-19	10-19	6-15	10-20	9-18	10-18		7-16		
Dehumidifier					9-18	15-23	15-23		10-20	14-22
Iron		14-22	13-22	6-15	9-18	14-23	13-23		10-19	9-18
Oven	11-20	12-20	11-19	12-21	11-19	11-19	12-20	11-21	11-19	12-20
Dishwasher	13-22	12-21	14-23	14-22	13-21	15-23	13-22	13-21	12-22	13-23
Washing Machine	0-10	15-23	0-9	15-23	0-9	0-8	0-9	10-20	11-19	15-23
Bread Machine		15-23	6-14		7-16	11-19	14-22			7-16
Microwave		12-20	11-19		11-20		12-20	11-20		12-20
Hairdryer	15-23	15-23	6-14		8-16			15-23	6-14	15-23

Sauna	15-23				14-22		14-23			14-23
Alarm Clock	0-23	0-23	0-23	0-23		0-23		0-23	0-23	
Stereo	0-23			0-23		0-23		0-23	0-23	
Air Conditioning	0-23	0-23				0-23	0-23		0-23	
Lighting	0-23	0-23	0-23	0-23	0-23	0-23	0-23	0-23	0-23	0-23
Freezer	0-23	0-23		0-23	0-23	0-23	0-23	0-23	0-23	
Refrigerator	0-23	0-23	0-23	0-23	0-23	0-23	0-23	0-23	0-23	0-23
PC	0-23			0-23		0-23	0-23	0-23		0-23
TV	0-23	0-23	0-23	0-23	0-23	0-23	0-23	0-23		0-23

Table 6. Constraints on the time slots for the Real test case.

It has to be noticed that household appliances that use a 24-hour time slot are considered Non-shiftable devices.

3.4.3 COMPLEX SCENARIO

The *Complex* condition is defined with shorter and temporally more overlapped time slots. In particular, time slots with an average duration of 5-7 hours are considered. The synthetic *Complex* dataset and the usage time slots are indicated in Table 7.

APPLIANCE	**USER**									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
PHEV	0-6	6-12	1-7	2-8			0-6	5-12	1-7	1-8
Slicer			11-16	12-17						

Dryer			0-7	17-23	0-6			17-22		0-6
Vacuum Cleaner	6-11	6-12	7-13	7-13	6-11	10-16		7-14		
Dehumidifier					10-17	11-18	9-16		15-22	11-18
Iron		15-20	14-20	14-19	15-20	14-20	14-20		16-21	9-15
Oven	17-23	11-17	18-23	11-17	11-17	17-23	12-19	18-23	17-22	11-18
Dishwasher	18-23	12-18	18-23	13-20	12-19	18-23	13-20	18-23	13-20	12-17
Washing Machine	0-7	17-22	0-6	0-6	0-6	17-22	0-7	0-6	2-8	17-23
Bread Machine		17-22	7-13		17-22	17-22	7-13			7-13
Microwave		10-17	18-23		12-18		10-17	17-22		11-16
Hairdryer	7-12	6-11	6-11		8-13			6-12	7-12	6-11
Sauna	18-23				17-23		16-23			17-22
Alarm Clock	0-23	0-23	0-23	0-23		0-23		0-23	0-23	
Stereo	0-23			0-23		0-23		0-23	0-23	
Air Conditioning	0-23	0-23				0-23	0-23		0-23	
Lighting	0-23	0-23	0-23	0-23	0-23	0-23	0-23	0-23	0-23	0-23
Freezer	0-23	0-23		0-23	0-23	0-23	0-23	0-23	0-23	
Refrigerator	0-23	0-23	0-23	0-23	0-23	0-23	0-23	0-23	0-23	0-23
PC	0-23			0-23		0-23	0-23	0-23		0-23
TV	0-23	0-23	0-23	0-23	0-23	0-23	0-23	0-23		0-23

Table 7. Constraints on the time slots for the Complex test case.

3.4.4 PAR Reduction vs User Scenario

The performance of the algorithm obtained in the different configurations of user preferences *Ideal*, *Real*, and *Complex* cases have been analyzed both in terms of total daily consumption (shown in Figure 29 and Figure 30) and in terms of PAR reduction (Figure 31 and Figure 32) comparing the two CP-based and PSO-based optimization techniques.

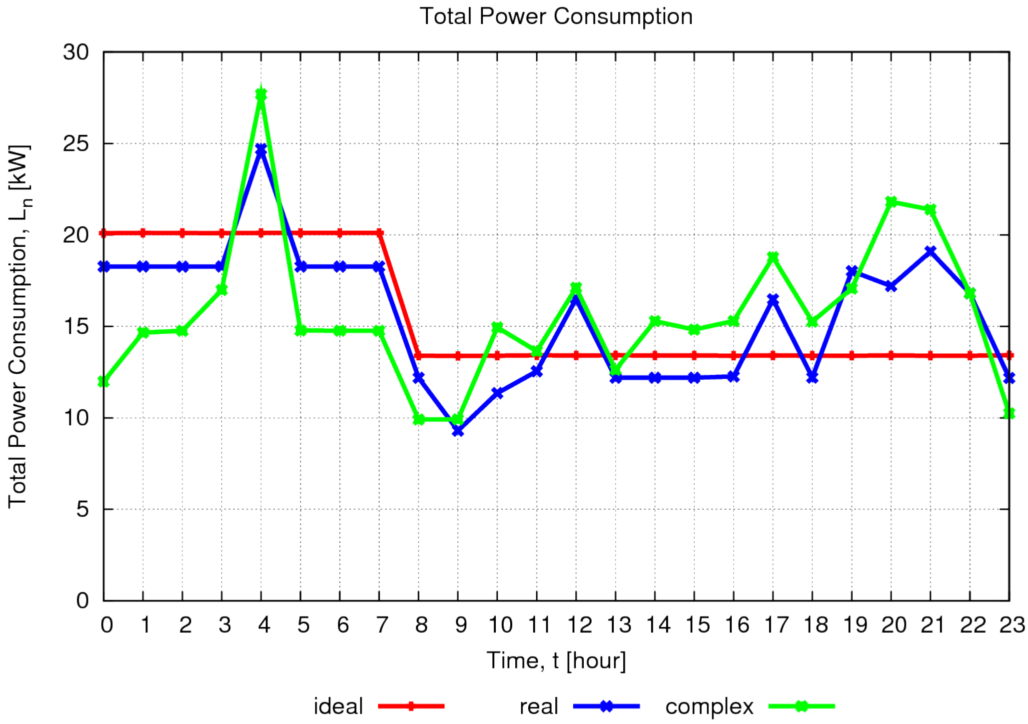

Figure 29. Optimized consumption profiles obtained in the user scenario Ideal, Real, Complex with the CP-based method.

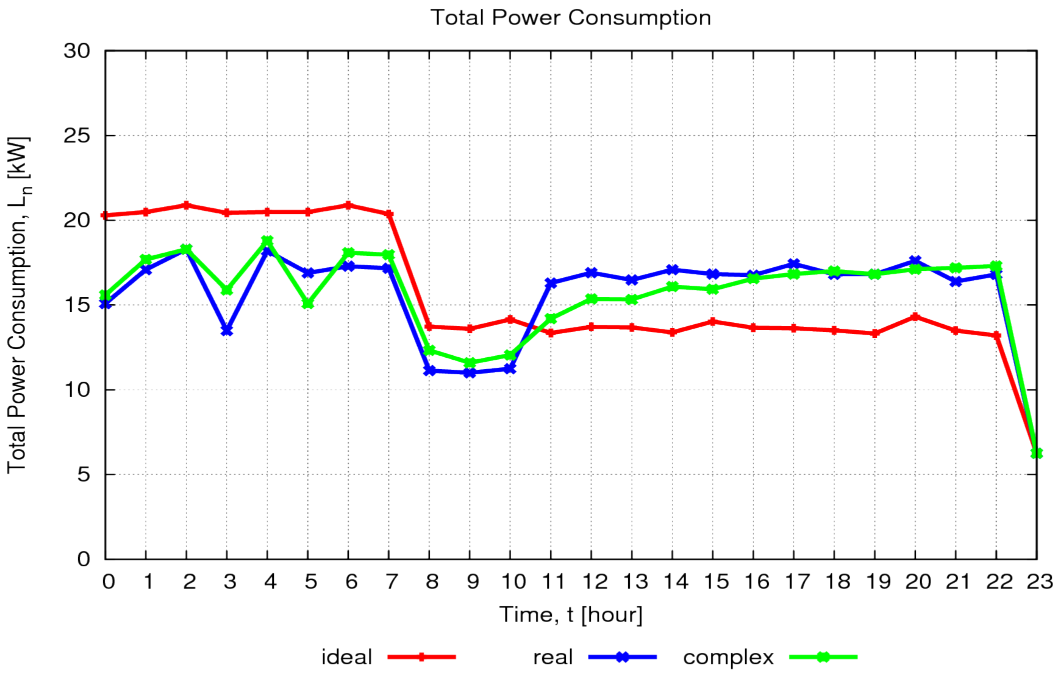

Figure 30. Optimized consumption profiles obtained in the user scenario Ideal, Real, Complex with the PSO-based method.

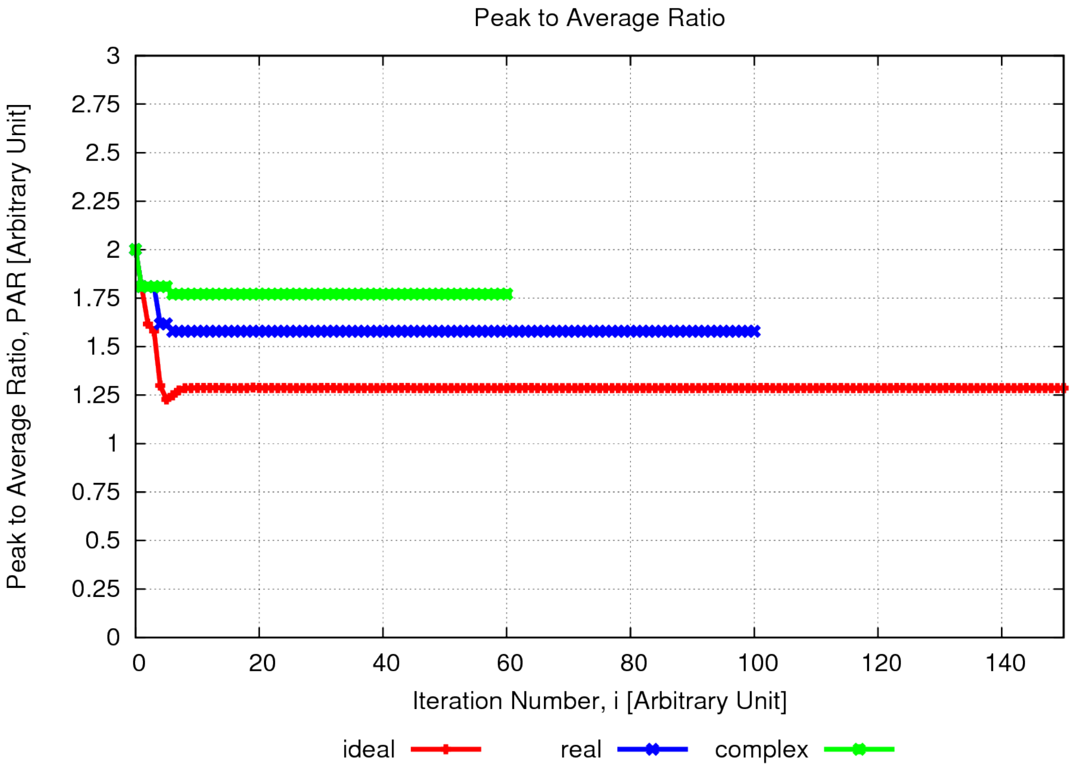

Figure 31. Evolution of PAR during the optimization in the three user scenarios Ideal, Real, Complex using the CP-based method.

As it can be noticed, the results point out better performance using the PSO-based technique when stronger constraints are imposed by the users. For example, the PAR value obtained in the *Complex* case with the CP-based technique is higher than 1.75, while the PSO-based method achieves PAR values lower than 1.25.

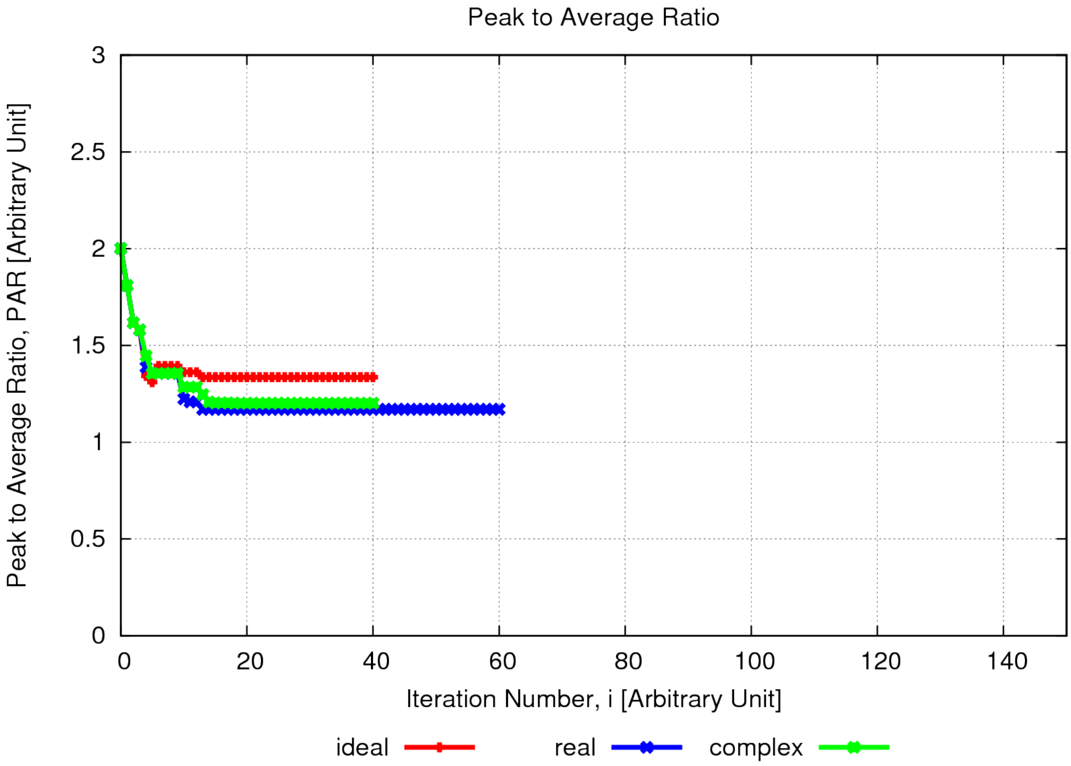

Figure 32. Evolution of PAR during the optimization in the three user scenarios Ideal, Real, Complex using the PSO-based method.

The performance validation has shown that:

- by changing the number of users, the PAR has been better minimized by the CP-based method than the PSO-based one, Table 8 , but in general both the approaches have reduced the PAR regardless of the number of users considered

Users	PAR Reduction [%]	
	PSO-based	CP
N=2	38.4	47.1
N=4	42.4	45.1
N=6	24.6	33.8
N=8	33.3	41.1
N=10	29.5	35.5

Table 8. Percentage of PAR reduction vs the number of users.

- As shown in Table 9, by changing the user preferences and the consequent problem complexity, the power consumption has been better optimized by the PSO-based method when the behaviour of the user imposes stronger constraints

Scenario	PAR Reduction [%]	
	PSO-based	CP
Ideal	33.1	35.5
Real	41.5	21.2
Complex	40.1	11.5

Table 9. Percentage of PAR reduction vs the user scenario Ideal, Real, Complex.

- In the more complex cases, where a more efficient exploration of the solution space is required, the PSO-based algorithm has shown better PAR reduction performance pointing out that it is more suitable to manage problems with real-world user behaviour and preferences.

- The computational load of the optimization algorithms is negligible compared to the duration of the suggested time slots. More in detail, the time slots have hourly duration while the convergence time of the optimization procedures takes less than 1 minute. The computational load of the optimization procedure is always compliant to the application requirements, whatever the complexity of the considered test case. With the assumption that shorter time slots are adopted (e.g., few minutes instead of one hour), the computational load of the algorithm can be controlled through dedicated parameter configuration, like for example more restrictive termination criteria (i.e., lower values of maximum number of iterations). The performance analysis with shorter time slots that reproduce the high variability of user behaviour will be considered in the future works.

4. CONCLUSIONS

The analysis of the occupants' behaviour and the corresponding impact on the energy efficiency of the smart buildings have been addressed in this thesis. In particular, the state of the art on the influence of the user behaviour on the power consumption has been revised in order to identify the main behavioural features that affect the energy modelling of the buildings. The analysis has pointed out that among the state of the art models, the ones based on user-building interactions have been particularly investigated since the user actions can be easily measured by distributed technologies and sensors. For example, the control of the thermostat, the window opening, the appliance usage are simple indicators of the environmental conditions and power consumptions determined by the occupants' behaviour. Many theories and models have been defined also starting from social practice theories in order to translate the stochastic nature of humans into numerical representations for direct integration into building simulations. However, it has been underlined that an interdisciplinary approach is fundamental to accurately model and apply how humans behave since a proper trade-off between complex theories (e.g., taken from psychology and behavioural analysis) and practical application into real-world scenario (e.g., using an engineering approach for building and human monitoring) is required. Toward this end, this thesis has presented a multi-feature approach for the representation of the user behaviour that is both (*i*) representative of the user needs and habits, and (*ii*) simple to be integrated into DSS to support the behavioural changing programs toward energy efficiency.

The proposed model has been defined using location-based and energy-habits features merged into a mixed representation of the building occupants. More in detail, the location-based feature has been extracted from the user presence, position, and movement within the monitored building in order to understand when and how the building is used. Such information has been obtained using a wireless localization method that is able to estimate the position of the wireless devices (e.g., the smartphone) of the users using the existing wireless technologies (e.g., the residential WiFi network already deployed for communication purpose). The adopted methodology has been validated in a real indoor scenario and the obtained performance have confirmed the ability to recognize the room occupied by the user. The achieved room-level accuracy is suitable for the considered problem of behaviour understanding because the main goal is to model in real-time how each user occupies the building.

The location-based information have been used as input to calibrate the user habits in terms of building occupation, which is strictly correlated to the usage of the appliance and the corresponding power consumption. In order to integrate such user habits, a DSS based on game theory has been customized in order to suggest the optimal appliance schedule that minimizes the PAR (and consequently the energy cost) and also reduces the impact on the user needs. Toward this end, the time slots of user presence into the building have been introduced as additional constraints to consider the user habits during the computation of the optimal schedule. The obtained results have pointed out that the DSS is able to compute the optimal schedule of the appliance for each user that reduces the PAR more than 40% even when complex combination of user constraints are considered. This achievement has verified the feasibility to optimize the energy consumption also considering the actual user behaviour within the building and not only a statistical representation of a user category as often proposed in the state of the art.

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