PART II

IoT Analytics Applications and Case Studies

7

Data Analytics in Smart Buildings

M. Victoria Moreno, Fernando Terroso-Sáenz, Aurora González-Vidal and Antonio F. Skarmeta

Department of Information and Communications Engineering,
University of Murcia, 30100 Spain

7.1 Introduction

Cities are becoming more and more of a focal point for our economies and societies at large, particularly because of on-going urbanisation, and the trend towards increasingly knowledge-intensive economies as well as their growing share of resource consumption and emissions. To meet public policy objectives under these circumstances, cities need to change and develop, but in times of tight budgets this change needs to be achieved in a smart way: our cities need to become "smart cities". In order to follow the policy of the decarbonisation of Europe's economy in line with the EU 20/20/20 energy and climate goals, today's ICT, energy (use), transport systems and infrastructures have to drastically change. The EU needs to shift to sustainable production and use of energy, to sustainable mobility, and sustainable ICT infrastructures and services. Cities and urban communities play a crucial role in this process. Three quarters of our citizens live in urban areas, consuming 70%[1] of the EU's overall energy consumption and emitting roughly the same share of Green House Gas (GHG). Of that, buildings and transport represent the lion's share. Within the worldwide perspective of energy efficiency, it is important to highlight that buildings are responsible for 40% of total EU energy consumption and generate 36% of GHG [1]. This indicates the need to achieve energy-efficient buildings to reduce their CO2 emissions and their energy consumption.

Moreover, the building environment affects the quality of life and work of all citizens. Thus, buildings must be capable of not only providing mechanisms

[1]Source: European Commission 2013.

to minimize their energy consumption (even integrating their own energy sources to ensure their energy sustainability), but also of improving occupant experience and productivity. In this chapter, we analyse the important role that buildings represent in terms of their energy performance at city level and, even, at world level, where they represent an important factor for the energy sustainability of the planet. Analysis of the energy efficiency of the built environment has received growing attention in the last decade [2–4]. Various approaches have addressed energy efficiency of buildings using predictive modelling of energy consumption based on usage profiles, climate data and building characteristics. On the other hand, studies have demonstrated the impact of displaying public information to occupants and its effect in modifying individual behaviour in order to obtain energy savings [5, 6]. Nevertheless, most of the approaches proposed to date only provide partial solutions to the overall problem of energy efficiency in buildings, where different factors are involved in a holistic way, but which, until now, have been addressed separately or even neglected by previous proposals. This division is frequently due to the uncertainty and lack of data and inputs included in the management processes, so that analysis of how energy in buildings is consumed is incomplete. In other words, a more integral vision is required to provide accurate models of the energy consumed in buildings [7].

The need for the robust characterization of energy use in buildings has gained attention in light of the growing number of projects and developments addressing this topic. Although much interest has been put into smart building technologies, the research area of using real-time information has not been fully exploited. In order to obtain an accurate simulation model, a detailed representation of the building structure and its subsystems is required, although it is the integration of all these pieces that requires the most significant effort.

The integration and development of systems based on ICT and, more specifically, the IoT [8], are important enablers of a broad range of applications, both for industries and the general population, helping make smart buildings a reality. IoT permits the interaction between smart things and the effective integration of real world information and knowledge in the digital world. Smart (mobile) things endowed with sensing and interaction capabilities or identification technologies (such as RFID) provide the means to capture information about the real world in much more detail than ever before.

Regarding this real-world data extraction, the great adoption of personal handheld devices, like smartphones, has enabled the crowdsensing paradigm as a prominent mechanism to capture a wide range of (mobile) data [9]. Unlike other sensing approaches, in this case the collected data is directly generated by the users' personal contrivances, so it can be a useful solution for soliciting feedback from a sheer number of people in an explicit or implicit manner. From a smart building perspective, such feedback provides information about its occupants' preferences and habits that could be considered in order to come up with customized energy-efficiency solutions.

Nevertheless, challenges related to: (1) the management of the huge amount of data provided in real-time by a large number of IoT and crowd based devices deployed, (2) the interoperability among different ICT, and (3) the integration of many proprietary protocols and communication standards that coexist in the ICT market applicable to buildings (such as heating, cooling and air conditioning machines), need to be faced before flexible and scalable solutions based on the IoT paradigm can be offered.

The structure of the present chapter is as follows: Section 7.2 describes the key issues involved in energy efficiency in buildings. Among these issues, relevant parameters affecting energy consumed in buildings are described and proposed to be included as input data of building management for energy efficiency. Then, Section 7.3 reviews the main related works which propose partial solutions to the problem addressed in this chapter. Section 7.4 presents a general architecture proposal for management systems of smart buildings, which is modeled in three layers with different functionalities. Section 7.5 describes our proposal for an energy efficiency building management system. This proposal tackles three different subproblems, each one of these is introduced here. Section 7.6 summarizes the experiments carried out to evaluate and validate the different proposals and mechanisms developed in this work. Finally, Section 7.7 gives some conclusions and an outlook of future work.

7.2 Addressing Energy Efficiency in Smart Buildings

Optimizing energy efficiency in buildings is an integrated task that comprises the whole lifecycle of the building. For buildings to have an impact at city level in terms of energy efficiency, different challenges have been identified in the building value chain (from design to end-of-life of buildings)[2], which can be summarized as follows:

1. *Design*. The design of buildings should be integrated, holistic and multi target.

[2] http://www.ectp.org/

2. *Structure*. The structure of buildings should provide features such as safety, sustainability, adaptability and affordability.
3. *Building envelope*. This should ensure efficient energy and environmental performance. Prefabrication is a crucial step to guarantee energy performance. Multifunctional and adaptive components, surfaces and finishes to create added energy functionality, and durability should all be built in.
4. *Energy equipment and systems*. Advanced heating/cooling and domestic hot water solutions, including renewable energy sources, should focus on sustainable generation as well as on heat recovery. Among these systems, thermal storage (both heat and cold) is recognized as a major breakthrough in building design. Distributed/decentralised energy generation should address the key requirement of finding smart solutions for grid-system interactions on a large scale. ICT smart networks will form a key component in such solutions. In [10], for instance, the authors study the communication requirements for smart grids and describe the most suitable communication protocols, wired and wireless, with special attention to the latest proposals in this field.
5. *Construction processes*. These should consider ICT-aided construction, improving the energy performance delivered, and automated construction tools.
6. *Performance monitoring and management*. This should ensure interoperability among the different subsystems of the building, including smart energy management systems that provide flexible actions to reduce the gap between predicted and actual energy building performance, occupancy modeling, the fast and reproducible assessment of designed or actual performance, and continuous monitoring and control during service life. Finally, knowledge sharing must be considered by means of open data standards that allow collaboration among stakeholders and interoperability among systems.
7. *End of life*. This should include decision-support concerning possible renovation or the construction of a new building and associated systems.

During these phases it is necessary to continuously re-engineer the indexes that measure energy efficiency to adapt the energy management system to the building's conditions. Hereinafter, we refer only to electrical energy consumption since other kinds of energy such as fuel, gas or water are beyond the scope of this work. Taking as reference the energy performance model for buildings proposed by the CEN Standard EN15251 [11], it proposes criteria for dimensioning the energy management of buildings, while indoor environmental requirements are maintained. According to this standard, there are static and dynamic conditions that affect the energy consumption of buildings. Given that each building has a different static model according to its design, we try to provide a solution for energy efficiency focusing on analyzing how dynamic conditions affect the energy consumed in buildings. Thus, we propose an initiative for the challenges involved in the living stage buildings: *Performance monitoring and management* mentioned in the above list. In this stage, we need to identify the main drivers of energy use in buildings. After monitoring these parameters and analysing the associated energy consumed, we can model their impact on energy consumption, and then, propose control strategies to save energy. The main idea of this approach is to provide anticipated responses to ensure energy efficiency in buildings.

Bearing in mind all these concerns, we enumerate below the stages [12] that must be carried out to achieve efficiency building energy management:

1. **Monitoring**. During the monitoring phase, information from heterogeneous sources is collected and analysed before concrete actions are proposed to minimize energy consumption, bearing in mind the specific context of a given building. Since buildings with different functionalities have different energy use profiles, it is necessary to carry out an initial characterization of the main contributors to their energy use. For instance, in residential buildings the energy consumed is mainly due to the indoor services provided to their occupants (associated to comfort), whereas in industrial buildings energy consumption is associated mostly with the operation of industrial machinery and infrastructures dedicated to production processes. Considering this, and taking into account the models for predicting the comfort response of buildings occupants given by the ASHRAE [13], we describe below the main parameters that must be monitored and analysed before implementing optimum building energy management systems. In this way, from this set of parameters affecting energy consumption in buildings, we can extract the input data to be taken into account.

(a) Electrical devices always connected to the electrical network. In buildings, it is necessary to characterize the minimum value of energy consumption due to electrical devices that are always connected to the electrical network, since they represent a constant contribution to the total energy consumption of the building. For this, it is necessary to monitor over a period of time the energy consumed in the building when there is no other contributor to the total energy being consumed. This value will be included as an input to the final system responsible for estimating the daily electrical consumption of the building.

(b) Electrical devices occasionally connected. Depending on the kind of building under analysis, different electrical devices may be used with different purposes, such as increase of productivity and comfort. On the other hand, the operation of such devices could be independent of the participation and behaviour of the occupants; for example, in the context of a factory or an office where there are timetables and rules. Whatever the case, recognition of the operation pattern of devices must be included in the final system responsible for estimating the daily electrical consumption of the building. To obtain these patterns it is necessary to monitor previously the associated energy consumption of every device or appliance. To monitor each component separately in the total power consumption in a household or an industrial site over time, cost effective and readily available solutions include Non-Intrusive Load Monitoring (NILM) techniques [14].

(c) Occupants' behaviour. Energy consumption of buildings due to the behaviour of their occupants is one of the most critical points in every building energy management system. This is mainly because occupant behaviour is difficult to characterize and control due to its uncertain dynamic. First of all, it is necessary to have solved the occupants' localization before behaviour models associated to them can be provided. Depending on the building context, the impact of occupants behaviour on total energy consumption is different. For example, in residential buildings the impact of the behaviour in the energy consumed is one of the biggest, followed by environmental conditions. However, in buildings with productive goals, the electricity consumed by the appliances and devices working for such goals is usually the main contributor to the total energy consumed in the building. Therefore, it is necessary to monitor and analyse this issue to be able to provide behaviour patterns that will be included in the final estimation of the daily energy consumption of the building. To do so, different techniques, like crowd sensing, can be used to extract a palette of underlying behavioural patterns. In that sense, occupants' behaviour can be characterized for features such as:

- Occupants localization data.
- Activity level of occupants.
- Comfort preferences of occupants.

(d) Environmental conditions. Parameters like temperature, humidity, pressure, natural lighting, etc. have a direct impact on the energy consumption of buildings. Nevertheless, depending on the specific context of the building and its requirements, this impact will differ and be greatest in the case of indoor comfort services (like thermal and visual comfort). Therefore, forecasts of the environmental condition should be also considered as input for the final energy consumption estimation of the building.

(e) Information about the energy generated in the building. Sometimes, alternative energy sources can be used to balance the energy consumption of the building. Information about the amount of daily energy generated and its associated contextual features can be used to estimate the total energy generated in the future. This information allows us to design optimal energy distribution or/and strategies of consumption to ensure the energy-efficient performance of the building.

(f) Information about total energy consumption. Knowing the real value of the energy consumed hourly or even daily permits the performance and accuracy of the building energy management program to be evaluated, and make it possible to identify and adjust the system in case of any deviation between the consumption predicted and the real value. In addition, providing occupants with this information is crucial to make them aware of the energy that they are using at any time, and encourage them to make their behaviour more responsible.

In this work we focus on residential buildings, where both comfort and energy efficiency is required. As regards the comfort provided in buildings, we focus on thermal and visual comfort.

2. **Information Management**. An intelligent management system must provide proper adaptation countermeasures for both automated devices and users with the aim of providing the most important services in buildings (comfort) and satisfying energy efficiency requirements. Therefore, energy savings needs to be addressed by establishing a trade-off between the quality of services provided in buildings and the energy resources required for the same, as well as the associated cost.

3. **Automation**. Automation systems in buildings take inputs from the sensors installed in corridors and rooms (light, temperature, humidity, etc.), and use these data to control certain subsystems such as HVAC, lighting or security. These and more extended services can be offered intelligently to save energy, taking into account environmental parameters and the location of occupants. Therefore, automation systems are essential to answer the needs for monitoring and controlling energy efficiency requirements [15]. At this respect, the 1888–2011 IEEE Standard for Ubiquitous Green Community

Control Network Protocol [16] describes remote control architecture of digital community, intelligent building groups, and digital metropolitan networks; specifies interactive data format between devices and systems; and gives a standardized generalization of equipment, data communication interface, and interactive message in this digital community network.

4. **Feedback and User Involvement.** Feedback on consumption is necessary for energy savings and should be used as a learning tool. Analysis of smart metering, which provides real-time feedback on domestic energy consumption, shows that energy monitoring technologies can help reduce energy consumption by 5% to 15% [5]. As can be deduced, a set of subsystems should be able to provide consumption information in an effective way. These subsystems are:

- Electric lighting.
- Boilers.
- Heating/cooling systems.
- Electrical panels.

On the other hand, to date, information in real-time about building energy consumption has been largely invisible to millions of users, who had to settle with traditional energy bills. In this, there is a huge opportunity to improve the offer of cost-effective, user-friendly, healthy and safe products for smart buildings, which increase the awareness of users (mainly concerning the energy they consume), and permit them to bean input of the underlying processes of the system. This would allow the collection of an unprecedented amount of data related to users' interactions and their associated contextual details (e.g. identity, location and activity) by considering the active involvement of users along with opportunistic sensing. Then, an appropriated processing of that user-related data will enable the development of even more customized services.

Taking into account all the aspects identified as relevant for their impact in energy consumption of buildings, we review how related works from the literature tackle them. In this way, we can extract the main limitations and constraints of these works, and suggest proposals to address them.

7.3 Related Work

A complete review of previous solutions from the literature was carried out during the development period of the present chapter. We tried to find ways that would enable us to propose holistic solutions to building energy management problems, which should address there relevant aspects mentioned previously, i.e. a complete monitoring phase, the efficient management of information, using automation systems and involving occupants during the system operation. Nevertheless, different proposals were found for different goals, but none was integrated all the aspects. This was the first constraint identified among previous solutions. Consequently, we decided to review the main related work tackling each one of these aspects separately.

As regards the monitoring aspect, initial solutions to energy efficiency in buildings were mainly focused on non-deterministic models based on simulations. A number of simulation tools are available with varying capabilities. In [17] and [18] a comprehensive comparison of existing simulation tools is provided. Among these tools are ESP-r [19] and Energy Plus [20]. However, this type of approach relies on very complex predictive models based on static perceptions of the environment. For example, a multi-criteria decision model to evaluate the whole lifecycle of a building is presented in [21]. The authors tackle the problem from a multi-objective optimization viewpoint, and conclude that finding an optimal solution is unrealistic, and that only an approximation is feasible.

With the incessant progress made in the field of ICT and sensor networks, new applications to improving energy efficiency are constantly emerging. For instance, in office spaces, timers and motion sensors provide a useful tool to detect and respond to occupants, while providing them with feedback information to encourage behavioural changes. The solutions based on these approaches are aimed at providing models based on real sensor data and contextual information. Intelligent monitoring systems, such as automated lighting systems, have limitations such as those identified in [22], in which the time delay between the response of these automated systems and the actions performed can reduce any energy saving, whilst an excessively fast response can produce inefficient actions. These monitoring systems, while contributing towards energy efficiency, require significant investment in an intelligent infrastructure that combines sensors and actuators to control and modify the overall energy consumption. The cost and difficulty involved in deploying such networks often constrain their viability. Clearly, an infrastructure-less system that uses existing technologies would provide a cheaper alternative to building energy management systems. On the other hand, building energy management must bare with the inaccuracy of sensors, the lack of adequate models for many processes and the non-deterministic aspects of human behaviour.

In this sense, there is an important research area that proposes techniques of artificial intelligence as a way of providing intelligent building management systems. Rather than solving the above drawbacks. This approach involves models based on a combination of real data and predictive patterns that represent the evolution of the parameters affecting the energy consumption of buildings. An example of such an approach is [23], in which the authors propose an intelligent system able to manage the main comfort services provided in the context of a smart building, i.e. HVAC and lighting, while user preferences concerning comfort conditions are established according to the occupants' locations. Nevertheless, the authors only propose the inputs of temperature and lighting in order to make decisions, while many more factors are really involved in energy consumption and should be included to provide an optimal and more complete solution to the problem of energy efficiency in buildings. Furthermore, no automation platform is proposed as part of the solution.

Regarding building automation systems, many works extend the domotics field which was originally used only for residential buildings. A relevant example is the proposal given in [24], where the authors describe an automation system for smart homes based on a sensor network. However, the system proposed lacks automation flexibility, since each node of the network offers limited I/O capabilities through digital lines, i.e. there is no friendly local interface for users, and most importantly, integration with energy efficiency capabilities is weak. The work presented in [25] is based on a sensor network to cope with the building automation problem for control and monitoring purposes. It provides the means for open standard manufacturer-independent communication between different sensors and actuators, and appliances can interact with each other with defined messages and functions. Nevertheless, the authors do not propose a control application to improve energy efficiency, security or living conditions in buildings.

The number of works concerning energy efficiency management in buildings using automation platforms is more limited. In [26], for instance, a reference implementation of an energy consumption framework is provided, but it only analyses the efficiency of ventilation system. In [27] the deployment of a common client/server architecture focused on monitoring energy consumption is described, but without performing any control action. A similar proposal is given in [28], with the main difference that it is less focused on efficiency indexes, and more on cheap practical devices to cope with a broad pilot deployment to collect the feedback from users and address future improvements for the system.

Regarding commercial solutions for the efficient management of building infrastructures, there are proposals such as those given by the manufacturer

Johnson Controls[3], a company that provides products, services and solutions that help increase energy efficiency and reduce the operation costs of its clients' buildings. Another well-known manufacturer is Siemens[4], who offer a technical infrastructure for building automation and energy efficiency in the form of market-specific solutions in buildings and public places. The main differences between these commercial solutions and our proposal for automation and energy efficiency management in smart buildings are those related with the open and transparent character of our proposal, as well as its capability to gather data from a large number of heterogeneous sources.

As regards user involvement, this can be done by means of their implicit or explicit feedback. When implicit feedback is considered, an important line of research focuses on the crowdsensing paradigm [9]. In brief, this paradigm intends to uncover meaningful behavioural patterns by automatically collecting the digital breadcrumbs of the different sensors that users' personal devices are equipped with. At the same time, a novel course of action has paid attention to social networks as a novel datasource to extend the collection implicit user feedback [29]. Despite its inherent uncertainty, several works are already able to extract meaningful behavioural patterns by mainly using social-network feeds [30, 31]. As for explicit user's feedback, the crowdsourcing paradigm centers on providing tools to allow the management of the information explicitly requested to sets of target users [32, 33]. In a smart building context, crowdsensing or crowdsourcing paradigms have been mainly used to flow management in indoor areas [34]. Last but not least, in the building energy management field, some proposals have involved uses in saving energy in buildings [5, 6]. However, few works have been addressed this aspect. It is important to note that energy usage feedback in building energy management systems needs to be provided to users frequently and over a long time, offering an appliance-specific breakdown, while presented in a clear and appealing way using computerized and interactive tools.

Concerning the fact that users have little awareness of the energy wastage associated with their energy consumption behaviours is due partly to the fact that most people do not know what the optimum comfort conditions are according to environmental features and their needs. It is clear that, while each person has his/her own comfort preferences and these preferences are strongly conditioned by subjective concerns, there are a minimal and a maximum set of

[3]http://www.johnsoncontrols.co.uk/content/gb/en/products/building_ efficiency.html

[4]http://www.buildingtechnologies.siemens.com/bt/global/en/energy-efficiency/Pages/Energy-efficiency.aspx

comfort conditions recognized as common to everyone to ensure the quality of life [35]. Therefore, the confidence and respect that users give to the intelligent services that are offered to them in terms of comfort and energy efficiency concerns in smart buildings, are crucial constraints in this type of system. Nevertheless, thanks to pervasive computing practices, the integration and development of systems based on IoT support and encourage the cooperation between humans and devices in terms of:

- Facilitating communication between things and people, and between things, by means of a collective network intelligence context.
- People's ability to exploit the benefits of this communication through their increasing familiarity with ICT.
- A vision where, in certain respects, people and things are homogeneous agents endowed with fixed computational tools.

Smart buildings should prevent users from having to perform routine and tedious tasks to achieve comfort, security, and effective energy management. Sensors and actuators distributed in buildings can make user life more comfortable; for example: i) room heating can be adapted to user preferences and to the weather; ii) room lighting can change according to the daylight; iii) domestic incidents can be avoided with appropriate monitoring and alarm systems; and, iv) energy can be saved by automatically switching off electrical equipment when not needed, or regulating their operating power according to user needs, thus avoiding any energy overuse. In this sense, IoT is a key enabler of smart services to satisfy the needs of individual users, who apart from being users of the system, can also be seen as sensors in the same way as temperature, thermal, humidity and presence sensors deployed in the building.

As can be noted, most of the approaches proposed to date only provide partial solutions to the overall problem of energy efficiency in buildings, where, although different factors are involved holistically, until now they have been addressed separately or even neglected by previous proposals. This division is frequently due to the uncertainty and lack of data and inputs in the management processes, so that analysis of how energy in buildings is consumed is incomplete. In other words, a more integral vision is required to provide accurate models of the energy consumed in buildings [7]. In this sense, no solutions have been proposed tackling the full integration of information related with all relevant aspects directly involved in the energy consumption of buildings (which are described in Section 7.2). For example, there are not previous solutions that fully integrate information about the occupants of buildings, despite of the fact that human behaviour has been recognized as one of the most important aspects affecting energy consumption in buildings. Information about the identities of occupants, their locations and activities, their comfort preferences, their levels of awareness with the problem of the high energy consumption of buildings, their participation to get energy saving, etc. must be included, jointly to other relevant information, in any building energy management system. In this chapter, we present our own smart system proposal, which is a holistic and flexible solution based on collecting and analysing information of both the building context and its occupants, and propose concrete actions which could be applied in the management of any controllable infrastructure of buildings to ensure their energy efficient performance. Our proposal of solution considers occupants as a key piece of our management system, and we demonstrate the benefits of following this approach in term of the energy saving achieved in various buildings used as reference.

7.4 A Proposal of General Architecture for Management Systems of Smart Buildings

The architecture of our proposal for smart building is modelled in layers which are generic enough to cover the requirements of different smart environments of cities, such as intelligent transport systems, security, health assistance or, as is the case analysed in this chapter, smart buildings. This architecture promotes high-level interoperability at the communication, information and services layers. The layers of such architecture are depicted in Figure 7.1, and are detailed below.

7.4.1 Data Collection Layer

Looking at the lower part of Figure 7.1, input data are acquired from a plethora of sensor and network technologies such as the Web, local and remote databases, wireless sensor networks, mobile devices, etc., all of them forming an IoT ecosystem. In this sense, and considering the instance of this architecture for the building management system proposed in this chapter, it gathers information from sensors and actuators deployed in the building. As for static sensors and actuators can be self-configured and controlled remotely through the Internet, enabling a variety of monitoring and control applications. Concerning mobile sensors, mechanisms to pro-actively or passively collect their reported data is also included in this layer. Given the heterogeneity of data sources and the necessity of seamless integration of devices and networks,

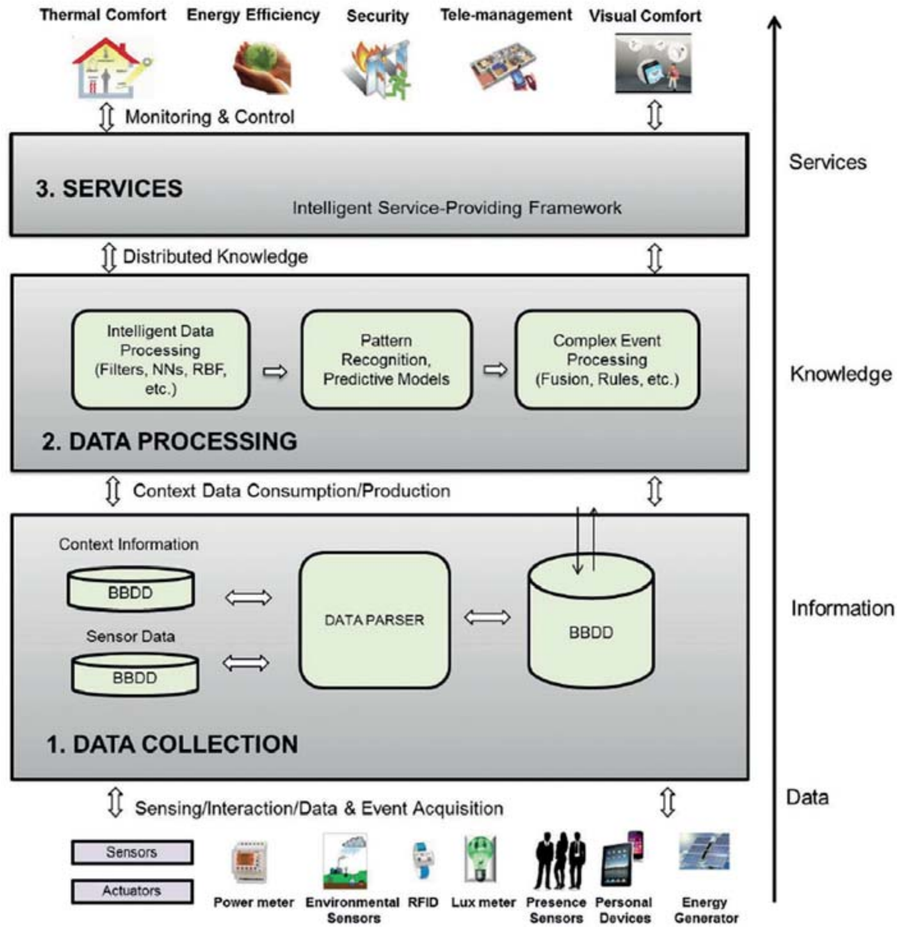


Figure 7.1 Layers of the base architecture for smart buildings ecosystem.

a common language structure to represent data is needed to deal with this issue. Therefore, the transformation of the collected data from the different data sources into a common language representation is performed in this stage.

7.4.2 Data Processing Layer

The data processing layer is responsible for processing the information collected and making decisions according to the final application context. A set of information processing techniques is applied to extract, contextualize, fuse and represent information for the transformation of massive input data into useful knowledge, which can be distributed later towards the services layer. Different algorithms can be applied for the intelligent data processing and decision making processes, depending on the final desired operation of the system (i.e. the services addressed). Considering the target application of smart buildings, data processing techniques for covering, among others, security, tele-assistance, energy efficiency, comfort and remote control services should be implemented in this layer. And following a user-centric perspective for services provided, intelligent decisions are made through behaviour-based techniques to determine appropriate control actions, such as appliances and lights, power energy management, air conditioning adjustment, etc.

7.4.3 Services Layer

Finally, the specific features for providing services, which are abstracted from the final service implementation, can be found in the upper layer of the proposed architecture (see Figure 7.1). Our approach offers a framework with transparent access to the underlying functionalities to facilitate the development of different types of final application. This generic proposal of architecture for smart buildings has been instantiated in the system known as City explorer. City explorer, which was developed at the University of Murcia, integrates an automation platform which is divided into an indoor part, and all the connections with external elements for remote access, technical tele-assistance, security and energy efficiency/comfort providing services in buildings. Figure 7.2 shows a schema of City explorer offering ubiquitous services in the smart buildings field. The main components of City explorer were presented in details in [36, 37]. The work developed in this chapter is based on using City explorer as platform of experimentation and validation of our proposal of building management to achieve energy efficiency. For this, we have instantiated each generic layer of the architecture shown in Figure 7.1, with the goal of offering a solution to energy efficiency in smart buildings.

7.5 IoT-based Information Management System for Energy Efficiency in Smart Buildings

As mentioned before, our proposal of IBMS uses the City explorer platform applied to achieve energy efficiency in buildings. Our proposed system has the capability, among others, to adapt the behaviour of automated devices

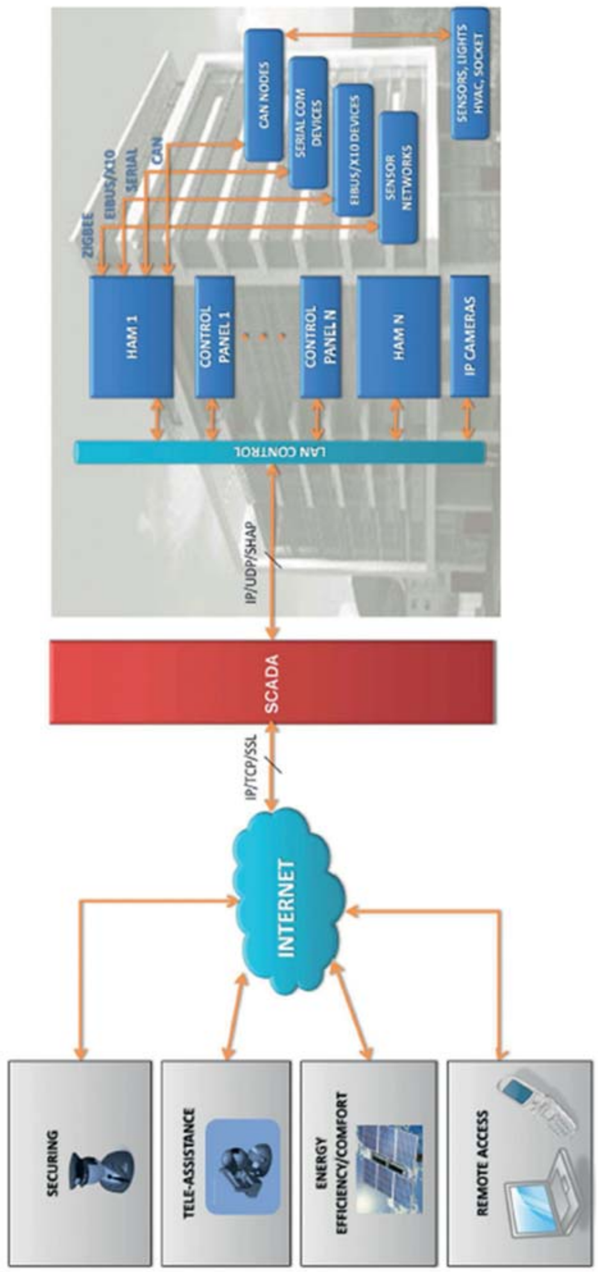


Figure 7.2 City explorer applied to smart buildings.

deployed in the building in order to meet energy consumption restrictions, while maintaining comfort conditions at the occupants' desired levels.

More specifically, the goals of our intelligent management system are the following:

- High comfort level: learn the comfort zone from users' preferences, guarantee a high comfort level (thermal, air quality and illumination) and a good dynamic performance.
- Energy savings: combine the control of comfort conditions with an energy saving strategy.
- Air quality control: provide CO2-based demand-controlled ventilation systems.

Satisfying the above control requirements implies controlling the following actuators:

- Shading systems to control incoming solar radiation and natural light as well as to reduce glare.
- Window opening for natural ventilation or mechanical ventilation systems to regulate natural airflow and indoor air changes, thus affecting thermal comfort and indoor air quality.
- Heating/cooling (HVAC) systems.

As a starting point, we focus only on the management of lights and HVAC subsystems, since they represent the highest energy consumption at building level. User interactions have a direct effect on the whole system performance, because the occupants can take control of their own environment at any time.

Thus, the combined control of the system requires optimal operation of every subsystem (lighting, HVAC, etc.), on the assumption that each operates normally in order to avoid conflicts arising between users' preferences and the simultaneous operations of such subsystems. Figure 7.3 shows a schema of the different subsystems comprising the intelligent management system integrated in City explorer, where the outputs of the system are forwarded to the actuators deployed in the building.

As can be seen in Figure 7.3, the first task to solve is related with user identification and localization, and the second problem is related with the issues of comfort and energy efficiency in the management of the building. In the following subsections we describe the different issues involved and which were solved during this work, and represent our proposal of building energy management system for energy efficiency.

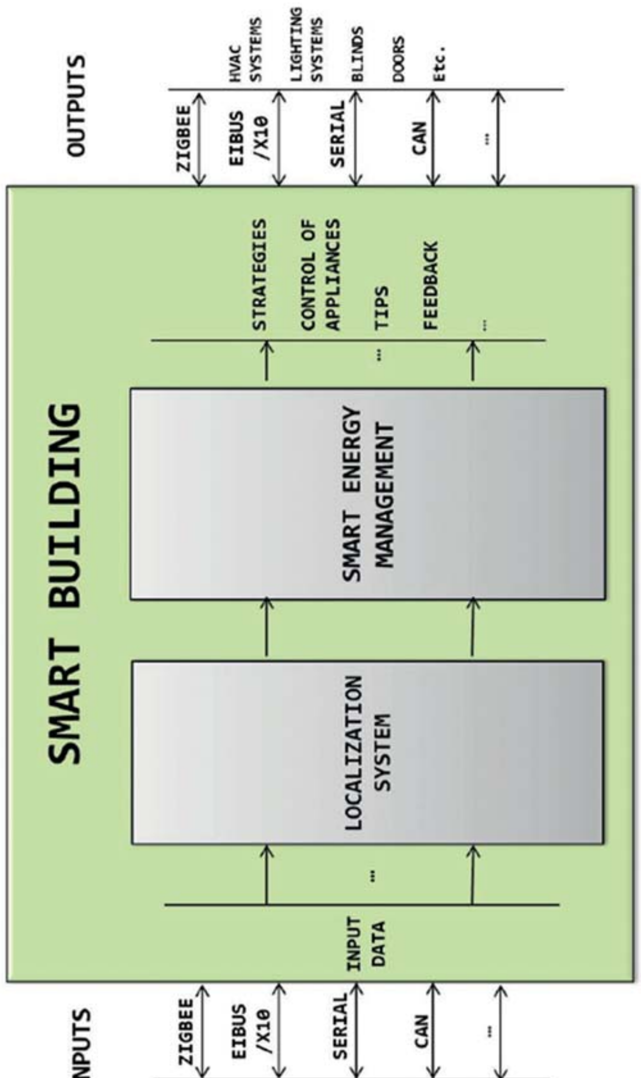


Figure 7.3 Schema of the modules composing the management system in charge of the building comfort and energy efficiency.

7.5.1 Indoor Localization Problem

In a smart building, embedded sensors measure and record user activities, making it possible to predict their future behaviour, prepare everything one step ahead according to the individual user's preferences or needs, and provide the most convenient energy efficient services. These services need to operate by acquiring contextual information both from users and the environment. Therefore, to make buildings smart and to be able to offer users customized services, it is indispensable to previously solve the implicit indoor localization problem. Furthermore, user identities need to be taken into account so that the intelligent system can learn and manage devices according to their behaviour and/or preferences. We obviously need to solve user identification in smart buildings to provide customized comfort services committed to energy efficiency, but while user privacy must also be respected because occupants care about their private and social activities, and want full control of how their personal location information and history are used. Hence, there is a need to rely on non-intrusive, ubiquitous and cheap sensors to minimise infrastructure deployment and prevent user dissatisfaction. Indeed, some sensors cannot be installed in buildings; for instance, in Spain video cameras cannot be legally used in offices. Problems like this make some localization systems unsuitable for use in smart buildings.

In the scenario addressed in this work, the whole area of a smart building is divided into locations (rooms, open areas, corridors, etc.) with different comfort conditions in each one; for instance, optimum lighting conditions in a corridor are different from those required in an office; or the optimum level of air conditioning in an individual bedroom is different from that required in a very crowded dining room. Furthermore, in each of these areas (an individual bedroom, a dining room, an office, etc.), it is necessary to carry out a further division depending on the service area of each comfort appliance deployed. Therefore, our indoor localization system must be able to locate a user in terms of regions, which correspond to the service areas of the appliances or devices involved in her/his comfort condition. Recent years have seen great progress in indoor localization systems, but there are still some weaknesses in terms of the accuracy of location data, the time required for calibration processes, poor robustness, or high installation and equipment costs [38]. Furthermore, when user identification is needed, most of the systems proposed present difficulties concerning complexity, computational load and inaccurate results. Since the indoor localization problem does not have obvious solutions, we review relevant solutions from the literature and identify the technological options most suitable in light of our problem. Accuracy is usually the most important requirement for positioning systems. In the location problem involved in energy efficiency of buildings, we conclude that the accuracy required for our localization system depends on the service areas of the appliances and devices involved in the comfort and energy balance of the building.

In Figure 7.4 a rough outline of some positioning systems is presented, with their accuracy ranges achieved until now according to the literature. Since each localization technology has its particular advantages and disadvantages, we suggest that by combining several complementary technologies and applying data fusion techniques, it is possible to improve the overall system performance and provide a more reliable indoor localization system, since more specific inferences can be achieved than when using a single kind of data sensor. Therefore, after analysing Figure 7.4, we choose a hybrid solution based on RF and non-RF technologies. Our technological solution to cover the localization needs (i.e. those required by smart buildings to provide occupants with customized comfort services) is based on a single active RFID system and several Infra-Red (IR) transmitters. In Figure 7.5 we can observe the data exchange carried out among the different technological devices that compose our localization system.

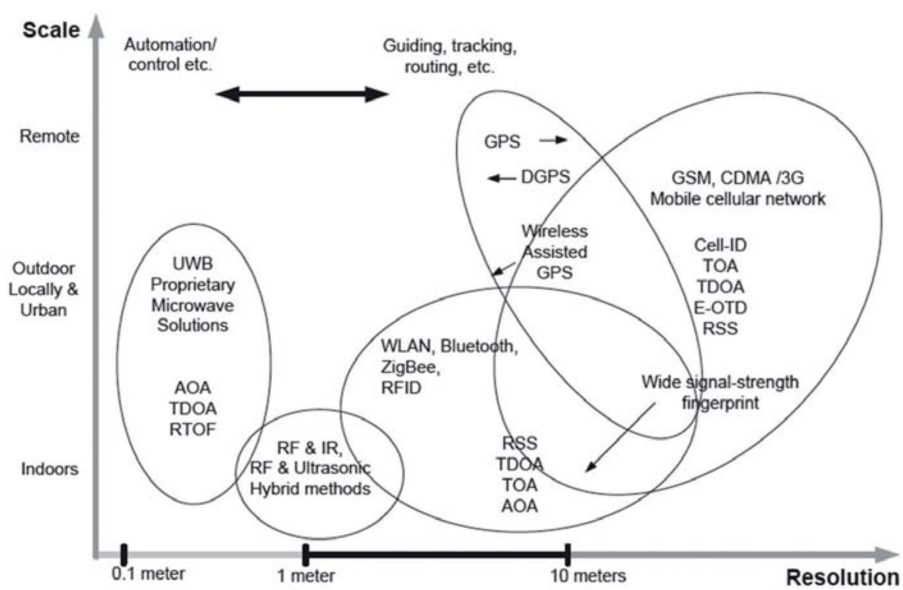


Figure 7.4 Outline of some positioning technologies [38].

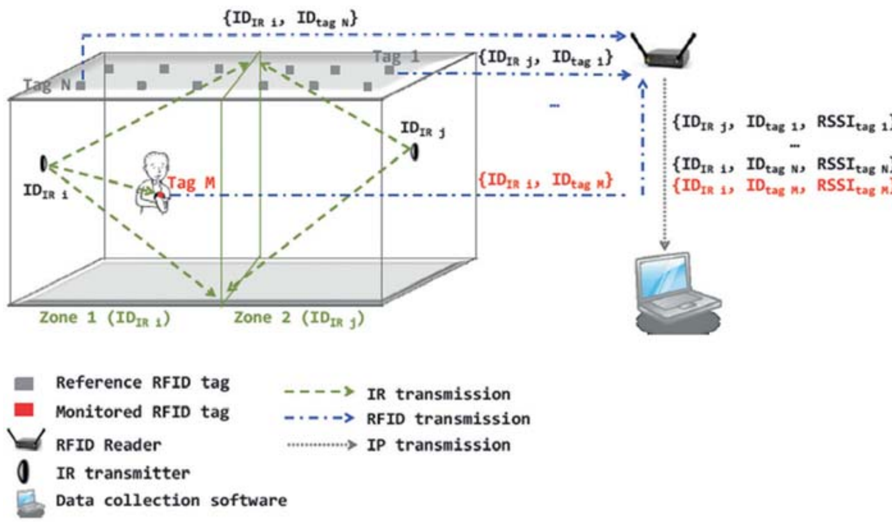


Figure 7.5 Localization scenario.

The final mechanism implemented for indoor localization is shown in Figure 7.6. In this figure, we can see that the first phase of our localization mechanism is the space division through the installation of IR devices in the walls of the building area where localization wants to be solved. Therefore, for each space division, there is an IR identifier value (IDir) associated to this region. For each one of these region, we implement a regression method based on Radial Basis Functions (RBF) networks. The RBF estimates user positions given different RFID tags situated in the roof. This RFID-based information coming from the different building's occupants conforms a data stream that could be also processed by means of a crowdsensing approach so as to track the flow of people within a building. In that sense, several proposals already exist that intends to reconstruct the behaviour of people by using the type of discrete locations [39].

In our localization mechanism, after the position estimation using the RBF network, a Particle Filter (PF) is applied as a monitoring technique, which takes into account previous user position data for estimating future states according to the current system model. In the PF, we modify particle weights according to the distances to the measurements during the correction stage, as the following equation shows:

$$w(\overrightarrow{x}_t) = w(\overrightarrow{x}_{t-1}) \cdot \frac{p(\overrightarrow{y}_t|\overrightarrow{x}_t) \cdot p(\overrightarrow{x}_t|\overrightarrow{x}_{t-1})}{q(\overrightarrow{x}_t|\overrightarrow{x}_{t-1}, \overrightarrow{y}_t)} \tag{7.1}$$

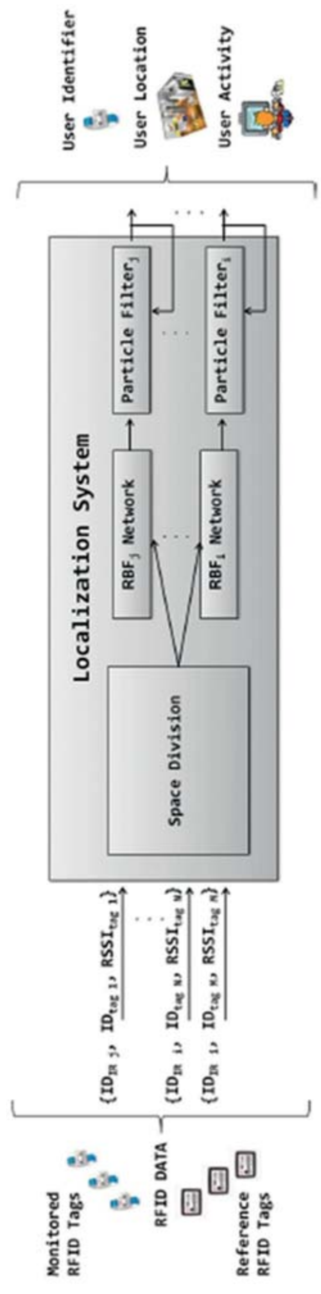


Figure 7.6 Data processing for location estimation.

where $w(\overrightarrow{x}_t)$ weights of the set of particles at instant t; $p(\overrightarrow{y}_t|\overrightarrow{x}_t)$ and $p(\overrightarrow{x}_t|\overrightarrow{x}_{t-1})$ gives the probabilistic behaviour of the output and the state model of the system respectively, and $q(\overrightarrow{x}_t|\overrightarrow{x}_{t-1},\ \overrightarrow{y}_t)$ is the approximation of the expectedly function.

Algorithm 7.1 provides a summarized version of the general definition of PF. The PF used in this work is slightly different from its generic definition. The main difference of our filtering algorithm is in the correction stage, which applies the resample using the Sequential Importance Sampling (SIS) algorithm [40] (step 13 of Algorithm 7.1). During this step, information about the specific IR region at a given instant of time is also used to benefit those particles which fall inside this area. Therefore, before applying Equation (7.1), we filter according to the condition given by Equation (7.2):

$$\{\mathrm{If}: y_t \in \Omega^j \Rightarrow w(x_t^i) = 0 \;\forall\; x_t^i \notin \Omega^j\}, \tag{7.2}$$

where Ω^j represents the coverage area of the IR transmitter with identifier j, and y_t and $w(x_t^i)$ denote, respectively, the measured parameter and the weight of the set of particles *i* at the instant of time *t*. The main advantage of this constraint is the faster convergence of the filter, because extra information is available to carry out the correction stage.

Algorithm 7.1 Generic PF

Require: $\{x_{t-1}^i, w_{t-1}^i\}_{i=1}^{N_s}, y_t$
Ensure: $\{x_t^i, w_t^i\}_{i=1}^{N_s}$
1: Given a particle number N_s
2: Given a threshold N_T value for resampling
3: **for** *i* = 1 **to** N_s **do**
4: Draw $x_t^i \sim q(x_t|x_{t-1}^i, y_t)$
5: Assign the particle a weight w_t^i
6: **end for**
7: Calculate total weight: *t* = SUM$[\{w_t^i\}_{i=1}^{N_s}]$
8: **for** *i* = 1 **to** N_s **do**
9: Normalize: $w_t^i = t^{-1} \cdot w_t^i$
10: **end for**
11: calculate $\widehat{N_{cff}} = \frac{1}{\sum_{i=1}^{N_s}(w_t^i)^2}$
12: **if** $\widehat{N_{cff}} \leq N_T$ **then**
13: Correction stage.
14: **end if**

7.5.2 Building Energy Consumption Prediction

The energy performance model of our BMS is based on the CEN Standard N15251 [41]. This standard proposes the criteria of design for any building energy management system. It establishes and defines the main input parameters for estimating building energy requirements and evaluating the indoor environment conditions. The inputs considered to solve our problem are the data coming from the RFID cards of users, the user interaction with the system through the control panels or the web access, environmental parameters coming from temperature, humidity and lighting sensors installed in outdoor and indoor spaces, the consumption energy sensed by the energy meters installed in the building, and the generated energy sensed by the energy meters installed in the solar panels deployed in our testbed. After collecting the data, it is mandatory to continue with their cleaning, preprocessing, visualization and correlation study in order to find determining features, which can be used to generate optimal energy consumption models of buildings (management layer of the architecture presented in Section 7.4). Over the input set, we perform the standardization and reduction of data dimensionality using Principal Components Analysis (PCA) [42], identifying the directions in which the observations of each parameter mostly vary.

Regarding the Artificial Intelligence (AI) techniques that have been already applied successfully to generate energy consumption models of buildings in different scenarios (as such we mentioned in the management layer of the architecture presented in Section 7.4), we propose to evaluate the performance of Multilayer Perceptron (MLP), Bayesian Regularized Neural Network (BRNN) [43], SVM [44] and Gaussian Processes with RBF Kernel [45]. They were selected because of the good performance that all of them have already provided when they are applied to building modelling. All these regression techniques are implemented following a model-free approach, which is based on selecting – for a specific building – the optimal input set and technique, i.e. such input set and technique that provides the most accurate predictive results in a test data set. In order to implement this free-model approach, we use the R [46] package named CARET [47] to train the energy consumption predictive algorithms, looking for the optimal configuration of their hyper-parameters.

The selected metric to evaluate the models generated for each technique using test sets is the well-known RMSE (Root-Mean-Square Error), which formulation appears in Equation (7.3).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{7.3}$$

This metric shows the error by means of the quantity of KWh that we deviate when predicting, but in order to get a better understanding of the uncertainty of the model, we also show its coefficient of variation (CVRMSE). This coefficient is the RMSE divided by the mean of the output variable (energy consumption) for the test set (Equation (7.4)), giving us a percentage of error adjusted to the data, not just a number in general terms.

$$CVRMSE = \frac{RMSE}{\overline{y}} \tag{7.4}$$

7.5.3 Optimization Problem

Once the building energy consumption is modeled we focus on the optimization of its use trying to keep comfort conditions. As starting point, we establish the comfort extremes considering location type, user activity and date [48]. Understanding the building thermal and energetic profiles allows us to quantify the effects of particular heating-cooling set point decisions. To derive a heating or cooling schedule, it is necessary to formulate the target outcome. In our buildings, it is possible to:

1. Optimize the indoor temperature during occupation, i.e. minimize the building temperature deviations from a target temperature.
2. Minimize daily energy consumption, or
3. Optimize a weighted mixture of the criteria, a so-called multi-objective optimization.

The definition of building temperature deviation influences the results strongly: taking the minimum building temperature will result in higher set point choices and higher energy use than using e.g. the average of building temperatures. Constraints on maximum acceptable deviation from target comfort levels or an energy budget can be taken into account to ensure required performance. For our optimization problem, we apply a genetic optimization implemented in R (using the "genalg" package [49]) to our predictive building models to derive schedules for heating/cooling setpoints.

7.5.4 User Involvement in the System Operation

Following this approach to provide human-centric services in the context of smart buildings, users can be seen as both the final deciders of actions, and system co-designers in terms of feedback that conditions future rules and contributions to the software issuing these rules. In this sense, in our energy building management system we consider the data provided directly by users through their interactions when they change the comfort conditions provided automatically by the system and, consequently, the system learns and autoadjusts according to such changes and to the control comfort/energy strategies defined by users using the graphic editor of City explorer. Furthermore, with the aim of offering users information about any unsuitable design or setting of the system, as well as to help them easily understand the link between their everyday actions and environmental impact, City explorer is able to notify them about such matters (i.e. acting as a learning tool). On the other hand, when the system detects disconnections and/or failures in the system, it sends alerts by email/messages to notify users to check these issues. All these features, which are included in our management system, contribute to user behaviour changes and increase their awareness as time passes, or detect unnecessary stand-by consumption of the controllable subsystems of the building.

Finally, to understand the background of energy behaviour of users involved in our experiments and to be able to form an initial context pattern for the usability of the system under different constraints, we carried out a follow-up study based on the feedback that users provide to City explorer through the SCADA-web and the control panels installed in the smart building. Another reason to carry out this study was the identified lack of research in the building energy management area, where large-scale deployment needs to be accompanied by a body of study on user behaviour, motivation and preferences. The same was pointed out by [6]. In Figure 7.7 is shown the schema of our final building energy management solution.

7.6 Evaluation and Results

7.6.1 Scenario of Experimentation

The reference building where our BMS for energy efficiency is deployed is the Technology Transfer Centre (TTC) of the UMU[5]. Every room of this building is automated through a Home Automation Module (HAM) unit of the City explorer platform. It permits us to consider a granularity at room level to carry out the experiments.

[5]www.um.es/otri/?opc=cttfuentealamo

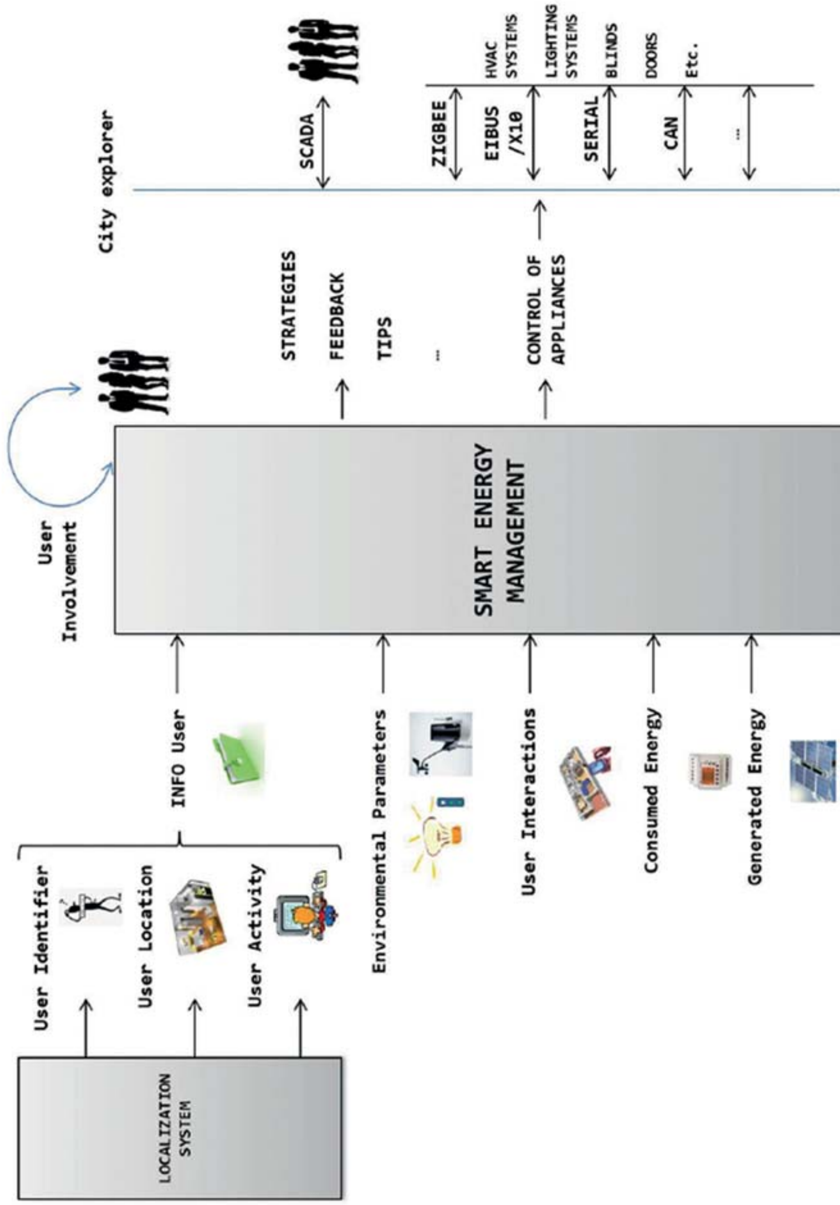


Figure 7.7 Schema of the definitive module of our building energy management system.

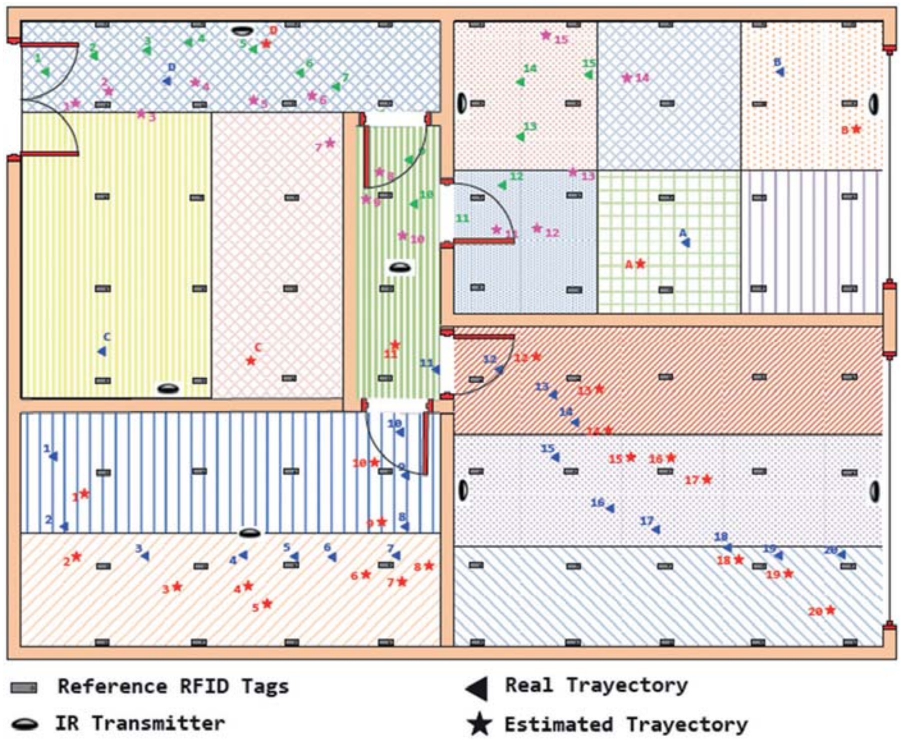


Figure 7.8 Tracking processes with a reference tag distribution of 1 m × 1 m.

7.6.2 Evaluation and Indoor Localization Mechanism

Different tracking processes are carried out in the environments considered in our tests (the TTC building) applying for this the implementation of the PF described in Algorithm 7.1. In Figure 7.8 an example of some tracking processes are carried out considering transition between different spaces of the TTC. For these paths, our system was configured to acquire data every T = 10 s. (whereas for the rest of the tests a value of T = 5 min. was considered). Taking into account the target location areas involved (represented in different colors), and the real and estimated location data provided by our mechanism, it can be safely said that it was able to monitor the user locations with a high degree of accuracy and precision.

With an 1m × 1m distribution of reference RFID tags placed on the roof of the test room, a 65% success percentage in localization is obtained having an error lower than 1 m. 98% of cases have as much 2.5 m. of error. Therefore, it can be safely said that our localization system is able to track users with a sufficient level of accuracy and precision for the location requirements associated with the comfort and energy management problem in buildings. More details about this indoor localization system can be found in [50].

7.6.3 Evaluation. Energy Consumption Prediction and Optimization

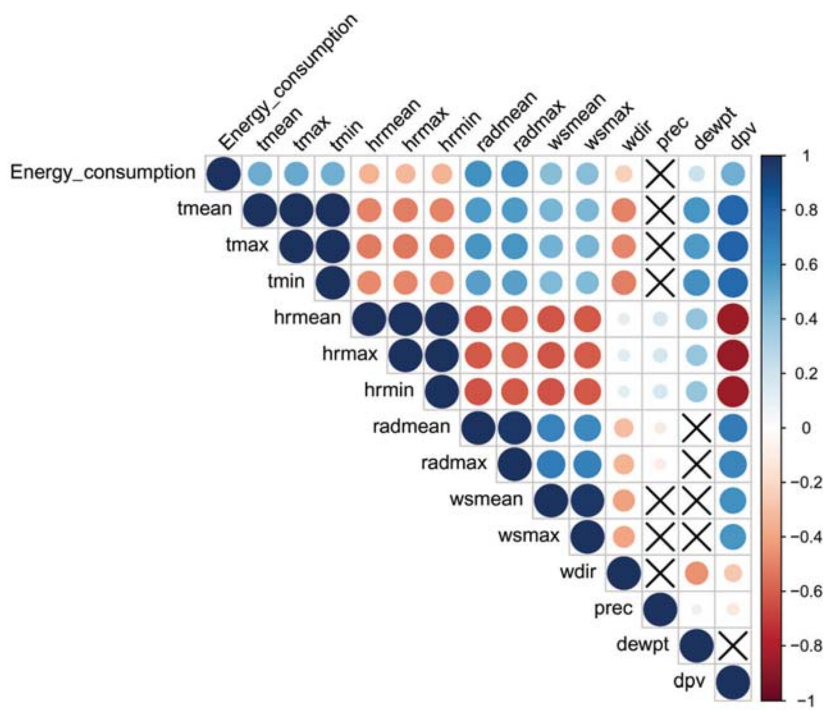
In Figure 7.9(a) it is shown the correlation heatmap between the electrical consumption of the TTC building and the outdoor environmental conditions.

It is observed that energy consumption correlates significantly (α = 0.95) and positively with temperature, radiation, wind speed variables, vapour pressure deficit and dew point, and negatively with wind direction and humidity variables. This means that we can use safely these variables as inputs of the energy consumption model of our reference building, because they have clear impact in the energy consumption. Otherwise, precipitations are so unusual that they don't have an association with the output.

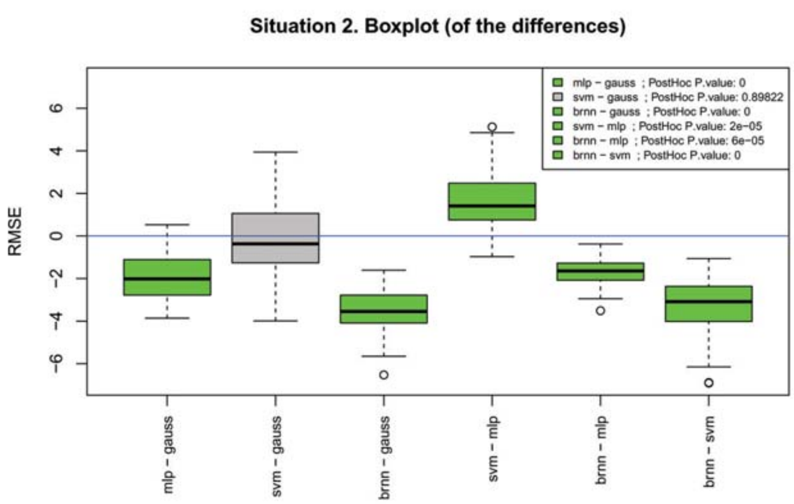
Also, a logic differentiation between situations has been considered in order to label behaviour. Situation 1: holidays and weekends, situation 2: regular mornings, and situation 3: regular afternoons. The non-parametric Kruskall Wallis test shows that energy consumption differs significantly between situations (H(2) = 547.7, $p < 0.01$). Also, the post hoc pairwise comparisons corrected with Holm's method retrieve a p-value smaller than 0.01, supporting the decision of creating 3 different models [51].

Thus, for each of the three situations identified for the TTC building, we have evaluated not only the punctual value of RMSE, but also we have validated whether one learning algorithm out-performs statistically significantly the others using the non-parametric Friedman test [52] with the corresponding post-hoc tests for comparison. Let xj i be the i-th performance RMSE of the jth algorithm, for this building, we have used 5-times10-fold cross validation, so $i \in \{1, 2, \ldots, 50\}$ and four techniques, so $j \in \{1, 2, 3, 4\}$. For every situation, we find significant differences (α = 0.99) between every pair of algorithms, except for SVM and Gauss RBF ($p > 0.01$), as it is shown in Figure 7.9(b) for the particular case of situation 2.

The three models have in common that BRNN yields a better result than the other tested techniques, based on the RMSE metric. Thus, BRNN is able to generate a model with a very low mean error of 25.17 KWh – which only represents the 7.55% of the sample (this is the most accurate result) in terms of the CVRMSE. And for the worst case, BRNN provides a mean error of



(a) Correlation heatmap betweeb consumption and outdoor environmental conditions



(b) Boxplots comparing models pairwise (situation 2)

Figure 7.9 Modeling results.

43.76 KWh – which represents the 10.29% of the sample in the reference TTC building – that is acceptable enough considering that the final aim is to save energy.

To evaluate our GA-based optimization strategy, controlled experiments were carried out in the TTC building with different occupant's behaviours. The results showed that we can accomplish energy savings between 15% and 31%. Trying to validate the application of our proposal we have applied it in a different scenario with limited monitoring and automation technologies, achieving energy saving of about 23%.

7.6.4 Evaluation. User Involvement

For the experiments described here, fifteen people took part in the focus group studies which help us extract user-preferences and pinpoint design concerns. Understanding user contexts, such as motivation for saving energy and the constraints for implementing energy saving behavior, enables better understanding of user preferences and how the energy monitoring system can work with users to achieve the best possible behavioral changes.

During the data collection process performed in the experiment, the subjects were asked to walk freely along the different scenarios considered, and to work or relax in the different areas designed specifically for such goals. This experiment was repeated during 3 hours per day considering different conditions of user movements and activities, environmental conditions, preferences, etc. At the time of writing, the system has just completed the first 62 days of measurement, so this time is the baseline period used to assess the impact of including users in the loop of our system. During the first 31 days of the experiment, users lacked any feedback about their energy consumption as well as any control capability over the setting of comfort and energy levels, but during the last 31 days of the experiment, users were empowered and were included as a holistic component of the system. During this second phase of the system operation, the system displayed real time energy usage in kW, cost of energy usage, energy saving tips, energy usage history (hourly, daily, monthly), etc. through both SCADA-web and the control panel installed in the target scenario. Also, during this last phase, users could define their own strategies to control any appliance or monitor any specific parameters sensed by the system.

Despite the relatively short time of evaluation (one month), a nearly analysis shows that the system has already had a positive impact on user behaviors, which can be translated into energy saving terms. Figure 7.10

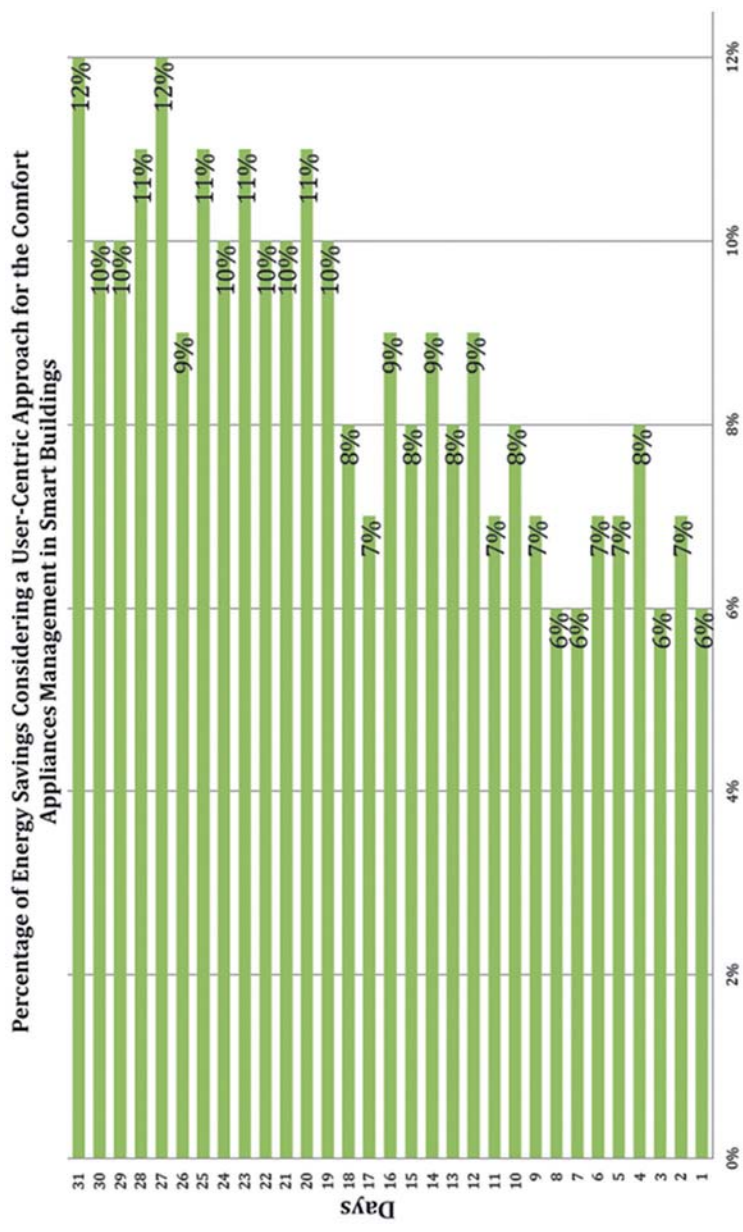


Figure 7.10 Percentage of energy consumption savings in comfort services considering a user-centric building management efficient.

shows the energy savings achieved during the second month of operation of our energy management system in contrast to the first experimental month. It can be seen how we achieved a saving of up to 12% of the energy involved, and the medium value of 9% for the experimental month. Furthermore, the results reflect how the increased savings become more stable with time, specifically from the 17th day of the system operation. The reason of this saving increasing is because our system is able to learn and adjust itself to any feedback indicated by users regarding their comfort associated profile, and to recognize patterns of user behavior.

7.7 Conclusions and Future Work

The proliferation of ICT solutions (IoT among them) represents new opportunities for the development of new intelligent services, contributing to more efficient and sustainable cities. In this sense, with the increasing urbanization seen in recent decades, there is an urgent need to achieve energy-efficient environments to ensure the energy sustainability of cities. But to achieve this goal, it is first necessary to solve energy efficiency concerns at building level, since this constitutes the cornerstone of the overall problem. For greater energy efficiency in buildings, smart solutions are required to monitor and control the capabilities offered by wide sensor and actuator networks deployed as part of the system. Furthermore, occupants play an important role in this type of system, since they are the recipients of the indoor services provided by electrical appliances installed in buildings, most of them responsible for providing them with comfort conditions. In this sense, it is required to propose building management systems able to tackle energy efficiency requirements while user comfort conditions are also taken into account. To date, however, the solutions proposed are mainly based on determinist models with few accurate predictions, and are not able to consider real-time data in most cases. Indeed, they do not even come close to reflecting reality.

In this chapter, we propose a building energy management system powered by IoT capabilities and part of a novel context and location-aware system that covers the issues of data collection, intelligent processing to save energy according to user comfort preferences and features that modify the operation of relevant indoor devices. An essential part of our energy efficiency system are the key aspects of integrating user location and identity, so that customized services can be provided to them while any useless energy consumption in the building is avoided. Furthermore, another relevant feature is users involvement with the system, through their interactions and their participation to get energy savings in the building.

The applicability of our system has been demonstrated through its installation in a reference building. Thus, using user location data, considering target regions of occupancy for comfort and energy management in the building, and finally including users in the loop of the system operation, we show that energy consumption in buildings can be reduced by a mean of about 23%. If we translate this mean value of energy saving to city level, assuming that buildings represent 40% of the total energy consumption at European level, a reduction of 9% at city level could be achieved by installing this energy management system in buildings.

The ongoing work is focused on the inclusion of people behaviour during the operational loop of this kind of systems for smart cities. Thus, for the case of smart building applications, users will be encouraged to participate in an active way through their engagement to save energy. On the other hand, in the case of the public tram service, data coming from crowd-sensing initiatives will be integrated to improve the estimation of the urban mobility patterns.

Acknowledgments

This work has been partially funded by MINECO TIN2014-52099-R Project (grant BES-2015-071956) and ERDF funds, by the European Commission through the H2020-ENTROPY-649849 and the FP7-SMARTIE-609062 Projects, and the Spanish Seneca Foundation by means of the PD program (grant 19782/PD/15).

References

[1] D. Petersen, J. Steele, and J. Wilkerson, "Wattbot: a residential electricity monitoring and feedback system," in Proceedings of the 27th international conference extended abstracts on Human factors in computing systems, pp. 2847–2852, ACM, 2009.

[2] Y. Agarwal, B. Balaji, R. Gupta, J. Lyles, M. Wei, and T. Weng, "Occupancy-driven energy management for smart building automation," in Proceedings of the 2nd ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Building, pp. 1–6, ACM, 2010.

[3] T. D. Pettersen, "Variation of energy consumption in dwellings due to climate, building and inhabitants," Energy and buildings, vol. 21, no. 3, pp. 209–218, 1994.

[4] R. Lindberg, A. Binamu, and M. Teikari, "Five-year data of measured weather, energy consumption, and time-dependent temperature variations within different exterior wall structures," Energy and Buildings, vol. 36, no. 6, pp. 495–501, 2004.

[5] S. Darby, "The effectiveness of feedback on energy consumption," A Review for DEFRA of the Literature on Metering, Billing and direct Displays, vol. 486, p. 2006, 2006.

[6] C. Fischer, "Feedback on household electricity consumption: a tool for saving energy?," Energy efficiency, vol. 1, no. 1, pp. 79–104, 2008.

[7] K. Voss, I. Sartori, A. Napolitano, S. Geier, H. Gonçalves, M. Hall, P. Heiselberg, J. Widén, J. A. Candanedo, E. Musall, et al., "Load matching and grid interaction of net zero energy buildings," 2010.

[8] C. Perera, A. Zaslavsky, P. Christen, and D. Georgakopoulos, "Sensing as a service model for smart cities supported by internet of things," Transactions on Emerging Telecommunications Technologies, vol. 25, no. 1, pp. 81–93, 2014.

[9] B. Guo, Z. Yu, X. Zhou, and D. Zhang, "From participatory sensing to mobile crowd sensing," in Pervasive Computing and Communications Workshops (PERCOM Workshops), 2014 IEEE International Conference on, pp. 593–598, March 2014.

[10] A. Llaria, J. Jiménez, and O. Curea, "Study on communication technologies for the optimal operation of smart grids," Transactions on Emerging Telecommunications Technologies, 2013.

[11] E. 15251:2006, "Indoor environmental input parameters for design and assessment of energy performance of buildings – addressing indoor air quality, thermal environment, lighting and acoustics," 2006.

[12] M. Hazas, A. Friday, and J. Scott, "Look back before leaping forward: Four decades of domestic energy inquiry," IEEE pervasive Computing, vol. 10, pp. 13–19, 2011.

[13] L. Berglund, "Mathematical modelsfor predicting thermal comfortresponse of building occupants," in Ashrae Journal- American Society of Heating Refrigerating and Air Conditioning Engineers, vol. 19, pp. 38–38, Amer Soc Heat Refrig Air-Conditioning Eng Inc 1791 Tullie Circle Ne, Atlanta, GA 30329, 1977.

[14] A. Zoha, A. Gluhak, M. A. Imran, and S. Rajasegarar, "Non-intrusive load monitoring approaches for disaggregated energy sensing: A survey," Sensors, vol. 12, no. 12, pp. 16838–16866, 2012.

[15] A. I. Dounis and C. Caraiscos, "Advanced control systems engineering for energy and comfort management in a building environment—a

review," Renewable and Sustainable Energy Reviews, vol. 13, no. 6, pp. 1246–1261, 2009.

[16] C. Ninagawa, H. Yoshida, S. Kondo, and H. Otake, "Data transmission of ieee1888 communication for wide-area real-time smart grid applications," in Renewable and Sustainable Energy Conference (IRSEC), 2013 International, pp. 509–514, IEEE, 2013.

[17] M. S. Al-Homoud, "Computer aided building energy analysis techniques, "Building and Environment, vol. 36, no. 4, pp. 421–433, 2001.

[18] D. B. Crawley, J. W. Hand, M. Kummert, and B. T. Griffith, "Contrasting the capabilities of building energy performance simulation programs," Building and environment, vol. 43, no. 4, pp. 661–673, 2008.

[19] J. Clarke, J. Cockroft, S. Conner, J. Hand, N. Kelly, R. Moore, T. O'Brien, and P. Strachan, "Simulation-assisted control in building energy management systems," Energy and buildings, vol. 34, no. 9, pp. 933–940, 2002.

[20] D. B. Crawley, L. K. Lawrie, F. C. Winkelmann, W. F. Buhl, Y. J. Huang, C. O. Pedersen, R. K. Strand, R. J. Liesen, D. E. Fisher, M. J. Witte, et al., "Energy plus: creating a new generation building energy simulation program," Energy and Buildings, vol. 33, no. 4, pp. 319–331, 2001.

[21] Z. Chen, D. Clements-Croome, J. Hong, H. Li, and Q. Xu, "A multicriteria lifespan energy efficiency approach to intelligent building assessment," Energy and Buildings, vol. 38, no. 5, pp. 393–409, 2006.

[22] V. Garg and N. Bansal, "Smart occupancy sensors to reduce energy consumption," Energy and Buildings, vol. 32, no. 1, pp. 81–87, 2000.

[23] H. Hagras, V. Callaghan, M. Colley, and G. Clarke,"A hierarchical fuzzy–genetic multiagent architecture for intelligent buildings online learning, adaptation and control," Information Sciences, vol. 150, no. 1, pp. 33–57, 2003.

[24] D.-M. Han and J.-H. Lim, "Design and implementation of smart home energy management systems based on zigbee," Consumer Electronics, IEEE Transactions on, vol. 56, no. 3, pp. 1417–1425, 2010.

[25] P. Oksa, M. Soini, L. Sydänheimo, and M. Kivikoski, "Kilavi platform for wireless building automation," Energy and Buildings, vol. 40, no. 9, pp. 1721–1730, 2008.

[26] D. O'Sullivan, M. Keane, D. Kelliher, and R. Hitchcock, "Improving building operation by tracking performance metrics throughout the building lifecycle (blc)," Energy and buildings, vol. 36, no. 11, pp. 1075–1090, 2004.

[27] G. Escrivá-Escrivá, C. Álvarez-Bel, and E. Peñalvo-ópez, "New indices to assess building energy efficiency at the use stage," Energy and Buildings, vol. 43, no. 2, pp. 476–484, 2011.

[28] V. Sundramoorthy, G. Cooper, N. Linge, and Q. Liu, "Domesticating energy-monitoring systems: Challenges and design concerns," IEEE Pervasive Computing, vol. 10, no. 1, pp. 20–27, 2011.

[29] G. Bello-Orgaz, J. J. Jung, and D. Camacho, "Social big data: Recent achievements and new challenges," Information Fusion, vol. 28, pp. 45–59, 2016.

[30] B. Pan, Y. Zheng, D. Wilkie, and C. Shahabi, "Crowd sensing of traffic anomalies based on human mobility and social media," in Proceedings of the 21st ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems, SIGSPATIAL'13, (New York, NY, USA), pp. 344–353, ACM, 2013.

[31] Massive Online GeoSocial Networking Platforms and Urban Human Mobility Patterns: A Process Map for Data Collection, ch. 197, pp. 1586–1593.

[32] D. E. Difallah, M. Catasta, G. Demartini, P. G. Ipeirotis, and P. Cudré-Mauroux, "The dynamics of micro-task crowdsourcing: The case of amazon mturk," in Proceedings of the 24^{th} International Conferenceon World Wide Web, pp. 238–247, International World Wide Web Conferences Steering Committee, 2015.

[33] C. Cardonha, D. Gallo, P. Avegliano, R. Herrmann, F. Koch, and S. Borger, "A crowdsourcing platform for the construction of accessibility maps," in Proceedings of the 10th International Cross-Disciplinary Conference on Web Accessibility, W4A'13, (New York, NY, USA), pp. 26:1–26:4, ACM, 2013.

[34] A. Piscitello, F. Paduano, A. A. Nacci, D. Noferi, M. D. Santambrogio, and D. Sciuto, "Danger-system: Exploring new ways to manage occupants safety in smart building," in Internet of Things (WF-IoT), 2015 IEEE 2nd World Forum on, pp. 675–680, Dec 2015.

[35] A. Handbook, "Fundamentals," American Society of Heating, Refrigerating and Air Conditioning Engineers, Atlanta, vol. 111, 2001.

[36] M. A. Zamora-Izquierdo, J. Santa, and A. F. Gómez-Skarmeta, "An integral and networked home automation solution for indoor ambient intelligence," Pervasive Computing, IEEE, vol. 9, no. 4, pp. 66–77, 2010.

[37] J. Santa, M. A. Zamora-Izquierdo, M. V. Moreno, A. J. Jara, and A. F. Skarmeta, "Energy-efficient indoor spaces through building automation,"

in Inter-cooperative Collective Intelligence: Techniques and Applications, pp. 375–401, Springer, 2014.

[38] H. Liu, H. Darabi, P. Banerjee, and J. Liu, “Survey of wireless indoor positioning techniques and systems, ”Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on, vol. 37, no. 6, pp. 1067–1080, 2007.

[39] H. Ji, L. Xie, C. Wang, Y. Yin, and S. Lu, “Crowdsensing: A crowd-sourcing based indoor navigation using rfid-based delay tolerant network,” Journal of Network and Computer Applications, vol. 52, pp. 79–89, 2015.

[40] A. Haug, “A tutorial on Bayesian estimation and tracking techniques applicable to nonlinear and non-Gaussian processes,” MITRE Corporation, McLean, 2005.

[41] E. Standard et al., “Indoor environmental input parameters for design and assessment of energy performance of buildings addressing indoor air quality, thermal environment, lighting and acoustics,” EN Standard, vol. 15251, 2007.

[42] H. Abdi and L. J. Williams, “Principal component analysis,” Wiley Interdisciplinary Reviews: Computational Statistics, vol. 2, no. 4, pp. 433–459, 2010.

[43] L. Hawarah, S. Ploix, and M. Jacomino, “User behavior prediction in energy consumption in housing using bayesian networks,” in Artificial Intelligence and Soft Computing, pp. 372–379, Springer, 2010.

[44] Y. Fu, Z. Li, H. Zhang, and P. Xu, “Using support vector machine to predict next day electricity load of public buildings with sub-metering devices,” Procedia Engineering, vol. 121, pp. 1016–1022, 2015.

[45] M. Alamaniotis, D. Bargiotas, and L. H. Tsoukalas, “Towards smart energy systems: application of kernel machine regression for medium term electricity load forecasting,” SpringerPlus, vol. 5, no. 1, pp. 1–15, 2016.

[46] R Core Team, R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria, 2015.

[47] M. Kuhn, “Building predictive models in R using the caret package,” Journal of Statistical Software, vol. 28, no. 5, pp. 1–26, 2008.

[48] J. A. Orosa, “A new modelling methodology to control hvac systems,” Expert Systems with Applications, vol. 38, no. 4, pp. 4505–4513, 2011.

[49] E. Willighagen, “Genalg: R based genetic algorithm,” R package version 0.1, vol. 1, 2005.

[50] M. V. Moreno, M. Zamora-Izquierdo, J. Santa, and A. F. Skarmeta, "An indoor localization system based on artificial neural networks and particle filters applied to intelligent buildings," Neurocomputing, vol. 122, pp. 116–125, 2013.

[51] J. M. Andy Field and Z. F. Niblett, Discovering Statistics Using R. Sage Publications Ltd, 1st ed., 2012.

[52] J. Demšar, "Statistical comparisons of classifiers over multiple datasets," The Journal of Machine Learning Research, vol. 7, pp. 1–30, 2006.