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# Smart and adaptive energy management and control system by ambient intelligence techniques and technologies

Roozbeh Sadeghian Broujeny

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## Thesis

Presented to obtain the title of  
DOCTOR OF UNIVERSITY of PARIS-EST in  
Signals, Images, and Automatics

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Smart and adaptive energy management and control system by ambient intelligence techniques and technologies

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## General introduction

In recent years the importance of energy-saving is increasing and becoming one of the top trending subjects in the world. At first glance, it is just a consequential subject for engineers and investigators. However, gradually it is turning a general topic for all sorts of consumers. On one hand, energy demand by consumers is growing, therefore, the energy companies must increment their products continuously and on the other hand, the fact that resources are limited is irrefutable. Also if installing new equipment to generate more energy (power) has been the main response of producers to cover the ever-increasing need of power over the last century, the negative consequences of this strategy have affected different sections emerging various central problems of the present decade: global warming, air pollution and their effects on nature and people's health degradation are two significant examples of the above-mentioned unfavorable consequences. Regarding the orientation of the user's consumption, they can play a substantial role to diminish the swelling of demand growth. Based on the energy consumption schema, the users can categorize in three main sectors: 1. Industrial 2. Transportation 3. Residential and commercial. [World Energy Council 2019].

The part of residential and commercial is the highest among all the aforementioned sectors. In the U.S 41% of global primary energy consumption is for the residential and commercial building sector and it is respectively 44% and 36% more than transportation and the industrial sectors [U. S. DoE 2011]. In 2009 total building primary energy consumption was about 48% more than in 1980 and, in this sector, lighting, space heating, and cooling were the dominant end uses in 2010. [U. S. DoE 2011].

In more detail, the Energy Information Administration (EIA) annually presents information about energy consumption in different sectors. According to EIA, residential and commercial sections both greatly contribute to energy consumption. In fact, the part of energy consumption of the residential section is estimated at 20.512 trillion BTU (British Thermal Unit) and the share of the commercial section is estimated at 18.152 trillion BTU in 2015 [Energy Information Administration, 2017]. Taking into account the total energy consumption, estimated as 97.324 trillion BTU by EIA, this means that the segment of residential and commercial sections together contributes 39% of the total energy consumption. Also, both commercial and residential buildings produce about 38% of greenhouse gas emissions. [Machinchick 2013]. In the EU also the portion of energy consumption in this sector is about 40% of total energy consumption (about 27% for the residential sector and 14% for the commercial sector). This amount of energy consumption in the EU was responsible for 17% (12% and 4.9% for the residential and commercial sectors respectively) of CO<sub>2</sub> emissions in 2017. [Commission of the European communities 2008],[European Commission, 2019]. Regarding this fact, it is apparent, not only that the residential and commercial sectors play a huge part in energy consumption but they also have a decisive role in pollution production.

A huge part of energy consumption and also pollution production is due to this sector. However, it is a global view. The energy consumption trend, country by country or region by region is different according to the energy policy of each region. In other words, in different regions, the behavior of energy consumption is different. Each state or region (European community) according to specific policies (constrained by cultural, economic, and social aspects) defines its own road map to face global warming.

In 2017, the part of energy consumption in France represents 64.4 Mtoe (Mega Tonne of oil equivalent) (45% of total energy consumption). 40.6 Mtoe for the residential sector (29% of total energy consumption) and 23.8 Mtoe for the commercial sector (17% of total energy consumption). These two parts respectively are responsible for 15% and 9% of CO<sub>2</sub> emission in France. The part of greenhouse gas emission is also the same as CO<sub>2</sub> emission [European Commission, 2019]. The Ministry of Ecological and Inclusive Transition of France set a goal to reach in 2030 and planned several policies and strategies (Multi-Annual Energy Plan MAEP). The French state defines the priorities and actions to carry out regarding energy policy for Metropolitan France [Ministry of Ecological and Solidarity Transition, 2019]. The fixed goal by 2030 horizon is to decrease by 40% the greenhouse gas emission, by 20% the final energy consumption, by 30% the primary fossil fuel energy consumption and to increase the energy efficiency by 27%. These goals can be achieved by the promotion of renewable energies and the development of the smart grid, local production of energy, self-production, and improvement in energy efficiency. Several incentive programs are defined in order to persuade users to change their consumption trends and also contribute to energy production. For instance, they cover expenses for the renovation of buildings, specific financial help for installing renewable energy equipment (like solar cells), and attractive prices for electrical energy.

This is a vital point that has to find creative ways in energy production and solution for facing a staggering increase in energy consumption. Improvement in energy efficiency is one of the key answers. All the investigators and engineers with disparate scientific backgrounds who are involved with this challenge are looking for innovative solutions. In fact, it is a sophisticated subject that can be reviewed from different view angles of science. For instance: modern building design and architecture by civil engineers in order to construct buildings with high energy performance, New insulating materials by chemists to decrease waste of energy, or utilizing different technologies by electrical and mechanical engineers to consume less energy. Smart building energy management systems (SBEMS) are one of the top attractive subjects in the energy efficiency field. Due to technological advancement in the field of internet of things (IoT) [Keyur K Patel 2016], control technics and sensory technology in parallel with development in computer science. The ability to avoid wasting energy is appealing, therefore, researchers in this area continuously quest to acquire new energy consumption trends and modern ways for designing SBEMS. But what is a smart building or an intelligent building?

There is a multitude of definitions of a smart building. Although introduced since 1985 by the National Association of Home Builders (NAHB), one of the largest trade associations in the United States as “building automation” (or “domestics”), the notion

of “smart home” has evolved significantly since its first definition. In 2003 the UK Department of Trade and Industry (DTI) came up with the following definition for a smart home: "A dwelling incorporating a communications network that connects the key electrical appliances and services, and allows them to be remotely controlled, monitored or accessed". Within this definition, a smart home, or smart house, is an edifice that incorporates advanced automation systems to provide the inhabitants with sophisticated monitoring and control over the building's functions. For example, a management system within a smart home may control lighting, heating, ventilation, and air conditioning (HVAC), multi-media, security, window, and door operations, as well as many other functions and devices such as home appliances (i.e. washer/dryers, ovens or refrigerators/freezers, etc.). The notion of smart home or smart edifice incorporates not only the above-mentioned features but also the skill of energy management and energy efficiency, scheduling the operation of heavy power-consuming appliances or cleverness of affording and optimizing inhabitants' or users' comfort [Mozer, 1998].

[Belani, Makwana & Vyas, 2014] defines the SBEMS: "The building that combines the best available concepts, designs, materials, systems, and technologies to provide an interactive, adaptive, responsive, integrated and dynamic intelligent environment for achieving the occupants' objectives over the full life span of the building. Or [Reza Naji, 2011] specified: "An intelligent building is one that utilizes computer technology to autonomously govern and adapt the building environment to optimize user comfort, energy consumption, safety, and work efficiency". As it is cited by definitions, controlling, monitoring, responsiveness, and adaptation to an environment concerning user comfort and energy efficiency are the significant factors in SBEMS.

It should be remarked, in the near future, the share of buildings in energy production will also increase (as it is already stated in MAEP by France until 2030) and the SBEMS will also not only manage and optimize the energy consumption but also control the production of energy, its sharing by means of smart grids.

Owing to the mentioned descriptions, the true nature of a SBEMS is to respond and control the environment in diverse conditions based on awareness of the environment. It should be able to adapt itself to the surrounded environment to decrease consumption and increase user comfort. There are plenty of dynamic parameters that affect the spaces in a building: weather conditions, occupancy, and unpredictable situations like fire. A smart building energy management system should bring up solutions for all these occurrences. Regarding this fact, it is a fundamental characteristic that a smart building energy management system should be aware of building spaces conditions and have ambient intelligence (AmI) [Augusto & Mccullagh, 2009].

The characteristics and properties of each SBEMS are depending on the architectural design of SBEMS and the functionalities of its subsystems. They are highly dependent on technological advancement in the field of IoT. Designing an appropriate architectural with choosing proper devices and technologies are playing a decisive role in launching a SBEMS. Accessibility to the huge number of sensors, actuators, devices, and also development in communication and networking technology and soft computing techniques give this opportunity to design a SBEMS with an infinite number of creative

ways. However, It also faces us with some challenges. Selecting appropriate technologies and devices and integrating them with a suitable architecture design is not an easy task. Nowadays SBEMS are suffering from a lack of proper design. Decent architectural design and technologies can provide good facilities and energy-efficient systems to the users. It can also offer a flexible platform for developing different subsystems of SBEMS. It is the first issue on this subject that we are going to encounter. It also ensures investigations regarding the development of two imperative subsystems of a SBEMS in this thesis.

A SBEMS is divided into several subsystems like lighting systems, space heating systems, security systems and according to the properties of each subsystem, the behavior and consequently controlling their behaviors are different. The most imperative subsystems of a building that consumed more energy in comparison with other parts are space heating and lighting systems. According to U.S Energy Information Administration (EIA) reports in 2018, the part of electricity consumption of lighting systems is 232 billion KWH (KiloWatt Hour) in residential and commercial sections. This represents about 8 percent of the total electricity consumption in both sections[EIA 2019], 5% for residential sector electricity and 10% for commercial one in 2018. In fact, on the one hand down to the continuous quest of the human's comfort and on the other hand as a result of the swelling of the business activity (economy), the lighting and heating energy consumption occupy an ever-increasing part of daily energy consumption. If for the individual dwelling the lighting energy consumption may appear as less consequential regarding the heating (and/or cooling) energy consumption, the quotient of this consumption may engage noteworthy percentages of overall energy consumption for commercial and public buildings.

Also based on US energy information administration (EIA) [U.S. EIA, 2017] and [U.S. EIA, 2018] reports, the part of energy consumption for space heating was 43 percent in residential buildings in 2015 and 25 percent in commercial buildings in 2012. In France, space heating has a share of 67% in energy consumption in buildings [Union & Commission, 2020]. It is showing a significant slice of energy consumptions related to space heating.

Each of these subsystems is interacting with various phenomena. As an example, a lighting system by considering the presence and user absence as a phenomenon should react. It should turn on or off the lighting elements, or in a higher level of control adapts the power lighting elements (dimming the light intensity) to the dynamical phenomenons of the space like reflectance of the surfaces or outdoor natural light. Regarding the heating subsystem, first of all, a proper heating device according to the physical properties of the space, like volume, isolation, the number of windows and, etc should be selected. Second of all an appropriate heating space controller that can react based on various parameters like the presence and absence of the user or pre-defined indoor temperature setpoint should design. Thus, regarding plenty of behaviors of each subsystem that is caused by various phenomena, the SBEMS should bring up a solution to control them, individually and simultaneously.

Since many years ago, several solutions are taken into consideration for designing and controlling systems. As an example, it is for years classical controllers like on/off controllers and Proportional, Integral, and Derivative (PID) controller [Ryniecki 2015], [Arab and Mp 2012] have been utilizing with various innovative ways. Although, most of the nowadays SBEMS and the relating controlling techniques and controllers design of their subsystems (especially the lighting and heating systems) are not able to face all the above-mentioned involving dynamical parameters. As a consequence, it leads to inefficient systems. For instance, recent technological advancement concerning the lighting systems is admirable, however, lack of development in designing a lighting system based on these technologies are undeniable. Or concerning the heating systems controllers design, there is always a simplistic look because of plenty of un-identified dynamical behaviors. One of these unidentified dynamical behaviors is regarding the presence of users in space. The users as a thermal object are highly affecting the variation of temperature in living spaces. However, it is always ignored or less in attendance in space heating controller designing, because of its extreme unidentified dynamics effects.

Nevertheless, investigators believe by development in soft computing techniques and existing technologies in the Internet of things (IoT) domain and the possibilities to integrate them, it is the time to take the next step and control the environment intelligently and cover the weakness of nowadays systems. In fact, this task has to be entrusted to intelligent systems without people's intervention. In other words, by technological advancement in AI systems, and computational developments, this is the time for developing the smart building energy management systems. The development of the SBEMS is including designing the next generation of SBEMS architectures and adaptive controllers in subsystems. A SBEMS that can make decisions on their own and adapt their behavior to dynamic behavior of the surrounded area such as various weather conditions or the presence and absence of the user.

In this thesis, first of all, we are aiming to introduce a new architectural design and approach for designing a smart building energy management systems. It is based on the integration of various recent available technologies in the market. It is promising the aforesaid new architecture proposes a powerful monitoring system and user interface for self-awareness and a flexible platform for developing subsystems of SBEMS. Second of all, we are going to propose new methods regarding the architecture design and development of subsystems. Regarding lighting systems, we are intending to propose an approach for designing the placement of lighting elements. In addition, a proper lighting system is going to propose in order to control the lighting elements adaptively to the surrounded environmental conditions. It is expected the proposed approach effectively decrease electricity consumption of the building.

Considering the heating systems, the investigation is divided into two main parts: identification of heating dynamics of building living space and designing a heating controller. In the first part, it is aiming to identify the thermodynamical effect of the presence and absence of the user in spaces and accordingly in the second part design an effective heating spaces controller. All the approaches in this part are on the basis of



artificial intelligence techniques. The identification of space heating dynamics is based on time series prediction with machine learning techniques. Due to their powerful abilities in black box modeling and system identification. Finally, for overcoming the heating control challenge of spaces, we are looking to design a fuzzy controller based on the identified behavior of space heating by taking into consideration the users as an additional thermal object. It is anticipated, the proposed approach by considering the share of the user as a thermal object in heat generation in spaces, decline the share of heating devices. It is hoped in this thesis by using appropriate approaches reduces energy consumption in different sections of a SBEMS and in parallel, leveling up the user comfort. In the following sections, the organization of the thesis and the content of each chapter is remarked.

## Frame of work

The research work of the present thesis has been done under the supervision of Professor Kurosh MADANI in the Laboratory of Images, Signals, and Intelligent Systems (LISSI EA 3956), one of 34 laboratories of the University Paris-Est Créteil (UPEC), France. As well the concepts as the experiments and validations have been performed on the campus SENART of UPEC located in Lieusaint. The concerned building is one of the buildings of SENART Campus of UPEC hosting one of four divisions as well of LISSI laboratory (namely, SYNAPSE) and at the same time as the Department of Electrical Engineering and Industrial Informatics of Senart-FB Institute of Technology (one of two institutes of technologies of UPEC).

## Organization of thesis

This thesis is divided into four chapters:

### Chapter 1:

The first chapter is a study on the domain of smart building energy management systems. In this chapter, different techniques, technologies, and methods whole of the architecture design of a SBEMS and its relating subsystems are reviewed. Due to this fact it is divided into three sections. In the first section, there are reviews on the implementation of different SBEMS architectures. The architecture of each is discussed and relating technologies are reviewed. Within this section, the proposed facilities and abilities of different SBEMS are studied. The focus of the second and third sections is on two important subsystems mentioned in the introduction: Lighting and heating systems respectively. Regarding lighting systems, investigations relating to architecture design and lighting technologies are studied. Finally, the advantages and disadvantages of each investigation are remarked. The last section of this chapter is concerning the review of the space heating controllers. The heating subsystem of a SBEMS is involving

with plenty of dynamics behaviors. Due to this fact, the identification of the heating dynamic of living spaces is inevitable. For this purpose, first of all, there are reviews on different studies concerning the control methods of space's heating in buildings and second of all there are reviews on system identification methods. Finally, considering the importance of the user's presence and its effect on the heating dynamic of buildings, different approaches regarding counting the number of people in a space are discussed.

## **Chapter 2:**

In this chapter, a multi-layer architecture for smart building energy management system is proposed. By reading this chapter you will be familiar with the architecture and facilities that the system can provide to the users. This chapter illustrates the hardware and software design, implementation, and abilities of the SBEMS in different aspects like user awareness, monitoring, integration with various technologies, etc. The proposed multi-layer system in this chapter is able to monitor the energy consumption and state of the building as well as controlling them. The investigated system has been implemented in a five-floors building (building A) of Senart Campus of UPEC (one of the main campuses of this Parisian university) providing an appealing experimental platform for experimentation and validation of the investigated concept.

## **Chapter 3:**

Within this chapter, the implementation of the smart lighting system for SBEMS is discussed. This chapter introduces the implementation of the lighting system in SBEMS. In this chapter, by taking advantage of recent technological advancement in the lighting systems domain, we propose a technic to cover the weakness of nowadays lighting systems. The first step is concerning the architecture of the lighting system under the cover of SBEMS. Regarding this step, DALI technology that is specialized for controlling lighting ballast in the automation system is proposed. In the second step, the Luman method and DIALux simulation software are introduced. The lumen method is utilizing to choose the proper number of lighting elements. Due to discovering the best architecture for lighting element placing, DuaLux software is introduced. Finally, in this chapter, the result and validation of the aforesaid lighting system are presented and the effect of an adaptive lighting system on electrical energy consumption and user comfort is evaluated.

## **Chapter 4:**

This chapter is dealing with the heating controller design of spaces in SBEMS. As mentioned earlier, space heating systems are under the affection of plenty of unidentified parameters that make the thermal behavior of the spaces highly dynamic. The presence and absence of users as a thermal object are one of these parameters. Due to designing a heating space controller that can face this challenge, identification of heating dynamic of spaces are unavoidable. Regarding this fact, chapter 4 is divided into 3 subsections:

1. Identification of space heating dynamic
2. Designing an adaptive heating controller for space heating
3. Virtual presence estimator (it serves as a part in heating controller)

The goal of this chapter is to cope with the dynamic behavior of the living space heating considering the environmental and ambient information recorded by SBEMS. In the first section of this chapter, an approach for identifying the dynamic behavior of the heating space by considering inhabitants as an additional heating resource will introduce. The approach is on the basis of an ANN-based Nonlinear Auto-Regressive exogenous model that is taking advantage of a feed-forward Multi-Layer Perceptron. Afterward, the dynamic properties of the system by considering the effect of the absence and presence of the user on the heating dynamics of the space will be analyzed. Accordingly, in the second part, an appropriate Takagi-Sugeno fuzzy heating controller to face this dynamic behavior will be proposed. As the presence and absence of people play a role in heating controller, in the third part, a fuzzy virtual presence estimator is presented based on the Mamdani technic. Finally, at the end of this chapter, the most recent schema of the architecture of the SBEMS according to recent changes will be proposed. All the approaches, methods, and techniques in this chapter are based on artificial intelligence techniques and the internet of things (IoT) platform.

# Chapter 1

## 1. State of art

### 1.1. Introduction

The idea of building energy management systems for commercial and residential buildings has seen a great development in recent decades. On one side, Investigators and engineers creatively are enhancing the SBEMS architectures and implementation methods for years and on the other side, ongoing technological advancement brings up innovative ideas and solutions. As it is aforementioned, SBEMS is divided into several parts, and each part in order to work properly needs its own demands. For instance, a powerful monitoring system needs to have proper sensors, user interface software, and hardware to represent awareness to the user. There are plenty of works and each of these works by focusing on different parts has been pointed to different needs and challenges in this domain. In this chapter, by reviewing different ideas and works, we are trying to have a clear view of this domain, its challenges, achievements, and failures. First of all, there will be a review of different infrastructure and architecture of smart building energy management systems. It is the first step and the base of the whole works in this research. Second of all, there will be a review of two important and most consuming part of SBEMS: Lighting systems, heating system's control. For each mentioned part, we are going to discover various proposed architectures, technologies, implementation, and methods by investigators. Furthermore, the guideline for facing the drawbacks of each part will be clarified, by remarking the advantages, problems, and defects of the reviewed investigations.

### 1.2. Review on the different architecture of SBEMS

Regarding the designing of an appealing architecture for SBEMS, there are plenty of approaches. One of the first and most important characteristics of SBEMS is a powerful monitoring system and self-awareness about the environment. The researches show monitoring and self-awareness of the system are oriented to the reduction of energy consumption. The authors in [Tianzhen Hong 2013] remark energy monitoring, data collection, and analysis play crucial roles to support the design and operation of low energy buildings. Several studies, including a National Institute of Standards and Technology (NIST) report, show that energy feedback devices can provide real energy savings by motivating building occupants to modify their behavior.

In [Attia & Ashour, 2011], the authors present a smart home that can reduce the domestic wasting energy based on sensory technology and adaptation to user habits and routines. The authors believe the air conditioning and lighting system sections can be considered as one of the most energy-consuming parts. Due to their high energy demand, It can

affect total energy consumption. They divide their works into three main sections: lighting system, air conditioning, and home appliances.

The authors in this investigation propose a case study which contains six different rooms with six different purposes of usage (kitchen, dining room, bathroom, bedroom, living room, hall). In each space, they use several occupancy sensors. Firstly, the occupancy sensor is used to detecting heat from the user's movements and control the light and secondly, the occupancy sensor is used to adjusting the temperature and lighting system with the purpose of energy saving.

The authors suppose using occupancy sensors has advantages to motion detectors. For example, there is a possibility that a person works behind the desk and due to his/her little movements, the motion sensor cannot detect him/her because it is just sensitive to moving objects. The authors mention several management scenarios that can be implemented based on the habitant's age and its social status, ability, disability, if they are individual that leaves in the morning and get back in the afternoon, etc. It allows users to define a set of behavior rules. In this work, they focus on the scenario of a wife and husband who leave their house in the morning and get back in the afternoon. The scenario for this couple is according to 16 steps of their behaviors and routines. It begins from the time that they get back home, take shower in the bathroom until they prepare their meal in the kitchen, eat their dinner in the dining room, go to bed, and finally when they leave the house in the morning. It should be noted the scenario studied on three different assumptions.

In the proposed investigation, SWEET HOME 3D is utilized to simulate the apartment and DIALux software is utilized to design the lighting system. The air conditioner capacity is calculated according to Canadian standards. The capacity of home appliances is calculated based on the U.S. Department of Energy's Office for Energy Efficiency and Renewable Energy. In the end, they found according to this strategy one of these assumptions could save up to 620 kWh per month or 39.95%. Considering that Egypt consists of about 17 million families according to the statistics of 2006, therefore a total energy saving could be about 3000 MW. This amount is equivalent to 3 power stations each is formed of 3 units and each unit capacity would be 300MW.

The first point that comes up about this work is the flexibility of the system, whereas the author noticed too. This research is based on three different assumptions and on specific scenarios of users who leave in the morning and get back in the afternoon. This research targets the limited number of users and their profiled activities. The proposed system should be un-flexible to different users with different behaviors. This is the most important drawback of the present work. The work is based on the user's quite simple daily reports. The case study is quite simplistic and the system is not flexible. Controlling the devices according to the predefined scenario is not reliable because the habits of users are dynamic and changeable.

An intelligent system for energy saving is proposed in work of [Alhamoud et al. 2014]. They call it SMARTENERGY.KOM. The main purpose of their work is to make people aware of their consumption and help them to save energy up. Their system can monitor

the energy consumption level of the electrical appliance. It also monitors environmental parameters, such as brightness, and temperature level, and motion detection. They design three different units for their systems: the first unit is containing several sensory technologies for motion detection and temperature measurement; This unit is in charge of data collection. The second unit is named processing units and it includes a control server and Raspberry Pi [Halfacree 2018]. The third unit can visualize and feedback the data by a smartphone. To make communication between different parts of the systems, Zigbee [Tomar 2011], Ethernet [Contemporary Control Systems 1999] and Wi-Fi [RABBIT 2008] have been utilized.

In this research by utilizing environmental sensors and power sensors, the current user's activities are detected and it are learned by machine learning approaches. Based on the monitoring system and user's activity detection, the system can detect electrical devices that are running and not relating to current user activities. Therefore, the user will be aware of the condition by a framework called "EnergyAdvisor" and may change the activity. The authors suppose by implementing such a system, the potential of energy saving is greater than 50%.

The work of [Alhamoud et al. 2014] seems quite interesting however it is based on one user/one activity and needs to level up to more complex behaviors. The energy-saving in this work is highly dependent on user decisions and the system works as an energy advisor. This research can be just seen as a self-awareness system in case of energy-saving. In the case of lighting systems control, heating systems, and also electrical appliances which the authors focus on, it needs more improvement.

In work of [Attia & Ashour, 2011] a predefined scenario is used. This approach is not reliable and can not be adapted to various situations or to environmental parameters evolution. Another remark is about communication technologies. There is no doubt, these are nowadays top technologies however according to [H. Kaur & Sharma, 2013] and [Anders, n.d.] other technologies consume less energy and do the same functionality. Although for deciding about this part, it needs to study more about the structure of space and the technological compatibilities of different parts of the system. Table 1 shows the differences between some of the communication technologies.

The investigators of [Alhamoud et al. 2014], [Barbato et al. 2010] propose a wireless sensor network that can monitor user presence and the physical environment such as temperature and light in each space of the home. However in this investigation according to receiving data by wireless sensors network and monitoring different parts of the system, the profile of the user is constructing. The author notes using a wireless sensor network (WSN [Benhaddou & Ala, 2015]) is the most flexible and low-cost system for deploying sensors networks. They propose a hierarchical hybrid network architecture consisting of different islands of sensor nodes that are interconnected through gateways. To manage the proposed sensor network and decreasing its complexity for the user, they propose a middle-ware that is called mobiWS.

	EnOcean	Z-wave or KNX-RF	Zigbee (802.15.4)	Zigbee (802.15.4)	Bluetooth (802.15.1)	WLAN (802.11)
Frequency(MHz)	868	868	868	2400	2400	2400
Data rate (kbyte/s)	125	9.6/20	20	250	720	11.000-54000
Minimum telegram length(ms)	0.6	20	30	4	0.7	-
Energy need (incl.startup)	Extremely low	low	low	low	medium	high
Basic load level of frequency band	low	low	low	high	high	high
Risk of data collision	Very low	medium	medium	low	Very low	high
Batteryless radio transmitter	yes	no	no	no	no	no
Life cycle costs	Very good	good	good	good	good	Not so good
Optimal solution for following purpose	maintenace-free batteryless wireless sensor systems	battery-powered wire-less sense systems	battery-powered wire-less sense systems	battery-powered wire-less sense systems	Computer networking with printers and PDAs	Computer networking(Web, e-mail,video)

Table 1. Comparison of different communication technologies (extracted from [Anders, n.d.]

The proposed energy management system is constructed according to the user profile. The authors mentioned that they made user profile in two ways:

1. Offline mode
2. Real-time mode.

In offline mode, three different profiles have been made:

1. Presence profile
2. Lighting profile
3. Heating profile

The presence profile is constructed by a sensor that can detect the presence and absence of the user. Regarding the heating and lighting profiles, They construct the profile by data collection from appropriate temperature and light sensors. The data collection has been done simultaneously for making these three profiles. For light and temperature, during the data collection, the user was able to adjust the lights and temperature manually, and later it would appear in his profile.

In real-time mode, sensors collected real-time data of physical parameters, and accordingly the energy management system adjusts automatically different parts of the system. Like adjusting the light according to natural light received from windows or set the temperature according to user profiles, etc.

The proposed system by [Barbato et al. 2010] is a kind of self-adaptive system and it can be seen from two points of view. From the first point of view, the system seems user-friendly, as we can see the user can easily interact with the system. However, for making profiles it is highly dependent on user actions and considers this action to the profile. Indeed, the system is like a platform to learn the user's behavior and manage the system based on the user's desires. It would bring user comfort by utilizing this approach although, from another view, there is a high probability that the user's decision is not appropriate. The proposed system neither manages the system according to a pre-defined standard nor gives any suggestion to the user with the purpose of fitting energy consumption. The common point between [Barbato et al. 2010] and [Alhamoud et al. 2014] is that they are both user-centric. One is working based on user profiling and predicting actual preference of the user based on the previously observed behavior, the other one is working by recognizing the current status activity of the user and works as an energy advisor.

Authors in [Anastasi et al., 2011] introduce an intelligent building called Greenbuilding. They focus on bringing user comfort and energy efficiency at the same time. They utilize a sensor-based system to monitor the system and automatically control the behavior of the system. They have been implemented their experiment on a real household scenario. The architecture of the proposed system is composed of two main subsystems: The monitoring subsystem and the Controlling subsystem.

The monitoring system on each floor has several environmental sensors and presence detectors. They are communicating through a wireless network with a base station. The collected data by the sensors and detectors will convey to a central server. The communication between the central server and base stations is through a wired LAN [Clark et al., 1978]. The server processes the data and calculates energy consumption periodically and provides it as a report to the user.

The control subsystem manages the system according to energy conservation rules specified by the user. On each electrical appliance, there is an actuator to control them by appropriate controllers. The controller is also connected to the central server by wired LAN technology. It is the server that commands to switch on or off the appliance through the appropriate controller. For controlling the behavior of the system, they present an energy conservation strategy. The energy conservation strategy has been made based on different strategies. The first strategy is user awareness. The system can periodically send a report or message about the state of each device and also energy consumption. To reduce consumption, it can suggest possible action to save more energy. The second strategy is the reduction of standby consumption. In this step, Greenbuilding allows the user to specify suitable energy management to reduce the standby wasting of energy. For example, if an appliance went to standby mode and after a specific time it stayed on standby mode, it can automatically switch off the device after a predefined time interval.

The third strategy is the Scheduling of flexible tasks. The cost of electricity at different times of the day differs. According to this fact, Greenbuilding allows the user to schedule a different task for various devices to decrease the cost of electrical energy.



The last strategy that is considered for Greenbuilding is the adaptive control of electrical appliances. The author believes the significant energy wasting is through unnecessarily active appliances. In Greenbuilding by using several sensors, the system can monitor the environment, and hence, based on rules that are defined by the user, the system can adapt itself.

The software architecture of Greenbuilding is illustrated in Figure 1.

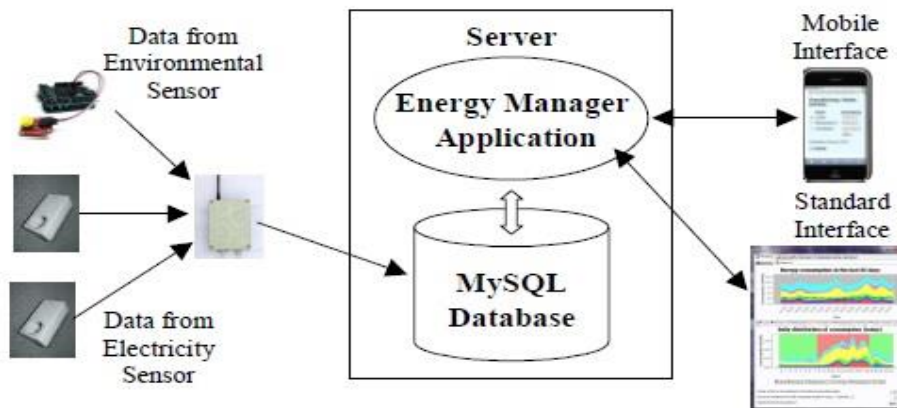


Figure 1. Example of SBEMS architecture (Greenbuilding) (extracted from [Anastasi et al., 2011])

The recorded data by sensors store on MYSQL database is located on the server. The MYSQL server is connected and in interaction with the energy manager application. The energy manager application is written in java [Layka, 2014] and it is in charge of several aspects:

1. Processing data on the power consumption of appliances measured by electricity sensors,
2. Providing appropriate reports to the user,
3. Processing data originated by environmental sensors,
4. Accepting configuration parameters and energy management rules from the user,
5. Sending appropriate commands to appliances.

Users can communicate with the system via a remote interface. The standard interface is on a computer server. In this work, to test this structure, they implement it in a small apartment with two users who are students and monitored the energy consumption for 15 days, and reviewed the effect of aforesaid strategies.

The user can monitor his/her consumption and based on different tariffs of electricity, change his/her behavior. In the case of standby wastes according to their reports, it saves energy consumption up to 26 percent, and in the case of adaptive control in the lighting section as the user has defined its intensity needs of light on 50%. They can save about 79% of the consumed energy by the lamp without reducing the level of user comfort.

The proposed Greenbuilding by authors of [Anastasi et al., 2011] can save energy in many cases that they have expressed, however, this system is highly dependent on user decision in the control part. The flexibility and adaptation of such a system are low and the user, all the time needs to interact with the system to have a comfortable environment. In the work of [Anastasi et al., 2011] a self-adapting system covers most of the properties that the work of [Attia & Ashour, 2011] and [Alhamoud et al. 2014] have proposed: making aware the user about the status of devices and letting the user set different scenarios according to several parameters like cost of electricity at different times of the day.

The authors of [Mataloto et al., 2019] like [Anastasi et al., 2011] propose an internet of things platform with three layers. They propose this investigation in order to optimize the energy consumption of buildings. It consists of a physical layer, a communication layer, and an application layer. In the physical layer, there are plenty of sensors and actuators. In the communication layer, there are several communication protocols. The application layer is in charge of fusing and processing the data for display. The core of the system is a Raspberry Pi. The proposed building energy management system by [Mataloto et al., 2019] has a user-friendly interface. It lets the user can easily manage the devices. For energy saving purposes, they propose several pre-defined templates. Users can monitor the system based on templates and according to their need activate the automatic rules or manually control the devices. It has 7 different templates: Dashboard visualization of environment variables, Time window graphic of the environment variable, Energy indicators, Energy consumption charts, User controllable devices and variables, Detailed usage of each device, and Global comparison chart. Each of these templates provides various data to the user. The provided data by the system according to aforesaid templates lets understand all possible saving action in order to define proper automation strategies.

The investigation of [Mataloto et al., 2019] as earlier mentioned is similar to [Anastasi et al., 2011]. It is dependent on user action. However, in the case of providing data for monitoring the system to the user, it shows advantages in comparison with the work of [Anastasi et al., 2011], as the user is able to monitor the system through several templates. There are plenty of works that are similar to the two aforesaid works. Investigation of [Zuolkernan et al., 2017] is another example that an internet of things platform collects the data and after analyzing the data user can be aware and make a decision about controlling the devices. Work of [Gilman et al., 2020] with same approach implemented an internet of things platform in a larger scale in an university campus in order to analyze data for development purposes of their smart campus.

One of the imperative challenges of designing a building management system is the integration of different technologies and devices that are utilized in each section. Because of widespread technologies and devices and due to different approaches for managing them, it is hard to integrate them easily. In [Jo and Yoon, 2018], investigators propose a system that contains three different models to overcome this challenge. The three models are Intelligence Awareness Target as a service (IAT), Intelligence Energy Efficiency as a service (IE<sup>2</sup>), and intelligence service TAS (IST). TAS is a technology

product company providing information processing automation solutions [“TAS Information Intelligence” n.d.].

IAT is in charge of recording data and brings awareness about different situations. It is divided into three different parts: Sensor IAT, Smartphone IAT, and Smart appliance IAT and in each part by different sensors, data would be gathered. Sensor IAT collects simple sensor data like sound, motion, and rotary. The purpose of these sensors is to gather data and be aware of the indoor situation of each space. The Smartphone IAT provides data that is needed to analyze the user’s status. It lets to find details relating to the user’s position, movement, etc. Data then is transmitted to the server and are added as a part of learning data. Finally, Smart appliance IAT collecting data from smart appliances to find user’s usage patterns and also awareness about the environment. Indeed, Smart appliance IAT has two roles: collect data from smart appliances and provide services at the level of service.

IE<sup>2</sup>S is the IoT platform and is playing the role of server. From one side it is interacting with IAT and from the other side, it is communicating with IST. Data collected by IAT and will transmit to IE<sup>2</sup> and at this moment by using a neural network learning algorithm, data will analyzing continuously. IE<sup>2</sup> through learning would recognize two things: the situation of user and User consumption pattern. IST is in charge of providing suitable services. It uses learning data from IE<sup>2</sup> and responds to the user's demands. Figure 2 shows the architecture of the system.

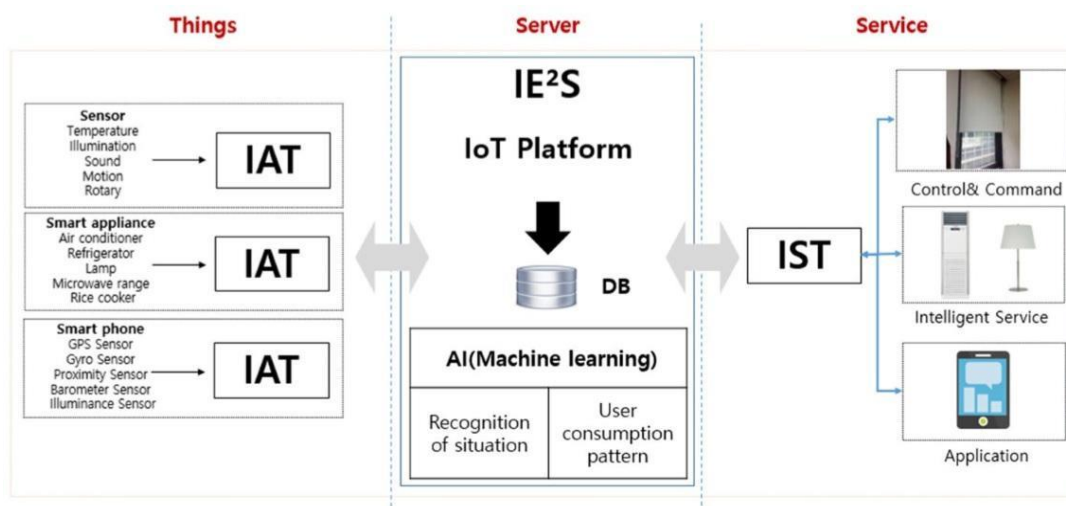


Figure 2. Example of SBEMS Architecture (extracted from [Jo and Yoon, 2018])

The authors of [Jo and Yoon, 2018] by proposing three models, IAT, IE<sup>2</sup>, and IST have tried to integrate several IoT technologies and in parallel by utilizing artificial intelligence techniques followed their approach to overcome the challenge of using various kind of these technologies which could lead to inefficient operating systems and waste of energy. The proposed system architecture is flexible. It successfully integrates several sections in the SBEMS. User convenience is considered in user pattern learning that is proposed by a machine learning algorithm. On one hand, it is an advantage due

to providing user comfort. However, on the other hand, it is a drawback. The system all the time learn from the user and the control section of the system reacts correspondingly. Most probably, learning from the user pattern is not an appropriate path for energy management.

The investigators of [Priyadarshana et al. 2017] present a multi-agent control system for the building management system which can control different subsystems. They propose an agent which is called "central agent" (CA). It is a computer server that is working based on controlling and database algorithm. It is the main agent in the system and can communicate with other agents and control them through a WIFI network communication. The commands by the user will send to an appropriate agent through a user interface after processing in CA. In this multi-agent system, there are local agents assigned to each of the electrical equipment. They are able to read data from sensors and accordingly operate the equipment based on the situations. They can also interact through the user interface by the user and operate equipment following the instruction from the user.

The central agent communicates with other agents. It is illustrated in Figure 3. Fan, Light, Fire agents, and access control agents in critical situations, like firing, will directly communicate with other agents to enhance the response of the system. As it is clear in Figure 3, several agents are interacting with each other. The air condition agent is in charge of control the operation of the air conditioner. It sends the control signal from the central agent. This agent is in interaction with several signals regarding control of the air conditioner: The smoke sensor signal, Temperature sensor signal, Operator command (user gives command through a user interface), Manual/Auto signal (a signal which gives an update to the agent whether the user interacts with the user interface or not.)

The light agent is responsible for lighting control in different situations. For example, when there is fire, and smoke sensor detected the signal, the lighting agent can show the emergency path or in normal conditions, it is interacting with the user interface to turn on or off the lights. Fan agents control fans based on user command or automatically.

It is programmed to work as an integrated system in an emergency condition according to a certain pre-defined logic. The agent for fans has a microprocessor, WIFI module, and power supply unit, and a relay. In this BMS a web server is the central agent. It controls and monitors the whole system. Based on receiving commands through the user interface, it is capable to communicate data with local agents, processing a database, and operate the system. All the local agents can be recognized by a unique internet protocol address (IP address).



Figure 3. Example of the architecture of a multi-agent system (extracted from [Priyadarshana et al. 2017])

In [Priyadarshana et al. 2017], investigators by using different subsystems try to make a flexible system in which different parts can easily communicate with other parts. The main idea about the architecture of the system is interesting however they did not specify how exactly control different parts. In some parts, it seems they are using simple control strategies, for example, in lighting agents they just control lighting elements according to on/off strategy. In conclusion, the proposed architecture has a good infrastructure in the area of smart buildings. There is good potential for developing the control parts of the system.

Concerning advanced control policies, in the work of [Hurtado et al. 2013], investigators introduce a multi-agent system to optimize building energy consumption. The author aims to design a BEMS which is flexible, user-friendly, and easy. Similar to previous works, the author proposes a system that is dependent on the user's actions and behaviors. In fact, the system should track and monitor user behavior and learn from it. In [Hurtado et al. 2013], investigators divide their works into two main parts: Energy systems and Control strategies.

Energy systems are divided into different subsystems like thermal, cooling, electrical subsystem, or measuring subsystem. The thermal subsystem is responsible for energy conversion and the measuring subsystem has to monitor and collect the net energy flow data. The space cooling and heating part are mentioned as the most energy-consuming part. They are consuming around 50% of total energy consumption. The rest is relating to the lighting system and other appliances in the building. According to the author's opinion, to control different parts of the building several control strategies can be used like fuzzy controllers or model predictive control however they preferred distributed

control techniques. In their opinion, distributed control by a multi-agent system can tackle complex problems.

The multi-agent system in this work is divided into seven different agents: Local zone agent, Local agent administrator, Zone agent, On-site generation agent, Building agent, Management building agent, and directory facilitator agent.

Each agent is in charge of special duties. One to record the data, one in charge of monitoring the occupancy, another one responsible for computing energy consumption and control, etc. All these agents are in interaction with each other to bring a flexible environment that can react appropriately to user demands.

The recent SBEMS that has been reviewed is divided into three different layers: Hardware layer, Communication layer, and Application layer. The agents reside in the software layer. The communication layer is responsible for data transmission between layers and in the hardware layer there are actuators and sensors. Regarding control of different zones, the system assigns different priorities or weight functions according to users or spaces (if it is a living room or a private room, etc.) The architecture of SBEMS is suitable and has good potential for development. Concerning this potential, the control strategies of each zone need much more improvement.

A context-aware framework for collaborative learning algorithms (CAFCLA) is proposed in [García et al., 2017] in order to develop the recommendation system for the home user. They believe it improves energy-efficient behavior in buildings. The CAFCLA integrates a wireless sensor network with a real-time localization system. It is divided into several layers: Physical layer, communication layer, context-aware layer, management layer, the application layer. In the physical layer, there are plenty of sensors (temperature sensor, lighting, electricity consumption plug, etc.). Several beacons and tags in order to identify each user individually with the purpose of localization. Smartphones and tablets are also included in this layer: allow to send recommendations advice to the user. The communication layer is composed of several protocols like Zigbee, wifi, GPRS/3G/4G to send and receive data from the server. In the context-aware layer, CAFCLA integrates with the n-core platform [Google, I. Nest Thermostat, n.d]. It consists of several devices and software tools exchanging information with Zigbee protocols (it constitutes a mesh network). They collect data from sensors, tags, and beacons to feed the recommendation system. The management system is in charge of the social, logical, and intelligence aspects of the framework. It is taking advantage of a social machine to provide intelligence to the system (the social machine is a creation of social computing) to configure the sensors and defines the area of interest (for example beds, to identify if users are sleeping). The neural network learns and identifies the activity of users. Finally, they concluded, by intelligence management of this information, it is possible to identify a situation that arise the potential of energy-saving and to send the recommended actions to the user. The proposed work has complex architecture and plenty of sensors that are working under the umbrella of a wireless network. According to the authors reports the proposed system leads to saving more energy. However, because of the high accuracy that the system provides (a huge number

of technologies and sensors) is leading to a huge cost for implementation. The authors also claim this point.

All the above investigations offered several building energy management systems with increment in energy efficiency purposes. They all integrate the architecture of systems with a communication network (mostly wireless). In order to manage different subsystems of BEMS, the duties of each part of the system were divided between several sections (layers and agents). What is undeniable and can be highlighted is the role of physical layers. In fact, this layer is playing an imperative role because it is directly in charge of data collection and monitoring. The data that is collected in this layer is provided to a server for monitoring or some process in order to give proper service through appropriate agents to the user. Indeed, the quality and the type of data utilized in each sub-system and its processing in the server can affect the performance of the system. Work of [García et al., 2017] and [Jo and Yoon, 2018] are two examples that the performance of the system in the level of data collecting is high because of plenty of facilities that they are utilizing in data collection. However, it is not avoidable that high quality and quantity of data in this part (physical layer) will lead to huge expenses.

The proposed multi-agent architecture by [Priyadarshana et al. 2017] is a good example of architecture in BEMS. The agents in this architecture are communicating with each other and also with a server. Each subsystem in this architecture is able to act as a stand-alone subsystem in emergency cases. Independency of subsystems and at the same time integration between them is the remarkable part between all above mentioned SBEMS architectures.

Authors of aforesaid researches based on environmental situations and user conditions give services to the users. In the work of [Attia & Ashour, 2011] and [Anastasi et al., 2011], the user can define rules or scenarios in order to control the system according to its desires, however [Anastasi et al., 2011], in parallel offers to users plenty of strategies to reduce consumption and it looks their work is far ahead to [Attia & Ashour, 2011]. The work of [Mataloto et al., 2019] also is similar to the work of [Anastasi et al., 2011], however, it provides the user a better interface for monitoring, and better communication technologies.

The authors of [Alhamoud et al. 2014], [Barbato et al. 2010], [Jo and Yoon, 2018], and [García et al., 2017] by different techniques are pushing their efforts to construct the profile of the user or predict their actions or identify it in real-time and accordingly to serve the user. Investigations of [García et al., 2017] because of the high quality of data that is collected by sensors in real-time looks far ahead to others, however, it is expensive as the authors also highlighted. In [Alhamoud et al. 2014], [Barbato et al. 2010], and [Jo and Yoon, 2018], investigators by constructing user profile and predicting user's behavior deals with the issue. However, the work of [Jo and Yoon, 2018] takes advantage of better architecture allowing better performance.

### 1.3. The outcome of SBEMS architecture review

Regarding the previously mentioned investigations, following drawbacks of existing SBEMS architecture should be considered which is the guideline for developing SBEMS in this thesis:

1. **Inappropriate selected technologies:** There is a wide range of technologies to obtain for serving in SBEMS, which is considering as the starting point of designing SBEMS architecture. While choosing proper technologies and devices plays a crucial role in SBEMS architectural designing, it also ensures the development of the next-generation of SBEMS. In fact, most of the devices and selected technologies in current SBEMS are chosen inappropriately and with a short sighted-look. As mentioned in section 1.2 a SBEMS is contained several subsystems like lighting systems, heating systems, etc. These subsystems are utilizing different communication protocols and standards which affect the integration and development of the system. Selecting un-appropriate technologies is leading to several challenges regarding the “technology integration” and development of SBEMS in the future.
2. **User-centric functionality:** Nowadays, most of SBEMS’s functionalities are highly dependent on user decision making. For instance in section 1.2, some works are suffering from a lack of specific automate functionalities to control different parameters of the SBEMS in the environment. They are just presenting awareness about the environment to the user and it is the user that has to decide how to react. In the best case, some of the aforesaid SBEMS are proposing to the user the proper instruction for controlling subsystems of the SBEMS. In contrast, other works are pushing an effort to cover aforesaid drawbacks. They enhance SBEMS functionalities by profiling user behaviors. However, In both cases, the user action should be based on a wrong habit that affects the SBEMS functionalities and as a consequence leads to an inefficient system. Due to, in most of the investigation, user comfort has the top priority. It is comprehensible user satisfaction is the first goal however optimizing between user comfort and the energy consumption is more promising. Besides, the user-centric problem can be relevant also to the first problem (un-appropriate selected technologies), Where the restriction in development and technology integration is leading to simplistic control strategies.

By taking into consideration two aforesaid problems, selecting the proper technologies with a fine architecture design of the SBEMS is promising to cover relevant concerns. As a consequence, it is leading to a high capacity of technology integration, software, and hardware development and finally proper functionalities for monitoring, user awareness, and implementing control strategies in subsystems of SBEMS.



## 1.4. Review on different smart lighting systems

Most of the few studies and investigations in this part focused on lighting design and luminary location optimization to bring lower energy consumption. In [Muhamad et al. 2010] the authors investigate the designs of a system for determining the suitable number of luminaries resulting in the increased energy efficiency of the current lighting system. The study is divided into two main parts: determining a suitable number of lamps and lamp replacement. A part of the proposed solution deals with replacement luminaries (lamp replacement) without changing the current lighting system. Although the proposed system had somehow improved the energy consumption (versus the previous state of the concerned building), but it leaks flexibility regarding the lighting devices' technology evolution as well as regarding the surrounding environment conditions' changes. In fact, the proposed solution doesn't take into account the luminance changes of the environment, working in the same regime independently from surrounding luminance conditions. Moreover, the only way for following the lighting technology evolution using the proposed solution is to continuously replace whole the lighting devices of the building by more recent and more efficient ones: a costly solution.

Some of those investigations deal with sophisticated schemes aiming at smart or intelligent lighting management systems. Focusing on entertainment applications and complex scene settings, authors of [Deng-feng, 2011] propose what they called an "intelligent lighting control system" for controlling the lighting quality. Criticizing a number of market-available protocols as DALI (Digital Addressable Lighting Interface) by calling to mind their shortage relating the consideration of color transformation properties of light, these authors propose a dual-CPU embedded system with CIE (Commission Internationale de l'éclairage) gamut [Momsen 2005] standard ensuring high quality for lighting. The proposed system is divided into two layers: a Top layer and a bottom layer. In the top layer, a Tcp/Ip protocol is utilized and is including the main controller and network node controller. The bottom layer consists of a network node controller and lights. It transmits data with DMX512 protocol [Elation Professional 2008]. Considering the network node controller, it is divided into two modules: The main controller and Data processing. The main controller implements the functions. The Data processing part is in charge of refreshing data in the control port. In the main controller, there is an ARM9 microcontroller [Berger 2005] and in the data processing part, there is Atmega8515 ["ATMEGA8515," n.d.].

The authors claim that the proposed system would be suitable for entertainment places, hotels, board rooms, offices, and complex landscapes. The first and the most critical point of the proposed system relates to the fact that it has been designed for exclusive control of lighting quality without considering the energy consumption issues. Thus, for instance, relating the hotels, this system would represent a quite costly solution regarding the prices' competition within the concerned sector of activity. Actually, the protocols as DALI appear more suitable for hotels where the purpose is achieving competitive room prices. Relating the other claimed applicative potentials, except the

very specific entertainment places, most of those cited by authors don't need such a sophisticated and costly system for daily activities that they are concerned with. From a technical point of view, the proposed system seems to have limitations if the objective is large scale projects as they utilized microcontrollers to implement network controller parts. In [Martirano 2011] authors deal with different technologies (as KNX standard [KNX.org 2016], known also as Konnex) to provide a more efficient lighting system. The presented work is founded based on two strategies:

1. Efficiency: Adopting new equipment and arranging lighting design practice.
2. Effectiveness: Adapting lighting automatic control.

The authors focused on designing an integrated lighting control strategy for working rooms, considering the available daylight and presence of people in those rooms. The proposed smart lighting control's strategies are based on:

1. Zoning
2. Scheduling
3. Daylight
4. Occupancy
5. Luminance control
6. Remoting
7. Integrating
8. Monitoring.

Each space is divided into several zones and according to the situation of each zone that is monitoring by presence and luminance sensors, appropriate action would take. The reported work presents appealing features by taking into account the current (available) lighting conditions and people's presence, however, the reported system seems to omit the obvious impact of the lighting elements in the working space versus the expected efficiency enhancement. The author announced the proposed lighting system is independent of the central controller like PC or Programmable logic controller (PLC [Siemens 1996]) and he remarked it as an advantage because the system can individually work even if a failure occurs, however, it can be reviewed from a different point of view. If the objective of work was to propose just smart lighting control then the author's claiming was reasonable, however complete independence of the lighting system from SBEMS may affect the integrity of the SBEMS and lead to complexity in case of monitoring and user interfacing.

The common concerning among all the works is energy consumption however the challenging part is, energy consumption reduction should not affect the work effectiveness; moreover, it should enhance user convenience. In [Bannamas & Jirapong, 2016], the authors propose an intelligent lighting management system for commercial and residential buildings. The system allows the user to select six different functions to reduce energy consumption:

1. Occupancy control: It is automatic lighting management. The lights will turn on or off according to the occupant detection by sensors.
2. Time scheduling: Lights can be programmed to turn on or off in a predefined schedule.
3. Daylight control: By splitting the room (space) into several zones, authors make a lighting balance between the zones located close to windows and the zones positioned far from windows (needing more luminance compared with those closer to the room's windows).
4. Task control: This function by dividing the room in different section turn on or off lights according to the occupant's presence in the concerning section.
5. Personal control: Users can control the lighting directly via a computer.
6. Variable power scheduling: This function computes the maximum required-power of building and if the total usage reaches the maximum, the system can aware user by an alarm. As a result, the user can turn off unnecessary luminaries.

The work is reviewed based on several case studies and based on the above-mentioned functions. Table 2 illustrates the case studies and implemented functions on each of them.

Case	Function						Remark
	1	2	3	4	5	6	
1							Fluorescent and LED lamps (switching control)
2	•						
3		•					
4			•				
5	•	•	•	•	•	•	
6			•				LED lamps (dimming control)
7	•	•	•	•	•	•	

Table 2. The function used in each case study in [Bannamas & Jirapong, 2016] intelligent lighting system

Based on obtained results, authors announced LED lamps are more effective than Fluorescent lamps. In case 1 just by using LED, they saved 68% by daily energy consumption. Besides, the comparison between cases 5 and 7 shows dimming control has advantages over the switching control and as a result, case 7 can save energy 12% more in comparison with case 5. Most energy conservation is achieved in case 7, where all the functions are used in parallel by utilizing LED lamps and dimming control. For managing the proposed system, authors use a microcontroller and Raspberry Pi device. Although, the designing of the lighting architecture and different functionalities of the

proposed system is the positive point of the aforesaid work, however, the extension of the proposed solution to large-scale-buildings remains questionable (regarding utilization of microcontroller and Raspberry Pi device). In addition, like the previous work, the authors omit the impact of the lighting elements' placement versus the topology of the considered working space.

In [Kumar et al. 2017] a smart LED lighting system implementation is presented. The proposed system aims to reduce energy consumption by 60 to 70% in comparison with the normal lighting system while satisfying the visual comfort of users. The proposed system can work in three different modes: Manual mode, Automatic mode, and Hybrid mode. In manual mode, the users can interact with the lighting system to control the lights and in automatic mode, the lights are actuated according to model-based or data-driven control in order to bring user satisfaction. The hybrid mode is a combination of two first modes. The lighting system works in automatic mode and if the user was not satisfied can interact with the system. Figure 4 reveals the flow diagram of the smart lighting system of [Kumar et al. 2017].

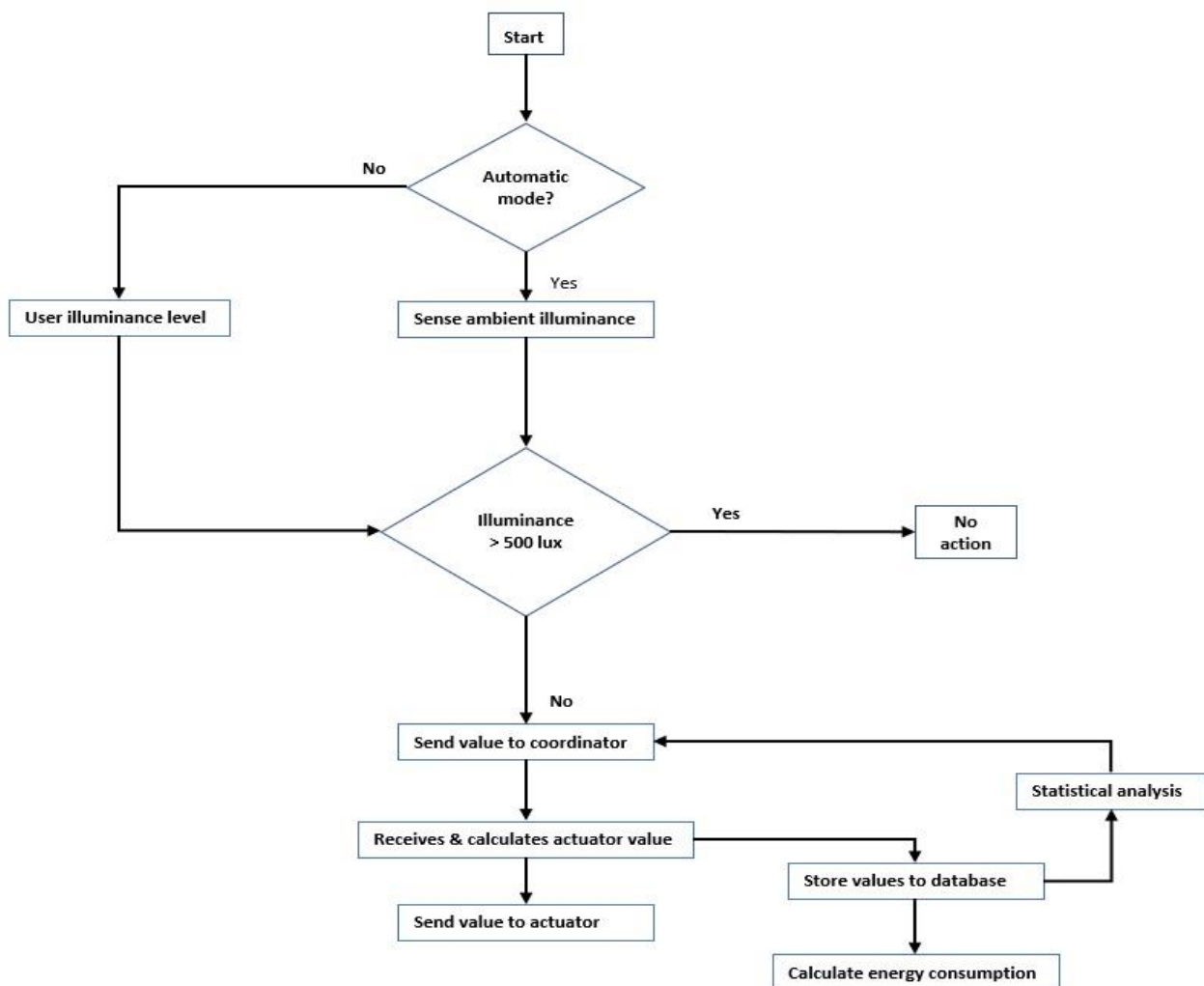


Figure 4. The flow diagram of the smart lighting system (extracted from [Kumar et al. 2017])

The proposed smart lighting system by [Kumar et al. 2017] utilizes wireless sensor-actuator network (WSAN). The authors claim the WSAN is used to analyze the physical and environmental parameters. The WSAN comprises several nodes. Each node is an autonomous entity in the network. WSAN transmits recorded data by the sensor node to a coordinator. There is a gateway node that facilitates the connectivity of WSAN with other nodes and actuation nodes will react based on coordinator instructions. The data in the proposed system is collected by sensors in a building management system and it stores in a database. The coordinator in this system is the main agent to collect all data from sensors and actuators and the personal agents via ZigBee and Wi-Fi network record relating data to user preferences values. The presented system shows another approach for the smart lighting system by using different kinds of technologies in comparison with previous works however as most of the works mentioned earlier authors did not notice the impact of the lighting elements placement.

## 1.5. The outcome of the nowadays lighting system review

Lighting systems in buildings used to be less in attendance of investigators. Recently it is one of the most attractive domains. As we obtained in section 1.4, lots of innovative solution is proposing by investigators. Although, it lasts a long way to go for enhancing lighting systems. Some main common limitations characterize the whole of the above-mentioned concepts (and of the issued systems):

1. The flexibility of the lighting system in a diverse environment: The first main shortage links the leakage of lighting system flexibility regarding the diversity of the building's indoor structure and the scale (size) to be set alight. Besides, some works are suffering from the flexibility of the lighting system to dynamic environmental conditions of the space (presence and absence of the user, outdoor light, the objective of space's usage, etc.).
2. The other main lack relates to the specificity of the chosen technologies in aforesaid works and making their solutions hardly extendable. In fact, because of the exclusive design of the lighting systems for aforesaid spaces, it is questionable if the proposed investigations and implementations are applicable to other spaces or not.
3. Almost all the works have missed the importance of lighting elements placement in spaces. The designing of lighting elements is as much as important to choose proper lighting technology. A good balance between two will lead to an efficient lighting system. Due to the lighting system is interacting with people's visual, the unnecessary high-performance systems took the efficient system place in most of the investigation of section 1.4.

The three above remarks indicate the guideline for covering the drawbacks of nowadays lighting systems. In this thesis, we are going to look for an approach that supports all demands for an efficient lighting system: Choosing suitable technology to cope with

diverse space's size and environmental conditions and designing lighting elements placement.

## 1.6. Review on different heating system's control design

The heating system is the most consuming part of the buildings. It remains a challenging task in SBEMS due to a quite large number of diverse kinds of involved parameters and their usually nonlinear inter-dependency in the living spaces. Occupation of the living space (presence and absence of users) is one of the aforesaid parameters which can play an essential role in the heating system's controller design. According to "black body law", the user as a thermal object is emitting heat by radiation. Due to these facts, the need for living-spaces' heating dynamics modeling appears as a foremost requirement for designing adaptive controllers scheming the complex behaviors of nowadays' smart buildings. In this section, we are going to review various heating system designs and heating controllers designs. There is also reviews on modeling of heating dynamics and system identification methods. Finally, owing to the important role of occupation in heating controllers design, the third part of this section is a review of different approaches for estimating the number of people in a space.

### 1.6.1. Modeling dynamic of heating spaces and designing heating controllers

A number of works address model-free approaches coping with building's heating. Relating conventional controllers, The authors of [Zungeru et al., 2018] introduce a control heating system for supporting the heating comfort of the user based on a very simple thermostatic controller (operating on "On/Off" strategy) with the help of a microcontroller. When the temperature is higher than the desired temperature the fan will be turned on and when the temperature is lower than the desired temperature the heater will turn on. The proposed simplistic control of the space heating operates on the difference between the desired temperature and actual temperature and could be seen as a model-free heating approach. While taking advantage of its independence from the effective complexity of the concerned edifice's heating-dynamics, the proposed strategy is applicable to very specific homogeneous living-spaces and not be generalized to more sophisticated buildings including heterogeneous living-spaces.

In [Purdon et al., 2013], the authors propose a model-free and sensor-free HVAC control algorithm that uses simple user input (hot/cold) and adapts to changing office occupancy or ambient temperature in real-time. As an alternative, the proposed strategy includes users in the HVAC control loop through distributed smart-phone based votes about their thermal comfort for aggregated control of HVAC. The developed iterative data fusion algorithm finds optimal temperature in offices with multiple users and addresses techniques that can aggressively save energy by drifting indoor temperatures towards

the outdoor temperature. The evaluation has been based on empirical data collected in 12 offices over a 3-week period and showed that the proposed control may save up to 60% of energy at a relatively small increase of 0.3°C in average occupant discomfort. While the idea is appealing, the concerned technique here also is very specific.

The designed control systems in [Zungeru et al., 2018], and [Purdon et al., 2013] operate without any pre-knowledge of the living-spaces that they are supposed to heat. In other words, the proposed solutions are based exclusively on data provided by temperature sensors within the frame of specific edifices for which the model of heating-dynamics is available. This makes the proposed models and issued controllers specific to the considered case-studies, and thus not applicable to other structures (i.e. other buildings).

There are a variety of controllers for managing the heating system. One of the widely used and well-known controllers is fuzzy controllers. In [Javaid et al. 2018], an adaptive thermostat controller model is proposed that is usable in hottest and coldest countries. The authors designed a controller based on MAMDANI and SUGENO [Researchhubs, n.d.; Ross, 2010] fuzzy techniques and wireless sensor capabilities. The proposed fuzzy controller for automating thermostat setpoints considers initialized set-point, outdoor temperature, home occupancy, and utility price (the price of electricity in the different hours of the day is different according to user's demand) as inputs.

The system is an HVAC that is working with electricity. The authors claim, at the minimum level, their system can save 6.5% energy. They compared several approaches for controlling the set-point of the system: fixed-set point, programmable set-point, fuzzy controller based on Mamdani, fuzzy controller based on Sugeno. They concluded both fuzzy techniques are more efficient than other methods, however, Sugeno is also illustrating better results than Mamdani. The idea of a floating set point is quite appealing, however, the optimal strategies for reaching the desired setpoint can play an important role in the result that the authors did not discuss it. It seems the controller is designed based on a model-free approach. According to this fact, the authors designed a controller based on general information that they have about the system and did not face the dynamic behavior and unidentified behavior of the system.

In [Tan kok khiang, Marzuki khalid, 1999] the authors are dealing with intelligent control and monitoring of an industrial chilling and heating system. As reported by authors, predominantly PID controllers are being used for this purpose, nevertheless, considering the nonlinearity behavior of these systems, PID cannot be the best choice. Concerning this point, the authors presented a fuzzy logic controller. The proposed fuzzy logic controller has two inputs and one output. Inputs are Error and the rate of error changes and output is a control signal. Individually, input and output have 5 membership functions with triangle shape. In Figure 5, the rule-based surface is illustrated and the nonlinearity in this fuzzy controller is obvious.

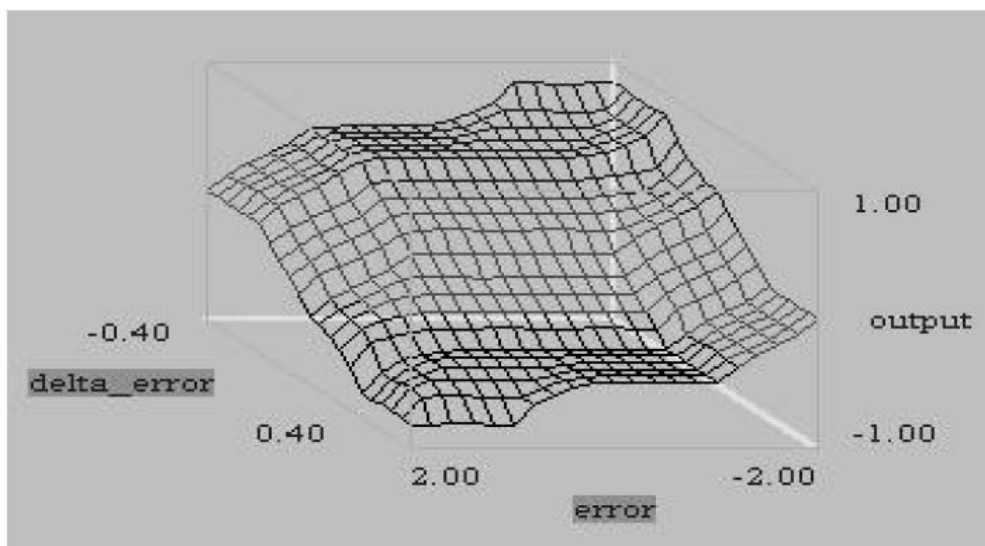


Figure 5. The control surface of fuzzy rules in 3D for the chilling/heating system (extracted from [Tan kok khiang, Marzuki khalid, 1999])

As stated by the authors, the result of this work shows, the fuzzy logic controller in the case of set-point tracking has a better performance in comparison with PID controller. It should be emphasized the proposed research is a controller design of heating chilling for industrial purposes and it may not be sufficient for the places that the user comfort has the priority. Despite that, the interesting point of this work is the ability of the fuzzy controller in set-point tracking. The authors in this work for the fuzzy controller just considered error and rate of error. In the work of [Tan kok khiang, Marzuki khalid, 1999] like [Javaid et al. 2018], they designed their controller based on a model-free approach however in comparison with [Javaid et al. 2018] number of factors for inputs of the fuzzy controller is limited to two (error and rate of error) and the authors did not take into consideration other factors that can affect the system.

An investigation by [Hamed & Alami, 2015] is about an adaptive Hierarchical Fuzzy controller. They believe the hierarchical structure has several benefits:

1. The number of rules in the fuzzy logic controller will decrease
2. The system is more accurate and less complex
3. The computational part of the work will decrease.

The proposed fuzzy system has two levels and the structure of controller is composed of:

1. System: Air temperature inside the room or hall.
2. Fuzzy Level1: Control the error of varying parameters to adjust the main controller.
3. Fuzzy Level2: Is the main temperature controller.
4. Disturbances: As for opening windows or doors and CO<sub>2</sub> concentration.



5. Temperature T0: The reference Air Temperature.
6. Temperature T1: Air Temperature after disturbances.
7. Temperature T2: Air Temperature after being heated from the heating system.
8. Temperature T3: Air Temperature inside the room.
9. Desired performance: The rules of fuzzy controllers from system experts (technicians).

As many traditional closed-loop controllers, the control process needs to be corrected during the operation. In this investigation, the responsibility of the correction is relating to the first level of fuzzy controllers to correct the second level. The unexpected changes in the system (like entering the new fresh air in the room) can affect and make an error in the controlling process. However, because there is no feedback about that, the error (T0-T3) will not change, and also because the true nature of heat spread is slow, the air temperature is unknown just after heating the system. That is why they try to avoid this unexpected error by correcting the process. The proposed control strategy is based on compensating for indoor temperature loss. The inputs of fuzzy level 2 are error (T0-T3) and output of fuzzy level 1. The inputs to fuzzy level 1 are: T0-T1 which observes the variations that come from entering new fresh air. It comes from air quality performance; and T2-T3 that is the difference between air temperature enters the room and indoor temperature.

The Hierarchical model suggested by [Hamed & Alami, 2015] is fitting and effective in the case of reducing the number of rules. However, As the investigation is on an integrated environment and the inherent behavior of the heating systems is very slow, it is questionable how they want to measure air temperature immediately after disturbances. The author did not discuss this part. In addition, in this work according to the proposed method, the goal is to reach setpoint temperature at any cost. It may improve user comfort, however, if the user behaves out of the right framework, not only it increases the cost but also the loss of energy. In opposite to recent works, the authors have proposed a solution to face dynamic parameters that affect the system.

Another investigation based on fuzzy approaches has been done by [Omarov et al. 2017]. A heating and cooling system controller is introduced to bring a level of comfort for users and in parallel save energy. They used Mamdani technique. As the inputs of the fuzzy controller, they have injected the deviation between the actual temperature and target temperature ( $\Delta T$ ), (in fuzzification mode, it contains 7 membership functions), Ratio of temperature changes in a certain time interval (same membership functions as  $\Delta T$ ) (Figure 6) and distance from heating/cooling device to the coldest/ hot area of the room (contains three membership function), (Figure 7). The output of the system is the power of the heating/ cooling device and it is composed of two different parts. The first part is about the operating mode of the heating/ cooling system composed of six membership functions. The second part is about the speed of the fan composed of four membership functions, (Figure 9). The membership functions have a triangle shape.

The identifiers of Membership functions in Figure 6 are Large Positive Deviation (LPD), Average Positive Deviation (APD), Small Positive Deviation (SPD), Zero Deviation (Z), Small Negative Deviation (SND), Average Negative Deviation (AND), Large Negative Deviation (LND). In Figure 8 each membership function represents the variables as below:

C3: Strong cooling, C2: Average cooling, C1: Slight cooling, NO: Without changes, H1: Heating 1, H2: Heating2.

Finally, in Figure 9 the defined rules regarding the fuzzy logic controller that mapped the inputs to outputs are presented.

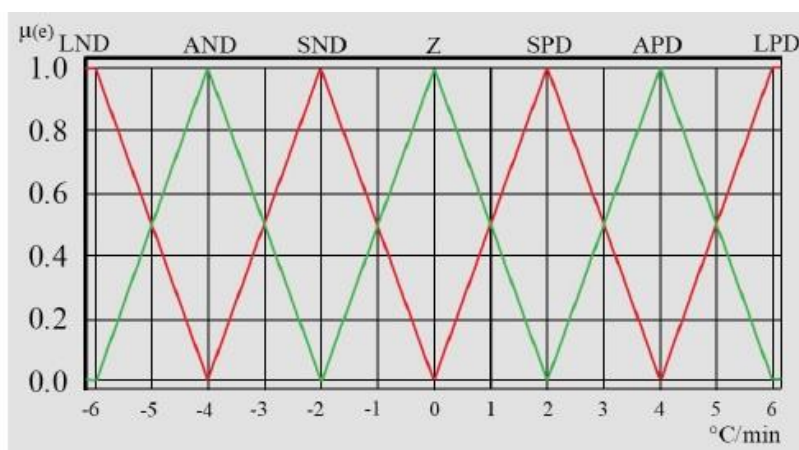


Figure 6. The deviation of actual temperature and target temperature ( $\Delta T$ ), Ratio of temperature changes in a certain time interval (extracted from [Omarov et al. 2017])

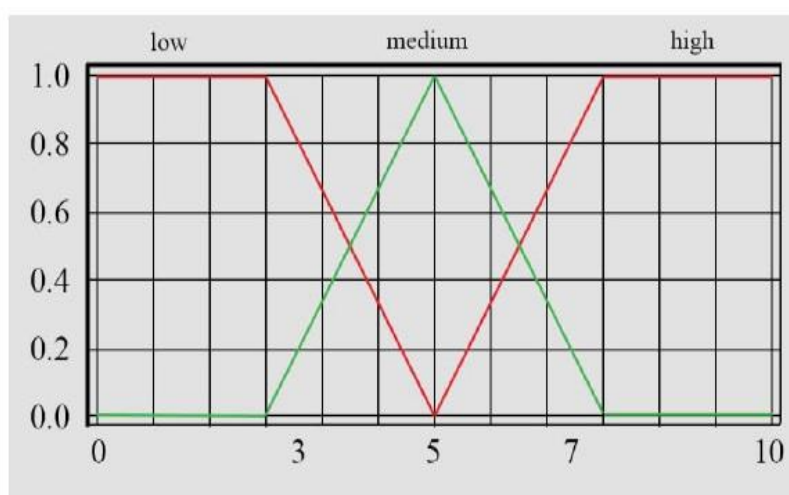


Figure 7. Membership function of heating/cooling device distance to the coldest and hot part (extracted from [Omarov et al. 2017])

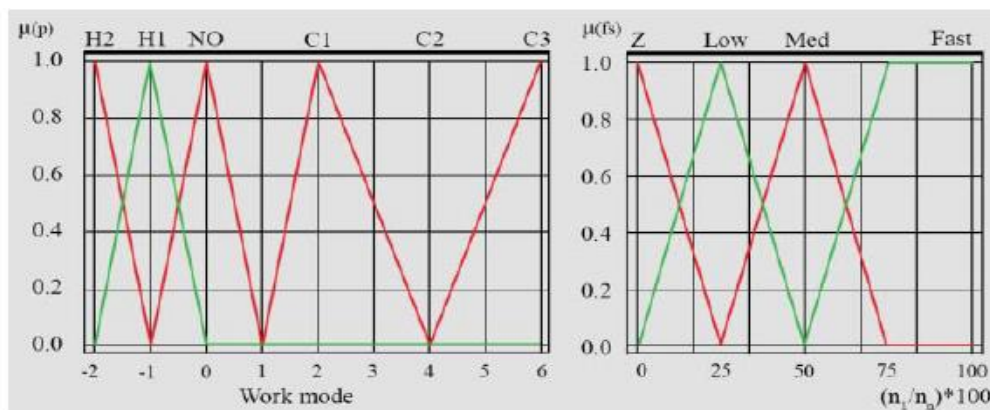


Figure 8. Membership functions of Output (operating mode of heating cooling (right), Speed of fan left)). (extracted from [Omarov et al. 2017])

		Temperature difference (e)						
		LND	AND	SND	Z	SPD	APD	LPD
Rate of temperature change	LND	C3	C3	C2	C1	NO	NO	H1
		Fast	Fast	Med	Slow	Z	Z	Med
	AND	C3	C2	C2	C1	NO	NO	H1
		Fast	Med	Med	Slow	Z	Z	Med
	SND	C3	C2	C1	C1	NO	NO	H1
		Fast	Med	Slow	Slow	Z	Z	Med
	Z	C2	C1	C1	NO	NO	H1	H1
		Med	Slow	Slow	Z	Z	Med	Med
	SPD	C1	C1	NO	NO	H1	H1	H2
		Slow	Slow	Z	Z	Med	Med	Fast
	APD	C1	C1	NO	NO	H1	H2	H2
		Slow	Slow	Z	Z	Med	Fast	Fast
	LPD	C1	C1	NO	NO	H2	H2	H2
		Slow	Slow	Z	Z	Fast	Fast	Fast

Figure 9. Rule of the fuzzy controller (extracted from [Omarov et al. 2017])

The notion of choosing a temperature rate and also the distance of the heating device to the hottest or cold section of the room is quietly appealing. It shows the authors have paid attention in every detail. Especially the related part to choosing the temperature rate is remarkable. Alike [Tan kok khiang, Marzuki khalid, 1999], error and rate of error are taken into consideration. However, the advantage of this investigation is about the third input of the fuzzy controller (distance to the coldest and hottest part of space). It would have a positive effect in the control chain. Although, it should be noted, this work is also based on a model-free approaches. In another investigation with the fuzzy approach, [Ekren & Küçüka, 2010] demonstrates how the fuzzy logic controller is effective to save energy in a chiller system. In the variable speed refrigeration systems, two important parameters should control:

1. Speed of compressor (it allows to match continuously the compressor refrigeration capacity to the load)
2. Opening percentage of the electronic expansion valve (EEV) [Tomczyk n.d. 2004]

The frequency of the compressor electric motor should be adjusted to change compressor speed and cooling capacity modulation. The fuzzy controller for this part has two inputs and one output. The first input is the difference between setpoint water temperature and real water temperature (water temperature error). The second one is the

previous value of frequency sent to the inverter by the controller. Output converted to a voltage which can be used by Pulse Width Modulation (PVM) [Nam, 2018] inverter in order to control the speed of the compressor.

Regarding controlling the EEV, the fuzzy controller is applied with the same number of input and output of the compressor speed controller. As inputs, the error of superheat temperature (the difference between setpoint superheat temperature and actual superheat temperature) and previous values of the opening valve of EEV is considered. The output is the values of the opening valve of EEV. Figure 10 and Figure 11 respectively demonstrate the water temperature changes and output power signal of the controller with fuzzy controller and on/off controller.

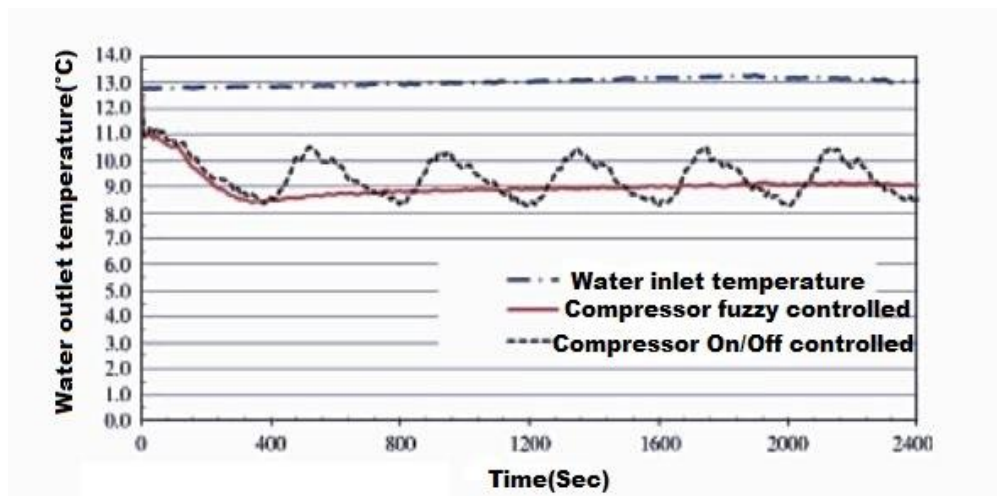


Figure 10. Water temperature changes (Red: Water temperature changes with the fuzzy controller, Black: Water temperature changes with on/off controller, Blue: Inlet water temperature). (extracted from [Ekren & Küçüka, 2010])

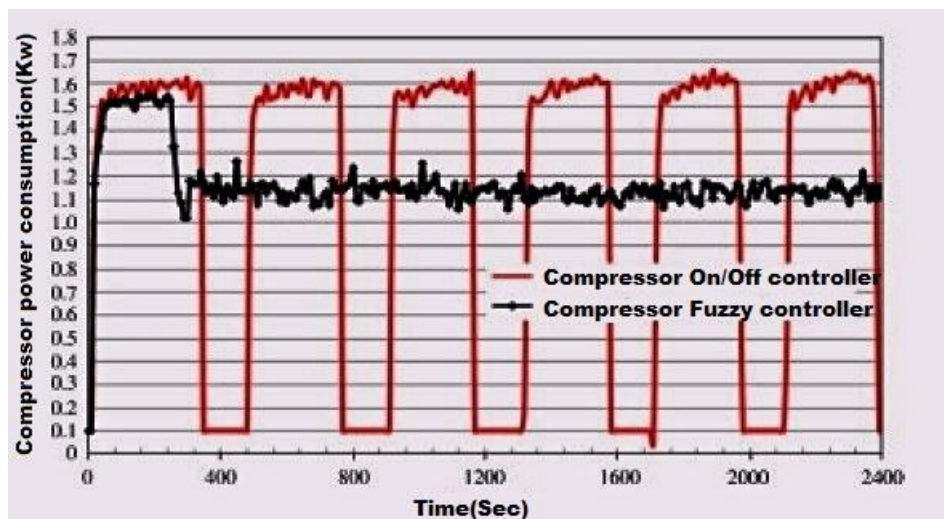


Figure 11. Output power signal of controllers (Black: Fuzzy controller, Red: On/off controller). (extracted from [Ekren & Küçüka, 2010])

The authors remark 17% performance improvement obtained by the fuzzy controller in comparison with the on/off controller. Like recently reviewed investigations, the work of [Ekren & Küçüka, 2010] is also designed based on a model-free approach. In order to take over the problem, besides the error as an input to the fuzzy controller, the past value of the opening valve of EEV, and the frequency sent to the inverter are considered.

The investigators of [Özgür et al. 2018] are designed an IoT based smart thermostat for the heating system in order to save energy. The case study in this work is a home with combi boiler [Viessmann n.d] for heating. In each room of this home, there is a sensor temperature and the system will calculate the average temperature of rooms, and accordingly, the combi boiler should heat the rooms. Each temperature node communicates with the smart thermostat by nRF24L01 module [Nodric 2006] and just root temperature node communicates through the internet by ESP8266 module.

The smart thermostat decides on the temperature of the combi boiler. This decision is making remotely by a mobile application that controls by the user. The decision also can be made automatically, depending on the user's location. The smart thermostat can turn on the combi boiler if the user is in the home or he is approaching home. If the user gets away from the home, it can turn it off. Figure 12 shows the diagram of the smart thermostat activity.

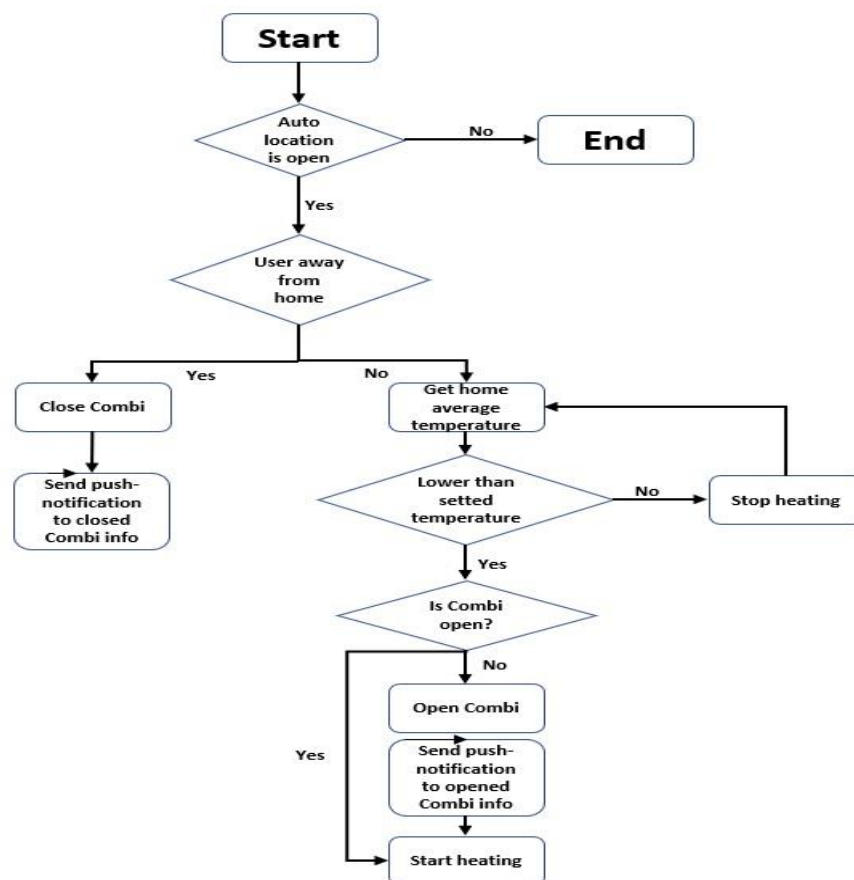


Figure 12. Smart thermostat activity diagram (extracted from [Özgür et al. 2018])

The idea of action and reaction of the thermostat according to user location is interesting. However, The flexibility of the system is low. Owing to there is just one smart thermostat that is responsible for setting the whole building temperature and it just has two modes of working: On or Off. The authors just paid attention to the localization of the user and did not consider the optimum operation of the thermostat. The presented work can be highly interesting if the smart thermostat was able to operate according to a control algorithm.

Most of the investigations regarding an effective heating controller design are on the basis of model-free approaches. Lack of information about the effect of dynamic factors in the aforesaid works is leading to simplistic solutions for facing control issues. In some works like [Hamed & Alami, 2015], the authors would like to decrease the effect of dynamic parameters by a hierarchical fuzzy architecture; or in work of [Omarov et al. 2017], and [Tan kok khiang, Marzuki khalid, 1999] the practical operation of error and error rate in a feedback loop helps reach the same goal. The authors of [Javaid et al. 2018] with a fuzzy controller and considering dynamic parameters that have an influence on the control chain are facing the problem, however, in [Özgür et al. 2018], authors by localization of user is dealing the control challenge and it is suffering from an effective algorithmic controller. The work of [Javaid et al. 2018], as it is noted earlier, considering several factors that affect the control chain. It is an interesting note, however, the control strategies (rule-based part of fuzzy controller) have mostly an empiric basis.

Based on the above-mentioned, the design and implementation of an identification system for modeling the building's living-space dynamic heating are necessary for pulling off of a comprehensive (i.e. interpretable) model that is handling the dynamic heating conduct of leaving-spaces. It can serve to design a model based-heating controller.

A large variety of identifiers taking into account systems non-linearity have already been proposed among which, Wiener and Hammerstein type models [Wiener, 1959], Volterra series [Schetzen, 1980] and Machine-learning based approaches as Fuzzy Logic-based models [Takagi and Sugeno, 1985] and Artificial Neural Networks (ANN) based approaches [Boussaada et al. 2018]. In [Linda Brus, 2005] author attempt to identify a solar heating system using Black-Box modeling BBS based on what they call "recursive prediction error method" (RPEM). The so-called RPEM is based on a state-space model. The target system (namely a solar heater) includes two inputs (solar radiation energy and speed of the fan) and one output (air's temperature). While claiming the small number of parameters and a small amount of required data as advantages of the proposed approach, the relative simplicity of the target system and quite rough identification of the expected behavior don't convince on the extensibility of the proposed approach to realistic systems comprising larger numbers of parameters (inputs and outputs). Authors of [Rabbani et al. 2013] investigated the identification of a heating system by means of Auto-Regressive (ARX) model, Auto-Regressive, and Moving Average (ARMAX) model, and Box-Jenkins (BJ) model. The target system (to be identified) includes a 300watts halogen lamp (as a heating device) and a metallic plate includes only one input

(the lamp's voltage) and one output (the metallic plate's temperature). The authors used the System Identification toolbox of MATLAB for simulating the above-mentioned case-study. However, the relative simplicity of the target system doesn't allow to state on the effectiveness of the investigated approach: it just shows that the MATLAB's System Identification toolbox simulates this quite simple case-study example. In the same way, authors of [LAHANE & A.KHANDEKAR, 2014] apply the MATLAB's System Identification toolbox to identify the behavior of a boiler and heat exchanger transfer functions. However, the reported results don't conclude on accurate identification of the target system resulting in rough modeling of the target device. In [Knudsen et al. 2017] authors report results relating the identification of a dwelling's thermal model (including two bedrooms) heated with electrical baseboard heaters. The authors model the target system using EnergyPlus [EnergyPlus n.d] (a building energy simulation program providing functional modeling of energy consumption for heating, cooling, ventilation, and lighting in buildings). The control signal generates by MATLAB via the Building Controls Virtual Test Bed open-source software of Berkley Lab[Berkeley lab n.d.]. Berkley lab proposes a freely available co-simulation software that is linking different simulation programs as EnergyPlus, Modelica [Openmodelica n.d.]), and MATLAB/ Simulink. For control, the model predictive controller (MPC) is applied. Regarding system identification, they used N4SID subspace identification [Van Overschee & De Moor, 1994]. The authors concluded on an acceptable average root-mean-square-error (RMSE) across the ten reported simulated apartments. However, the same authors concluded on a very time consuming (time costly) execution making difficult the extension of the reported work to more complex systems (structures).

The aforesaid investigations emphasize the pertinence of the identification approaches for modeling the buildings' heating dynamic. Indeed, all of the referenced investigations underline the tough limitations of the overviewed solutions in matching the complex behavior of space heating systems in buildings. Main shortages are either related to the eager simplification of the actual operative complexity of involved equations, in order to ease their computational solutions, or inherent to nonlinearity and the outsized number of involved parameters. In fact, in all of the aforementioned works, the obtained models reach serious limitations for matching the complexity of the real systems' (real heating spaces in buildings) behavior. The identification of space heating behavior is the first step for designing a heating controller. In fact, it supposes to offer an appealing application for modeling the behavior of the heating spaces. It lets analyze the sophisticated behavior of the system and accordingly design the appropriate heating controller. The aforesaid investigations are studied in order to have a perspective about various approaches regarding identification and modeling systems.

### **1.6.2. The outcome of reviews on heating system's control design**

Considering the above-mentioned investigations, there is a shortage of works regarding the effective design of heating controllers. Most of the works have a simplistic look at the subject. Due to plenty of nonlinear factors that affect the spaces and they are not

identified. In fact, All the above researches are designed controller or control strategies based on model-free approaches. As it is stated earlier, the role of the user as an additional heating source in spaces is one of the important factors that can have an influence on the heating dynamics of spaces however its effect on spaces is unidentified. Not only can they have an operator role for controlling the heating devices but also they can be seen as an additional heating source (device). The user as a thermal object is emitting heat by radiation. Regarding this fact, taking advantage of this heat may lead to the decrement of generating heating energy by heating devices in spaces. it should not be exaggerated if we say most of the present controllers do not take into account this phenomenon in designing adaptive heating controllers. Indeed there is some investigation like [Özgür et al. 2018] that considers the location of the user in order to control the heating system however it is suffering from the lack of optimum operation of the thermostat.

Considering identification approaches, there are also shortages that are related to the simplification of the complexity of involved factors. Finally, due to designing an effective heating controller, identifying the heating dynamic behavior of the spaces (especially the dynamic effect of the presence and absence of the user in the spaces as one of complex involved factors) is unavoidable. Unfortunately, all the above investigations dramatically suffer from the lack of that. Modeling the heating dynamic of spaces lets to discover the capacity of energy-saving in order to increase the efficiency of the heating devices operation. According to aforesaid fact whole of the importance of user, estimating number of people in a space is becoming an important aspect. Thus, in the next section, we are going to review different studies about methods regarding the presence estimation.

### 1.6.3. Presence estimator

Nowadays, there is a wide range of technologies regarding estimating the number of people in places. According to the rules, accuracy, and purpose of using, the proper technology that is utilized in different spaces is differing [Traf-Sys, 2015]. The well-known technologies for counting people can be listed:

1. Camera people counting
2. Infrared people counting
3. Wireless people counting
4. Thermal people counting.

The authors of [IEE, 2018] new technology for counting people. Based on the reflection of light on an object, a 3D image can be constructed, and then the number of people can be estimated. They use a technology that is called Modulated Light Intensity technology. The proposed technology, according to [IEE, 2018] has an accuracy of more than 99% for people counting. It can be the new generation of presence counting estimators.



The most basic counters are Horizontal Wired/Wireless retail counting systems. However, they have their disadvantages in accuracy. When two people entering, the counting accuracy would be affected. One of the most popular and vast technologies is camera counting systems. In [Serrano-Cuerda, 2013], the authors present an approach for counting people with a video camera. They utilize image processing techniques to count the people. According to the author reports, there is no restriction on a number of people detection by this approach. The proposed result by the authors is outstanding. Regarding the people counting by image processing technic and utilizing a camera, there are some advantages and disadvantages that can be remarked. On one hand, regarding the counting accuracy and price, it has advantages to other technologies but on the other hand in some places using the camera is forbidden because of security restrictions rules.

Some approaches are based on virtual counting. It means, by integrating several sensors that are not relating to the counting of occupants, the number of people can be counted, or by using sensors that are not relating to the detection of the user, the presence or absence of user can be detected. In [Shetty et al. 2018] authors investigate to estimate the number of people by using PID (passive infrared detector) sensor and plug-load meters. The test case in this work is containing a room with 4 desks. On each desk, there is a PID sensor and a plug-load meter is connected to each desktop computer. In order to collect data, they used a ZigBee based energy meter called Circle provided by Plugwise. They use k-mean clustering method to analyze the presence and absence of each individual user. The accuracy of presence detection according to the author's report is between 89 to 99% in comparison with the ground-truth data for 4 different users. The proposed work without using the camera and image processing achieved good results. However, this work has a restriction. Cause by this approach only the people who are involving with computer desktop and sitting behind the desk can be counted.

The authors of [Jiang et al., 2016] propose an approach for indoor occupancy estimation from CO<sub>2</sub> concentration. They utilize a machine learning algorithm for estimating the number of occupants. Authors mention the occupancy level as a function of CO<sub>2</sub> data, the venting level, and the past occupancy level in a moving time horizon. They take advantage of feature scaled extreme learning machine (FS-ELM) which is a variation of ELM algorithm for identification of occupants. the proposed approach is tested in an office room and according to their results, it is able to reach up to 94% accuracy. The work of [Jiang et al., 2016] is interesting however, it is questionable how is the performance of the model in rooms with different volumes because the volume is an important parameter versus other abovesaid parameters.

In another work, authors of [Kleiminger et al. 2013] present an approach to detect occupancy according to electricity consumption detection. They use PIR (or PID) sensor and smart power outlets for 5 different households. To analyze and discuss, they obtain the result of four different classifiers: support vector machines (SVM), K-nearest neighbor, (KNN), thresholding (THR) and to evaluate stateful classification they use a hidden Markov model (HMM). Finally, they get about 80% accuracy in comparison with ground truth occupancy data. This approach just gives a general view of the

presence and absence of people in the environment and cannot show in detail in each space how many people are there.

The above-mentioned works can be divided into two groups. The first group is the works that the sensors are designed specifically for occupation detection or occupation counting. This group of works by using different technologies and techniques can directly count or detect occupants. On the other hand, there is the second group of works. This group by using third-party sensors or information estimates the occupant's number. In fact, they are virtual sensors. Like the investigation of [Jiang et al., 2016] that used data relating to CO<sub>2</sub> for estimating the occupant's number. This group of sensors can be utilized in places that security is important and the user prefers to know the number of occupants through third part sensors for security reasons. Or in places that users want to virtually estimate the number of occupants with existing sensors and data that they have without spending extra money on a new sensor. The first group has high accuracy as they are designed especially for occupation counting. However, the second group needs development in order to increase accuracy and also be responsive to diverse conditions. Because they are using dynamic parameters for estimation. As a result, it leads to poor accuracy of estimation or leads to the proper responsiveness of the sensor just in limited cases.

## 1.7. Conclusion

In this chapter, various ideas and works whole of SBEMS architecture and its subsystems were reviewed to have a clear view of this domain, its challenges, achievements, and drawbacks. In the first section 1.2, various architecture regarding building energy management systems was reviewed. Because of an infinite number of facilities and advancements in soft computing technics, sensory technologies, and IoT, the investigators follow plenty of approaches to enhance the SBEMS architecture. The abundance of facilities and technologies for developing the design of SBEMS is a bright point in this domain however when it comes to the integration phase of these technologies, it is also a negative point, due to different communication protocols and standards that they use, as mentioned in section 1.3. The user-centric functionalities of nowadays SBEMS are pointed as another drawback. It is remarked, selecting proper technologies and devices besides a suitable architecture could cover the two imperative shortage of current SBEMS.

In sections 1.4 and 1.6, the reviews on two important subsystems of a SBEMS in case of energy consumption were studied: Lighting systems, Heating system's control. Regarding lighting systems, a Short-sighted look for designing lighting systems is leading to inefficient lighting designs. The flexibility of the lighting system in a diverse environment, Shortage-look for choosing the proper technologies that can extend in other places, and negligence to the design of lighting elements placement are remarked as disadvantages of lighting systems in SBEMS. The solution for covering leakage of the actual lighting system is highlighted in section 1.5. Architecture design of the

lighting element placement with a flexible lighting system technology is the two key points that could face the existing challenge of the lighting systems.

Regarding heating system control, in section 1.6.2, the outcome of reviews in this domain is addressed. The missing part in almost all of the investigation regarding the heating system's controller design is the thermodynamical effect of the occupation (presence and absence of the user) and un-identified dynamical heating behaviors in spaces. Indeed, most of the investigations for designing heating controllers are model-free based approaches. Designing an adaptive heating system controller by taking into consideration the impact of the heating dynamic of living spaces, especially the thermodynamical effect of occupation in space heating systems can face this problem. Although we noted the identification of the heating dynamics of the living space is the first step for designing an adaptive heating controller. At last, Considering the occupation importance in heating system's control design in section 1.6.3 various investigation relating to presence estimator is studied. Most recent technologies regarding the presence estimators are on the basis of visual technologies and there is a lack of non-visual virtual presence estimator that can serve in SBEMS as an alternative solution.

## Chapter 2

### 2. The architecture of a multi-layer system for SBEMS

#### 2.1. Introduction

It's been years that building energy management systems (BEMS) have been developing. Since the primary BEMS with just a simple monitoring and automatic system till nowadays SBEMS with sophisticated monitoring and control systems. In general, SBEMS integrates and computerized several systems for monitoring and controlling, like lighting systems, ventilation systems, heating systems, etc. The objective of a SBEMS is to provide some facilities to the user with the objective of user comfort and energy efficiency. The first step toward designing a SBEMS is to design its architecture. The architecture has to contain several imperative properties to work properly. This architecture must propose a flexible environment. It lets the subsystems of SBEMS integrate harmonizingly and the likely development of the system in the future does not face many challenges. The second step is to choose the proper devices and technologies to fit the proposed architecture. Due to the many options in the current market and high competition among provider companies, selecting suitable devices and technologies is not easy. In fact, a wide range of choices from providers leads to confusion of consumers, and as a consequence, it causes un-appropriate selection of technologies and devices.

The proper technologies and devices that fit the architecture of SBEMS would provide a powerful platform to the users. A powerful platform of SBEMS should have several crucial properties. Providing monitoring systems, user interface, and several controlling strategies that should lead to improvement of energy consumption. These are some remarking properties. However, we should note that flexibility in software and hardware development of SBEMS is also a valuable characteristic. It shows its importance in the future when the system needs to upgrade or if the system is utilized as a platform for research purposes. As it remarked in section 1.3 most of the current SBEMS are suffering from lack of aforesaid feature.

In this chapter, a smart building multi-layer management system, based on sensors and various technologies is presented aiming fine self-awareness of the ambient and internal states of the edifice. The proposed SBEMS that will be proposed in this chapter also will act as a research platform (framework).

#### 2.2. The multi-layer architecture design of campus SENART

A multi-layer architecture is also called a multi-tier architecture. It proposes a flexible environment for managing a system. The software is engineered to have the processing,

data management, and presentation functions physically and logically separated. [Stackify 2017]. A general model for a multi-layer architecture system is a compound of three layers. The system is divided into three parts: User interface, Business logic, Data access. [Finnish Software Measurement Association, 2014].

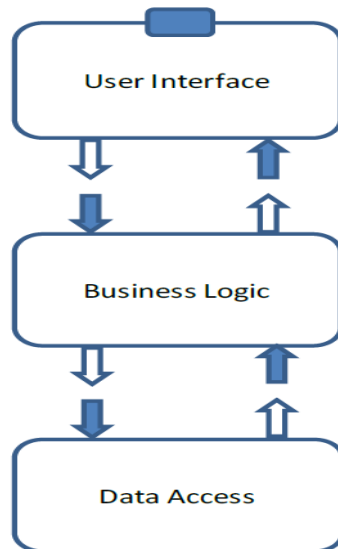


Figure 13. Multi-layer system architecture (three layers)

The top part of a multi-layer system is a user interface. In this part, some functions translate the result and tasks to somethings that are readable for the user. Business logic part coordinate, logical decision, calculations, and command process and it connects the user interface to data access. The last layer is data access. This layer is responsible for providing data to upper layers by sensors, actuators, etc.

The multi-layer systems have several advantages that make highly appealing, here there are some of their benefits:

1. Secure: In comparison with other systems they are more secure, as it can use different secure methods for each layer separately.
2. Easy to manage: These kinds of systems give the possibilities to manage each layer individually without affecting other layers.
3. Flexible: It can expand each layer in any manner without affecting other layers.

The operational architecture that we propose is organized in a multi-layer structure including four key layers. Each layer may include hardware as well as software or virtual components (or modules). Figure 14 depicts the block diagram of the system. As it is visible from this figure, the system includes a “Supervision Layer” (SL), a “Control Layer” (CL), an “Agents Layer” (AL), and a “Physical Layer” (PL). On the basis of the multi-layer architecture of Figure 13, the supervision layer is the user interface layer, control, and agent layers are the business logic layer and the physical layer is the data access layer.

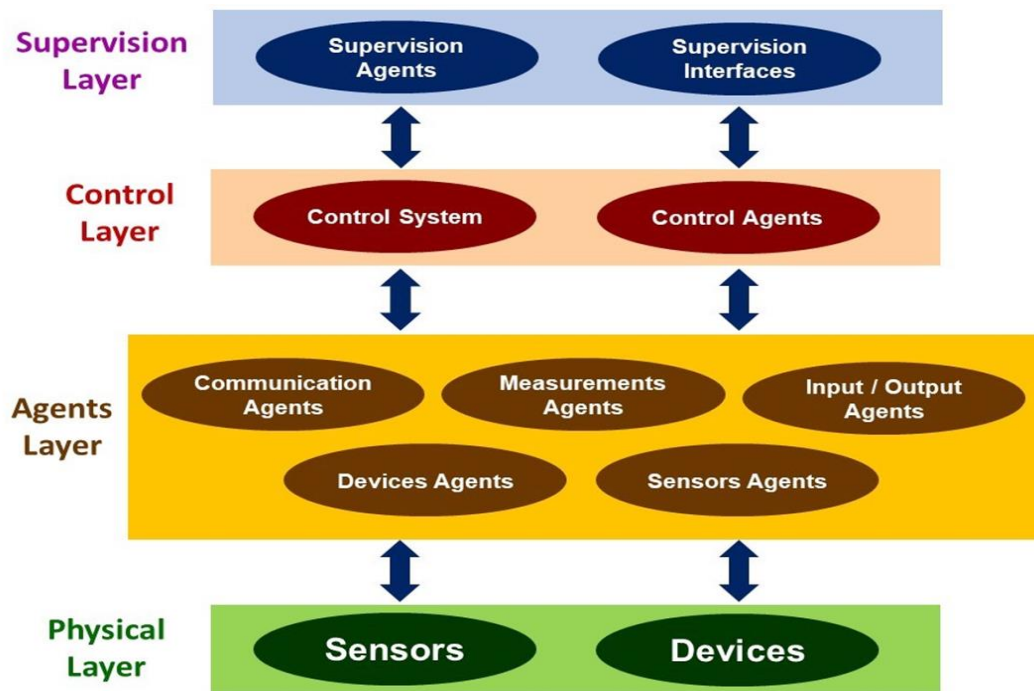


Figure 14. The architecture of the multi-layer system

The SL is the top level of the architecture includes mainly the server, namely a computer in charge with the system's parameters setting (i.e. modification), monitoring the system, and collecting the data in real-time. The CL is composed of a set of Programmable Logic Controllers (PLC) that connect from one side to the server (i.e. SL) and on the other side the AL (i.e. communicate with agents). This layer is in charge of the operational control of sensors and devices through appropriate agents in AL.

The next layer is namely AL. it is devoted to various agents. It is in charge of specific tasks relating sensor's operation (i.e. data acquisition) and those relating executive drive of various devices. The responsibility of this layer is to perform the appropriate action of each connected device. Even though AL can integrate any type of agent, It contains a number of essential agents as:

Communication Agents: managing communications and related protocols,

Input / Output Agents: handling various involved inputs and outputs of the system's components,

Devices Agents: in charge of correct operation and protocols of connected device,

Sensors Agents: controlling the correct process of connected sensors and related data collection,

Measurement Agents: in charge of correct conversion and representation of measured parameters.

Finally, the PL includes whole sensors through which various data are collected and devices acting to control accurately the edifice's performance.

The multi-layer organization of this architecture provides the issued SBEMS independency and also various technological choices relating to the effective implementation of the system. In fact, Different kinds of hardware and software technologies with various protocols can be used for implementing SBEMS.

### 2.3. Implementation of proposed multi-layer architecture

The implementation of the investigated SBEMS has been performed in a five-floors building located at Senart Campus of UPEC, providing a real-world experimental platform for validation, evaluation, and further investigations relating smart-building subjects: one of the topics on which LISSI and especially its SYNAPSE research division have focused efforts. The building an edifice comprising five floors, each of which includes different types of working spaces (office-rooms, classrooms, practice-rooms, etc.). Main categories of working spaces can be listed as following: Office-rooms (occupied by one to four staffs per office), Classrooms (with the capacity of 24 to 28 users), Programming-training practical rooms equipped essentially with computers and printers (designed for hosting 12 to 18 users) and Machines' workrooms equipped with heavy plants or lighter apparatuses (designed for hosting 12 to 16 users). Finally, a number of corridors ensuring the linkage (access) between working spaces characterize each floor of the building. Figure 15 shows the implementation block diagram of the investigated system identifying previously-described layers.

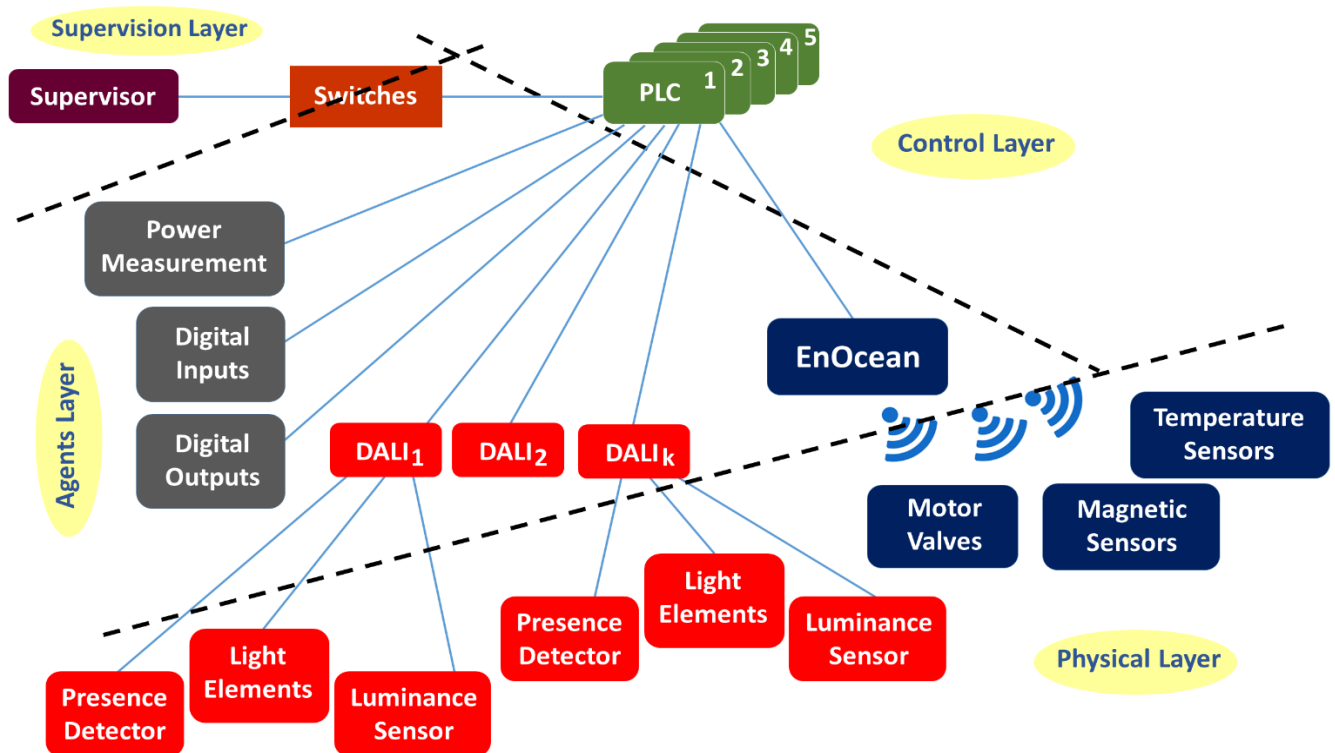


Figure 15. Implementation block diagram showing different layers and related components

### 2.3.1. Physical layer's implementation

Four kinds of sensors have been deployed equipping each working space (including corridors) of each floor: “Temperature Sensors” (TS), “Magnetic Sensors” (MS), “Presence Detectors” (PD) and “Luminance Sensors” (LS).

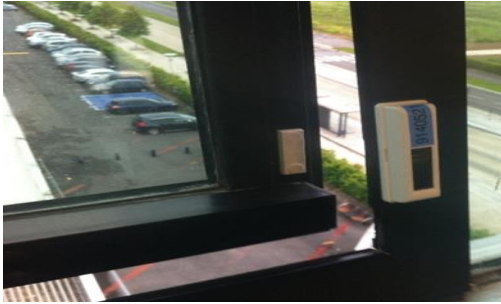


Figure 16. Magnetic sensor



Figure 17. Temperature sensor



Figure 18. Luminance and presence sensor

The main connected devices deployed in the aforementioned experimental building are: “Motor Valves” (MV) controlling heaters (i.e. radiators supplied by a central water-flowed heating system), connected “Lighting Elements” (LE), equipping each working space of the building and 16-channel relay interfaces on each floor to avoid standby energy waste. It should be noted, the concern building is equipped with Double-Glazed windows and the ventilation is through windows trickles. The localization concerning the placement of different sensors and detectors is according to the standard that the manufacturer of the sensors is suggesting.



Figure 19. Motor valve

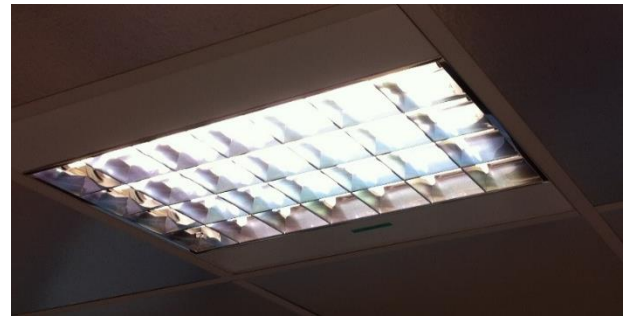


Figure 20. Lighting element



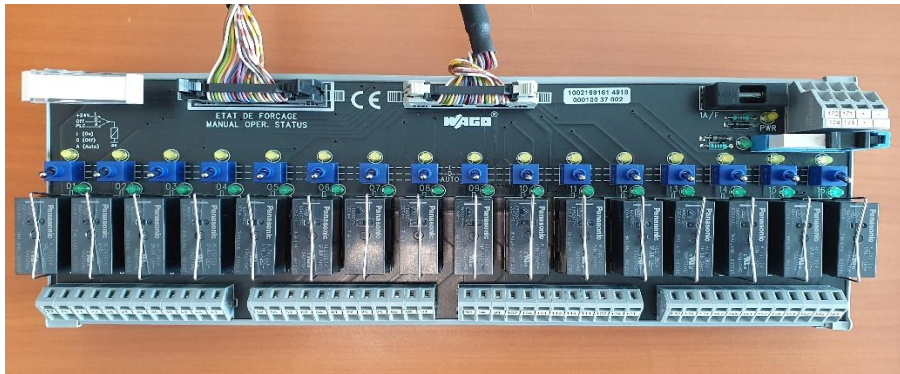


Figure 21. 16-channel relay interfaces

TS, MS, and MV use “EnOcean” technology, an energy harvesting wireless technology provided by EnOcean [EnOcean Alliance, 2016]. EnOcean-technology-based modules combine micro-energy converters with ultralow power electronics and reliable wireless communications, allowing to create self-powered wireless sensors or actuators solutions for energy management systems in the building and industrial applications. TS and MS sensors are using solar power for operations and they are supported with battery in case of no daylight. MV is operating with batteries. Main appealing features of EnOcean technology are [Anders, 2011]: It can easily integrate with different communication software, energy converters, energy management, and radio modules; this technology is battery-less, and thus doesn’t need to handle energy supply installation; its outdoor range of transmission of 300 meters and indoor field of diffusion of 30 meters cover the whole working and/or living spaces of the building; the technology offers the reliable connection of several hundreds of connected sensors and devices compatible with EnOcean; finally, communicating with PLC by a serial interface (STC65-RS485 Modbus protocol [RS485\_datasheet 2016], [NI n.d]), EnOcean devices are compatible with most of market-available PLCs.

Concerning PD, LS, and LE, they use a different technology known as DALI (Digital Addressable Lighting Interface). DALI is a protocol for standardizing control of electronic ballasts in lighting applications. Various complex lighting scenarios (and configurations) may be defined and functionalized within DALI environment. For example, DALI/DSI Master Module within the WAGO-I/O-SYSTEM PLC allows combining whole the building’s lighting with other building services. DALI supports 64 individual addresses, 16 different group addresses, and 16 different scenarios [Wago, 2005], [Luminaire, 2001].

Depends on working spaces’ sizes, LEs, LSs, and PDs have been deployed in each working space. Smaller working spaces (like office-rooms) include one LS and one PD. While other working spaces include two or more of each of the above-mentioned modules. It is useful to notice that each PD and LS manage a group of LEs (2 LEs for smaller spaces and up to 5 LEs for large working spaces). Detecting the presence (through PD) the PLC sets the power of lighting elements through DALI network. In the same way, the luminance measured by LS allows PLC to tune LE group according to the lighting control strategy implemented in PLC. Regarding other modules, MS is

deployed in order to inform the system about the window's state (i.e. open or closed). In case it detects the windows are opened, a cut off function on PLC will directly act and close the radiator valve. Therefore, each window of the building is equipped with an MS. TS equips each working space as well as a number of outdoor points of the building. Finally, in all working spaces (or corridors) each heating unit is controlled by an MV device. In chapters 4 and 5, we will discuss it in more detail.

On each floor, there is a 16 channel relay interface. It is connected to an input-output wago module on PLC. This relay is utilized in order to avoid waste of energy when the system is on standby mode. As the concern building is a commercial building, during nights, between 8 PM until 6 AM there is no activity in the building and SBEMS is working on standby mode. Standby mode in this condition when there is no activity for a long time is counting as a waste of energy. Regarding this fact, the mentioned relay cut off the power during these hours.

### **2.3.2. Agent layer's implementation**

Agents Layer comprises various agents (software or hardware agents). Digital inputs and outputs are handling various inputs and outputs of involved components that are constituting different layers. Power Measurement Agent handles data and protocols relating to energy consumption issues. As it could be seen in Figure 15, the implemented AL includes two groups of additional agents labeled as "DALI" and "EnOcean" agents. Each group of aforementioned agents integrates its specific communication, sensors, and devices agents. For this reason, the "communication agents", "devices agents" and "sensors agents" are not reported in this figure.

### **2.3.3. Control layer's implementation**

The CL has been implemented using "WAGO-I/O-SYSTEM" PLC: a family of ETHERNET programmable Fieldbus controllers distributed by WAGO. This PLC can support digital, analog modules. The PLC supports both MODBUS/TCP and a wide variety of standard ETHERNET/IP protocols for easy integration into IT environments. This controller can be used for applications dealing with machines' and plants' control, industrial processes' control, and building technology [Kontakttechnik GmbH, 2016]. An integrated Web-Server also provides the user with configuration options and status information from the controller. It is interesting to note that the PLC has a slot for a removable memory card, allowing device parameters or files to be transferred from one controller to another. The memory card can be accessed via FTP and be used as an additional drive.

Within the context, five WAGO-I/O-SYSTEM PLCs have been deployed (i.e. one PLC for each floor of the building) with the aim of acquiring data from sensors and controlling devices of each floor.

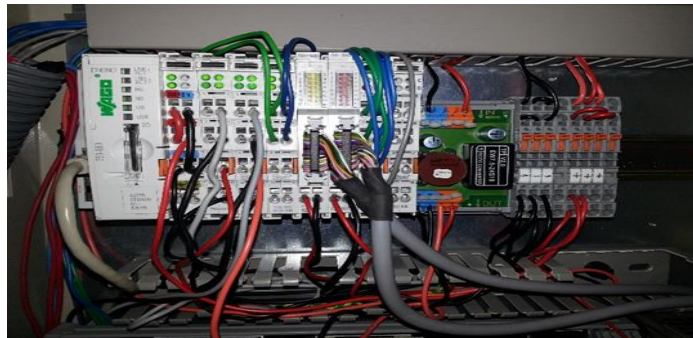


Figure 22. WAGO-I/O-SYSTEM Programmable logic controller

The PLC is programmed by the “control development system” (CodeSys) software. It is a development environment for programming controllers based on industrial standard IEC 61131-3 and accordingly it is a powerful software that gives this ability to program in 5 different programming language standards [Manual and Programming, n.d.]:

1. Ladder diagram (LD),
2. Function block diagram (FBD),
3. Structured text (ST),
4. Instruction list (IL),
5. Sequential function chart (SFC),

ST and IL are textual language programming and LD, FBD and SFC are graphical language programming. The CodeSys provides a User Interface (UI) for monitoring and controlling the SBEMS. The discussion about this part (UI by Codesys) will be proposed later in this chapter.

### 2.3.4. Supervision layer’s implementation

Supervision Layer (SL) can be a computer, tablet, or mobile phone with relating software and application for user interfacing. The user can be aware of the status of the environment and consequently control and set the relating parameters to their desires. About the functionality and facilities regarding the control different parts of the system (lighting and heating system control) will talk in chapters 3 and 4, however, the discussion in this section is toward UI facilities (monitoring, taking control action, and user awareness) to the user by SBEMS. The proposed architecture is flexible and open to any software, protocols, and technologies. In SL that is the top level of the SBEMS architecture. The SBEMS can be supervised and controlled with plenty of existing top trends software in the market: Topkapi by SCADA, Matlab by Mathworks, Codesys, MySQL, etc are some examples of available software in the market that are compatible with proposed SBEMS. Figure 23 shows the supervision layer properties and their relation to the control layer and local intelligence distributed in the agent layer.

This layer (SL) has been materialized by a PC computer including TopKapi server supervision software (a product of SCADA Software) acting as the main supervision agent. It includes also a number of adequate interface agents (software units) relating to the control layer and storage memory. it provides all the usual functions of SCADA software systems [Scada n.d.]:

1. Communication with field devices (via dozens of direct protocol drivers or third-party open platform communication servers)
2. Calculation and data formatting
3. Data logging
4. Display with a graphic editor (mimics)
5. Alarms and events management
6. Remote control with any kind of workstation (client/ server architecture)

TopKapi has a Full HTML5 Web server for easy access to clients. Users can easily have access to the TopKapi application by using cellphones or tablets.

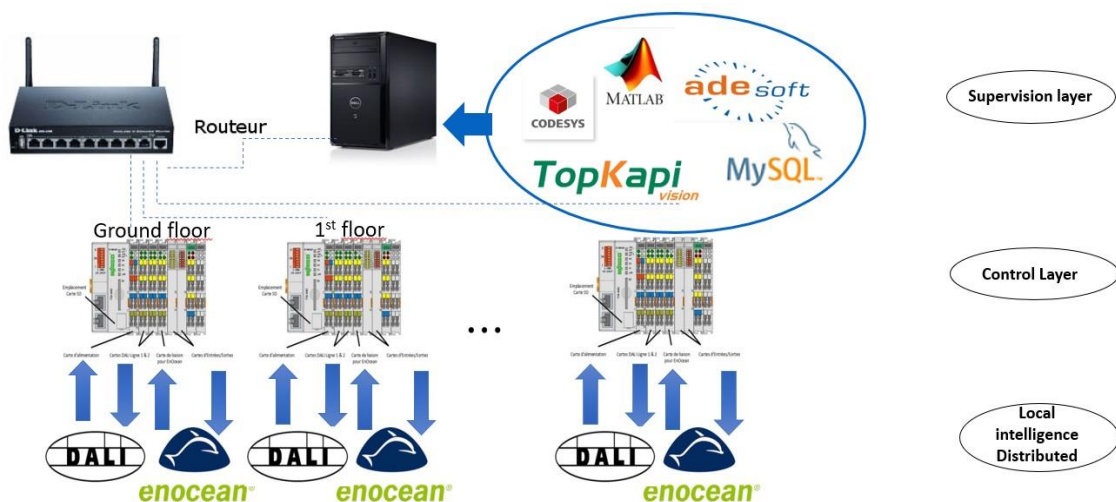


Figure 23. The supervision layer property and its connectivity to the control layer and local intelligence distributed in agent layer

In SL, TopKapi is the main application that is responsible for monitoring the SBEMS. On the other hand, in order to take user commands and do the actions on systems' parameters, Codesys is utilized. CodeSys software has powerful tools to not only program the PLC but also monitor some parts of the system and propose a user interface for receiving commands from the user and take action to control the system. The CodeSys has a user interface and it can be used in different types of displays. It also has a web-based variant which enables remote access, remote monitoring, and services and diagnosis of the system over the internet. [CodeSys (Visualization), n.d.].

Each layer of the proposed architecture is able to communicate with other layers in a two-way direction. It provides the user with high flexibility to monitor each individual parameter of the system and also command to set and act on a different part of the system. In the next section of this chapter, we are going to illustrate the ability of the system in monitoring and user awareness. The result in the next section is provided by SBEMS based on the contribution of SL, CL, AL, and PL in a two-way direction.

### 2.4. User awareness facilities and relating results provided by SBEMS

Each device (sensors and actuators, etc.) in the proposed system has an address that is defined on PLC. Topkapi by accessing each individual address of devices is able to read and translate the information to readable language for the user. TopKapi is also able to provide a graphical visualization of each space. It provides awareness about the user activity and working space's ambient state (namely temperature and lighting history) and the devices' operational states (namely lighting and/or heating elements' tuning history).

Figure 24, shows the graphical architecture of the whole five-floor building by Topkapi. In Figure 24, the visualize of the whole building is illustrated with time, date, and outdoor temperature which is captured by the outdoor temperature sensor and send wirelessly via the EnOcean technology to PLC.

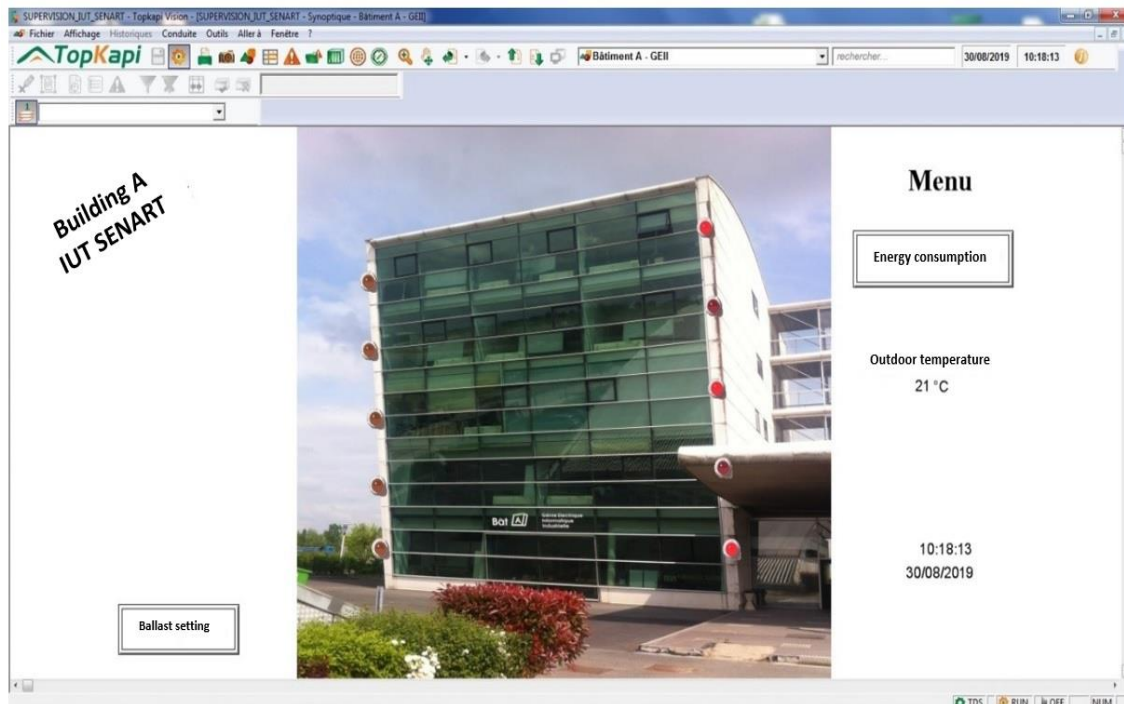


Figure 24. The graphical architecture of the five-floor building in TopKapi with date, time and outdoor temperature

Figure 25 presents one of the floors of the building. Within this figure, the temperature of each space can be monitored. Figure 26 shows on a smaller scale, one of the rooms within the location of all sensors, actuators, and their statements with necessary relating information to each one. It shows the state of each device individually in a room (the location of LISSI lab in campus SENART). For example, according to the proposed captions in Figure 27, the group of lighting elements in the bottom is on but on the top, it is off. Or the window in the bottom is open but in the top right, it is closed, and the statements of motor valve batteries show that the batteries are discharged. This information is providing by TopKapi.

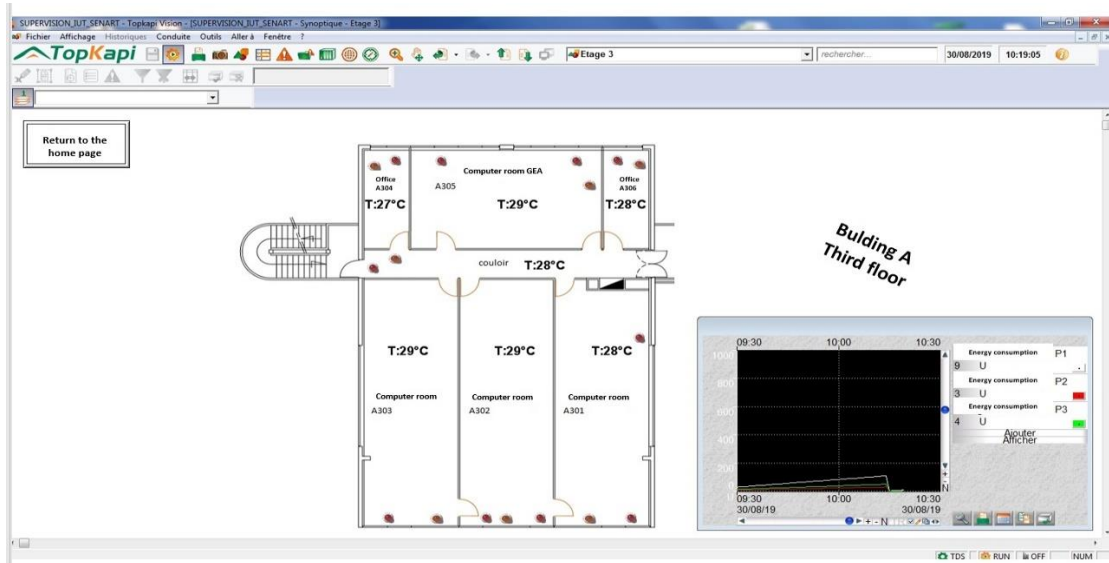


Figure 25. 3rd floor of the building with all necessary information (indoor temperature of each space, energy consumption, statement of motor valve's batteries)

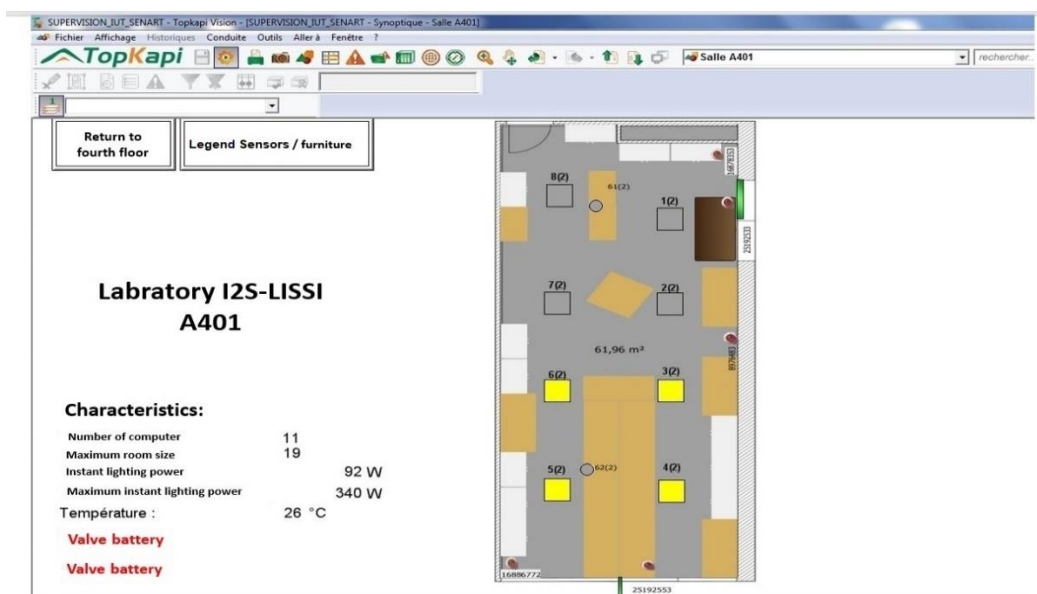


Figure 26. A classroom in 4th floor with all necessary information (state of windows, lights, motor valve's battery, Mac address of MS, MV)

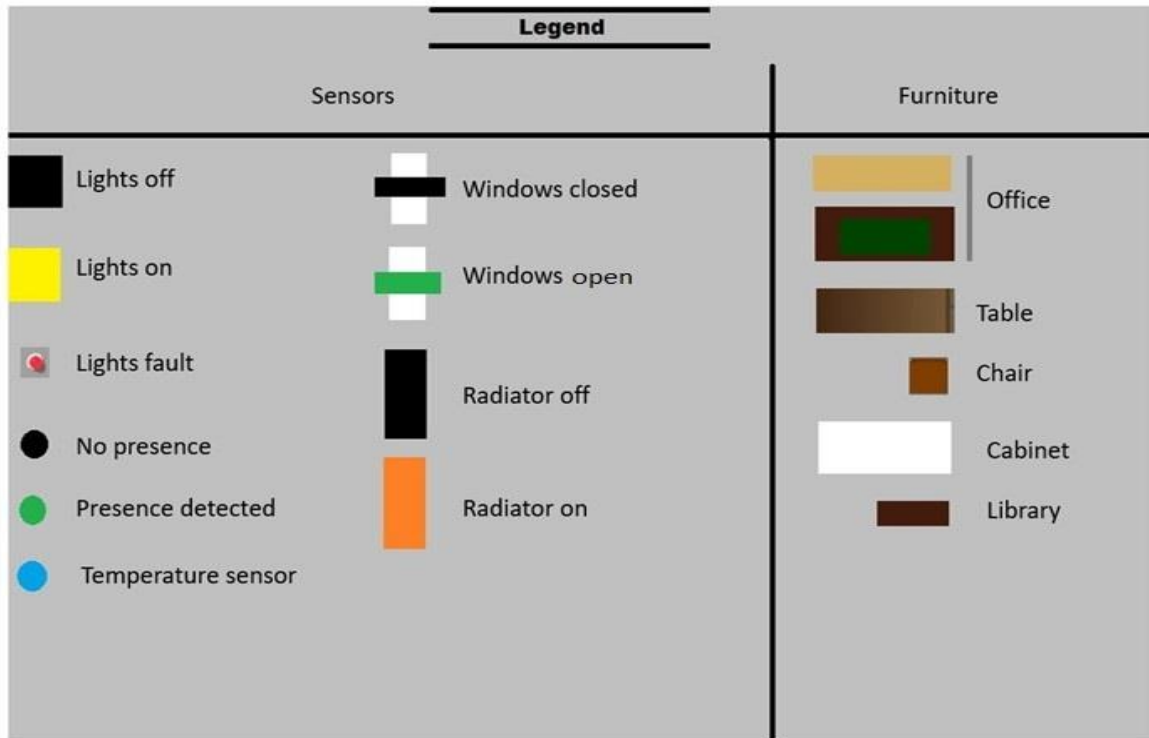


Figure 27. The caption of each element in the proposed architecture

Besides the visualization part of each floor provided by Topkapi, it is possible to monitor, the state of each device and ambient situation of the system on the board. TopKapi also can save the data of the board in each minute on a CSV file. Figure 28 shows the monitoring board relating to the 3<sup>rd</sup> floor. Each floor of the building has a board in TOPKAI. The boards provide the user, real-time data that the sensors and actuators in each space (rooms, corridors, etc.) are detecting or measuring:

1. The power of LE and their status (if they are on or off by PD),
2. The luminance measuring by LS,
3. Position of the radiator's Motor valves,
4. Status of the motor valve's batteries,
5. Indoor temperature, outdoor temperature,
6. Energy consumption of each floor and state of the windows (open/close).

TopKapi is a powerful software for monitoring and profiling the system however in parallel, Codesys provides information about different parts of SBEMS. The Codesys individually is a tool for controlling, monitoring, and also programming PLC. Figure 29 shows the user interface of CodeSys on a computer that is in charge of supervisory.

Room	Brightness(%)	Power On/Off	Mat	0	Fault	Fault	Non
301	0	OFF	DALI 1	OFF	DALI 1	Normal	DALI 1(2)
302	0	OFF	DALI 2	OFF	DALI 2	Normal	DALI 2(2)
303	0	OFF	DALI 3	OFF	DALI 3	Normal	DALI 3(2)
304	0	OFF	DALI 4	OFF	DALI 4	Normal	DALI 4(2)
305	0	OFF	DALI 5	OFF	DALI 5	Normal	DALI 5(2)
306	0	OFF	DALI 6	OFF	DALI 6	Normal	DALI 6(2)
307	0	OFF	DALI 7	OFF	DALI 7	Normal	DALI 7(2)
308	0	OFF	DALI 8	OFF	DALI 8	Normal	DALI 8(2)
309	0	OFF	DALI 9	OFF	DALI 9	Normal	DALI 9(2)
310	0	OFF	DALI 10	OFF	DALI 10	Normal	DALI 10(2)
311	0	OFF	DALI 11	OFF	DALI 11	Normal	DALI 11(2)
312	0	OFF	DALI 12	OFF	DALI 12	Normal	DALI 12(2)
313	0	OFF	DALI 13	OFF	DALI 13	Normal	DALI 13(2)
314	0	OFF	DALI 14	OFF	DALI 14	Normal	DALI 14(2)
315	0	OFF	DALI 15	OFF	DALI 15	Normal	DALI 15(2)
316	0	OFF	DALI 16	OFF	DALI 16	Normal	DALI 16(2)
317	0	OFF	DALI 17	OFF	DALI 17	Normal	DALI 17(2)
318	0	OFF	DALI 18	OFF	DALI 18	Normal	DALI 18(2)
319	0	OFF	DALI 19	OFF	DALI 19	Normal	DALI 19(2)
320	0	OFF	DALI 20	OFF	DALI 20	Normal	DALI 20(2)
321	0	OFF	DALI 21	OFF	DALI 21	Normal	DALI 21(2)
322	0	OFF	DALI 22	OFF	DALI 22	Normal	DALI 22(2)
323	0	OFF	DALI 23	OFF	DALI 23	Normal	DALI 23(2)
324	0	OFF	DALI 24	OFF	DALI 24	Normal	DALI 24(2)
325	0	OFF	DALI 25	OFF	DALI 25	Normal	DALI 25(2)
326	0	OFF	DALI 26	OFF	DALI 26	Normal	DALI 26(2)
327	0	OFF	DALI 27	OFF	DALI 27	Normal	DALI 27(2)
328	0	OFF	DALI 28	OFF	DALI 28	Normal	DALI 28(2)
329	0	OFF	DALI 29	OFF	DALI 29	Normal	DALI 29(2)
330	0	OFF	DALI 30	OFF	DALI 30	Normal	DALI 30(2)
331	0	OFF	DALI 31	OFF	DALI 31	Normal	DALI 31(2)
332	0	OFF	DALI 32	OFF	DALI 32	Normal	DALI 32(2)

Figure 28. Monitoring board of TopKapi

10:13
Main page

**Date**

Friday

30/08/2019

**T °C ext.**

+ Adding a sensor.

**Navigation**

DALI

Consumption

Derogation

Parametres

A201 T: 27.5 °C	A202 T: 28.1 °C	A203 T: 27.8 °C	A204 T: 24.5 °C
A205 T: 26.7 °C	A206 T: 25.9 °C	A207 T: 27.8 °C	A208 T: 27.5 °C
A209 T: 28.1 °C	Corridor T: 26.8 °C	Corridor1 T: 0.0 °C	

Window(s) open

Alarme : No

Figure 29. The user interface of CodeSys for 2nd floor

This figure shows the user interface of CodeSys relating to the 2<sup>nd</sup> floor. On the right panel, Each part illustrates the number of corresponding rooms with some information about them; like their indoor temperature and their occupancies. For example, room A201 is occupied because the PD detected the presence of a person and the temperature in this room is 27.5 °C. On the left side, the navigation bar helps the user to enter the part that would like to monitor or change the parameters (like temperature setpoint of



each space or Light intensity setpoint). Figure 30 to Figure 32 show other parts of CodeSys user interface.

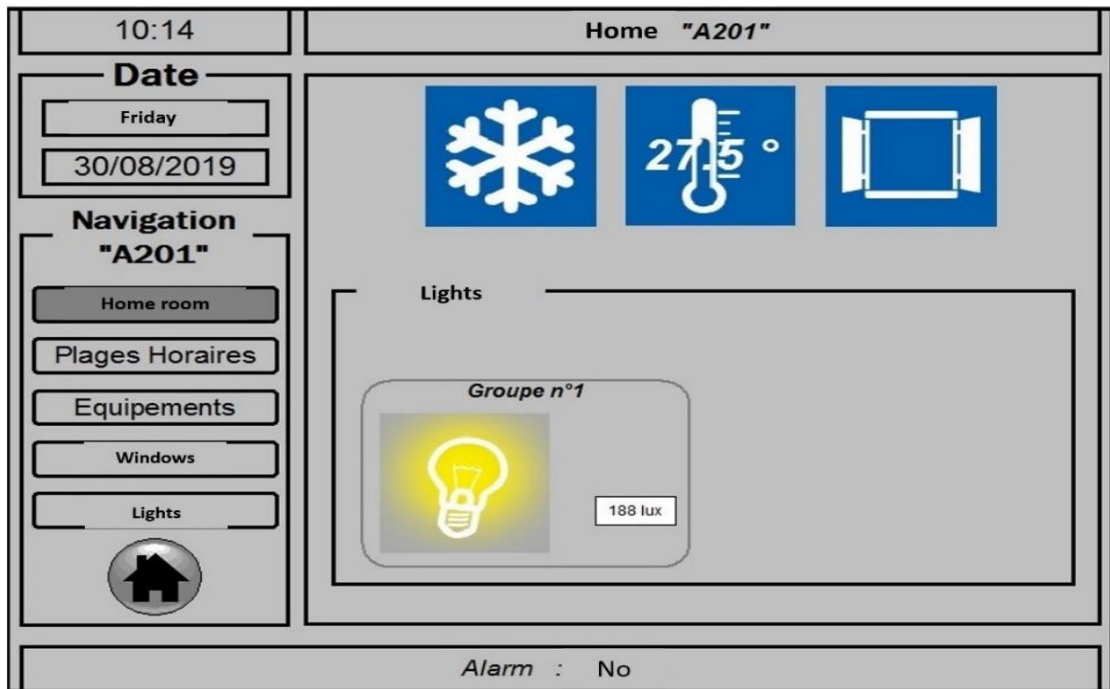


Figure 30. Ambient Statement of room A201 in CodeSys (illuminance, indoor temperature, window condition)

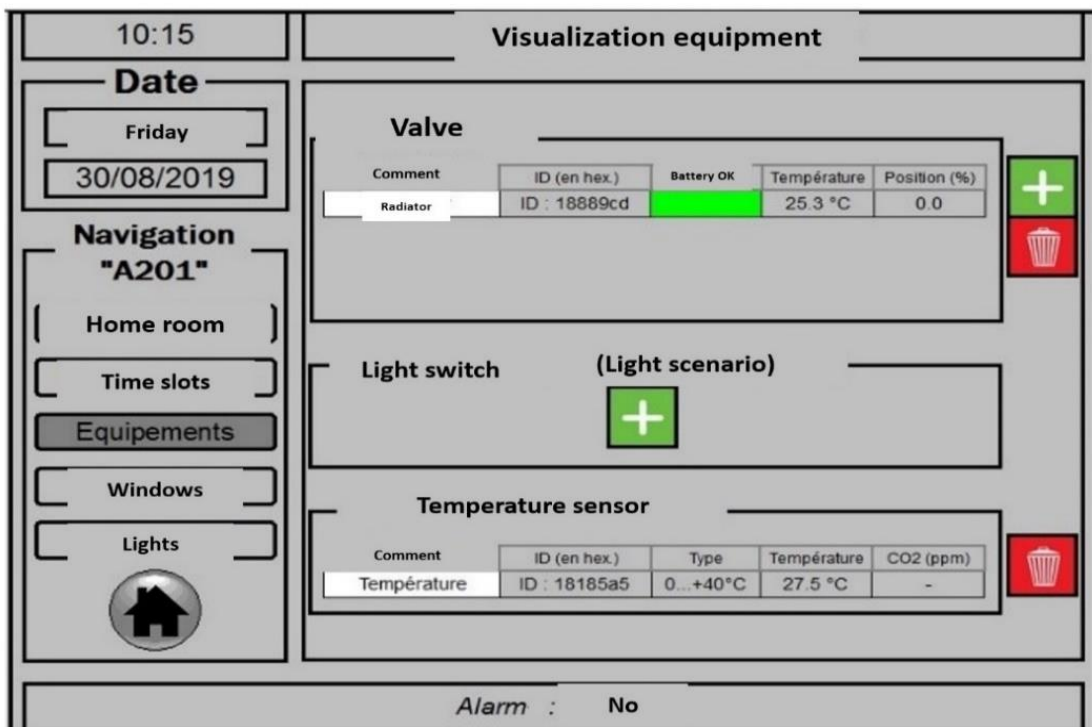


Figure 31. State of radiator temperature in room A201 (position of MV, Battery state of MV and temperature in room A201)

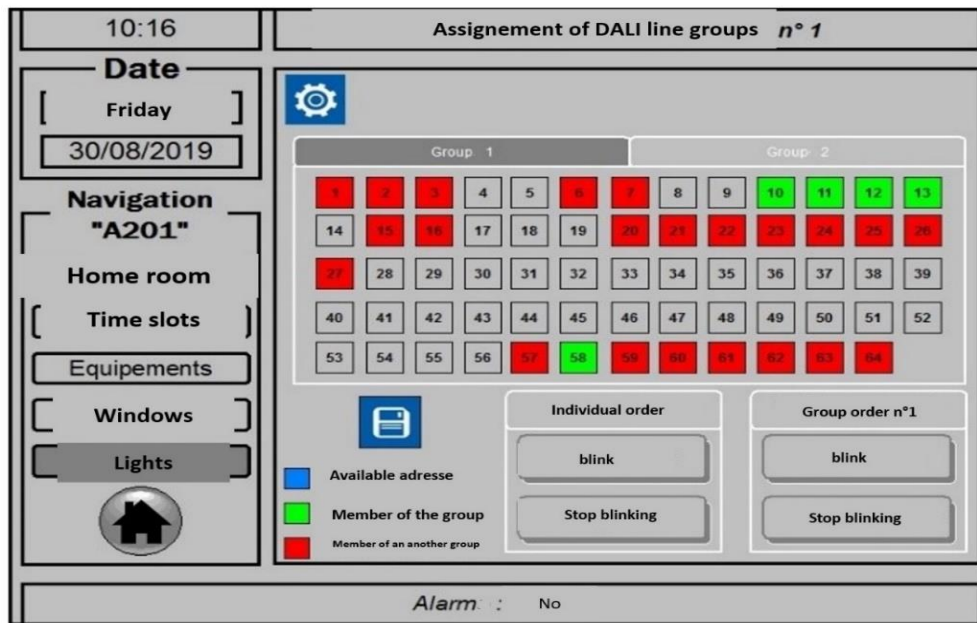


Figure 32. Statement of lighting devices (LE, PD, LS) in room A201

Concerning data collection by TopKapi and Codesys, an experiment has been done to see the ability of the system in data recording. The reported results have been obtained considering two working spaces of the experimental building. The first is a classroom (located on the 2<sup>nd</sup> floor) and the other is a programming-training practical room (located on the 3<sup>rd</sup> floor). Each working space has been monitored by the implemented system. The two sets of collected data for each space are RVS-1 and RVS-2. RVS-1 includes data resulting from 9 hours recording (i.e. from 7:00 AM to 4:00 PM) relating the concerned room's activities: occupation by 24 users from 8:00 AM to 12:30 PM, then unoccupied until 4:00 PM. RVS-2 includes 8 hours of data-recording (i.e. from 12:30 PM to 8:30 PM) relating the concerned room's activities: occupation by users from 1:30 AM to 5:30 PM, then unoccupied until 8:30 PM.

Figure 33 gives temperature changes profiles relating to RVS-1 and RVS-2 and Figure 34 gives the presence and absence information of users. As it could be seen from RVS-1 diagram (the left-side diagram), the room being unoccupied at 7:00 AM, the heating system regulates the temperature around 20°C (programmed heating conditions). 90 minutes later, the room is occupied by 24 users, and the ambient temperature rises reaching 24°C to 26°C. The outdoor temperature shows a continuous rising of external temperature during the day: from 9°C early in the morning to 20°C during the warmest hours of the day. It is pertinent to notice that the indoor temperature's relative Constance around 24°C (confirmed by the RVS-2 diagram, recorded on a different date and within different outdoor conditions) highlights the human activity and users' presence in the considered working spaces. It is also interesting to notice that the energy produced by users (i.e. human bodies occupying the considered space) may be used for decreasing the energy consumption if a smart and adequate control policy taking into account the human activity is applied.

## The architecture of a multi-layer system for SBEMS

Recorded Validation Samples (RVS)	Start Collecting Data	Start of Human Activities	End of Human Activities	End of Collecting Data
RVS-1	07:00 AM	08:00 AM	12:30 PM	4:00 PM
RVS-2	12:30 PM	1:30 PM	5:30 PM	8:30 PM

Table 3. Schedule of experiment

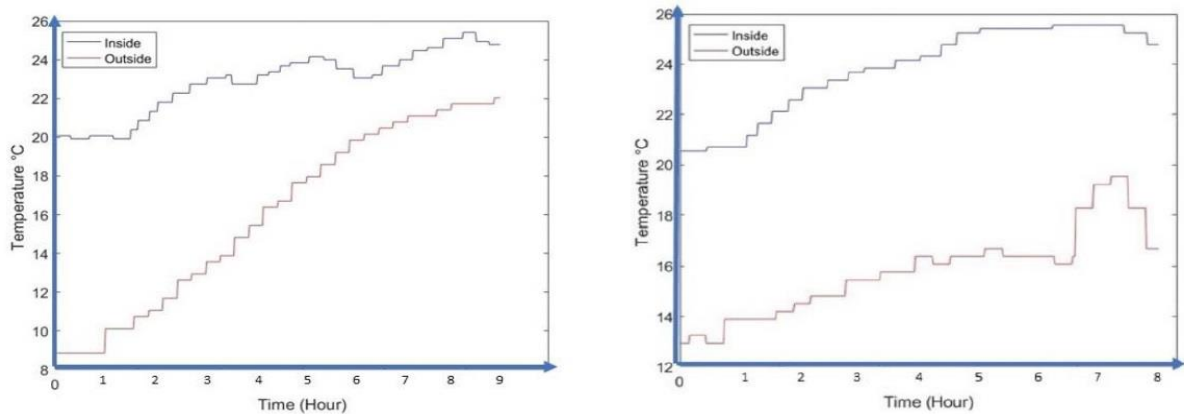


Figure 33. Temperature changing profiles relating RVS-1 (left-side diagram) and RVS-2 (right-side diagram)

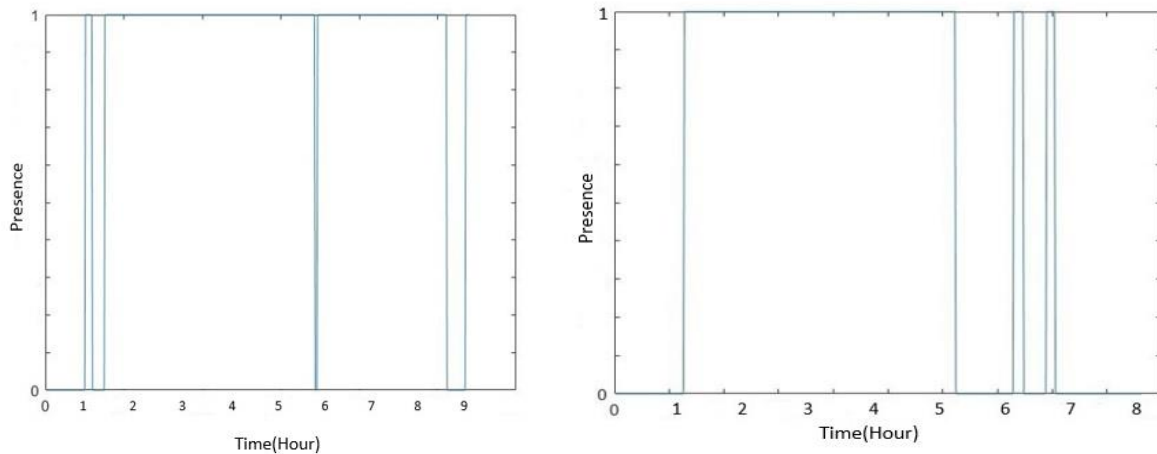


Figure 34. Presence and absence detection by presence detector relating to RVS-1 (left-side diagram) and RVS-2 (right-side diagram).

The system can record data for all other parameters of the system like the power of LE, Motor valves position with the same approach.

Topkapi and Codesys provide a user interface and the user can be aware of each part of SBEMS. The user by the Codesys can give a command to the system or set the parameters to its desires. In the case of user interfacing and monitoring, the proposed

SBEMS is highly flexible and can interact with plenty of other application that is accessible in the market.

### 2.5. Conclusion

In this chapter, we proposed a multi-layer SBEMS and its effective implementation in a five-floor building. The implemented SBEMS provides the user with:

1. A flexible software and hardware environment to modify or access to different parts of the system
2. Widely open to various other technologies and hardware
3. A powerful monitoring system and user awareness
4. A powerful user interface

We have shown the various providing facilities of the investigated system. The multi-layer organization of this architecture offers the issued SBEMS autonomy. It also provides plenty of technological options for the implementation of SBEMS.

Indeed, the wide range of technological options and choosing the proper ones in a flexible multi-layer architecture design lets to cover the shortage of reviewed SBEMS which is remarked in chapter 1. Wago PLC in the control layer within Enocean and DALI technology in the agent layer perfectly fits the demand for heating and lighting systems. The power of programming of Wago PLC with Codesys is a perfect example of software and hardware matching. Where on the one hand, the PLC is open to a wide range of communication protocols and standards technologies, and on the other hand Codesys proposes a high-level environment for programming and monitoring the system. The combination of these two with the TopKapi software in the supervision layer and proper technologies like Enocean and DALI standard in the agent layer is offering an extremely powerful and flexible SBEMS in a multi-layer architecture.

The ability of the system in data collection, along with the robust user interface that is providing by Topkapi and Codesys for user awareness plus controlling the SBEMS, and also open accessibility to a wide range of software and hardware is remarkable. Not only is it offering a powerful and flexible SBEMS but also a research platform that provides a great opportunity to develop the subsystems of SBEMS.

According to the mentioned ability of the proposed SBEMS, in the next chapter, We are going to show the integration of the lighting system in the architecture of SBEMS. In addition, It will show the aptitude of the proposed SBEMS toward dealing with the problem of lighting systems that we previously remarked in chapter 1. In the next chapters, the proposed SBEMS as a research platform will show its ability for implementation, evaluation, and validation of various approaches in this thesis.

## Chapter 3

### 3. Smart lighting system design for SBEMS

#### 3.1. Introduction

During recent decades, the cutback of energy consumption has become a popular and important topic, partly due to the ever-increasing care toward the environmental aspects and partly because of manifest limited energy resources. As mentioned in the general introduction, the lighting system as one of the most important subsystems of a SBEMS can play an imperative role in decreasing the total energy consumption in residential and commercial sectors.

Recent investigations relating lighting devices and accomplished progress in lighting technologies (as new LED-based lighting devices) led to an alluring reduction of lighting energy consumption. Based on EIA report, it is expected to reach 56 percent decreasing in light intensity by changing lighting standard and through efficiency enhancement of light-emitted diode (LED) bulb between 2017 and 2055 [Energy Information Administration 2018]. If the aforementioned progress and progressive replacement of conventional lighting devices by these less-energy-demanding devices offer appealing perspectives in decreasing lighting part of energy consumption, however, these solely endeavors wouldn't be enough to face the upcoming ever-increasing portion that lighting is supposed to occupy in future years.

During recent decades, smart building energy management systems (SBEMS) appeared as an alternative solution for reducing the overall energy consumption in modern buildings. If nowadays SBEMS contributes to the consequent decline of the modern buildings' overall energy consumption, most of the efforts relating to energy management and optimization in these systems have been oriented toward ventilation, heating, and cooling of the equipped buildings. However recently, growing attention and consideration seem to be devoted to lighting systems. As it is stated in section 1.5, lighting system designs are suffering from some shortages. They are not efficient in diverse condition of indoor environment, they are designing for specific places and it makes it hard to generalize them in different places. In this section of the thesis, we would like to introduce an approach to design an adaptive lighting system in order to obtain energy efficiency and visual satisfaction. It would cover the shortages that are mentioned earlier. The first step is to find an optimized number of lighting elements for each space on the basis of the Lumen method[Gardner 2002]. The second step is to design the best architecture for placing lighting elements in space by DIALux software and finally, integrate the lighting architecture with a smart lighting technology and evaluate the performance.

### 3.2. The proposed lighting system technology and relating architecture in the SBEMS

The lighting system is a part of the proposed SBEMS on campus SENART of UPEC. Concerning the lighting system, there is plenty of equipment: sensors and devices. According to the property and purpose of usage of each individual place (room), the number of lighting equipment would be different. The equipment of different places is Presence Detectors (PD), Luminance Sensors (LS), Lighting Elements (LE), EnOcean Rocker switches (RS).

The illumination in this building is providing by several lighting cells (what we call LE). Each lighting cell containing several Fluorescent–triphosphor. Every single fluorescent lamp is consuming 14-watt power. According to the number of lamps in each LE the relating consuming power is different. In our case, each LE contains 4 lamps. As a result, the power of every single LE by considering the control device is 61 watts (56-watts responsible for four lamps and 5 watts for electronic ballast). The luminous flux for each lighting element is 4800 Lumen.

DALI protocol is in charge for standardizing control of electronic ballasts in lighting applications. DALI/DSI Master Module (DALI control unit) within the WAGO-I/O-SYSTEM PLC combines whole the building's lighting with other building services on SBEMS, as it is stated in 2.3.1. Indeed, the lighting system is acting as a stand-alone subsystem with SBEMS. Figure 35 shows the connection of DALI area as a stand-alone subsystem to SBEMS.

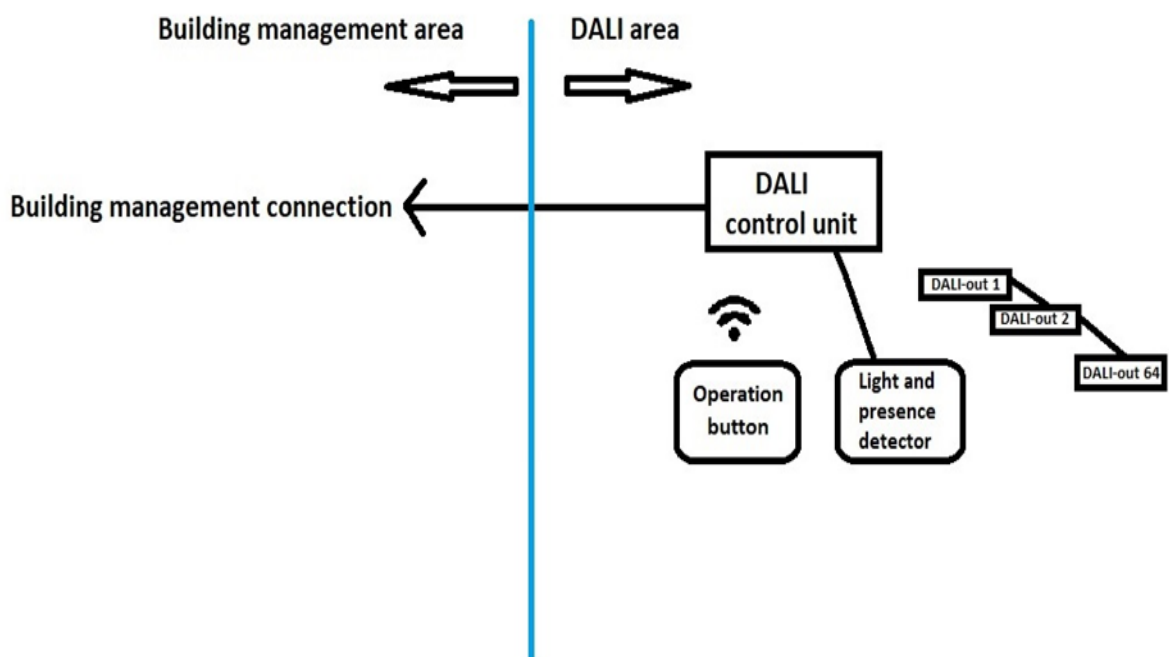


Figure 35. Connection of DALI as a standalone subsystem to SBEMS

The advantage of stand-alone subsystem architecture is the SBEMS can oversee the lighting system. Within this architecture firstly, PLC is able to modify and monitor the lighting system's parameters through DALI/DSI Master Module.. Secondly, in emergency cases where for instance, the SBEMS is facing a problem, the lighting system can operate independently from SBEMS as an individual subsystem. Figure 36 specifically shows the implementation of the lighting system in the multi-layer architecture of SBEMS. In the agent layer, DALI integrates its specific communication, sensors, and devices agents.

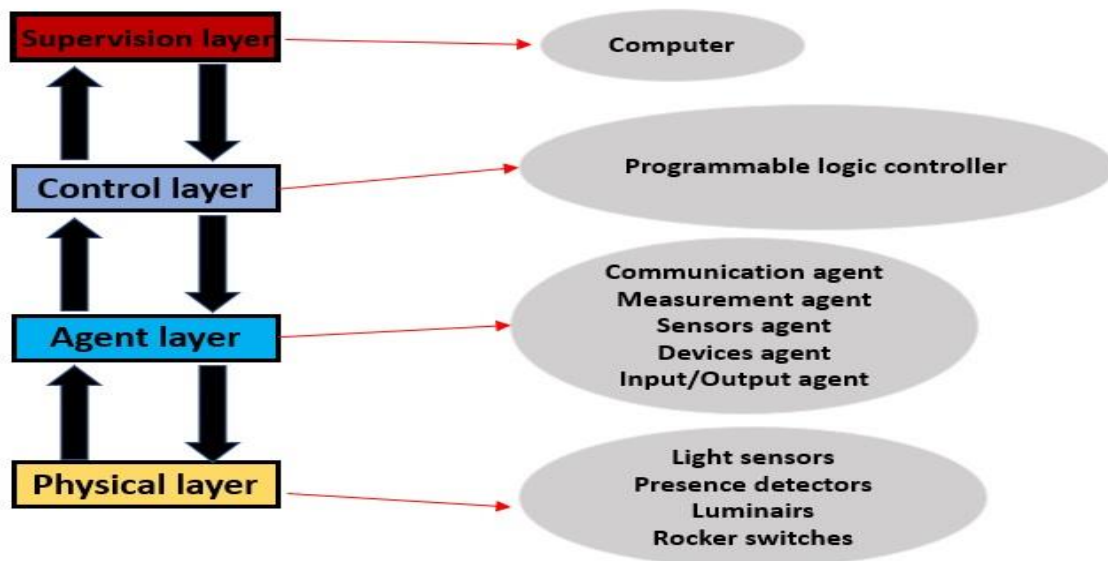


Figure 36. The implemented architecture of lighting system in SBEMS

The proposed architecture within DALI technology provides a flexible lighting system to users. One of the most indicators of this lighting system is adaptability. The intrinsic property of natural light is dynamic behavior. This dynamic behavior is relating to weather conditions, the reflection of the surrounding material, etc. As regards section 2.3.1 in chapter 2, DALI is a protocol for standardizing control of electronic ballasts in lighting applications. DALI/DSI Master Module can regulate the LE power and set the light intensity by electronic control gear, considering the detected luminance by LS. However, the placement and a suitable number of LE is playing an important role. It affects LE's dimming and consequently energy consumption and visual satisfaction.

The integration of good architecture design of LE with a proper technology is leading to an energy-efficient system while offering visual comfort and satisfaction to the user. Visual comfort means always providing the user with suitable light intensity on its working plane. In the following sections, we are going to introduce a method for finding an optimized number of LE for spaces and their placement architecture design.

### 3.3. The proposed method for designing lighting elements placement architecture

The proposed approach for designing of LE placement is based on the Lumen method and simulation facilities by DIALux [IESNA 2000]. DIALux is a software specialized in lighting. Within DIALux, engineers and also interior designers can design, calculate, and visualize light professionally. It is one of the top software in the lighting industry. It provides users to plan and design the lighting architecture using the electronic luminaire catalogs of the world's leading luminaire manufacturers. [DIAL 2016].

DIALux simulates the space with all possible conditions like weather conditions, different geographical locations, the architecture of concern building. Then according to the placement design of LE in the space, it provides the relating outcome and effect of LE placement design on the aforesaid space. However, the first step is to find the optimum number of LE. The appropriate number of LE is selected by the Lumen method. The lumen method by considering the needed light intensity on the working plane estimates the proper number of LE in spaces. According to the Lumen method, several factors should take into consideration in order to select the appropriate number of LE and satisfy the luminance desired target in space. Equation 1 presents the imperative factors concerning choosing LE (Equation (1)). [Gardner 2002]

$$N = \frac{E \times A}{L \times UF \times M} \quad (1)$$

Where:

N: Number of required LE

E: Luminance target

A: Area of the working plane (m<sup>2</sup>)

L: Luminous flux of each light

UF: Luminance utilization factor

M: Maintenance factor

The Luminance target (desired intensity of light) on the working plane is the first factor that should take into account for choosing the proper number of LE. It plays a crucial role in user comfort and satisfaction. According to the activity of users, the desired light intensity is different. Table 4 shows the standard of appropriate light intensity by considering various user activities [nao 2015].



Activity	Illumination (Lux)
Public area with dark surroundings	20-50
Simple orientation for short visits	50-100
Working areas where visual tasks are only occasionally performed	100-150
Warehouses, Home, Theaters, Archives	150
Easy office work, Classes	250
Normal Office work, PC work, Study Library, Groceries, Showrooms, Laboratories	500
Supermarkets, Mechanical workshops, Office landscapes	750
Normal drawing work, Detailed mechanical workshops, Operation theaters	1000
Detailed drawing work, Very detailed mechanical works	1500-2000
Performance of visual tasks of low contrast and very small size for prolonged periods of time	2000-5000
Performance of very prolonged and exacting visual tasks	5000-10000
Performance of very special visual tasks of extremely low contrast small size	10000-20000

*Table 4. The standard of appropriate light intensity by considering various user's activities (extracted from [nao 2015] and[Gardner 2002])*

The second most important factor for estimating LE numbers is the luminance utilization factor (UF). It is individually depending on four various parameters:

1. Room index
2. Room reflectance of wall
3. Room reflectance of floor
4. Room reflectance of ceil.

The room index is calculating based on several parameters. Equation (2) is illustrating relating parameters for the computing room index.

$$RI = \frac{W \times L}{H \times (W + L)} \quad (2)$$

Where:

RI: Room Index

W: width of the room

L: Length of the room

H: Height of luminaires above the horizontal working plane

According to room index and room reflectances of ceil, wall, and floor, the utilization factor can be specified, and finally based on the environmental condition of the space and relating maintenance factor, the number of LE in the space should calculate.

Room index	0.75	1.0	1.25	1.5	2.0	2.5	3.0	4.0	5.0
Room reflectances C W F									
70 – 50 – 20	0.36	0.42	0.47	0.51	0.56	0.60	0.63	0.66	0.69
30	0.31	0.36	0.42	0.46	0.52	0.56	0.59	0.63	0.66
10	0.27	0.32	0.37	0.41	0.47	0.52	0.55	0.60	0.63
50 – 50 – 50	0.33	0.38	0.43	0.46	0.51	0.54	0.57	0.60	0.62
30	0.29	0.34	0.38	0.42	0.51	0.51	0.53	0.57	0.59
10	0.25	0.30	0.35	0.38	0.44	0.48	0.50	0.54	0.57
30 – 50 – 30	0.31	0.35	0.39	0.42	0.46	0.49	0.51	0.54	0.57
30	0.27	0.31	0.35	0.38	0.43	0.46	0.48	0.52	0.54
10	0.23	0.28	0.32	0.35	0.40	0.44	0.46	0.50	0.52
0 - 0 - 0	0.20	0.24	0.28	0.30	0.34	0.37	0.39	0.42	0.44

*Table 5. Utilization factor (UF) according to reflectances (Ceil (C), Wall (W), Floor (F)) and room index (extracted from [Gardner 2002])*

Color or clarity	light	average	dark
Reflectance of wall	50% (0.5)	30% (0.3)	10% (0.1)
Reflectance of floor	70% (0.7)	50% (0.5)	20% (0.2)
Reflectance of ceil	70% (0.7)	50% (0.5)	20% (0.2)

*Table 6. Room reflectance: based on color or clarity of different parts of the room (extracted from [Gardner 2002])*

Environmental condition	Maintenance factor
Clean	0.9
Average	0.8
Dirty	0.7

Table 7. Maintenance factor: based on the different conditions of the environment (extracted from [Gardner 2002])

The SENART campus of UPEC is containing classrooms and offices. By considering this fact, according to Table 4, the needed luminance target on the working planes should be between 250 to 500 LUX.

The test case (space) that we are focusing on is one of the offices of the SENART campus of UPEC. It is the office of LISSI lab in this building. The dimension of the room is 4.5×12.6×3 (Width×Length×Height). The working plane according to the table height is 80CM. It means the height from the lighting element to the working plane is 220CM. In order to find N, first of all, the luminance target and room index (RI) should be specified. The luminance target is chosen 300 lux which is in the range of needed light intensity for offices and classrooms. The room index of LISSI lab is equal to 1.5 based on Equation (2). At this stage, based on room index and room reflectances (Table 6), the utilization factor of the test case can choose from Table 5. The room reflectance respectively for ceil, walls, and floor are 70, 50, and 20. As a consequence, the utilization factor is equal to 0.51. The maintenance factor is chosen as average (0.8) (Table 7). Considering the Equation (1) N for the LISSI lab that is our test case is 8.6. According to this result, the number of LE can be selected 8 or 9. If 9 is chosen, the light intensity would be higher than the luminance target and in the case of 8, it may be a bit lower than the luminance target. However, according to Table 4 that shows the recommended range (250-500), 8 number of LE is also acceptable. As another example, if the light intensity was a high value (a value between 400-500) like 420 lux, then according to the lumen method N is equal to 12.1 and as it is aforementioned for 8 LE, in this case, 12 LE is acceptable too.

In order to determine if the results of the Lumen method and LE quality is energy efficient or not, the result should meet “Chartered Institution of Building Services Engineers” (CIBSE) code target for “average installed power density” (AIPD). It is quoted in terms of  $W/m^2$  for a range of situations and illuminances [Gardner 2002]. The following equation and table show the target values of CIBSE for fluorescent troposphere lamps in commercial buildings.

$$AIPD = \frac{P_L \times N}{A} \tag{3}$$

Where:

$P_L$  is the total power of luminaires (Watt)

N is number of luminaires;

And A is the dimension of the area of the space ( $m^2$ )

Lamp type	Luminance (LUX)	Average installed power density (W/m <sup>2</sup> )
Fluorescent – triphosphor	300	7
Fluorescent - triphosphor	500	11
Fluorescent - triphosphor	700	17

Table 8. Chartered Institution of Building Services Engineers (CIBSE) code target for average installed power density (extracted from [Gardner 2002]).

Considering this fact and regarding 8 and 12 numbers of LE for the test case with different light intensity, the average installed power densities are equal to 8.6 and 12.9 respectively. It means for the test case, 8 number of LE is more matching according to the CIBSE code target, because the installed power density for 12 LE is a bit higher than the CIBSE code target in comparison with 8. The result of CIBSE code target also confirms the preference of 8 and 12 LE to 9 and 13 LE respectively, as discussed earlier in this section. In case the installed power density was so higher than the CIBSE code target, the LE should replace it with more efficient ones or find another solution to improve efficiency.

In accordance with the Lumen method, the number of LE for the test case was calculated for two different light intensities and it shows 8 number of LE is more proper in order to have visual satisfaction and also an efficient system based on the CIBSE code target. The proposed approach by the Lumen method is reliable. Due to several involved factors for calculating the number of LE and also the final test of CIBSE code target. However, the placement design of the LE in the space is still questionable. It can enhance the performance of the lighting system. In the next section, as mentioned above, the role of DIALux software for the optimized placing of the LE will be remarked.

### 3.4. Case study: Example of LE placement design simulation and first evaluation

The placement of LE in each space can play an imperative role in many aspects. It can provide the user visual comfort, and besides decreasing the consumption of electricity. Concerning this fact, we are going to find the appropriate architecture of lighting placement by defining and simulating different scenarios in DIALux software for the test case in the previous section. The purpose of this step is to analyze and discover the best fit of architecture for LE placement. Figure 37 and Figure 38 present the LISSI lab and the table that researchers work behind in DIALux in 3D and 2D respectively. To begin the simulation, several parameters regarding the architecture of the room (size, windows, etc.), the geographical situation of the place (location, time, etc.) should set.

The DIALux software automatically can provide the design of LE placement based on user-defined parameters mentioned earlier. However in order to test several LE placement design and find the best fit several simulations has been done.

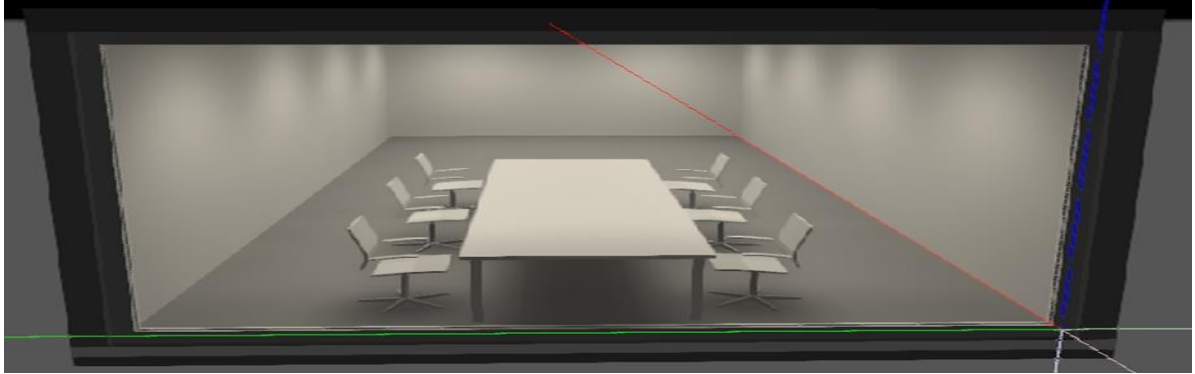


Figure 37. Simulation of LISSI lab in 3D by DIALux

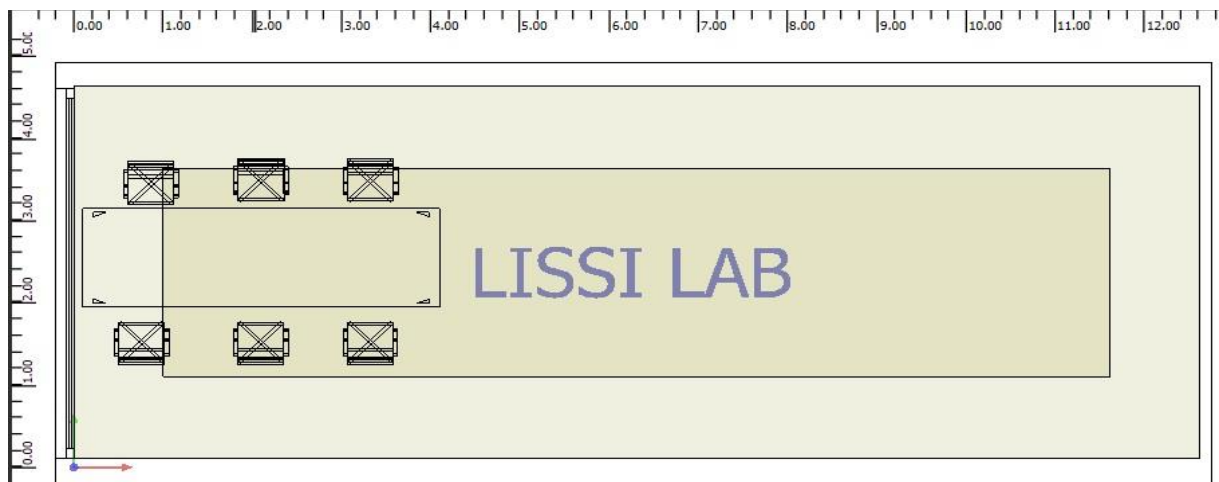


Figure 38. LISSI lab architecture and relating dimension in 2D by DIALux

Considering the lumen method results, the appropriate number of LE is 8 in order to meet the desired light intensity (300 lux) and 12 to obtain 420 lux light intensity on working planes. Respecting this approach, several simulations with different light intensity target and different LE placement architecture is run:

1. Parallel architecture simulation with 12 LE
2. Line architecture simulation with 8 LE
3. Parallel architecture simulation with 8 LE

Figure 39 shows the architecture design of LE while the target of light intensity is chosen 420 lux (the recommended design architecture by DIALux is also a parallel architecture with 12 LE). The width and length of the room are divided into three equal rows and 4 equal columns, center to center, respectively for placing LE. It is evident in different

parts of the room, the intensity of the light is different however DIALux proposed the average light intensity in the room. According to the report of simulation that is proposed by the software, the average intensity of light is 518 lux. This value is more than the maximum desired target (luminance target in office rooms). It should also be re-noted 12 LE can not respect the CIBSE code target.

It should be noted the aforesaid result is in the case where the effect of outdoor light is not considered in the simulation.

In the second simulation, a line architecture is designed according to the computation of section 3.3 (8 LE for 350 light intensity). Figure 40 shows the effect of line architecture on a different part of the space.

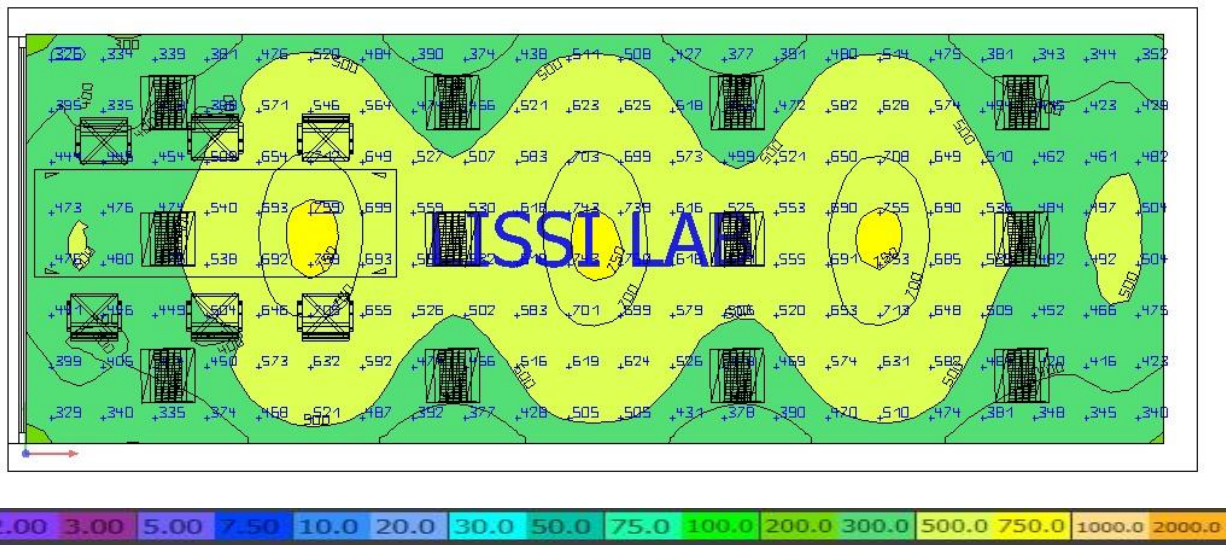


Figure 39. The parallel architecture with 12 LE without considering outdoor light. (the bar illustrates the light intensity in colors and in LUX)

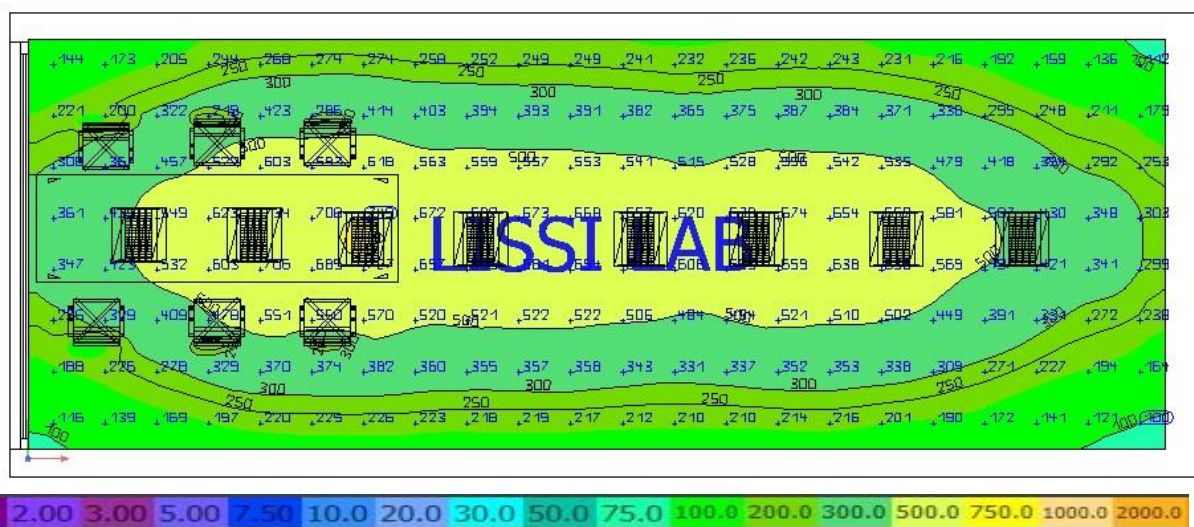


Figure 40. The line architecture with eight lighting elements without considering outdoor light. (the bar illustrates the light intensity in colors and in LUX)

The reported result by software shows the average light intensity is 393 lux which higher than desired light intensity. The figure shows the focus of light intensity in the center of the space (the first circle) is high although suddenly the intensity of light is dropped by 150 to 200 lux in the second circle in comparison with the central circle and third circle in comparison with the second circle. Indeed the light scattering in the line architecture is not appropriate in a different part of the space. Regarding the 12LE parallel architecture by DIALux for 420 lux light intensity target, the light scattering in parallel represent better performance. Due to this fact by replacing the line architecture with parallel architecture, another simulation is done. The width of the room is divided into two equal rows and the length of that is divided into 4 equal columns for placing the LE. Figure 41 illustrates the result of the parallel architecture simulation. It should be noted the recommended architecture by DIALux while the light intensity target is set at 300 lux is the same (parallel architecture with 8 LE).

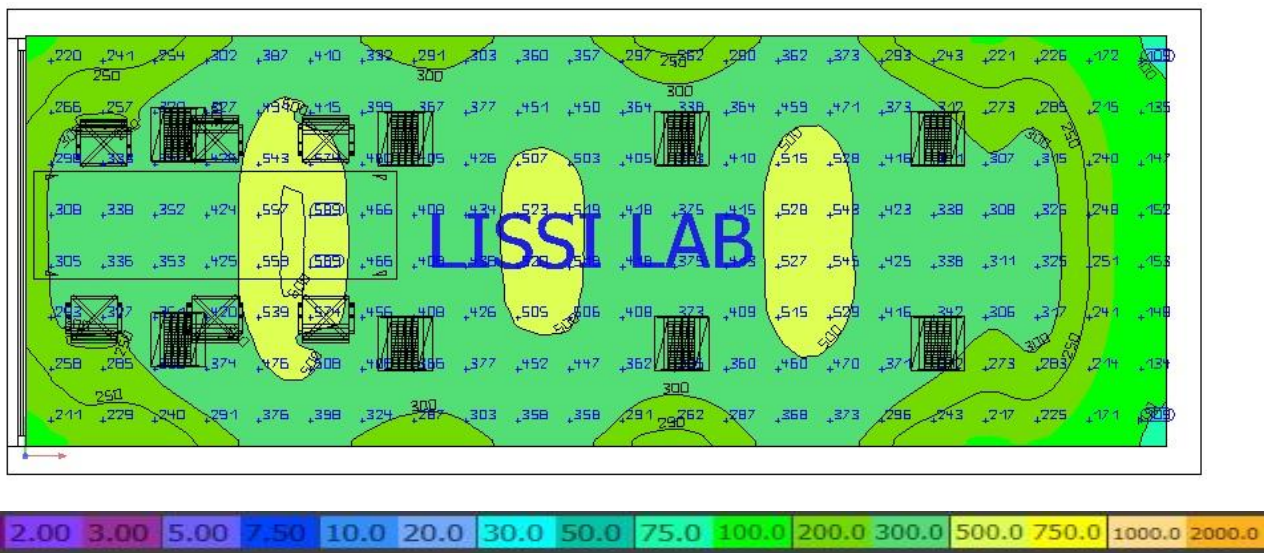


Figure 41. The parallel architecture with eight lighting elements without considering outdoor light. (the bar illustrates the light intensity in colors and in LUX)

In the aforementioned design, the average light intensity is 361 lux. The result shows the light intensity is in the range of desired light intensity target for offices (250lux to 500lux) and higher than the desired light intensity that is chosen for simulation (300 lux). The light scattering in comparison with line architecture shows much better performance.

The previous simulations as mentioned earlier was in cases that the outdoor light was not considered. However, among them, the parallel architecture with 8 LE illustrates a more satisfying environment and average light satisfaction while respecting the CIBSE code target. In order to have a better perspective of different proposed architectures, the next simulations are done where the outdoor light is affecting the space during the simulations. The time of the simulation is at noon. The simulations for the proposed architectures are run in various outdoor lights. Figure 42 is a sample of aforesaid

simulations. It shows how average daylight can affect light intensity in parallel architecture with 8 LE (while LE is working in nominal power). Table 9 shows the result of simulation in average daylight and overcast daylight where the power of LE was adjusting from 0 to 100% of the nominal power.

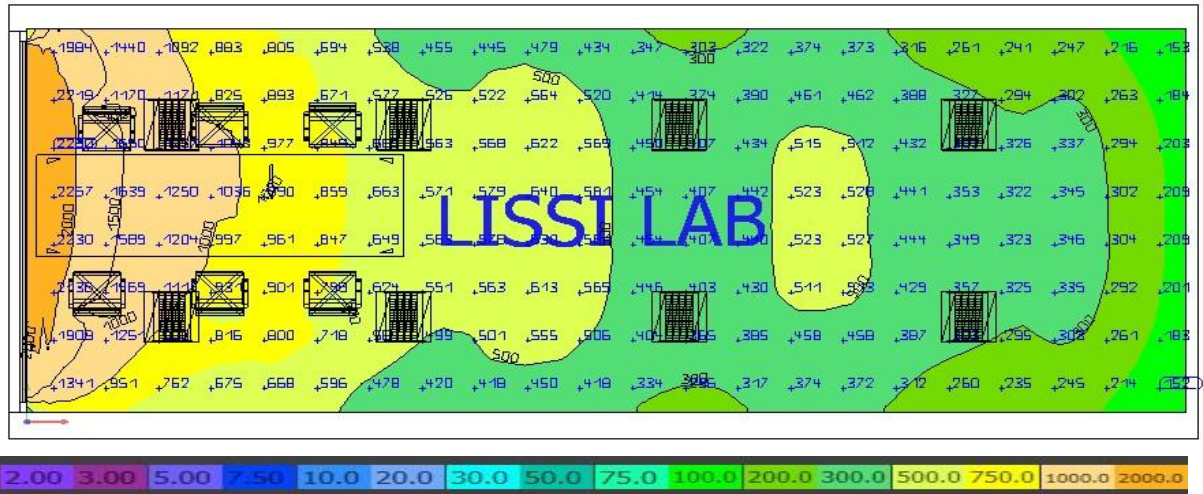


Figure 42. The parallel architecture with eight lighting elements (while they are working in nominal power) and considering outdoor light. (the bar illustrates the light intensity in colors and in LUX)

Power (%)	Luminance in Average daylight (LUX)			Luminance in Overcast daylight (LUX)		
	Parallel-8 LE	Parallel-12 LE	Line	Parallel-8 LE	Parallel-12 LE	Line
100	620	779	651	563	723	594
90	584	727	612	527	671	555
80	548	676	573	491	619	516
70	512	624	534	456	567	477
60	477	572	495	420	515	438
50	441	520	456	384	464	399
40	405	468	417	348	412	360
30	369	417	378	312	360	322
20	333	365	339	276	308	283
10	297	313	300	241	256	244
0	261	261	261	205	205	205

Table 9. Luminance in overcast and average daylight in different power of lighting elements and different architectures (parallel architecture with 8 LE, Parallel architecture with 12 LE, and Line architecture)



The average intensity of light for all the cases, while the LE are working in nominal power, is more than 500 lux. It shows during the day, LE should work in lower powers. In case of average daylight and parallel architecture with 8 LE, the LE can work between 0 to 70% of the nominal power in order to meet the demand of luminance target for various type of offices (range of 250 to 500lux for offices), while respectively for line architecture and parallel architecture with 12 LE the range of LE dimming can be 0 to 70% and 0 to 50% of nominal power. Also in overcast daylight, the range of dimming for line architecture and parallel architecture with 8 LE should be respectively between 20 to 80% and 20 to 90% of the nominal power and considering the parallel architecture with 12 LE, this range should be between 10 to 60% of the nominal power to meet the demand of luminance target.

In both cases (average daylight and overcast daylight) the dimming range for line architecture and parallel architecture with 8 LE almost is the same in each case. However, it should be noted again, the scattering of luminance in the line architecture in comparison with parallel architecture with 8 LE is not satisfying. Also according to the Lumen method and CIBSE code target, the appropriate number of LE for the test case is 8. It shows the parallel architecture with 8 LE has advantages over the parallel architecture with 12 LE. It has to be re-noted the parallel architecture with 12 LE in case of no daylight has the average light intensity more the range of 250 to 500 lux. It re-confirms this number of LE is not suiting for the aforesaid test case.

To sum it up, the result of simulations regarding parallel architecture with 8 LE in the case study shows its advantages over other architectures. It indicates in case of no daylight, visual satisfaction is achieved while LE work in nominal power, and in case that there is daylight, the light intensities almost in all cases that LE power is more than 20 are more than desire. The functionalities of DALI technology for controlling the diming of LE in different lighting conditions in spaces can perfectly fit the presented lighting placement architecture design in order to save energy. According to this fact, the LE is divided into two groups of DALI (each group contains four LE) in the aforesaid case study. Two PD and LD is responsible for controlling each group of LE in the abovementioned case study in order to bring visual satisfaction harmonization and also an energy-efficient lighting environment in diverse lighting conditions.

In the next section, first of all, we are going to validate the simulation, and second of all by validating the approach on the real building, the effectiveness and performance of lighting placement architecture design along with DALI technology will be remarked and the results will evaluate.

### **3.5. Validations, results, and evaluation**

#### **3.5.1. Validation of simulation**

Before validating the proposed approach for designing the whole system, it is necessary to validate the simulation and give a basis of elaboration versus reality. Due to this fact,

an experimental protocol is considered. The experimental protocol has been performed on the basis of an experimental evaluation involving an “office room” of the target building (i.e. Building A) of the Campus de Senart. It is a small office on the ground floor of building A. The height of this room is 3 meters, the width 3.5 meters and its length is 6 meters. The considered room is equipped with two lighting elements, one PD and one LS. According to the proposed architecture of the SBEMS in section 2.4, the LE can be controlled through PLC. We are going to do some experimentation in this office: In simulation and reality in order to obtain the characteristic of LE in both cases. Thereafter, according to the obtained characteristic of LE, we can compare the results in order to validate the simulation.

We suppose to study the effect of height on light intensity on the working plane. Consequently, three different working planes with three different heights are considered. Their heights are respectively 230cm, 140cm, and 100cm to the ceil. Regarding aforesaid protocol, to obtain the characteristic of each LE, the effect of daylight is omitted and only one of the LE is supposed to work. Due to that, all doors and all windows are covering. Figure 43 shows the 2D architecture of the office room.

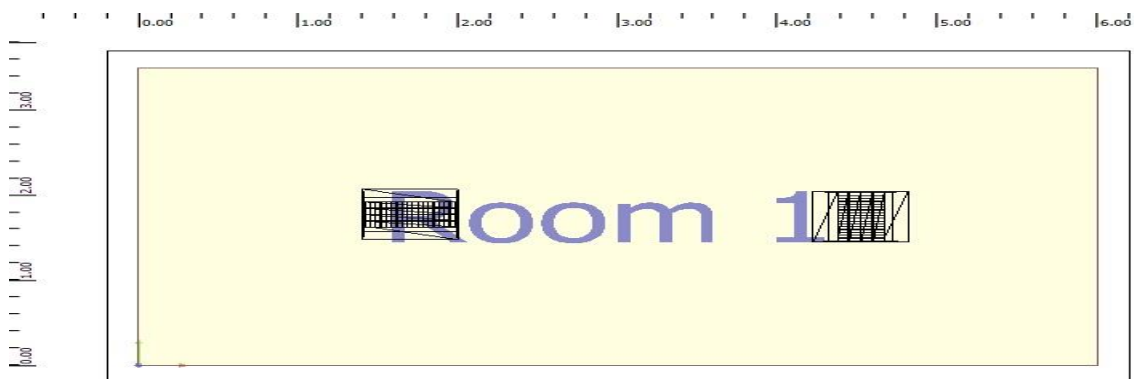


Figure 43. The architecture of lighting places and the dimension of the office room in 2D

Concerning the experiment, in reality, the LE power gradually increased from 0 to 100. On each step, by utilizing LUX meter the luminance is recorded exactly under the LE on the working plane for three different aforementioned heights. Table 10, Figure 44, and Figure 45 illustrate the recording data and results concerning the experimentation in reality.

Table 10 reveals the increment and decrement of LE’s power are leading to light intensity rising and falling on the working plane respectively. This fact is in opposition to the distance of LE to the working plane and relating light intensity. To be more clear, the light intensity on a surface is a function of height and LE’s power. it has a direct relation to the power of LE’s and opposite relation to height. Figure 44 shows the relation between luminance on the working plane and power of LE regarding three different heights (the distance of working plane to the ceil). Figure 45 evident the

relation between height and luminance on the working plane when LE are working in 100 percent of their powers.

$$L = f(H, P)$$

↑ Power → ↑ Luminance

↑ Height → ↓ Luminance

Where L is luminance, H is the height of LE from the working plane and P is the power of LE.

Height (CM)	230	140	100
Power (%)	Luminance1 (LUX)	Luminance2 (LUX)	Luminance3 (LUX)
10	20	50	100
20	40	98	205
30	60	143	330
40	80	193	440
50	108	240	500
60	120	270	600
70	150	340	740
80	170	370	820
90	185	405	905
100	207	445	995

Table 10. The relation between the power of lights- height and luminance

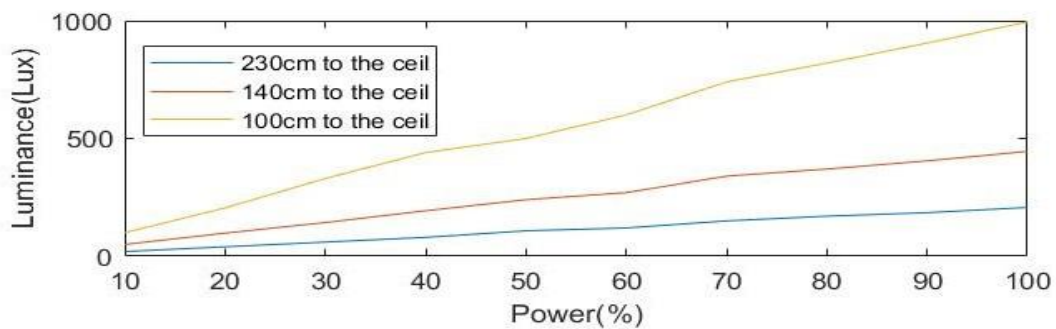


Figure 44. The relation between luminance and power of LE in three different height to the ceil (yellow's height=100 centimeters, red' height =150 centimeters, and blue's height=230 centimeters).

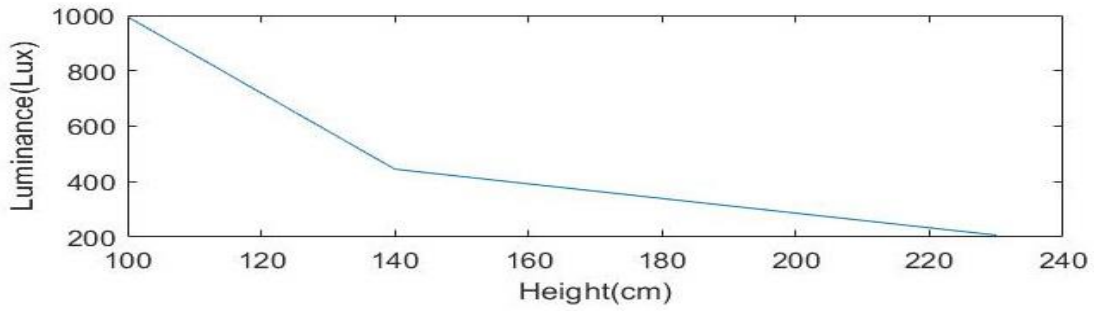


Figure 45. The relation between height and luminance when the power of lamps is in 100 percentage

With the same approach, the experimentation in reality is simulated in DIALux. Figure 46 shows a sample of the simulation results when the height is 140 centimeters, while the power of LE is set in 100% (nominal power). It supposed there is no daylight, like reality experimentation. Finally, Table 11 shows the result of simulation and reality while the LE is working in nominal power in three different distances between the working plane and LE.

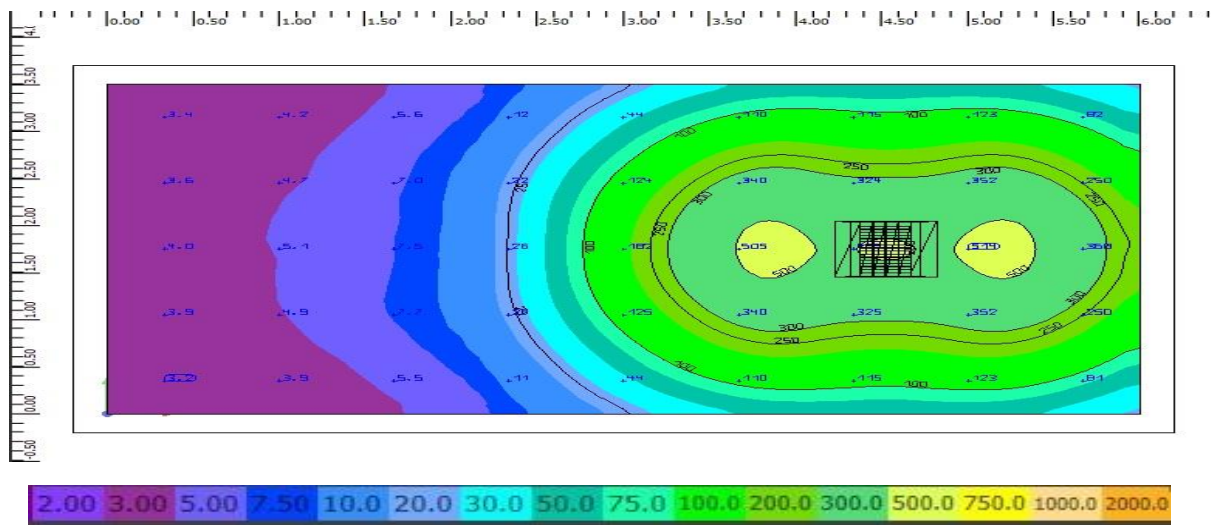


Figure 46. The result of simulation when LE works in nominal power (100%) and the working plane height is 140 centimeters to ceil (each number in this figure represents the intensity of light in LUX in that area). (the bar illustrates the light intensity in colors and in LUX)

HEIGHT (CM)	230	140	100
Luminance in reality (LUX)	207	445	995
Luminance in SIM (LUX)	200	499	946

Table 11. The relation between working plane distance to ceil and luminance in simulation and experimentation where the LE working in nominal power in three different height to the ceil

In this section, an experiment has been done according to the mentioned protocol. The objective of the protocol was to obtain the characteristic of individual LE in simulation and reality. Finally, the result of simulation and reality based on the obtained characteristic of LE is compared in order to validate simulation results. The validation of the simulation result will lead to the generalization of the proposed approach of the lighting placement architecture design in a real building. Due to this fact, by considering three different heights between LE and the working plane, the light intensity on the working plane is obtained and the characteristic of LE is illustrated with simulation and reality. In both cases, the obtained results regarding the light intensity on the working plane follow the same approach: By increasing the height of LE to the working plane, the intensity of light is declining and, by decreasing the height it is increasing. Regarding the effect of LE's power, falling of power leads to declining of light intensity, and rising of power leads to increasing of light intensity on the working plane. The small differences between simulation and experimentation are an interesting part of the result that is illustrated in Table 11. It shows the result of the simulation is reliable regarding the LE placement architecture design. The proposed protocol for finding the characteristic of LE in simulation and reality was effective. It clearly addressed the differences between reality and simulation and represented a basis for evaluating and validating the simulation. Due to this fact, in the next section, we are aiming to explain a protocol regarding the validation of the proposed approach on campus SENART of UPEC. We are going to introduce the protocol and step by step to evaluate the relating results.

### **3.5.2. Results, validation, and evaluation of the proposed lighting system on building A of UPEC SENART campus**

In the last section, the reliability of the proposed approach by validating the simulation was presented. In this section, we are aiming to represent a protocol for validation and evaluation of the proposed method on building A. Building A of SENART campus is including several offices and classrooms. The size of each room is different. In addition, because of the equipment and properties of each space (i.e. color of walls, ceiling, and floor, etc.), the parameters regarding calculating the number of LE by the Lumen method and placement design of LE by DIALux are different. As a consequence, for validation and evaluation of approach, we are facing a sophisticated system with different properties. Due to the powerful monitoring system of SBEMS, we are able to record and store the data relating to the power of LE and the luminance of each space. It lets to analyze the operation of each individual space in building A. Regarding this fact, we are going to define protocols and study the approach from different perspectives: Adaptability of the system in different conditions of space, energy efficiency, and user comfortability.

3.5.2.1. The adaptability of the proposed lighting system

For evaluating the adaptiveness of the proposed lighting system in different conditions, we are going to analyze the relating recorded data of one of the classrooms during an experiment. The recording data is relating to LS and PD in a classroom on a third floor during 8 hours. It is recorded between 12:30 PM to 8:30 PM. From 13:30 to 17:30 there were human activities.

As Figure 47 illustrates bypassing the time the lighting is increased and then decreased, it is because of the fluctuation of daylight. It shows LS which is closed to windows catches more light in comparison with the one far from windows. Due to this fact, the power of LE for groups of lighting closed to the windows is less than the one far from the windows. Figure 48 shows the power of LE during this period.

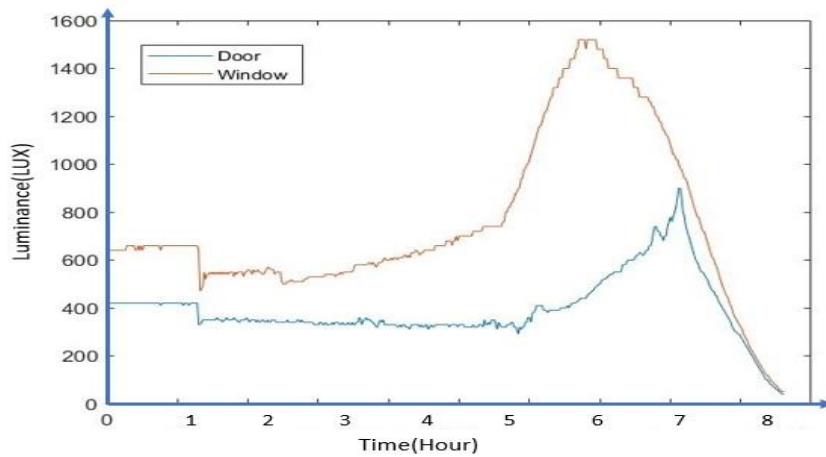


Figure 47. The detected luminance by LSs during 8 hours (from 12:30 PM to 8:30 PM) for two groups of lighting (One group close to the windows (red), one group close to the door (blue))

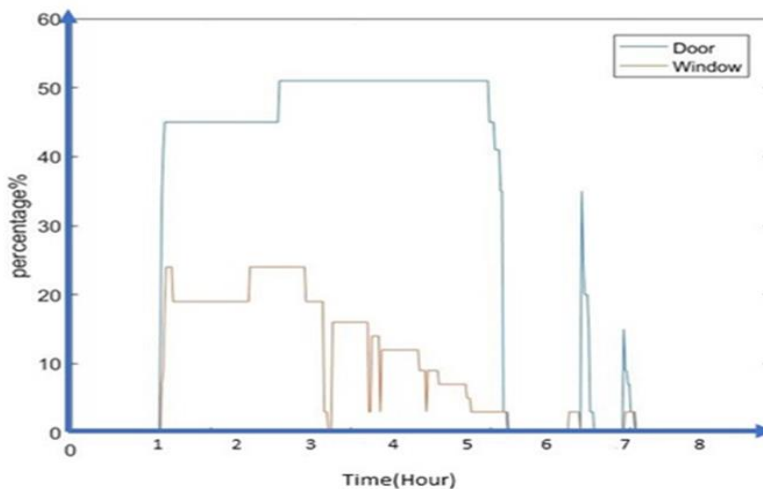


Figure 48. The power of lighting elements during 8 hours (12:30 PM to 8:30 PM) for two groups of lighting (one group close to the windows (red), one group close to the door (blue))

DALI as a lighting technology shows its powerful functionalities in case of lighting control of the LE in different conditions. The control functionality of DALI regarding the regulating of LE by DALI/DSI Master Module is activating when the PD detects the presence of the user. According to provided luminance data by LS, LE is regulated (dimming). The LE during the aforesaid experimentation according to different outdoor light is regulated perfectly in order to keep the indoor luminance in the range of luminance target. The proposed lighting system that lets to control LE adaptively, alongside the architecture design of LE leads to user visual comfort as it provides the proper luminance on the working plane with a good light scattering. However, in order to obtain the benefit of the aforesaid adaptability functions in case of energy saving in the next section we are going to present a protocol for evaluating the energy-saving power of the proposed system.

### 3.5.2.2. The energy efficiency of the proposed lighting system

Regarding evaluating the energy saving of the system, 9 different spaces with different sizes and properties are chosen. These spaces are including classrooms and offices with medium size, large size, and small sizes. The data collocation has been done at various times of days in different months of the year, randomly. In each case, three hours of the data is picked as a sample when there is user activity. The total number of samples is 20. Finally, the consumption of energy based on the power of LE dimming is calculated for each sample and compared to an On/Off lighting system. In an On/Off lighting system, LE during the presence of people is working in 100% of the nominal power and in lack of presence it turns off. Due to this fact, the energy consumption regarding the On/Off lighting system is calculated, and according to Equation (4), the energy-saving is estimated for each sample.

In the final step, the standard deviation regarding the energy saving of samples is calculated in order to evaluate and measure the amount of energy saving variation. It helps to have a perspective of the total energy saving of the proposed lighting system in building A. Figure 49 illustrates the energy-saving histogram of the proposed adaptive lighting system in comparison with the On/Off control lighting system for each sample. It also shows the relating standard deviation.

$$\begin{aligned}
 & \text{Electrical energy saving} && (4) \\
 & = \left(1 - \frac{\text{Electrical energy consumption}_{\text{Dimming}}}{\text{Electrical energy consumption}_{\text{On/Off}}}\right) \times 100
 \end{aligned}$$

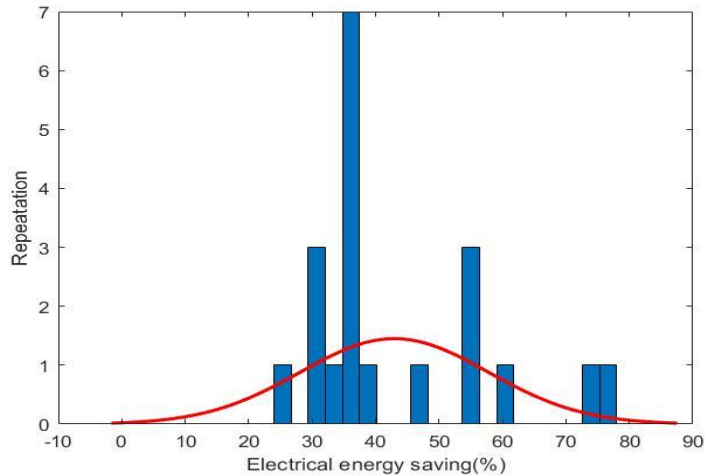


Figure 49. Histogram of electrical energy saving in twenty different samples (X-axis is electrical energy-saving and Y-axis shows the repetition of electrical energy saving in the samples)

According to Figure 49, the average energy saving is 42.95 percent, and based on standard deviation which is 14.85, the disseminating of electrical energy saving is between 28.1 to 57.8 percent. In some cases, the system is saving up to 80% energy. However, 7 repetitions of 38% energy-saving show the most frequent of percentage in 20 samples. The proposed lighting system design in the worst-case reveals 26% saving of energy that is highly interesting if it is seen on a larger scale than just a building. The proposed methodology for designing and implementing of the lighting system in buildings show its effectiveness for saving energy while considering the user comfort. In all spaces, the adaptive lighting system offers visual comfort by respecting the desired light intensity on working planes (based on Table 4). Saving more energy while respecting user comfort will lead to producing less pollution and reducing the cost of energy.

### 3.6. Conclusion

In this chapter, we focused on designing, implementation and validation of an adaptive lighting system in five-floor building of SENART campus of UPEC. The capacity for energy saving in the lighting section is high. Due to the high dynamic impact of outdoor light and also different user activities in space that may need different light intensity on working planes. In this chapter of the thesis, an adaptive lighting system is proposed in order to take advantage of this capacity. The proposed approach is on the basis of three main steps:

1. Select an appropriate lighting technology for lighting system network and dimming control of lighting elements
2. Selecting optimized number of lighting elements by lumen method



### 3. The designing best fit of architecture for placing lighting elements in spaces by DIALux software

In the first step, regarding the smart technology for integration with designed lighting architecture, DALI technology is utilized. It provides functionalities in order to manage the lighting devices. It integrates with SBEMS as a stand-alone subsystem. In the second step, the proper number of LE is selected by the lumen method, and simulation by DIALux lets to visualize and find the best architectural design of the LE placement. For instance, the optimized number of LE and its proper placement architecture design for the test case was parallel architecture with 8 LE. In the third step, the simulation is validated through an experiment, and finally, the validation of the proposed lighting system design on building A of the SENART campus is evaluated.

The obtained results by the monitoring system of SBEMS show the good performance of the lighting system. In case of lighting control functionality, the lighting system is able to regulate LE power in different lighting conditions (outdoor lights, reflections of objects, etc) efficiently. The proposed lighting system is highly adaptive to the surrounded environment and brings visual satisfaction. It always offers proper light intensity on the working plane to provide user visual comfort.

In the last part of this chapter, the proposed approach is compared with an On/Off lighting system. The results show the high performance of the proposed lighting system regarding the light dimming control in comparison with an On/off lighting system. According to this approach, in the worst case, we achieved about 30 % electrical energy saving. In some cases, this value is about 80%. The proposed lighting system is able to save energy in an average of 42.95% with a standard deviation of 14.85 % of electrical energy. Indeed, the proposed approach for obtaining optimized LE number and architecture alongside DALI which is a high-level technology provides inhabitants visual satisfaction and in parallel an energy-efficient system.

Considering the drawbacks of the existing lighting systems that it remarked in chapter 1, the placement architecture design of LE with a proper technology like DALI can cover most of the challenges relating to the lighting systems. A good harmonizing between user comfort and an efficient system in case of energy is the remarkable achievement of this chapter. With this methodology, the restriction about the generalization of the lighting systems design that we reviewed in chapter one is removed. The proposed approach can be implemented in different buildings easily. Due we showed how it can be implemented in different spaces with various properties. The powerful platform of the SBEMS with robust monitoring and controlling system and data collection abilities reveals its important role in designing and developing a lighting system.

## Chapter 4

### 4. Adaptive heating controller for SBEMS

#### 4.1. Introduction

The conjunction of the perceptive decrease of the fossil fuel resources and unremitting increase of energy consumption inherent to the escalation of human urban activities during the last decades made the management of energy consumption in commercial and residential buildings a crucial question. Among the most efficient trends for coping with the growth of energy consumption in residential and commercial sections, by controlling and reducing the share of space heating in energy consumption is the recent development of Smart Building Management Systems (SBMS) or Smart Building Energy Management Systems (SBEMS) in smart dwellings, provide the inhabitants of such smart buildings with sophisticated monitoring and control of the building's functions and clever management of heavy power-consuming appliances' (as heating devices) energy efficiency, while optimizing and maintaining the inhabitants' (or users') comfortable environment. [Alhamoud et al. 2014].

Although the sensors' quality and the technological features of the remote devices forming the physical part of the automated or smart buildings play an undeniable role in the performance of SBEMS in optimizing the building's energy consumption, however, the chief-part in the efficiency of such systems in declining energy consumption goes to the quality of the models that bear either the identification of the relationship between the building's behavior and the controller which hatches up the actions of implemented sensors and remote devices or to the excellence of the control strategy in charge of building's behavior control. Thus, the identification and modeling of the building's operational dynamics are a key-points in BMS and especially in SBEMS. On the other hand, as well the diversity of the involved factors (parameters) as their highly nonlinear variation make the identification and modeling of the dynamic behavior of a building a challenging task. Within this context and by considering that besides the living space's intrinsic structural features, the occupation of the living-space (by users or residents) may affect the model of heating dynamics of the concerned living-space, in the first step we have investigated the design, implementation, and validation of a data-driven Machine-learning-based identifier supplied by the time-series prediction paradigm's formalism. In fact, the human body continuously produces thermal energy, mostly in form of heat radiation emission. Regarding black body law, a human in a sitting position and about 1.80 meters height can emit 100 watts [D.Hardy 1934], [Fang et al. 2006], [Johnson 2012]. The second step is regarding, the control strategy for designing an adaptive heating space controller on the basis of a FUZZY logic by taking into consideration the human body heat radiation. In the final step in this chapter, as the presence and absence of people is an important thermal parameter, we are going to introduce a virtual presence estimator on a basis of FUZZY logic inference.

## 4.2. Identification of heating dynamics of building living space

### 4.2.1. Introduction

Based on the above-mentioned, in the present section, we focus on the design and implementation of a data-driven Machine-Learning-based identification of the building's living-space dynamic heating conduct taking into account the occupancy (by the residents) of the heated space. This step is necessary for pulling off of a comprehensive (i.e. interpretable) model handling the dynamic heating conduct of living-space with and without human presence. The proposed data-driven Machine-Learning-based identifier will be applied for modeling the dynamic heating conduct of a real five-floor building's living-spaces located at Senart Campus of University Paris-Est Créteil taking into account their occupancy (by users of this public building).

From a general standpoint, identification approaches are divided into two main categories: White-Box Modeling (WBS) and Black-Box Modeling (BBS) [Asgari et al. 2013]. In WBS-based methods, the modeling of a system is performed on the basis of the formal relationship of the physical properties of the concerned system. If the main advantage of WBS-based methods remains their comprehensive and interpretable nature, however often the effective complexity of real-world conditions made WBS leading to insolvable equations and hence frequently to a strongly simplified issued model, making it quite far from realistic behavior of the target system. In BBM-based methods, the modeling is done by mapping an approximate behavior of the target system through the input-output relationship of that system. In contrast to WBM, if BBM-based methods achieve a more accurate approximation of effective complexity of the modeled system's behavior, however, and often they lead to a shortfall of comprehensive and interpretable foundation relating to the issued model.

If the analysis of the research works in section 1.6.1 highlights the diversity of covered fields and applications, they confirm what we mentioned before relating the advantages and shortages of each category (i.e. WBS-like and BBS-like) of identification-based nonlinear systems' modeling approaches. Meanwhile, the overviewed research works reveal the appealing capacity of the nonlinear autoregressive exogenous (NARX) in modeling and forecasting complex systems' behaviors. In fact, the proposed modeling strategy takes advantage of the one hand from the time-series forecasting capacity of the NARX model, and on the other hand from the Multi-Layer Perceptron's (MLP) learning and generalization skills. If the NARX model has already been used for modeling in various paradigms, the originality of its application in the present article concerns its usage, and especially it's closed-loop version, in uninterrupted (i.e. continual) identification of the heating dynamics within a fully data-driven context. However, the additional novelties of the reported investigations relate on the one hand the application of the aforementioned model for solving real-world problem addressing complex behaviors, and on the other hand, concerns the effective implementation of the developed system by the use of standard technology (i.e. market available), overcoming complex technological obstacles.

In this section, we present an ANN-based Nonlinear Auto-Regressive exogenous model (NARX, [A. Billings, 2013]) for dwelling heating dynamics identification. The proposed approach takes advantage of the learning and generalization capabilities of Machine-Learning algorithms, namely from those characterizing the feed-forward Multi-Layer Perceptron (MLP [Du and Swamy, 2014])) ANNs.

#### **4.2.2. Machine-Learning based identification of the heating dynamics of the living-space**

Before bestowing the proposed living-space heating dynamic's identification approach, we consider the following work-hypothesis relating the identification strategy:

1. Concerned living-space is supposed to be part of a typical building including various quarters (as flats and rooms for a residential building or working spaces, office-rooms, classrooms, practice-rooms for a public building, etc...).
2. The building is supposed to be heated by a central heater supplying radiators located in the afore-mentioned living-spaces.
3. The regulation is supposed to be done by a conventional controller adjusting the radiators' valves versus the magnitude of the outdoor temperature and the target (i.e. desired) indoor temperature.
4. The target model considers the system to be identified as an overall system including the heat transmitters (radiators) and the heating space.
5. The concerned living-space is supposed to contain an amount of  $N$  (with  $0 \leq N \leq N_{Max}$ ) occupants (residents or users).  $N = 0$  corresponds to an empty living-space while  $N = N_{Max}$  characterize a fully occupied living-space. Thus  $N_{Max}$  corresponds to the maximum capacity of the living space and is determined accordingly to the construction norms and occupation regulations.

Thus, within the aforementioned work hypothesis, the considered parameters are: "Valve-position at time  $t$ " (denoted by  $\vartheta_p(t)$ ) providing the heated water's flow (expressed as a normalized ratio of debit versus the maximum debit of the valve), "Outdoor-Temperature measured at time  $t$ " (denoted by  $T_{Out}(t)$ , expressed in °C), "Indoor-Temperature measured at time  $t$ " (denoted by  $T_{In}(t)$ , expressed in °C) and "Occupancy-Rate at time  $t$ " (denoted by  $O_{CC}(t)$ , expressed in %).

As mentioned in the introductory section, the identification method of the proposed system is accomplished by an MLP-based NARX ([Gao & Er, 2005], [Johansen and Foss 1993], [A. Billings 2013]) with a feed-forward back-propagation learning algorithm ([Rumelhart, Hinton, and Williams 1986] and [Hastie, Tibshirani, and Friedman 2008]). Equation (5) and (6) respectively specify the overall open-loop NARX model, where  $F(\cdot)$  is the activation function of the ANN,  $\hat{y}(t + 1)$  estimated (i.e. predicted) output,  $y(t)$  is the actual output value of the model (i.e. at time  $t$ ),  $y(t - 1), \dots, y(t - n)$  are  $n$ -past values of the  $y(t)$ ,  $x(t)$  is the present input value and

$y(t), y(t - 1), \dots, y(t - m)$  are actual and the tapped delayed exogenous inputs, in m-past input values. Figure 50 illustrates the overall schema of NARX model.

$$\hat{y}(t + 1) = F(y(t), y(t - 1), \dots, y(t - n), x(t), x(t - 1), \dots, x(t - m)) \quad (5)$$

$$\hat{y}(t + 1) = F(\hat{y}(t), \hat{y}(t - 1), \dots, \hat{y}(t - n), x(t), x(t - 1), \dots, x(t - m)) \quad (6)$$

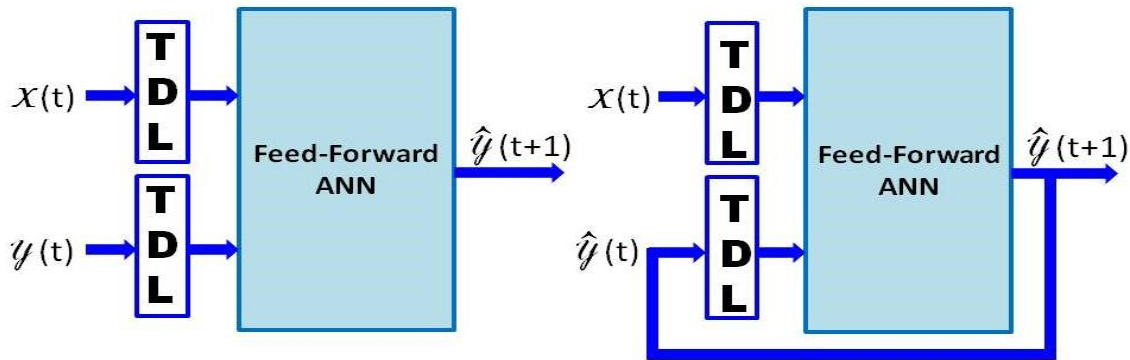


Figure 50. General ANN-based NARX model: Open-Loop (left) and Close-Loop (right) architectures

Figure 51 reveals the proposed identification structure of the target heating model taking into account the above-stated work hypothesis including the influence of the occupancy. The learning process is performed by utilizing the open-loop NARX scheme. The learning dataset contains the operation of the real system's sequences within different valve positions (i.e.  $\vartheta_p(t)$ ) providing various heating powers, the Occupancy-Rate at time t (i.e.  $O_{CC}(t)$ ), the actual and m-past measures of outdoor temperature (i.e.  $T_{Out}(t)$ ,  $T_{Out}(t - 1)$ , ... and  $T_{Out}(t - m)$ ) and the actual and the n-past values of indoor temperature (i.e.  $T_{In}(t)$ ,  $T_{In}(t - 1)$ , ... and  $T_{In}(t - n)$ ).

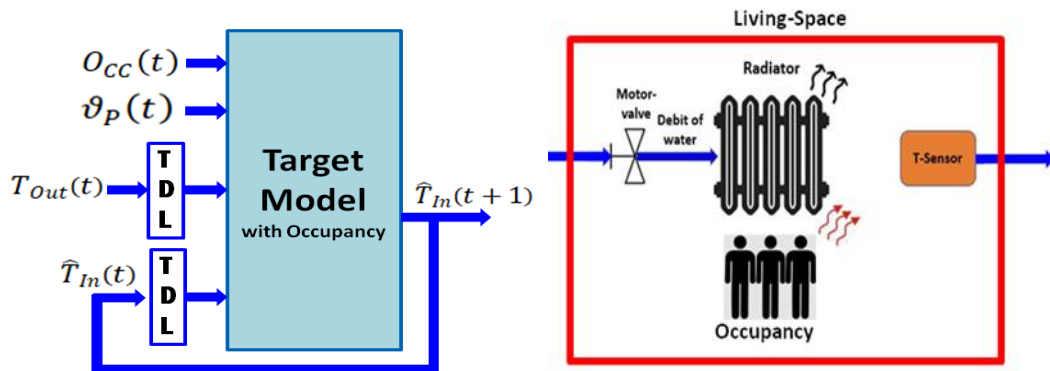


Figure 51. Proposed identification architecture of the target heating model (left-side) and general diagram of the modeled living-space including the influence of its occupancy (right-side)

The influence of occupancy is modeled through the following hypothesis: *occupancy of the living-space by residents increases the effective overall heating power*. The right-side picture of Figure 51 gives the general diagram of the modeled living-space within the aforementioned hypothesis. In other words, we assume that occupation of the living-space by residents (i.e. bodies providing additional heating sources) is equivalent to an incensement of the heating device's nominal power. To determine the above-mentioned equivalent nominal power, we exploit the usual policy of setting the adequate heater's nominal power versus the living space's characteristics. In fact, building designers determine the adequate heater's nominal power on the basis of the volume of the concerned living-space (i.e. the living-space which is supposed to be heated by the heating device) by keeping constant a parameter called "*Heating Ratio*" (denoted by  $HR_0$ , expressed in  $W/m^3$ ), defined by Equation (7) where  $P_{No}$  denotes the heating device's nominal power (which depends to technological and structural features of the heating device) and  $V_{LS}$  denotes the volume of the living-space (room, etc...). The appropriate value of  $HR_0$  is determined versus construction norms (used materials, processes, etc... used for constructing the concerned building) and urban, social, and environmental regulations (imposed by legal authorities).

$$HR_0 = \frac{P_{No}}{V_{LS}} \quad (7)$$

Taking into account the hypothesis relating the occupancy's influence, Equation (7) may be extended in terms of Equation (8) taking into account the occupancy's influence. In this equation,  $HR(N)$  denotes the "*Heating Ratio*" taking into account the occupancy,  $P_{OCC}(N)$  states for additional heating power provided by the leaving-space's occupancy (with  $P_{OCC}(N = 0) = 0$ ) and  $V_{LS}$  denotes the volume of the living-space (room, etc...).

$$HR(N) = HR_0 + \frac{P_{OCC}(N)}{V_{LS}} \quad (8)$$

One can notice that  $HR(N = 0) = HR_0$  corresponding to the *Heating Ratio* of the same living-space when it is empty. We determine  $P_{OCC}(N)$  through a fuzzy-logic-based concept by considering, on the one hand, three categories (fuzzy intervals) of leaving-spaces (i.e. three fuzzy intervals of living spaces volume) and on the other hand by considering five categories of Occupancy-Rate" (denoted by  $O_{CC}$ , expressed in %). Namely, the three categories for living space's volume are: "Large", "Medium" and "Small". Concerning the five categories of Occupancy-Rate, they are: "Empty" (corresponding to  $O_{CC} = 0\%$ ), "Small occupation" (i.e.  $O_{CC} = 25\%$ ), "Medium occupation" (i.e.  $O_{CC} = 50\%$ ), "High occupation" (i.e.  $O_{CC} = 75\%$ ) and "Full" (i.e.  $O_{CC} = 100\%$ ). Within this formulation, the Equation (8) may be written in term of Equation (9), where  $V_{LS}^F$  denotes the "*fuzzy value*" of  $V_{LS}$ .

$$HR(O_{CC}) = HR_0 + \frac{P_{Occ}(O_{CC})}{V_{LS}^F} \quad (9)$$

The main advantage of such formulation is that the above-mentioned intervals may be quantified by the use of data-driven statistical clustering methods reflecting the reality of the concerned building's usage (occupancy). Thus, the equivalent nominal power of a given living-space occupied by N bodies may be estimated as:  $HR(O_{CC}) \times V_{LS}$ .

Flooding back to the hypothesis we made relating the effect of living space's occupancy, another way of interpreting the aforementioned hypothesis is to note that the occupancy of the living-space by residents will decrease the required time for reaching the target indoor temperature. In other words, higher will be the living space's occupancy shorter will be the necessary delay to heat it. In order to quantify this, we introduce what we call “*Heating Slop*” (denoted by  $h(t)$  and expressed in °C/s), defined as the derivative of  $T_{In}(t)$  versus the time and approximated by Equation (10) within the context of a discrete sampling (i.e. discrete measurement) of the indoor temperature. In Equation (10),  $T_{In}(t_k)$  and  $T_{In}(t_{k-1})$  stand for consecutive values of indoor temperature (supposed to be provided by the temperature sensor at times  $t_n$  and  $t_{n-1}$ , respectively) and  $\Delta t = t_k - t_{k-1}$ .

$$h(t) = \frac{T_{In}(t_k) - T_{In}(t_{k-1})}{\Delta t} \quad (10)$$

It is pertinent to notice that an escalation of living space's occupancy (introducing additional bodies and thus additional sources of heating) or decrease of occupancy will result in the so-called Heating Slop's modification: higher will be the living space's occupancy stronger will be the Heating Slop. Within the general standpoint and as formulated by Equation (10),  $h(t)$  is time-dependent and thus may vary along with time. However, due to the fact that the heating of buildings abides by slow dynamics, often  $h(t)$  remains constant (with regard to the time), albeit its value would vary along with the Valve-position (i.e. with  $\vartheta_p(t)$ ) that controls the heating device's actual power. Based on the aforementioned, actually, the predicted indoor temperature (i.e.  $\hat{T}_{In}(t_{k+1})$ ) may be computed from Equation (11), where  $\hat{h}(t) = f(\vartheta_p(t), O_{CC})$  denotes the identified (estimated) value of  $h(t)$ .

$$\hat{T}_{In}(t_{k+1}) = \hat{h}(t) (t_{k+1} - t_k) \quad (11)$$

### 4.2.3. Implementation of the proposed living-spaces' dynamic heating model

As it has been mentioned, a real five-floor building located at Senart Campus of University Paris-Est Créteil (UPEC) served as an experimental platform for evaluation and validation of the proposed model. The concerned building (namely the Building A of the campus) is a fully automated building hosting the Electrical Engineering and Industrial Informatics Department of Senart-Fontainebleau Institute of Technology of UPEC. The building (i.e. system to be identified) is heated by a conventional central heater supplying radiators (i.e. heating devices) located in various living-spaces (namely, office-rooms, classrooms, practical rooms, etc.) of the building. The central heater is common to three buildings of the campus and thus, the control of the local heating devices of the concerned buildings (including the Building A) is performed through the local valves of each radiator. The two other buildings are conventional buildings (i.e. not automated) and sole Building A is automated. In fact, the Building A is equipped with numerous sensors and connected devices allowing to record data relating the environmental information (such as temperatures in each living-space, the outdoor temperature, etc...) and the operational states of whole installed connected devices (such as radiators' valves, etc...). Four different kinds of sensors outfit each living-space (including corridors) of whole the five floors of this building: "Temperature Sensors" (TS), "Magnetic Sensors" (MS), "Presence Detectors" (PD) and "Luminance Sensors" (LS). The main connected devices (actuator) deployed in the aforementioned experimental building are: "Motor Valves" (MV) that control radiators supplied by the above-mentioned central water-flowed heating system and connected "Lighting Elements" (LE).

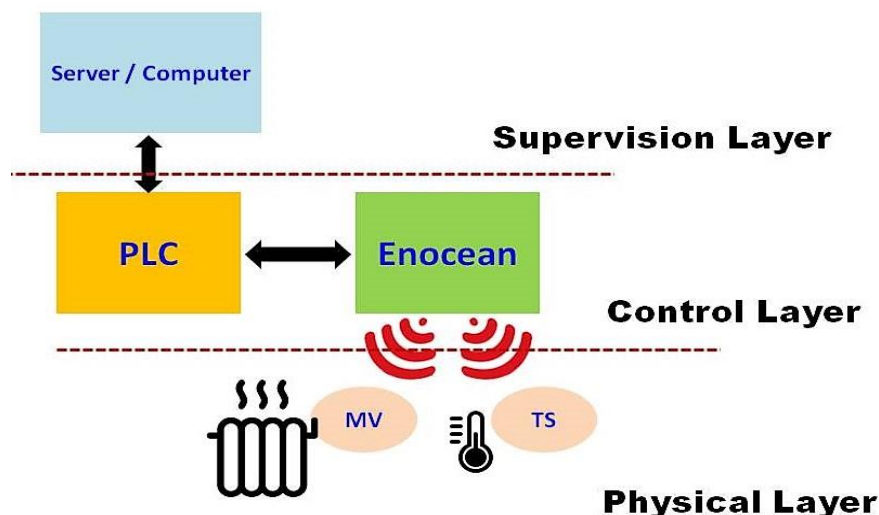


Figure 52. Implementation diagram of the heating system equipping the Building A of Senart Campus of UPEC



Sensors and connected devices concerned by the purpose of the present chapter of the thesis are TS and MV. They use “EnOcean” technology: an energy harvesting wireless technology provided by EnOcean. EnOcean-technology-based modules fuse micro-energy converters with ultralow power electronics and reliable wireless communications, allowing to provide self-powered wireless sensors or actuators as well for building energy management systems as for industrial applications (explained in chapter 2). Figure 52 presents the implementation diagram of the concerned building (building A) heating system.

Composing the heating control chain of the SBEMS of the aforementioned fully automated experimental building, CL and PL are replicated for each floor, making able the set up collecting data characterizing the heating state of each living-space of the building and controlling valve-position of each heating device (radiator) in the building through the five PLC (one for each floor). The proposed identification approach has been implemented in the SBEMS of the aforementioned fully automated experimental building.

For evaluating the proposed identification strategy and the issued model, two experimental assessments have been considered: the first one appraises the obtained model’s “One-Step Prediction” (OSP) accuracy and the second one sizes up the ability of the issued model on “Multi-Step Prediction” (MSP). The purpose of the OSP aims to predict the living space's immediate upcoming indoor temperature from its previous history. Therefore, as well Open-Loop as Closed-Loop architectures could be used. Whereas the objective in the MSP relates prediction of several successive future steps of the concerned living space's indoor temperatures, and thus the Open-Loop architecture remains no more pertinent.

## 4.2.4. Experimentation and results

### 4.2.4.1. Experimental protocol’s description

Both of the two aforementioned evaluations are performed keeping the same experimental protocol. This protocol considers a living-space of the Building A belonging to the category of “middle-size” working-spaces of this building (i.e.  $V_{LS}^F = \textit{Medium}$ ) able to soak up 28 residents (individuals). The considered living-space is equipped with a 3kW heating device (namely, a 3160W radiator supplied by the central heater), responding to the construction and legal norms applicable to this category of working-spaces.

The collected data consists of remote values (time history) of outdoor temperature  $T_{Out}(t)$ , radiator’s valve-position  $\vartheta_P(t)$  and indoor temperature  $T_{In}(t)$ . Two sets of experimental data have been collected. The data sampling period is 1 minute, meaning that the value of each considered parameter is collected periodically every 60 seconds.

The first one, that we tag as “Empty-working-space” (EWS), includes the time history of aforementioned parameters’ values during 18 hours (i.e. 1080 minutes) when the considered working-space is empty (i.e.  $O_{CC}(t) = 0\%$ ). The left-side diagram of Figure 53 depicts the experimental conditions, showing the local heating device's operational conduct and the outdoor temperature’s evolution during the data collection sequence. As it is visible from this diagram, the working space has been heated during 6 hours by the radiator operating with 50% of its nominal power (i.e.  $\vartheta_p(t) = 50\%$  during 6 firsts hours). Then, the heating was stopped during the 6 next hours (i.e.  $\vartheta_p(t) = 0\%$  from  $t = 360'$  to  $t = 720'$ ). Finally, during the last period of 6 hours, the work-space has been heated by the radiator developing its maximum nominal power (i.e.  $\vartheta_p(t) = 100\%$  from  $t = 720'$  to  $t = 1080'$ ).

The second one, that we tag as “Fully-occupied-working-space” (FWS), includes the time history of the aforementioned parameters’ values when the same working-space is occupied by 28 individuals (i.e.  $O_{CC}(t) = 100\%$ ) during 100 minutes of a period of 4 hours. The right-side diagram of Figure 53 depicts the experimental conditions relating to this second set of collected data, showing the local heating device's operational conduct and the outdoor temperature’s evolution during the data collection sequence. As it is visible from this diagram, the working space is not heated during the firsts 140 minutes assuming that the working space is empty and thus doesn’t need to be heated). Then fully occupied (i.e.  $O_{CC}(t) = 100\%$ ) during next period of 100 minutes it is heated by the radiator developing its maximum nominal power (i.e.  $\vartheta_p(t) = 100\%$  from  $t = 140'$  to  $t = 240'$ ).

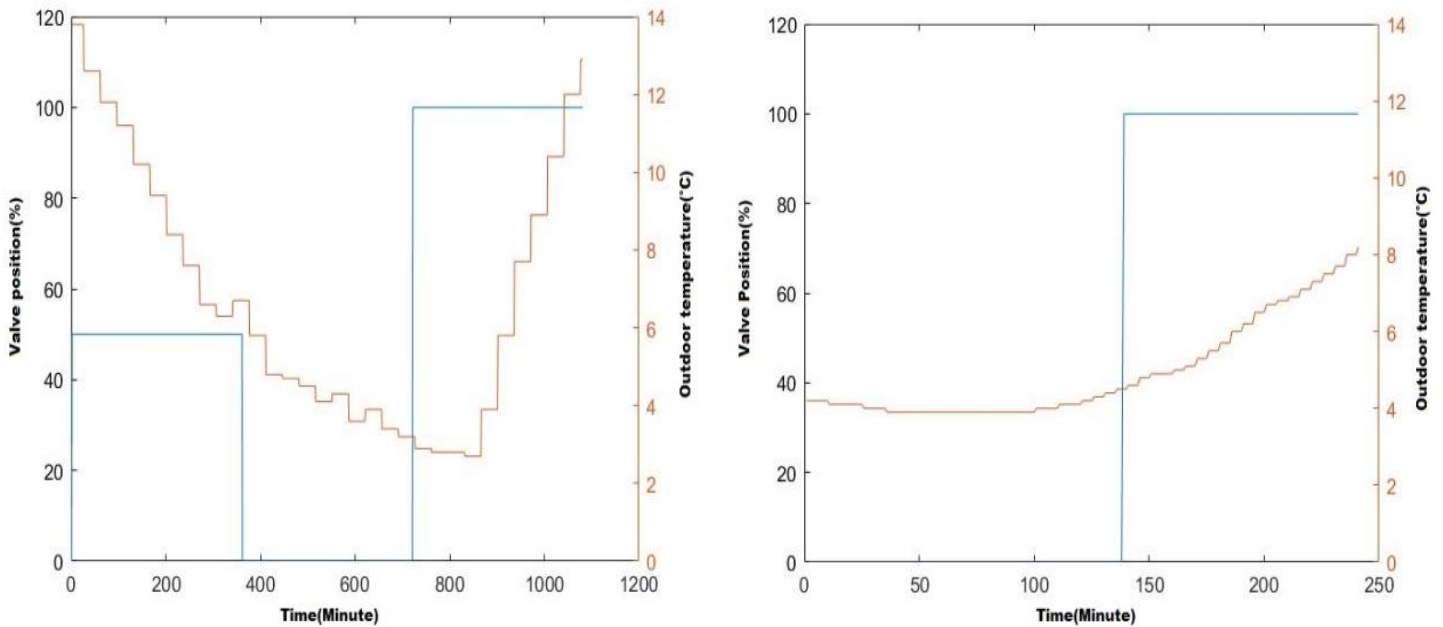


Figure 53. Experimental data- collection conditions comply with empty working-space (left-side diagram) and fully occupied working-space (right-side diagram), respectively, showing Valve-position and outdoor temperature-time history.

A part of the collected datasets serves for the training of the proposed ANN-based NARX identifier and a ratio of the collected data is used as a testing data. The parameters of ANN for all constructed models are as follows:

- Identification of empty working space has been performed using ANN including one hidden layer with a size of 5 (number of neurons in the hidden layer). The number of neurons in the hidden layer has been set empirically. Relating the training and validation, 85% of data was utilized for training, and 15% for testing.
- Identification of fully occupied working space was performed using ANN including one hidden layer with a size of 10 (number of neurons in the hidden layer). The number of neurons in the hidden layer has been set empirically. Relating the training and validation, 90% of data was utilized for training, and 10% for testing.

The training and testing operations were repeated 10 times for each collected dataset. The evaluation of the obtained model's accuracy has been done based on Mean Squared Error (MSE) and Mean Absolute Error (MAE) criteria. It is illustrated by Equation (12) and Equation (13), respectively, where  $N$  is the number of samples,  $y_i$  is the effectively recorded data and  $\hat{y}_i$  represents the estimated (predicted) value.

$$MSE = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2 \quad (12)$$

$$MAE = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}_i| \quad (13)$$

It is relevant to precise that part of the data of the EWS dataset served for settlement of the opposite number of time-delayed data samples to be considered in the prediction task. The concerned data correspond to the 3-hours sequence of the EWS when the considered working-space is heated by the radiator developing its nominal power leading to a swell of 2.7°C of the indoor temperature (i.e. data recorded between  $t = 720'$  and  $t = 900'$ ). A part of the extracted sequence has been used for identification and the rest of the sequence's data served for testing the forecasting ability of the issued model.

Twenty models have been constructed differing with regard to the number of the considered time-delayed data samples involved in the prediction task. Figure 54 depicts the obtained results representing the minimum and maximum value of MSE versus the number of the considered time-delayed data samples involved in the prediction task.

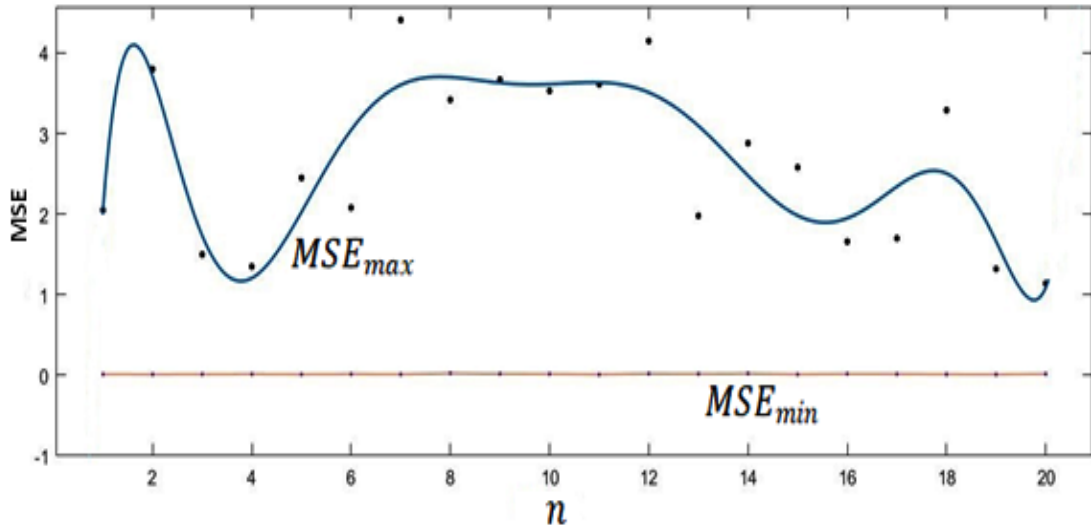


Figure 54. Minimum and maximum MSE ( $MSE_{min}$  and  $MSE_{max}$ ) versus the number of the considered time-delayed data samples involved in the prediction task ( $n$ ).

If  $MSE_{min}$  remains within the interval  $[0.12, 0.26]$ , the lowest obtained  $MSE_{max}$  values are obtained with  $n = 4$  and  $n = 20$ . Taking account implementation's computational constraints,  $n = 4$  (corresponding to  $MSE_{min} \cong 0.12$  and  $MSE_{max} < 1.5$ ) appears offering a suitable compromise. Thus, the experimental evaluation has been performed using  $n = 4$ .

#### 4.2.4.2. Experimental Results

The two constructed datasets have served for evaluating OSP and MSP models of the considered working space's heating conduct. Following the experimental protocol described in the previous section, the data-driven learning-based issued model has been pointed out by using partly data from EWS and partly from FWS. Two operational scenarios corroborating experimental recorded data conditions (i.e. those depicted by Figure 53) were considered.

The first case study, focusing on OSP accuracy, considers two painless operational situations:

The first situation assumes that the considered working-space is empty (i.e.  $O_{CC}(t) = 0\%$ ), the outdoor temperature is up to  $T_{Out}(t) = 10^\circ C$  and the indoor temperature at the beginning of the heating sequence is  $20.86^\circ C$  (i.e.  $T_{In}(t = 0) = 20.86^\circ C$ ). Starting under the above-mentioned conditions, the considered empty working-space is supposed to be heated during two hours (i.e. during 120') by the radiator developing its nominal heating power (i.e.  $\vartheta_p(t) = 100\%$ ).

The second situation assumes that the considered working-space is fully occupied by 28 residents (i.e.  $O_{CC}(t) = 100\%$ ), the outdoor temperature is up to  $T_{Out}(t) = 5^\circ C$  and the

indoor temperature at the beginning of the heating sequence is  $21.80^{\circ}\text{C}$  (i.e.  $T_{In}(t = 0) = 20.80^{\circ}$ ). Starting under the above-mentioned conditions, the considered occupied working-space is supposed to be heated during 350' by the radiator developing its nominal heating power (i.e.  $\vartheta_p(t) = 100\%$ ).

The second case study, focuses on MSP accuracy evaluation, considering two more tricky situations:

Assuming that the considered working-space is empty (i.e.  $O_{CC}(t) = 0\%$ ), the first situation of this second case-study presumes that the working-space is heated in accordance with the left-side diagram of Figure 53. In other words, it supposes that the radiator heating the considered living-space heats it during 6 hours developing 50% of its nominal power (i.e.  $\vartheta_p(t) = 50\%$  for  $t \in [0', 360']$ ), then after a 6-hours halt (i.e.  $\vartheta_p(t) = 0\%$  for  $t \in [361', 720']$ ), it reheats this same working-space during 6 additional hours developing the whole of its nominal power (i.e.  $\vartheta_p(t) = 100\%$  for  $t \in [721', 1080']$ ). The outdoor temperature (i.e.  $T_{Out}(t)$ ) is supposed varying during those 18 hours within the interval  $[2^{\circ}\text{C}, 14^{\circ}\text{C}]$ , also in line with the left-side diagram of Figure 53. The indoor temperature at the beginning of the heating sequence is  $19.60^{\circ}\text{C}$  (i.e.  $T_{In}(t = 0) = 19.60^{\circ}\text{C}$ ).

Presuming that the considered working-space is empty at the beginning (i.e.  $O_{CC}(t) = 0\%$  at  $t=0$ ), the second situation of this second case-study assumes that the concerned working-space becomes fully occupied during 100 minutes and reheated in accordance with the right-side diagram of Figure 53. In other words, it supposes that the radiator is off during the firsts 140 minutes when the living-space is empty (i.e.  $\vartheta_p(t) = 0\%$  and  $O_{CC}(t) = 0\%$  for  $t \in [0', 140']$ ), it heats the considered living-space during 100 minutes when the room is fully occupied, developing its nominal power (i.e.  $\vartheta_p(t) = 100\%$  and  $O_{CC}(t) = 100\%$  for  $t \in [141', 240']$ ). The outdoor temperature (i.e.  $T_{Out}(t)$ ) is also supposed varying within the interval  $[4^{\circ}\text{C}, 8^{\circ}\text{C}]$  in line with the right-side diagram of Figure 53. The indoor temperature at the beginning of the heating sequence is  $17.25^{\circ}\text{C}$  (i.e.  $T_{In}(t = 0) = 17.25^{\circ}\text{C}$ ).

Figure 55 to Figure 58 show the obtained results relating to the two above-mentioned case-studies. Relating the first case-study, Figure 55 plots the estimated (i.e. model-based OSP) indoor temperature and measured (i.e. real) indoor temperature of the considered living-space when it is empty. Figure 56 gives model-based predicted and real indoor temperature values when the considered living-space is fully occupied. Linking the second case-study, the diagram of Figure 57 gives the estimated (i.e. model-based MSP) indoor temperature and measured (i.e. real) indoor temperature of the considered living-space when it is empty. The diagram of Figure 58 depicts the model-based multi-step prediction of indoor temperature values and the measured temperature when the living-space is fully occupied during 100 minutes.

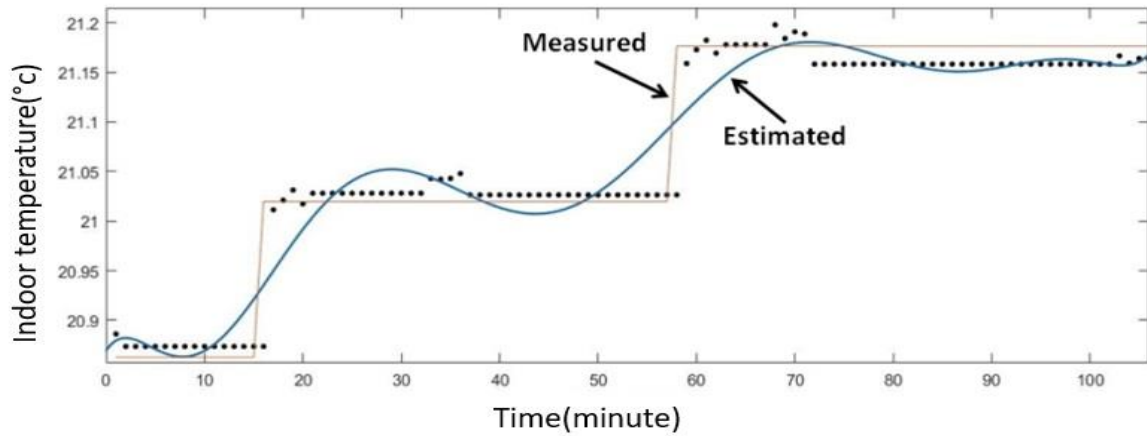


Figure 55. Model-based one-step predicted indoor temperature's time history when the living-space is empty

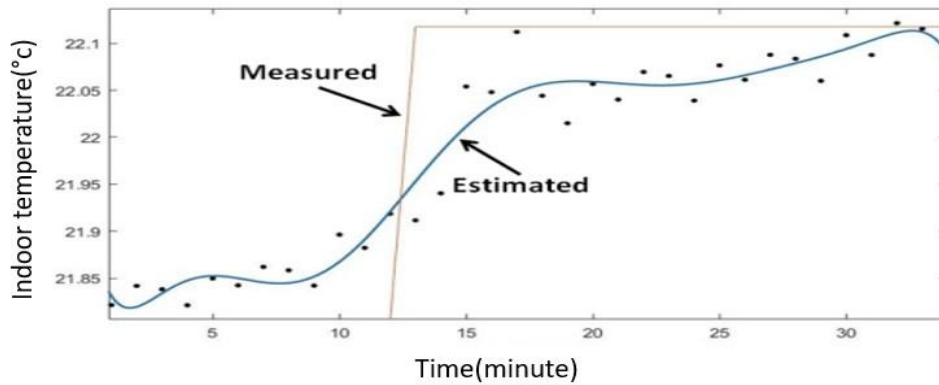


Figure 56. Model-based one-step predicted indoor temperature's time history when the living-space is fully occupied

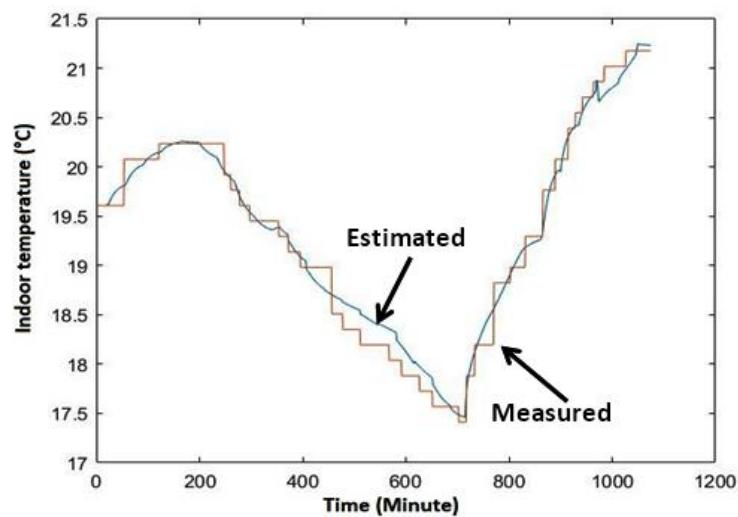


Figure 57. Model-based multi-step predicted indoor temperature's time history when the living-space is empty

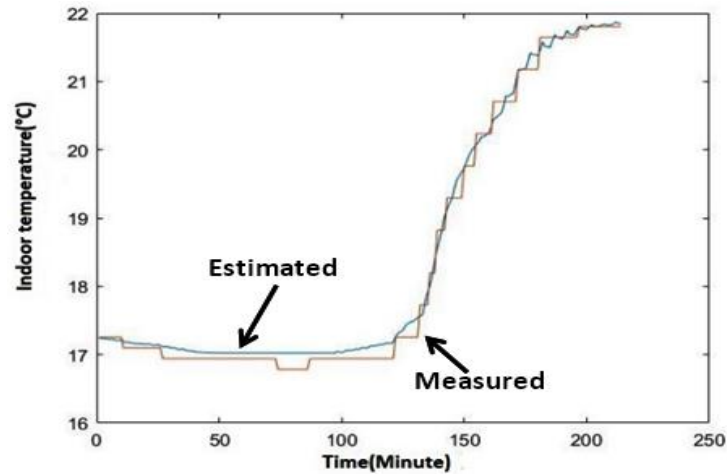


Figure 58. Model-based multi-step predicted indoor temperature’s time history when the living-space is fully occupied

Tests	One step ahead prediction	Multi-step ahead prediction (test data)	Multi-step ahead prediction (Total data)
Errors			
Min. MSE	0.0004	0.012	0.006
Min. MAE	0.008	0.08	0.07
Max. MSE	0.03	1.45	0.25
Max. MAE	0.15	1.23	0.44

Table 12. Estimation’s maximum and minimum MSE and MAE with 4 delayed samples considered for each involved parameter

Table 12 summarizes the overall accuracy of OSP and MSP models of the considered working space's heating conduct. As expected, the OSP model of the aforementioned heated living-space forecasts the upcoming value of the indoor temperature with less than 0.2 °C blunder comparing to the measured value. Actually, the achieved high prediction accuracy is due to the fact that in OSP model, the prediction is performed using the four effectively-measured past values of the indoor temperature and thus representing the effective time-history of indoor temperature evolution. However anchored in an open-loop NARX scheme, the main shortage of this model would appear when longer-term forecasting of indoor temperature is needed.

The MSP model of the aforementioned heated living-space forecast the upcoming value of the indoor temperature with lower accuracy comparing to OSP model: an average error up to 0.4 °C, while attaining some long-term predicted values of indoor temperature an error exceeding 1.23 °C. The finer analysis of indoor temperature forecasting, supported by results depicted in Figure 59, provides the incentive of the observed gap. The left-side diagram of Figure 59 reports the estimation’s absolute error

for 35 consecutive estimated indoor temperatures (i.e. prediction of the 35 upcoming values of indoor temperature) of the modeled heated working-space. The right-side diagram of Figure 59 plots the forecasting-error of the between the so-called “Heating Slop” (i.e.  $h(t)$ ) defined and introduced in Section 4.2.2. In fact, as visible from those diagrams, if both estimation-errors (i.e. the estimation-error relative to  $T_{In}(t)$  and the forecasting-error relating  $h(t)$  values’ estimation) remain contained close to zero for short-term (5 values) and middle-term (15 values) forecasted indoor-temperature’s values, both of them admit a continuously increasing evolution for long-term predicted values, especially those surpassing the next thirty-minutes predicted period. Actually, within such a longer-term prediction requirement, the generalization of MLP neural net seems to reach its limitation regarding the learning dataset.

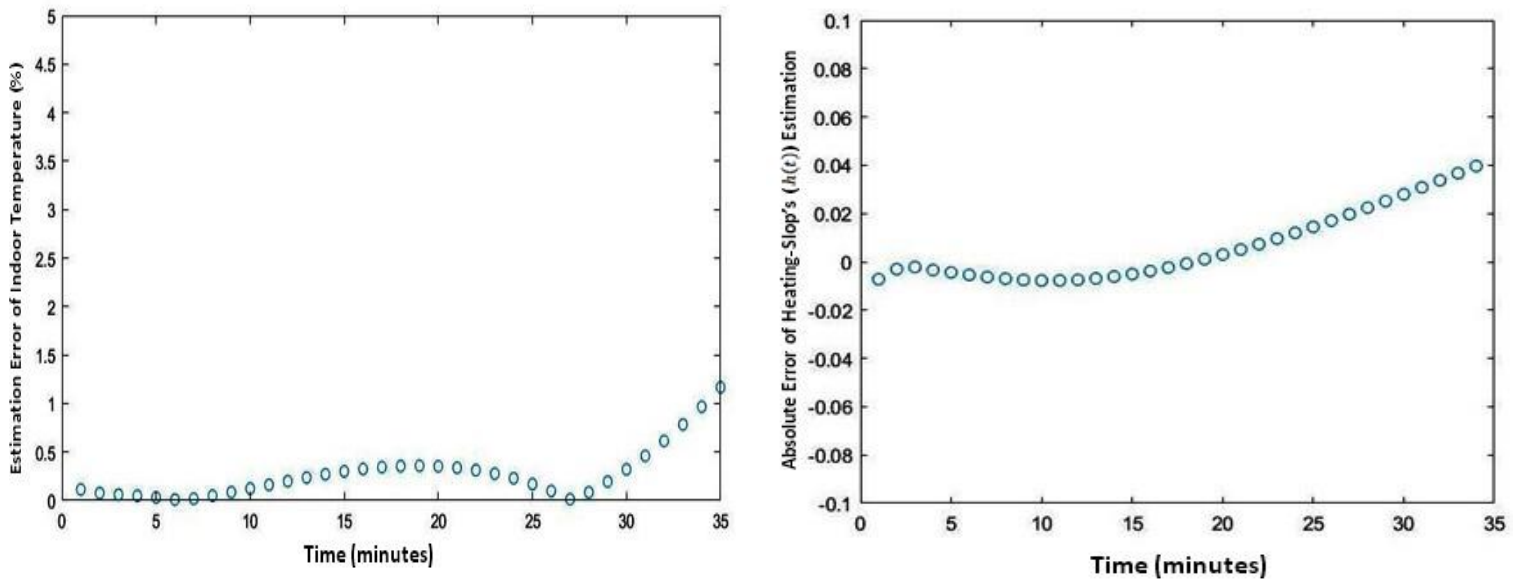


Figure 59. Indoor temperature estimation’s absolute error (left-side) and Heating-Slop’s forecasting-error (right-side).

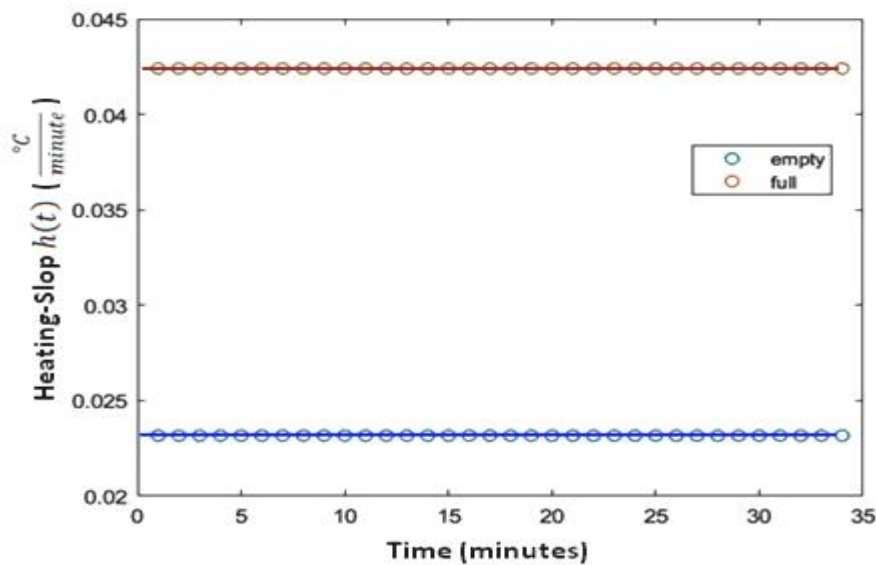


Figure 60. Heating Slop when the living-space is empty and when it is fully occupied.



Figure 60 depicts the Heating Slop (i.e.  $h(t)$ ) when the considered living-space is heated by its radiator in two different situations: the blue curve corresponds to  $h(t)$  when the living-space is empty and the other curve relates the situation when the same heated space is fully-occupied. It is pertinent to notice that the average estimated Heating Slop for the empty living-space is  $\overline{h(t)} = 0.023 \frac{^{\circ}\text{C}}{\text{minute}}$  while, for the same fully occupied living-space it is about two times stronger ( $\overline{h(t)} = 0.043 \frac{^{\circ}\text{C}}{\text{minute}}$ ) showing up the occupancy's impact on the considered living space's heating dynamics. In fact, the indoor temperature of the considered living-space heated with the same radiator will increase up to  $0.5^{\circ}\text{C}$  in 35 minutes when it is empty, while, it will increase up to  $1.5^{\circ}\text{C}$  when the living-space is fully occupied.

Finally, Figure 61 and Figure 62 show  $\frac{P_{Occ}(O_{CC})}{V_{LS}^F}$  (introduced in Equation (9) of the section 4.2.2) versus occupancy-rate for the three considered categories of living-spaces of building A, where  $O_{CC} = 100\%$  corresponds to the occupancy of each considered living-space category's by up to 28 individuals. Figure 61 is based on the identified heating space behavior model on the first series of data sets of building A, in the third year of Ph.D. (what we call "**living-spaces of building A<sub>1</sub>**") and Figure 62 is based on the identified heating space behavior model on the second series of data sets of building A, in the fourth year of the Ph.D. (what we call "**living-spaces of building A<sub>2</sub>**"). The  $V_{LS}^F = \textit{Small}$  is an office room  $V_{LS}^F = \textit{Medium}$  is a theoretical classroom and  $V_{LS}^F = \textit{Large}$  is a practical classroom. It should be noted the constructed models of living spaces are based on each individual time series data set that contains all possible conditions (EWS and FWS) in one model with the same method and parameters that are explained before in this section of the thesis. (see appendix A). However, in the explication of the approach, we constructed two individual models for EWS and FWS for studying and evaluating the approach.

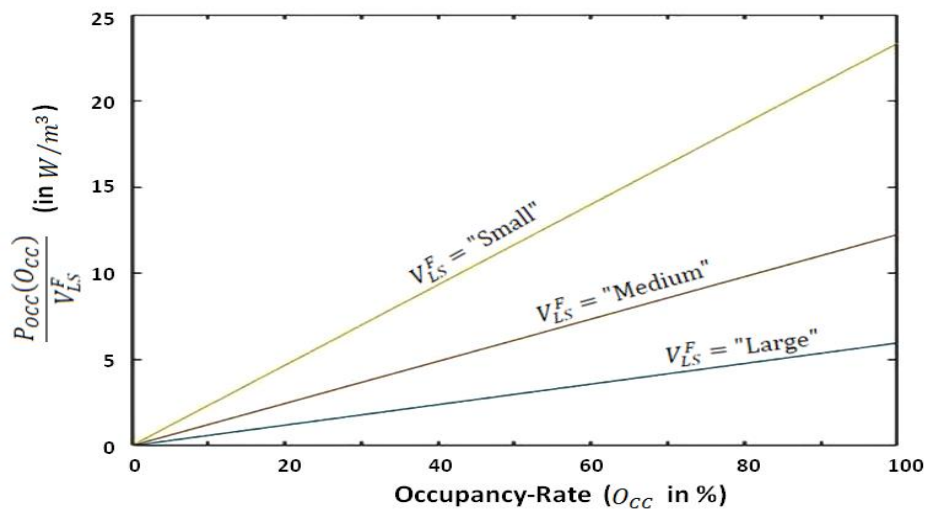


Figure 61.  $\frac{P_{Occ}(O_{CC})}{V_{LS}^F}$  versus occupancy-rate for the three considered categories of living-spaces of building A<sub>1</sub>

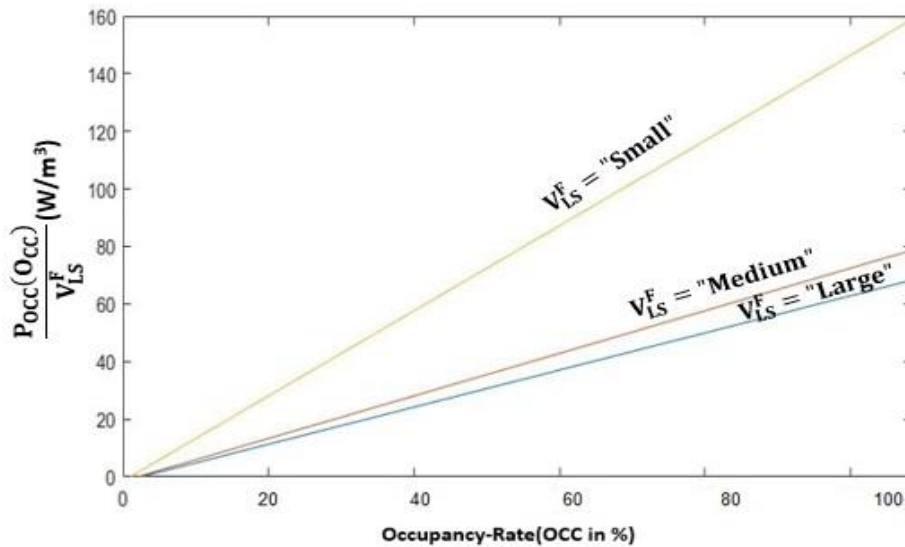


Figure 62.  $\frac{P_{occ}(OCC)}{V_{LS}^F}$  versus occupancy-rate for the three considered categories of living-spaces of building A<sub>2</sub>

As an example, according to Figure 62, 10 individuals occupying a medium and large living-space of this building, equipped with a 3kW and 6kW radiator respectively, would correspond to an additional heating power of 3000W and 5056W accordingly. According to Figure 62, the part of occupants in heat production in spaces in comparison with Figure 61 is higher and  $V_{LS}^F = Large$  diagram is closer to  $V_{LS}^F = Medium$ . Indeed, the large space is a practical room and occupants are active during their presence. In addition, in practical rooms, there are devices like portable computers and PLC that producing heat and students work with during the lectures. Because of the better quality of data that there was for constructing the living spaces of building A<sub>2</sub>, the aforesaid fact is visible.

#### 4.2.5. Conclusion on the identification of heating dynamics of building living space

Considering that alongside the living space's intrinsic structural features, the occupancy of the living-space (by users or residents) may affect the model of heating dynamics of the concerned living-space, we have investigated the design, implementation, and validation of a data-driven Machine-learning-based identifier supplied by the time-series prediction paradigm's formalism. The proposed data-driven Machine-Learning-based identifier has been applied for modeling the dynamic heating conduct of a real fully automated five-floor building's living-spaces located at Senart Campus of University Paris-Est Créteil taking into account their occupancy (by users of this public building). The proposed modeling strategy takes advantage on the one hand from the

time-series' forecasting capacity of the NARX model, and on the other hand from the Multi-Layer Perceptron's (MLP) learning and generalization skills.

If as expected the one-step-prediction (OSP) model, operating on the basis of an open-loop scheme, achieved high prediction accuracy in the forecasting of the upcoming value of the indoor temperature (i.e. less than 0.2 °C blunder comparing to the measured value), however, anchored in an open-loop NARX scheme, its main shortage appears when longer-term forecasting of indoor temperature is required: especially when the target model is used for designing an adaptive heating control strategy. While achieving lower accuracy comparing to OSP model (i.e. an average error up to 0.4 °C and a maximum error of 1.23 °C for long-term prediction), the multi-step-prediction (MSP) model, operating in closed-loop, represents an attractive compromise for longer-term forecasting of the dynamic heating behavior and thus offers an appealing application for designing adaptive heating controllers for SBEMS.

The achieved results stress several appealing issues relating as well the denotation of these results as the status of the NARX-based forecaster regarding data-driven identification of heating dynamics in real smart-buildings. The first points come across the ability of the proposed approach in modeling complex thermal conduct of buildings including the effect of inhabitants' presence on the discrepancy of their heating dynamics. In fact, this is visible through the obtained MSE and MAE values highlighting a prediction of indoor temperature with less than 0.2 °C blunder comparing to the measured value. This foretells the perspective of effectual usage of the proposed approach for designing data-driven adaptive controllers of buildings' heating behavior versus the context of their usage by potential residents. The second remark relates the possibility of a standard-technology based effective implementation of this investigated Machine-Learning-based identifier in authentic smart-buildings keeping advantage from the robustness of those standard (and market available) technologies and avoiding the complexity and the cost of designing specific implementation policies. Finally, the last mention goes to the accuracy of the achieved predictions relating as well short-term (i.e. one-step) as long-term (i.e. closed-loop) forecasters. Another attractive feature, arising from the theoretical foundation of the proposed approach, relates the comprehensive interpretation of the living space's occupancy effect with a quantitative appreciation of its influence on smart building's heating conduct's deviation.

The proposed approach offers an interesting application for designing heating controllers in spaces. It can serve as an application due to study the thermal behavior of the spaces. Most of the current controllers are designed according to model-free approaches and it leads to designed controllers with low efficiency. With the proposed approach we are able to design a heating controller based on the thermal behavior model of the spaces. It is promising. This approach leads to a new generation of smart heating controllers with high energy efficiency.

## 4.3. Fuzzy heating controller design

### 4.3.1. Introduction

From the very beginning, engineers have faced plenty of challenges regarding constructing and designing a building. One of the important problems is regarding the heating system and relating energy issues. This problem can be explained from different perspectives and each engineer who co-operates in a project of building construction and designing, face this challenge from his side by considering several factors. For example, a civil engineer according to facilities would like to utilize insulation materials for walls and roofs and interestingly benefit from maximum solar light during days to not only satisfy the user by gaining luminance but also decreasing the consumption of energy in lighting and space heating systems. This challenge can be seen by mechanical engineers differently: according to the type of space heating system which is conceived earlier in the preset layout by the architectures, he or she would like to have enough space and absolutely appropriate facilities to occupy the place with proper tools and devices. For instance, if space would be heated by a central radiator system, the engineer prefers to use double glazed windows and enough space close to the windows for installing a radiator with a suitable size and type.

The common goal among all of them is to build a suitable environment for users which is comfortable and energy-efficient. However, there is another imperative factor that their effects have not been taking into account and it has huge effect on space heating system; especially in control strategies of heating devices. It recently attracts attention: "User presence" or "Space occupation". Typically due to installing heating devices, British thermal unit (BTU) calculation is utilized to find the right required power of a heating system whereas it is an HVAC or a radiator. In BTU calculation several factors are examined and accordingly the right heating device with suitable characteristics will be chosen. In other words, designers imagine an empty space that needs to be heated, and consequently based on several factors, they find symmetrical devices like radiator type and size or controller device like a motor valve or a thermostat. The importance of occupation in a room can be as much important as other aforementioned factors, however, because of the highly dynamic impact that it has on the environment and usually sophisticated calculation considering the part of the thermal human body emitting in heating space, it has been missed or less in attendance. Taking advantage of thermal energy that is emitting from the body can affect the control strategies of heating systems and it is still questionable. SBEMS as a key solution by providing plenty of sophisticated control algorithms and also various opportunities for the development of them can face this challenge. However, as mentioned in section 1.6.1, there is still a lack of work on proper controller designing.

In this section, we are aiming to introduce a closed-loop control system on the basis of a FUZZY INFERENCE SYSTEM (FIS) for the SBEMS. The control strategies for designing the controllers are according to analysis regarding the model of heating dynamics of living spaces (the approach for modeling the dynamic of the heating spaces

is provided in section 4.2). The proposed approach is taking advantage of the Takagi-Sugeno fuzzy model in order to adapt the heating device functionalities to dynamic situations relating to different occupancies. The goal is to provide the user an energy-efficient model-based heating controller and thermal comfort.

### 4.3.2. Fuzzy controller for facing control of living-spaces heating dynamics

Earlier the identification of the heating dynamic of the building living space is discussed and the capacity of energy harvesting (or energy saving) considering the additional heating source (heating radiation by resident’s bodies) is clarified. Now, in this section, the Ph.D. will enhance to propose a solution to take advantage of this capacity: by proposing an adaptive controller. Before going through presenting the controller, we are aiming to propose the control system structure (Figure 63) which is a feedback controller system (closed loop controller).

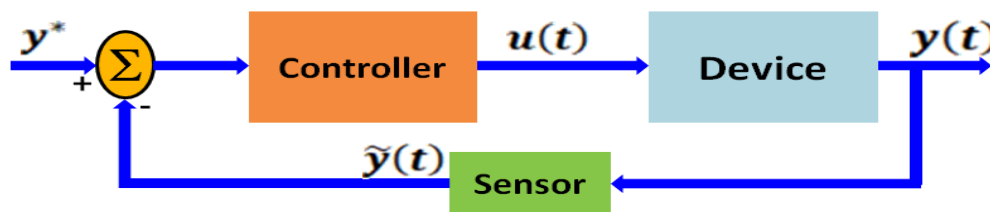


Figure 63. The conceptual structure of the feedback controller

The vast majority of the output feedback controller is based on the following general model:

$$u(t) = h \left[ y(t), \dot{y}, \int y \right] \quad (14)$$

Where  $u(t)$  is the control signal (i.e. controller’s output),  $y(t)$  is the controlled device’s (or system’s) output,  $\tilde{y}(t)$  is the measuring device’s (or system’s) output,  $y^*$  is the desired device’s (or system’s) output and  $h(\cdot)$  represents control law that is supposed to stabilize the feedback control system. [Ross 2010].

According to the structure of aforesaid feedback controller, the proposed fuzzy controller involves several parameters as inputs on its control loop:

1. Outdoor temperature ( $T_{Out}$ )
2. Occupation (OCC)
3. The volume of the living space ( $V_{LS}$ )
4. The temperature error ( $\Delta T$ ) (it is a subtract of the desired temperature and measured indoor temperature).

Each aforesaid parameter plays a role in the rule-based part of the fuzzy controller. The inputs of the fuzzy controller are the aforesaid parameters and the output signal would be the valve position of the radiator which has an effect on the output power of the radiator. Figure 64 presents the block diagram of the fuzzy controller (FC) with inputs and output in the closed-loop control system.

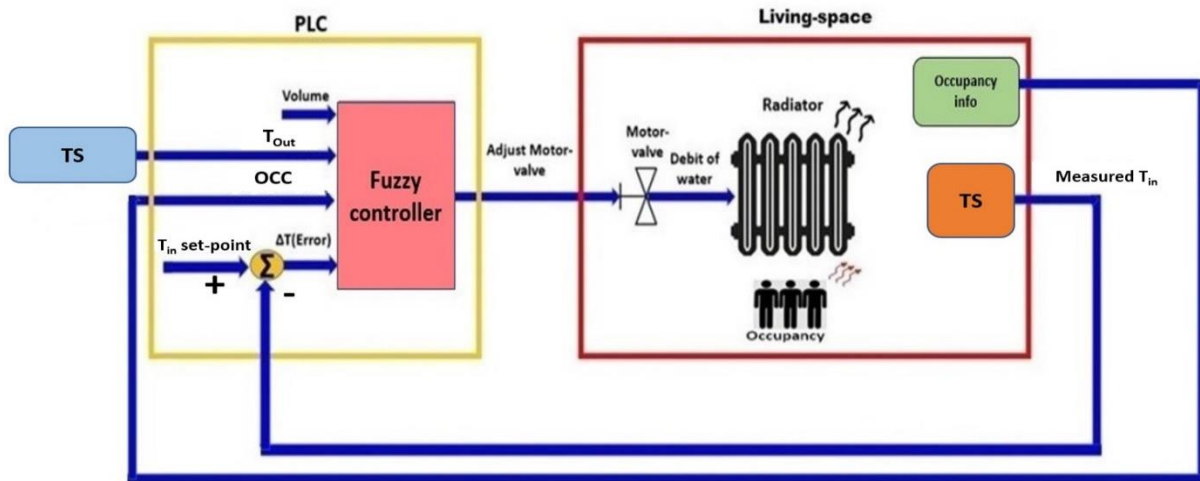


Figure 64. Block diagram of a Fuzzy Controller in feedback for controlling the temperature of living space

The fuzzy controller integrates with the control agent on the PLC and according to information that it receives about ambient by appropriate sensors or existing data, it can act on the motor valve of the radiator. By changing the valve position of the radiator, the output power of the radiator is changing and can adapt its functionalities in different situations. The proposed controller structure will lead to a fully automated and efficient system for controlling the thermal environment of the spaces that brings also user comfort. In the case of comfortability, it declines the involvement and unnecessary interaction of the user for controlling heating devices to a minimum while it is offering him thermal satisfaction. Thermal satisfaction means "reaching to the desired temperature on a proper time while automatically adjusting heating devices in different spaces according to proper strategies (without involving users) and reducing consumption of energy". In the following section, the control strategies of the aforesaid fuzzy controller are introduced.

### 4.3.3. Control strategy

Due to the automatic control of the heating device, Takagi-Sugeno fuzzy model is proposed. It is more attractive for control and nonlinear problems in comparison with Mamdani fuzzy model. [A. Kaur and Kaur 2012]. The fuzzy inference architecture is split into three different parts (Figure 65):

1. Fuzzification
2. Inference engine and rule based part

3. Defuzzification.

In Fuzzyfication the input value (fuzzy set) is mapping by a function to a degree of compatibility in linguistic variables. The Knowledgebase consists of a rule base and a database. The rule base contains a number of fuzzy if-then rules. The Inference engine is the process of formulating the mapping from a given input to an output. And finally, in defuzzification, the fuzzy set is mapping to output crisp set. [Imran and Alsuhaibani 2019], [Mitiku & Manshahia, 2018].

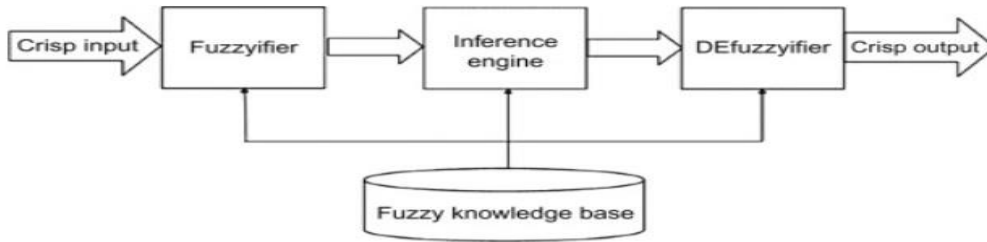


Figure 65. Fuzzy inference system architecture

The crisp inputs to the fuzzifier are as following:

1. The volume of the space ( $V_{LS}$ ): It contains three Gaussian membership functions (Equation (15)): Small(S), Medium(M), Large(L)[Ross 2010] (Figure 66).

$$f(x; \sigma, c) = e^{-\frac{(x-c)^2}{2\sigma^2}} \quad (15)$$

Where  $\sigma$  is the standard deviation,  $c$  is mean for each Gaussian membership function; membership value is calculated for each input value in  $x$ .

2. The outdoor temperature ( $T_{Out}$ ) has 7 Gaussian membership functions: Very Very Small (VVS), Very Small (VS), Small (S), Medium (M), Large (L) and Very Large (VL), Very Very Large (VVL) (Figure 67). The outdoor temperature besides other input parameters plays a role to reach the desired temperature (setpoint).
3. The occupancy is divided into 5 different Gaussian membership functions: Very Small, Small, Medium, Large, and Very Large (Figure 68).
4. The last input is  $\Delta T$  (error) (Equation (16)) with two Gaussian membership functions (Figure 69): 1. Small 2.Large. As long as  $\Delta T$  is bigger than 0 the valve position which is the output of the fuzzy controller will work in higher values and when  $\Delta T$  is 0 or negative values the valve position will decrease.

$$\Delta T = T_{Setpoint} - T_{Actual} \quad (16)$$

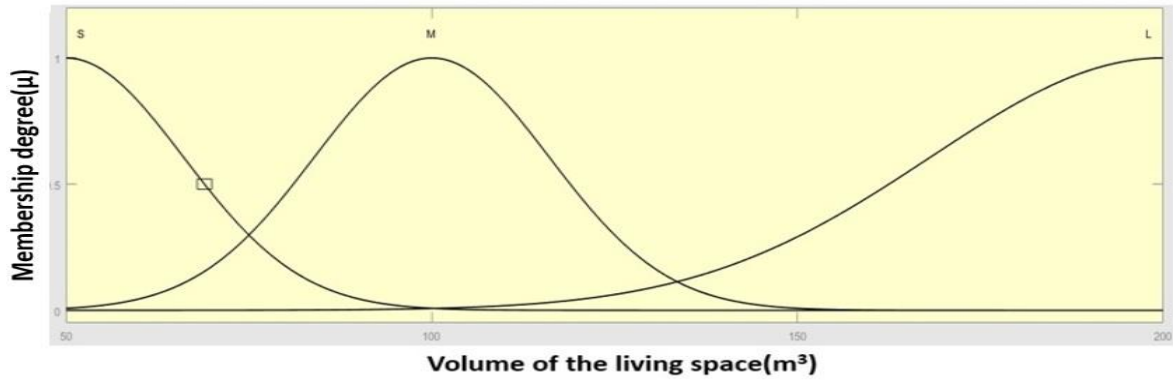


Figure 66. Membership functions of the volume of the living space ( $V_{LS}$ )

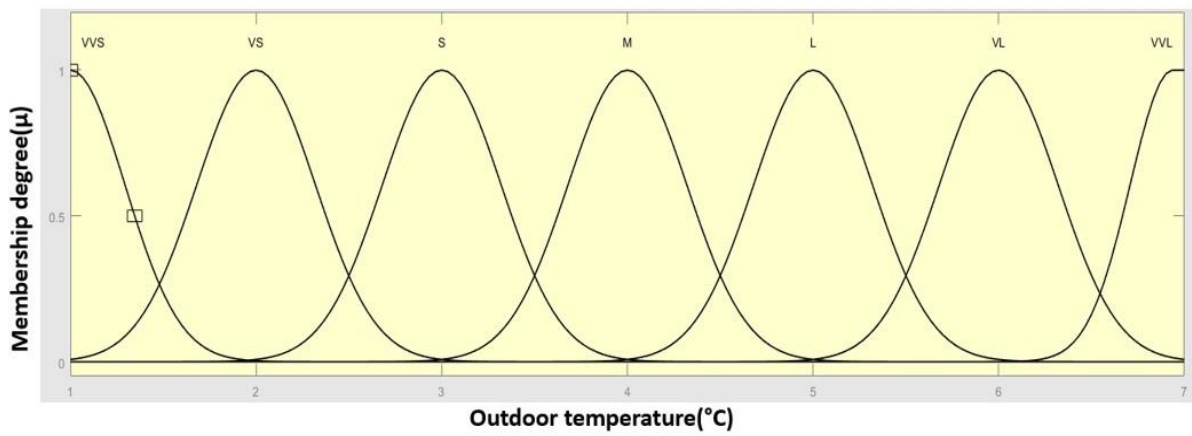


Figure 67. Membership functions of Outdoor temperature

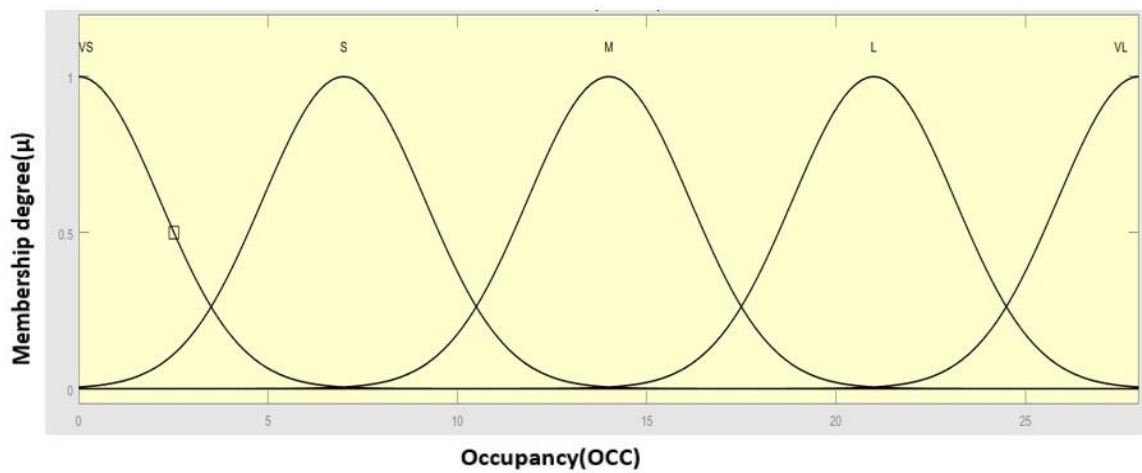


Figure 68. Membership functions of occupancy (OCC)



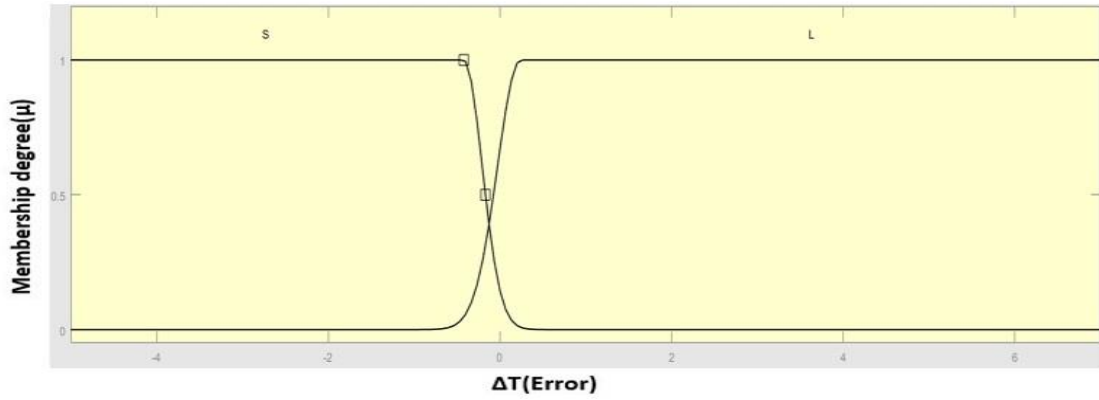


Figure 69. Membership functions of  $\Delta T$  (error)

The crisp output of the fuzzy controller is a valve position. The values of the valve position illustrated in Table 13 (the following table is based on the modeling of living-spaces of building A<sub>2</sub>). They are in the range of 0% (off) to 100% (nominal power).

VP1	VP2	VP3	VP4	VP5	VP6	VP7	VP8	VP9	VP10	VP11	VP12	VP13
0	20	22	25	30	36	69	71	74	76	77	78	100

Table 13. The crisp output of the fuzzy controller

As it is aforementioned, input crisp in the fuzzification process is mapped to linguistic variables by membership functions which are stored in fuzzy knowledge-based and the grade of memberships are quantified by membership degree ( $\mu$ ). The next step after fuzzification is relating to the rule-based part (knowledge base) and inference engine. In this part, according to the defined rule, the inputs are mapped to an output. They are mapped with weighted average defuzzification method (Equation 17).

$$Z^* = \frac{\sum_{i=1}^N w_i \cdot z_i}{\sum_{i=1}^N w_i} \quad (17)$$

Where  $w_i$  is the rule firing strength of membership functions,  $z_i$  is the rule output level and  $Z^*$  is the output.

$$w_i = \text{AndMethod}(F_1(x), F_2(y)) \quad (18)$$

Here,  $F_1(x)$  and  $F_2(y)$  are the membership functions for inputs 1 and 2, respectively.

The rule-based part of the fuzzy controller is constructed by considering the conditions of input crisps. Among all input crisps, the presence of people (occupants) plays the most imperative role (regarding their additional heating power). With regard to this fact, by taking into consideration the additional heating power by occupants that are presented by Figure 61 and Figure 62 in section 4.2.4.2, the knowledge-based part of the fuzzy controller is constructed. By considering Figure 61 and Figure 62, as an example, if the medium space is equipped by 28 people, the installed 3kW radiator should work in lower power to bring thermal satisfaction. Because the additional heating power relating to occupants is higher than the installed radiator sized in the mentioned room.

The objective of the rule-based part is the indoor temperature reach the desired value at a certain time interval by adjusting the radiator valve ( $\vartheta_p(t)$ ) considering the presence or absence of inhabitants in spaces. As mentioned in section 4.2.2, the identified heating slope is a function of valve position and occupancy ( $\hat{h}(t) = f(\vartheta_p(t), OCC)$ ). In order to reach the desired temperature efficiently, the optimized valve position should be estimated. The rules always offer an optimized valve position. It leads to optimum total output power (the power of heating devices and additional power by occupation ( $P_{total}(OCC) = P_{OCC}(OCC) + P_{Heating\ device}(OCC)$ ) in diverse conditions. It finally lets to have an optimized  $\hat{h}(t)$  and reach the desired temperature in a certain time interval.

On a basis of the rules, the total output power in presence of people is never less than the output power of heating devices while the room is empty ( $P_{total}(OCC \neq 0) \geq P_{Heating\ device}(OCC = 0)$ ). Also in all cases, based on the proposed control strategies, the desired temperature in presence of people reaches the setpoint not later than while the room is empty and the radiator is working to reach the desired temperature (by considering the same initial temperature).

Following abovesaid strategies, the rules-based part is constructed and illustrated in Table 14. The fuzzy controller is always offering a radiator's power to have an average temperature velocity of 1.1 ( $^{\circ}C/h$ ) when space is occupied. It will lead to having a harmonized heating environment offering thermal comfort for the user. It should be noted, in cases that the number of occupants causes a higher temperature velocity than what is expected, the radiator will turn off (VP=0). As an example of rules:

**If (Volume is M)And (Delta is L)And (OCC is M)And (Outdoor temperature is L) Then VP11**

Based on the "If" clause part, VP11 (=77) is estimated by the fuzzy controller in order to reach the set-point temperature by taking into account the additional heat source that is radiated by occupants (OCC=M). It lets reach the desired temperature with an average velocity of 1.1 ( $^{\circ}C/h$ ).

VOLUME	DELTA	OCC	OUTDOOR TEMPERATURE						
			VVS	VS	S	M	L	VL	VVL
S	S	VS	VP1	VP1	VP1	VP1	VP1	VP1	VP1
		S	VP1	VP1	VP1	VP1	VP1	VP1	VP1
	L	VS	VP13	VP13	VP13	VP13	VP13	VP13	VP13
		S	VP7	VP8	VP9	VP10	VP11	VP12	VP12
M	S	VS	VP1	VP1	VP1	VP1	VP1	VP1	VP1
		S	VP1	VP1	VP1	VP1	VP1	VP1	VP1
		M	VP1	VP1	VP1	VP1	VP1	VP1	VP1
		L	VP1	VP1	VP1	VP1	VP1	VP1	VP1
		VL	VP1	VP1	VP1	VP1	VP1	VP1	VP1
	L	VS	VP13	VP13	VP13	VP13	VP13	VP13	VP13
		S	VP13	VP13	VP13	VP13	VP13	VP13	VP13
		M	VP7	VP8	VP9	VP10	VP11	VP12	VP12
		L	VP1	VP1	VP1	VP1	VP1	VP1	VP1
		VL	VP1	VP1	VP1	VP1	VP1	VP1	VP1
L	S	VS	VP1	VP1	VP1	VP1	VP1	VP1	VP1
		S	VP1	VP1	VP1	VP1	VP1	VP1	VP1
		M	VP1	VP1	VP1	VP1	VP1	VP1	VP1
	L	VS	VP13	VP13	VP13	VP13	VP13	VP13	VP13
		S	VP13	VP13	VP13	VP13	VP13	VP13	VP13
		M	VP2	VP2	VP3	VP3	VP4	VP5	VP6

*Table 14. Fuzzy rule of the controller*

As much as the occupancy increases, the optimized value of valve position declines and that is because of heating energy exploiting by human bodies radiation. Regarding delta in this table, as long as the delta is positive and far from the setpoint, the valve position based on a number of occupants would choose by the fuzzy controller, and when the delta is close to the setpoint the valve position will decrease until the delta becomes zero. The output temperature as one of the inputs also plays a role. It has a small effect on heating slopes (for reaching setpoints) and it is assisting in order to optimize valve position better. In the next section, we are going to evaluate the proposed approach in simulation according to several scenarios.

#### **4.3.4. Simulation, and evaluation of the fuzzy controller in comparison with On/Off control strategy**

In order to evaluate the proposed controller, several experimental simulation assessments have been considered. The purpose of these simulations is to evaluate the

adaptiveness and energy-saving advantage of the fuzzy controller in various conditions. Regarding these facts, several scenarios have been implemented with two different controllers in a feedback loop control structure:

1. Fuzzy controller
2. On/Off controller

The feedback loop control with fuzzy controller is earlier mentioned in Figure 64. Regarding the On/Off controller, it is in the same feedback loop structure however it just considers the difference between actual temperature with setpoint temperature in the feedback as the only input. In the first experimental simulation, a scenario is implemented in a theoretical classroom with a medium size. The second experimental simulation is done in a practical classroom with a large size. Finally, the last simulation is in an office room with a small size. It should be mentioned, the experimental simulation relating to the modeling of living-spaces of building A<sub>1</sub> is taken place first, in order to study the approach and speed up for achieving research results in Ph.D. Finally, modeling of living-spaces of building A<sub>2</sub> is done for final evaluation and validation of approach.

#### 4.3.4.1. **Experimental simulation in the theoretical classroom with a medium size (living-spaces of building A<sub>1</sub>)**

Concerning the first experiment, it is assumed to reach the setpoint temperature (20°C) and keep the smoothness of temperature evolution and consequently the user comfort. The first experimental simulation is done in a theoretical classroom room (which is a room with a medium size ( $V_{LS}^F = \text{Medium}$ )). During the first 150 minutes, it is supposed that the room is empty (no occupation) and the initial indoor temperature is 17°C. Afterward, the rooms are getting fully occupied (28 students) by students for 4 hours of a lecture. Finally, the lecture is accomplished and students begin to leave the classroom and the room will remain empty for the rest of the day. The outdoor temperature is supposed to be 5°C during the simulation. The control of the radiator in all experimentations are done by an On/Off controller and the fuzzy controller (FC).

According to the functional nature of the FC, it is expected the controller shows its adaptiveness capabilities and adjust the motor valve to different conditions. Figure 70, Figure 71 and Figure 72, respectively illustrate the occupancy signal, Indoor temperature evolution and output signal of the fuzzy controller ( $\vartheta_p(t)$ ) in 3 hours of the first experimentation.

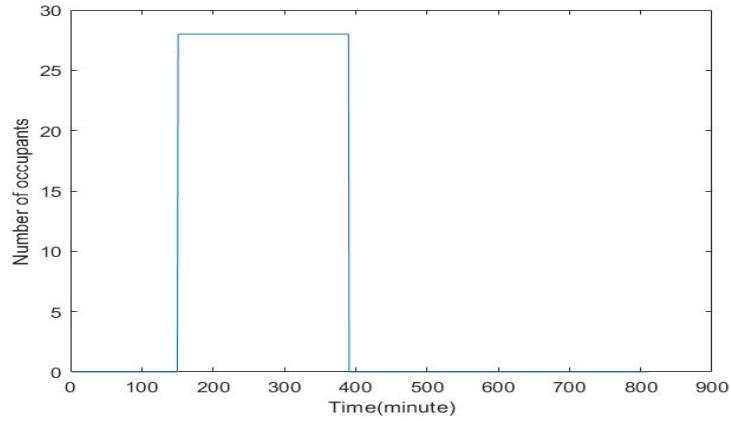


Figure 70. Occupancy versus time in 12 hours of experimentation in a theoretical classroom with a medium size

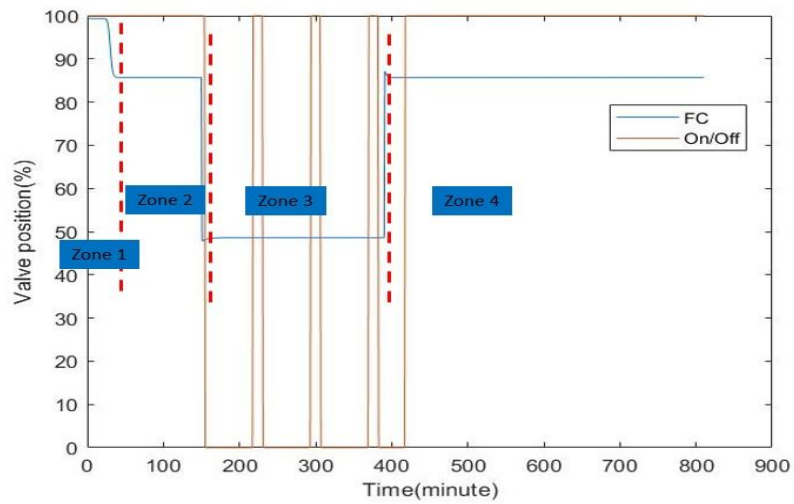


Figure 71. Valve position ( $\vartheta_p(t)$ ) variations regarding FC and On/Off controller during experimentation in a theoretical classroom with a medium size (living-spaces of building  $A_1$ )

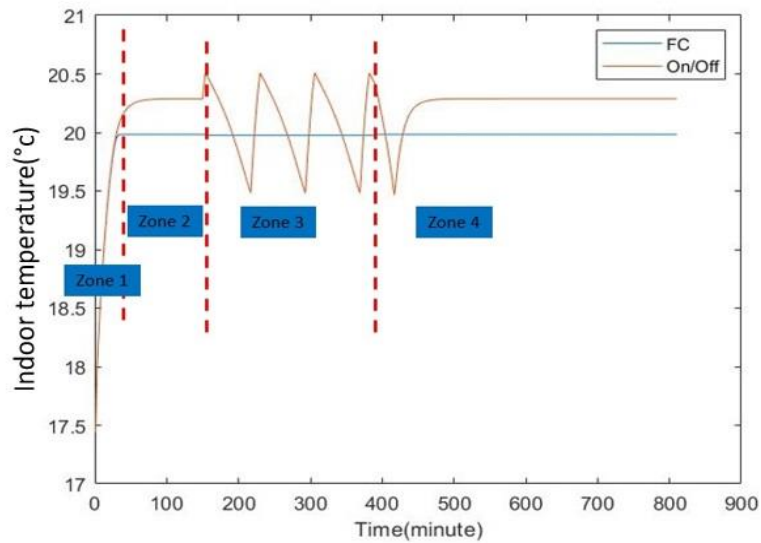


Figure 72. Temperature evolution in a theoretical classroom with a medium size by using FC and On/Off controller (living-spaces of building  $A_1$ )

According to Figure 71, in the first 60 minutes (zone 1) when the room was not occupied FC opens the valve position to maximum (valve position=100%) in order to the radiator works at nominal power to reach the setpoint temperature (desired temperature). On/off controller is also open the valve position in order to temperature reaches to the upper limit of hysteresis. In zone 2 the temperature reached the setpoint temperature ( $\Delta T = 0$ ) and the room is still empty. That is why the FC declines the valve position to 85% of nominal power to keep the temperature on the setpoint. Although the On/Off controller is still working at 100% in order to reach the upper limit of the hysteresis ( $20.5^{\circ}\text{C}$ ). In zone 3, space gets occupied and the FC adapts itself to new conditions. As soon as the presence is detected the output signal of the controller is changed and decreased the valve position to 50%. it lets the environment (space) gains part of the heating needs from human body heat radiation. Due to the functionality of the On/ Off controller the valve position in zone 3 is changing between 0 and 100% in order to temperature evolve between the upper and lower limit of hysteresis.

Finally, after 390 minutes, the students leave the classroom and it means the human body heat radiation does not exist anymore (zone 4). As soon as FC detects the new condition, in order to keep the temperature at  $20^{\circ}\text{C}$  in a lack of human body radiation, it increments the power of the radiator by opening the valve position to 85 percent of the nominal power. The On/Off controller in zone 4 after reaching the lower hysteresis is working in nominal power to reach again the upper limit of hysteresis.

#### 4.3.4.2. Experimental simulation in the theoretical classroom with a medium size (living-spaces of building A<sub>2</sub>)

The same scenario as section 4.3.4.1 is implemented in this section for model 2. Figure 73 and Figure 74 respectively present the valve position and temperature evolution of FC and On/Off controller in a theoretical room with medium size.

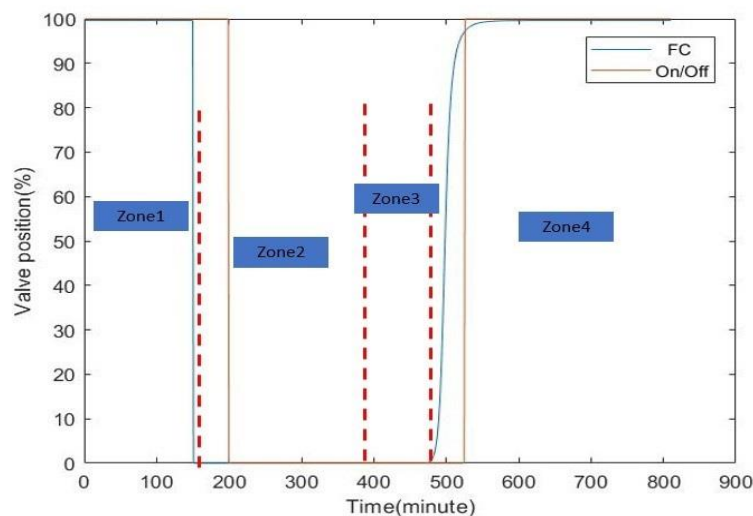


Figure 73. Valve position variations ( $\vartheta_p(t)$ ) regarding FC and On/Off controller during experimentation in a theoretical classroom with a medium size (living-spaces of building A<sub>2</sub>)

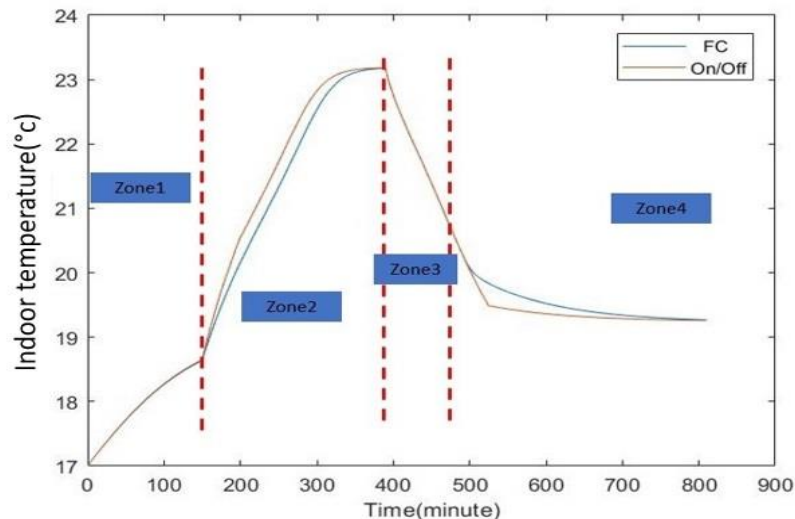


Figure 74. Temperature evolution in a theoretical classroom with a medium size by using FC and On/Off controller (living-spaces of building A<sub>2</sub>)

The initial indoor temperature is 17°C. In zone 1, while the room is empty both controllers let that motor valve open the valve position to 100% (radiator works in nominal power). After 2 hours and a half, the indoor temperature in both cases is 18.5°C. When the room is occupied (zone2) by 28 people FC changes its functionalities and the valve position turns to 0. That is because 28 people in a room are able to produce even more power than what is needed to reach the setpoint (it lead to higher average temperature velocity ( $2.2 \text{ } (^{\circ}\text{C}/\text{h})$ ) than expectation). It should be noted 200 minutes after beginning the experimentation indoor temperature reached the setpoint temperature ( $\Delta T = 0$ ) and then passed it ( $\Delta T < 0$ ). However, on the other hand, the On/Off controller is still working in nominal power cause it is still far from the upper hysteresis limit and it reached there one hour later. At time 390 minutes (beginning of zone 3) the room is getting empty. However, the temperature is high (23°C) in both cases as a result, both controllers remain at zero power. When the temperature decreased and goes lower than 20°C, FC changes its functionalities in a lack of occupation power and turns the valve position to 100% to keep the temperature at 20°C. About 50 minutes later when the indoor temperature reaches lower limits of the hysteresis (19.5°C) On/Off controller turns the valve position to 100 percent in order to increase the temperature again.

In the next section, we are going to implement another scenario in practical classrooms where the size of space is large.

#### 4.3.4.3. Experimental simulation of the practical classroom with a large size (living-spaces of building A<sub>1</sub>)

The experimental simulation in this section is in a practical classroom. The maximum capacity of occupants is 15 people. The physical activity in this room is higher than the theoretical room and occupants during the lectures are using devices that produce heat

(i.e. Computers, PLCs, power supplies, etc.). Figure 75 shows the occupation of the room during the experimentation. The first one hour and half the room is empty and after, 4 hours of a lecture it is getting occupied by 15 people. Finally, after the lecture, it becomes empty and remains unoccupied for the rest of the experimentation. The outdoor temperature is set 5°C during the simulation like the theoretical classroom the heating device is controlling once with FC and once with On/Off controller. Figure 76 and Figure 77 show the valve position changes during the time ( $\vartheta_p(t)$ ) and temperature variation during experimentation for FC and On/Off controller respectively while the prediction of indoor temperature is doing by living space model 1.

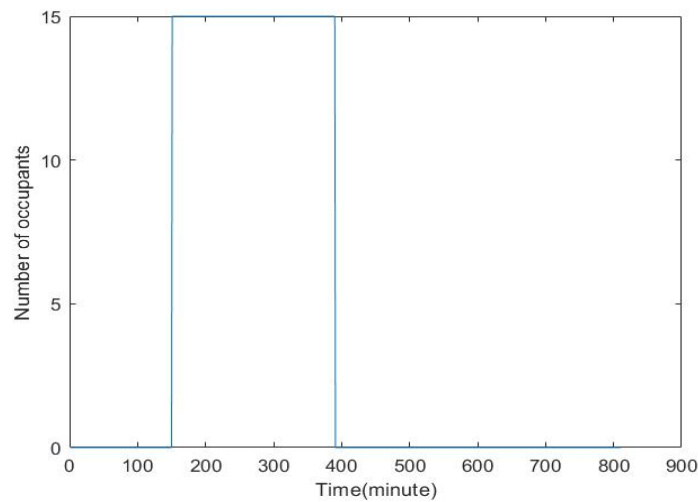


Figure 75. Occupancy versus time in 12 hours of experimentation in a practical classroom with a large size

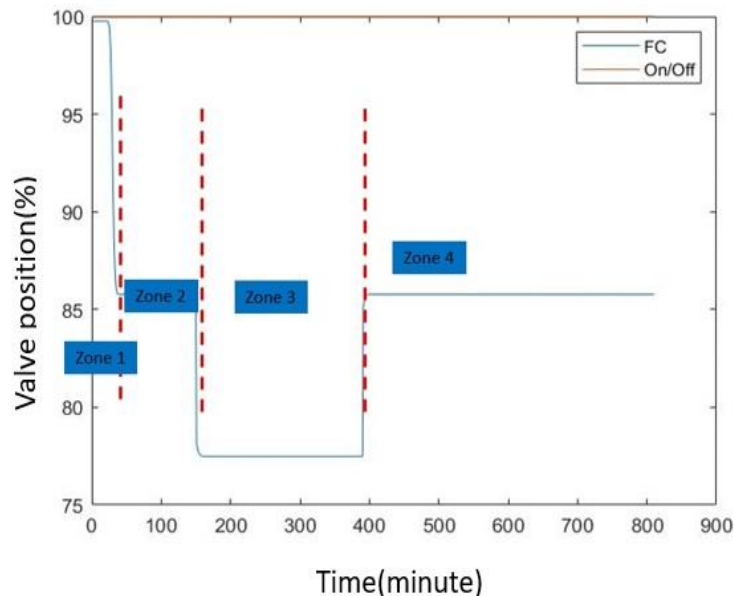


Figure 76. Valve position variations ( $\vartheta_p(t)$ ) regarding FC and On/Off controller during experimentation in a practical classroom with a large size (living-spaces of building A<sub>1</sub>)



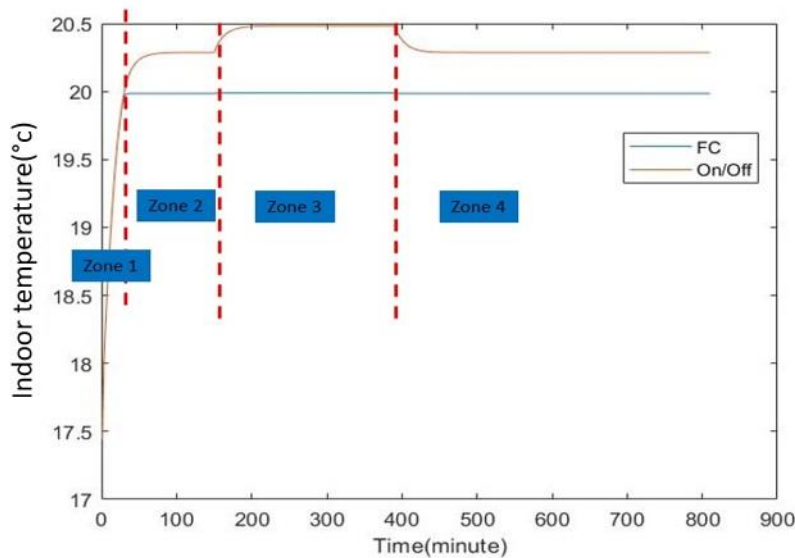


Figure 77. Temperature evolution in a practical classroom with a large size by using FC and On/Off controller (living-spaces of building  $A_1$ )

In zone 1, the number of occupants is zero and as a result, both controllers let the radiator works in nominal power to reach the setpoint temperature. In zone 2 when the indoor temperature reaches the desired temperature ( $\Delta T = 0$ ), the FC turns the valve position to 86% of nominal power while the On/Off controller remains in 100% of the valve position (because the indoor temperature is not reaching the upper limit of hysteresis). In zone 3, space is occupied by 15 people. FC changes its functionalities in order to adapt to the new condition. It turns the valve position to 77% of nominal power. However On/Off controller doesn't change the power of the radiator because it can not reach the upper limit of hysteresis. After 390 minutes the room is getting empty. The FC changes the valve position to 86% in order to indoor temperature remain at the desired temperature in lack of occupants while the On/Off controller doesn't change the valve position cause it is still a bit below the upper limit of hysteresis.

#### 4.3.4.4. Experimental simulation of the practical classroom with a large size (living-spaces of building $A_2$ )

The valve position ( $\vartheta_p(t)$ ) and temperature variations regarding FC and On/Off controller on the basis of indoor temperature prediction of model 2 for a practical classroom is illustrated in Figure 78 and Figure 79.

In zone 1, the space is empty and radiators are working in nominal power in both controller cases and the indoor temperature reaches  $19.2^\circ\text{C}$  in both cases. In zone 2, the room is getting occupied by 15 people. FC changes the radiator output power to 25% (valve position=25%) of nominal power in order to adapt itself to new conditions however On/Off controller lets the radiator work in nominal power (valve position=100%) for 60 minutes more because it needs more time to reach the upper limit

of hysteresis. When occupants start to leave the classroom the indoor temperature is 21.5°C in the case of the FC and 21.7°C in the case of the On/Off controller (beginning of zone 3). In both cases, the radiators remain off because the indoor temperature is higher than the desired temperature. When the indoor temperature reaches 20°C, FC controller increases the valve position to 65% in order to keep it on desired values (setpoint indoor temperature) although the On/Off controller keeps the valve position zero until the indoor temperature reaches to downer limit of hysteresis and then turn the valve position to 100%, 550 minutes after the beginning of the experimentation.

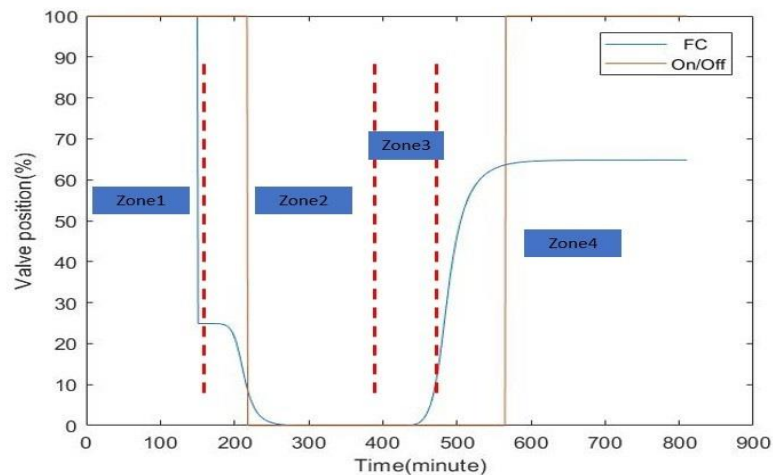


Figure 78. Valve position variations ( $\vartheta_p(t)$ ) regarding FC and On/Off controller during experimentation in a practical classroom with a large size (living-spaces of building  $A_2$ )

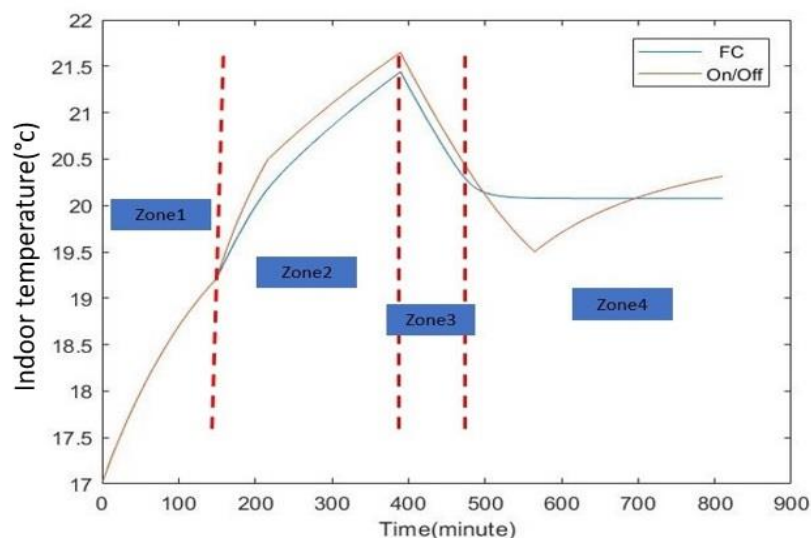


Figure 79. Temperature evolution in a practical classroom with a large size by using FC and On/Off controller (living-spaces of building  $A_2$ )

4.3.4.5. **Experimental simulation office room with a small size (living-spaces of building A<sub>1</sub>)**

With the same approach as the last sections, an experiment is done in an office room. The size of this room is small ( $V_{LS}^F = Small$ ). The scenario is happening during a meeting. In the first 2 hours and half of the experiment, there are two people in the room and then four more people are joining and the meeting will start. The meeting is holding for 4 hours. Finally, the meeting will finish and just 2 people remain in the room until the end of the experimentation. The outdoor temperature is 5°c during the simulation. Figure 80, Figure 81 and Figure 82 respectively present the occupation during the experimentation, the output signal of fuzzy and On/Off controller  $\vartheta_p(t)$ , temperature fluctuation during the experiment.

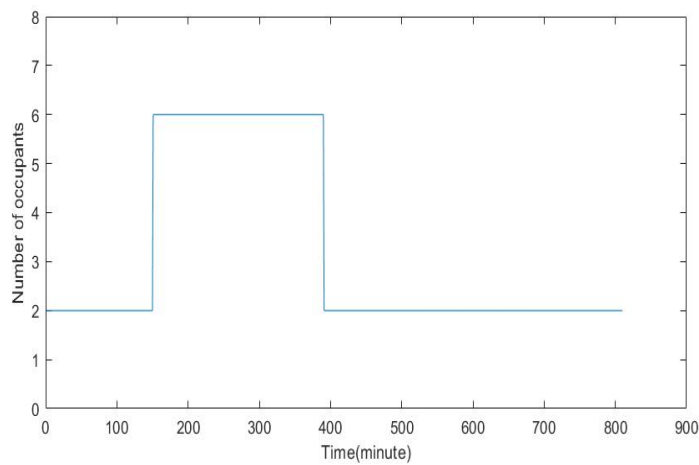


Figure 80. Occupancy versus time during experimentation in an office room with a small size

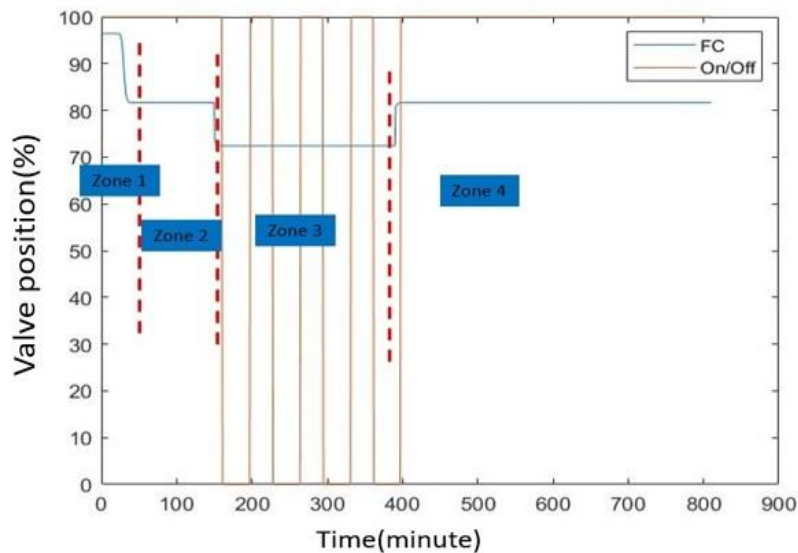


Figure 81. Valve position variations ( $\vartheta_p(t)$ ) regarding FC and On/Off controller during experimentation in an office room with a small size (living-spaces of building A<sub>1</sub>)

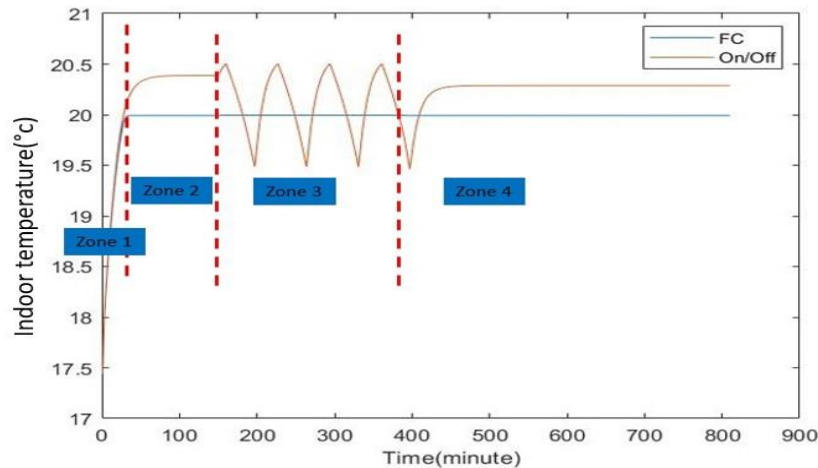


Figure 82. Temperature evolution in an office with a small size by using FC and On/Off controller (living-spaces of building A<sub>1</sub>)

In the first zone, there are just two people in the room and the initial indoor temperature is 17°C. The FC sets the radiator motor valve at 98%. In zone 2 temperature reached the desired indoor temperature ( $\Delta T = 0$ ) and that is why the FC changes the valve position to 82% of nominal power. Although, the On/Off controller lets the radiator work in nominal power cause it is still far from the upper limit of hysteresis. In Zone 3, 4 peoples join for the meeting and consequently, the FC adapts the output power of the radiator to new conditions by reducing valve position to 72%. Simoustanly the On/Off controller is changing the valve position between 0 and 100%. After 4 hours when the meeting is finished, the room remains with 2 occupants and again FC adapts the radiator power by increasing the valve position to 82%.

#### 4.3.4.6. Experimental simulation office room with a small size (living-spaces of building A<sub>2</sub>)

The simulation of section 4.3.4.5 is repeated in this section however for predicting the indoor temperature of the room, Model 2 is utilized. Figure 83 and Figure 84 shows the valve position and the temperature changes during the experimentation.

In zone 1 while there are two occupants, FC sets valve position at 98% of nominal power and On/Off controller at 100. In zone 2, while the room is getting occupied with 4 additional people at the beginning the indoor temperature is 19°C in the case of FC and 19.2°C in the case of On/OFF controller. The FC adapts the radiator power to the next condition by decreasing 20% of the valve position however On/Off controller still works at 100% in order to reach the upper limit of hysteresis. In zone 2, In both cases, the valve position is declined. For FC when setpoint achieved ( $\Delta T = 0$ ) and for On/Off controller when indoor temperature meets the upper limit of hysteresis. FC sets the valve position in 42% and On/Off to zero. When the meeting finished the indoor temperature declined (zone3) and according to this fact both controllers increase the valve positions.

However, the FC turns the valve position to 95%; 30minutes earlier than the On/Off controller in order to keep the indoor temperature at the desired temperature ( $\Delta T = 0$ ).

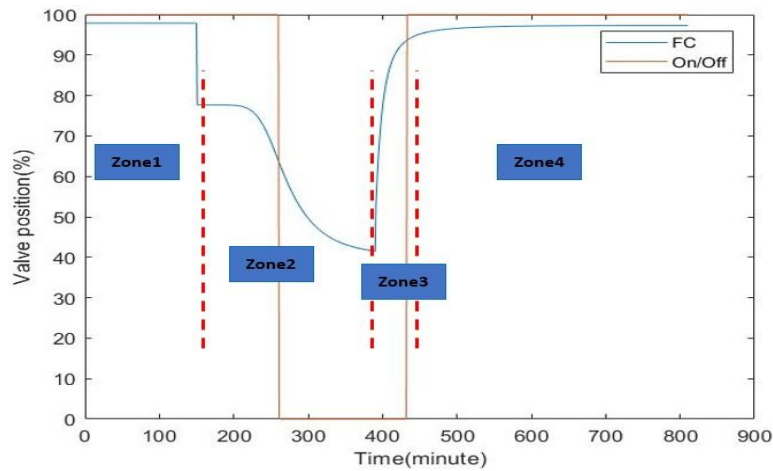


Figure 83. Valve position variations ( $\vartheta_p(t)$ ) regarding FC and On/Off controller during experimentation in an office room with a small size (living-spaces of building  $A_2$ )

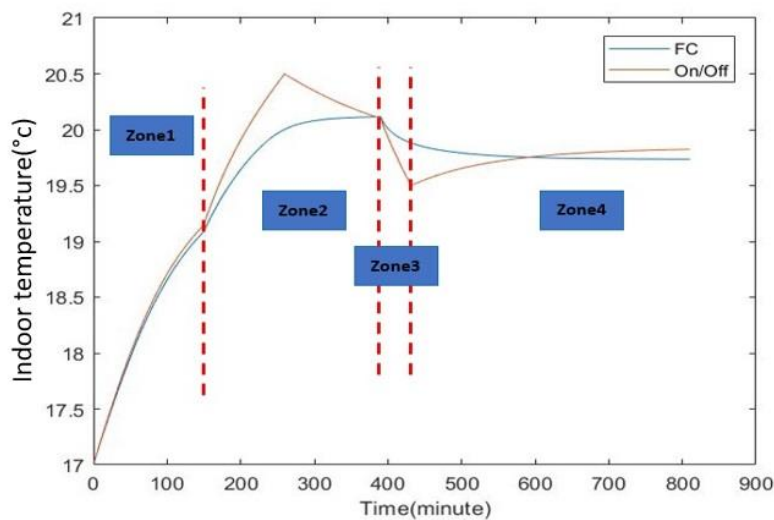


Figure 84. Temperature evolution in an office with a small size by using FC and On/Off controller (living-spaces of building  $A_2$ )

In all scenarios, FC shows its sensitivity to the number of inhabitants in living spaces while in contrast On/Off controller changes the state of valve position based on the error between indoor and desired temperature without taking into consideration any other parameters. FC always optimizes the valve position according to ambient information that it receives through a feedback loop from sensors and actuators. However on the other hand, On/off controller switches the valve position between nominal power and off mode. The obtained results show the FC perfectly is able to adapt its functionalities to different situations. It harmonizes the generation of thermal energy by radiators,

according to human body heat radiation. In the case of user comfort, it should be noted, the reaching time to the desired temperature in all cases is approximately the same to have a harmonized environment in different spaces with different occupations. For example, by looking at the results of the simulations regarding the model of living spaces of building A<sub>2</sub>, in all cases temperature reached the range of 19.4°C to 20 °C approximately after 180 minutes, while the initial temperature was 17°C. In addition, the self adaptiveness functionality of the proposed controller declines the involvement of users or inhabitants for controlling the indoor temperature of spaces.

In all the above experimental simulations, in contrast with the heating model of living-spaces of building A<sub>1</sub>, living-spaces of building A<sub>2</sub> show the slower dynamic of temperature and higher part of thermal energy production by occupants. The heating model of living-spaces of building A<sub>2</sub> represents the prediction of indoor temperature more realistic and it is considered for final evaluation and validation of approach. By considering this fact, in the next section, the results regarding energy consumption and efficiency according to FC and On/Off controller will be discussed and the validation of the FC will be evaluated.

#### 4.3.5. Results and validation:

Evidently, Temperature-Time curves show the advantage of the fuzzy controller on the thermostatic (On/Off) controller in terms of setpoint tracking. Thanks to the optimization functionality of the fuzzy system that lets the temperature track the setpoint smoothly. Consequently, it brings temperature satisfaction and comfortability to the user. In regards to energy saving and comparison the performance of FC with on/off controller, it is necessary to refer to thermodynamics law and specific heat capacity. [Van Wylen, Sonntag, and Dybbs, 1975]. All elements absorb or desorption heat. Nevertheless, with regards to the importance of indoor temperature of spaces, the one that is important in our case is the amount of heat gained or lost by space's air. Based on this fact, the specific heat capacity can indicate the amount of thermal energy that is absorbed or lost by the air in the room (Equation 19).

$$Q = mc\Delta T \quad (19)$$

Where Q is the Absorption heat,

M is the mass of air in the room,

C is the specific capacity,

And  $\Delta T$  is the difference between the initial temperature and the final temperature.

In order to find the mass of air in a room the following equation should be utilized:

$$m = \rho \times V \quad (20)$$

Where  $\rho$  is the density of air ( $\frac{kg}{m^3}$ ), [Blevins, 1984]

And  $V$  is the volume of the room in  $m^3$ .

The Temperature-Time curve is analyzed in order to obtain the heat loss and gain during experimentations. It is split into several parts for analyzing (Figure 85):

1. Profitable heat Gain ( $Q_{Profitable-gain}$ )
2. Unnecessary heat Gained ( $Q_{Unnecessary-gain}$ )
3. Heat loss ( $Q_{Loss}$ )

The profitable heat gain on this figure is the blue parts where the temperature is reaching the indoor temperature setpoint for the first time. The unnecessary heat gain is the red parts where the temperature for the second and more is reaching the setpoint and also it passes the setpoint and finally, the heat loss is the green parts wherever there is a loss of temperature. It should be remarked  $Q_{profitable-gain}$  and  $Q_{unnecessary-gain}$ , individually are split into three parts:

1.  $Q_{gain-R}$ : It is the heat that is gain just from the radiator in absence of occupants during the experimentation.
2.  $Q_{gain-OCC}$ : It is the heat that is gain just from occupants in absence of radiators during the experimentation.
3.  $Q_{gain-R\&OCC}$ : It is the heat that is gained at the same time from occupants and radiator during experimentation.

Based on Equation (19) the portion of each part (the profitable gain, unnecessary gain, and loss) for two control modes (On/Off controller and FC) are analyzed. Table 15 illustrate the portion of each part.

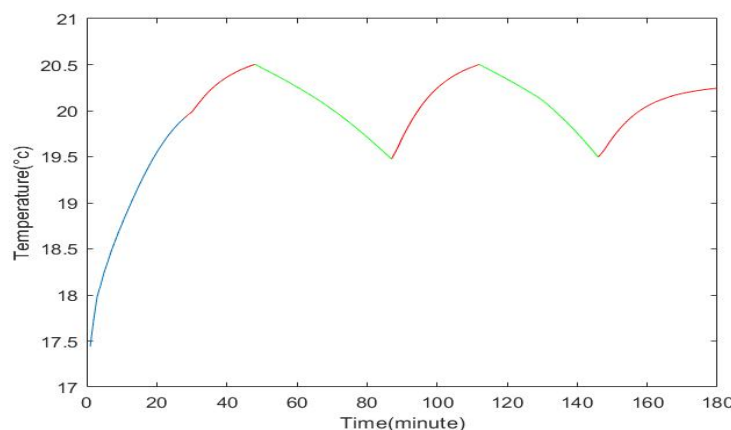


Figure 85. Profitable gain (blue), unnecessary gain (red) and loss (green)

Controller	Experimentations	Thermal energy (kJ)					
		Q profitable-gain	Q Unnecessary-gain	Q Loss	Q gain-R	Q gain-OCC	Q gain-OCC&R
On/Off	Medium classroom (theoretical)	362.52	384.271	473.692	199.386	323.851	223.554
	Large classroom (practical)	725.04	565.53	512.361	674.286	268.264	348.019
	Office room	181.26	58.589	60.42	0	0	240.471
FC	Medium classroom (theoretical)	362.52	383.062	472.484	198.177	540.154	0
	Large classroom (practical)	725.04	335.935	319.017	500.277	229.596	331.101
	Office room	181.26	7.25	22.959	0	0	188.51

*Table 15. The portion of thermal energy that is gained or lost in kilo-joule (kJ) in the living-spaces model of building A<sub>2</sub>*

According to Table 15, the part of the heat that is gain or is lost in different spaces is illustrated. The effect of the operation of each controller individually in the presence and absence of the occupants regarding the abovesaid scenarios are presented. The profitable heat gain ( $Q_{Profitable-gain}$ ) in each case for FC and On/Off is equal because the initial temperature is defined at 17°C and the desired temperature is defined 20°C and all cases achieved the desired temperature. Although, the unnecessary heat gain ( $Q_{Unnecessary-gain}$ ) in all cases for FC is less than the On/Off controller except the medium classroom that is equal. However, the interesting part is about  $Q_{Loss}$  that in all cases the FC has a smaller part. In another word, it represents the loss of energy in FC is less. Finally, the results relating to  $Q_{gain-OCC\&R}$ , shows heating gain from occupants and radiators at the same time is reduced for the FC in comparison with the On/Off controller. It is due to the reduction of the radiator's participation in heat generation because of the occupant's presence.

In order to have an estimation of the thermal energy saving capacity that is achieved by FC, Table 16 is presented. Thermal energy saving is computed according to Equation (21).

$$Thermal\ energy\ saving = \left(1 - \frac{Q_{FC}}{Q_{On/Off}}\right) \times 100 \quad (21)$$



Experimentation	Thermal energy saving			
	Unnecessary-gain	Loss	Gain-R	Gain-OCC&R
Medium classroom	0.3%	0.25%	0.6%	100%
Large Classroom	40%	37%	25.8%	4.86 %
Office room	89%	62%	0	44%

*Table 16. The thermal energy saving of FC vs. On /Off controller in the living-spaces model of building A<sub>2</sub>*

The thermal energy saving regarding the unnecessary-gain for the medium classroom is zero cause in both cases (FC and On/Off controllers) indoor temperature increased to the same upper limit. However, in the case of large classroom and office, this amount is 40% and 89% respectively that shows a great part in energy saving. In all spaces (rooms) loss of heat is reduced. In the office room, this amount is remarkable (62%). Regarding the heat that is gaining just by radiator as it is apparent in large classroom 25.8% less energy is consumed. In the case of the office room, this amount is zero cause during all the experimentation, there were at least two occupants in the space. The last part is relating to heat that is gain from the radiator and occupants at the same time. This amount for the medium classroom is 100%. it means there was no time that space is occupied and radiators work at the same time. In fact, this indicates when there were occupancies in the experimentation the radiators did not work and gain the heat just from human body heat radiation.

In the large classroom and the office room, saving energy regarding gain from occupants and radiators at the same time is 4.86 % and 44% respectively. It represents while there were occupants, radiators were working in less power.

In the final step, the readable code of FC for downloading on PLC is generated by MATLAB PLC CODER and it downloaded on PLC for validation. To validate the results, two classrooms are selected. The first one is a theoretical classroom with a  $V_{LS}^F = Medium$  size. The data is recorded by the monitoring system of SBEMS for 233 minutes. During the mentioned time a lecture with 28 occupants is held. The second classroom for validation is a practical classroom with  $V_{LS}^F = Large$  size. The data regarding the practical classroom is recorded for 560 minutes. During this period, a lecture for 4 hours is held.

Figure 86 and Figure 87 show the recorded measurement and also simulation with same condition as reality in a theoretical classroom with a medium size that is monitored by SBEMS.

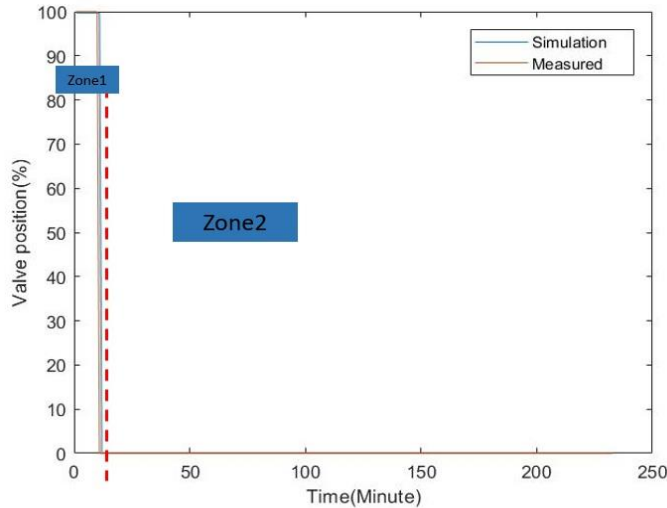


Figure 86. Valve position fluctuations in a theoretical classroom (measured values and simulation values)

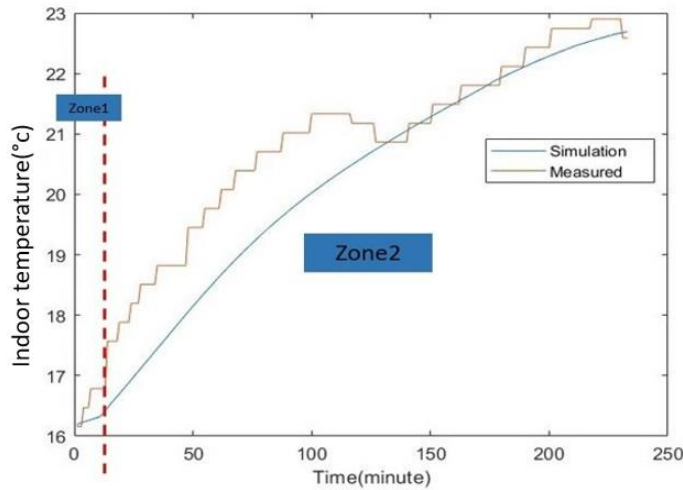


Figure 87. Temperature changes in theoretical classroom (measured values and simulation values)

The outdoor temperature is increasing from 8°C to 11.69°C during the recording of data. In the first 15 minutes, the space is empty and the initial indoor temperature is 16.2°C. The radiator is working in nominal power in order to reach the desired temperature ( $\Delta T > 0$ ). After 30 minutes the lecture began and space is occupied by 28 people. As 28 people in this room generate more heat than the nominal power of the radiator, the FC turns the valve position to 0 and gain needed heat from human body heat radiation. Finally, after 60 minutes from the beginning of the lecture, the indoor temperature reaches the desired temperature ( $\Delta T = 0$ ). It shows the indoor temperature keeps increasing until the end of the lecture to 23°C ( $\Delta T < 0$ ).

Figure 88 and Figure 89 illustrate relating results to a large room during a practical lecture. The simulation with same condition as reality is also visible in aforesaid figures.

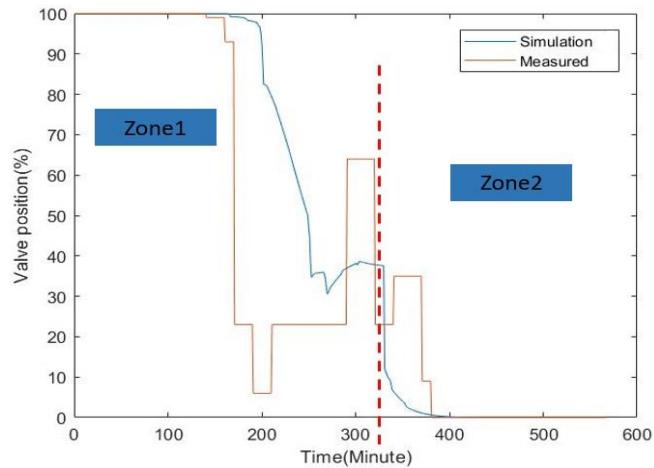


Figure 88. Valve position fluctuations in a practical classroom (measured values and simulation values)

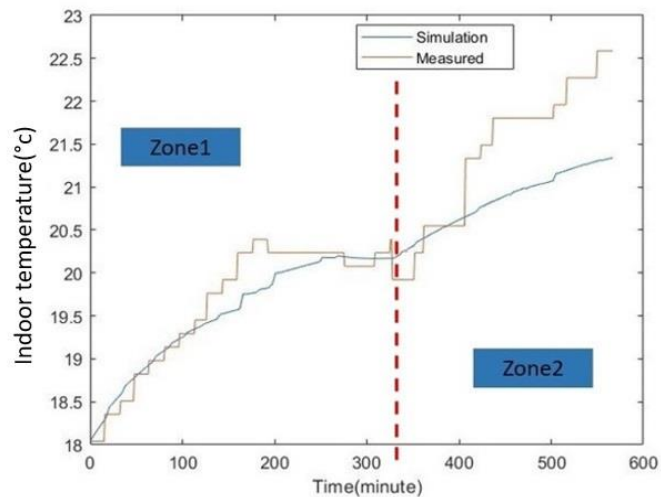


Figure 89. Temperature changes in practical classroom (measured values and simulation values)

The outdoor temperature is increasing between  $3.8^{\circ}\text{C}$  to  $14.2^{\circ}\text{C}$ . At first 330 minutes the room is empty. The initial indoor temperature is  $18^{\circ}\text{C}$  ( $\Delta T > 0$ ). In zone 1, after 170 minutes the indoor temperature is reached to the desired temperature ( $\Delta T = 0$ ). The FC changes its functionality to adapt itself to new conditions in order to keep the indoor temperature on the desired temperature. As a result, the valve position is changing from 100% to 25% of nominal power. it is fluctuating between 5% to 65% in order to keep the desired temperature. In zone 2 when the room is get occupied by 15 people, FC adapts to new conditions and decreased the valve position in order to gain some part of the needed heat from human body radiation. By increasing of indoor temperature and passing the desired temperature to higher indoor temperature ( $\Delta T < 0$ ) FC turns off the radiator by changing valve position to zero. Alike to simulation result of the theoretical room, in the practical room, the simulation result is relating to the model of living-spaces of building A<sub>2</sub>.

The results of validation confirm the results that are obtained in section 4.3.4 based on the simulation-scenarios evaluation. The proposed approach shows its effectiveness for designing and developing a controller on a basis of the model of living spaces-approaches by considering the inhabitants as additional heating power. According to the obtained results, the presented controller illustrates its performance in the case of energy efficiency and also user comfort.

Regarding the idea of occupants and their effects on the heating slopes, in the next section, we are going to represent a solution to estimate the number of occupants with a CO<sub>2</sub> sensor and on a basis of the influence of occupants on the concentration of CO<sub>2</sub> and its relating slopes.

## **4.4. Presence estimator**

### **4.4.1. Introduction to presence estimator**

Nowadays, one of the most in attendance information that is needed in any system is the occupation of the systems. The importance of the presence and absence of people plays a key point in any system and any places. It can provide statistical information and consequently has an influence on the decision-making process of a system. The awareness about occupation can be utilized for different purposes, for instance, in shopping malls or offices for estimating the statistics of their costumers in order to provide better services or for employers to monitor their employees or in a higher-level in controlling field, this statistical information can be used for designing ventilation systems or heating systems.

The precision of presence estimation according to needs can differ. In some systems maybe detection of absence and presence could be enough however in some systems estimating the exact number of people is vital. In our case regarding each people are seen as a heating device, we are looking to estimate the exact number of people as accurately as possible.

In this section, we will propose a fuzzy approximator that is working as a virtual presence estimator (VPE) sensor. It is able to estimate the occupancy according to driven data from the carbon dioxide sensor with co-operation with the presence detector sensor by using MAMDANI method.

### **4.4.2. The proposed Virtual presence estimator sensor based on the fuzzy inference**

The mechanism of the human body is to consume oxygen with inhaling and produce carbon dioxide with the exhale. In indoor places where the air transfer with outdoor is limited, the consequences of people's presence are leading to increment in carbon

dioxide. As much as the number of occupants in a certain volume is higher the density of carbon dioxide will increase faster. In fact, it indicates, the number of occupants is a function of two parameters (22):

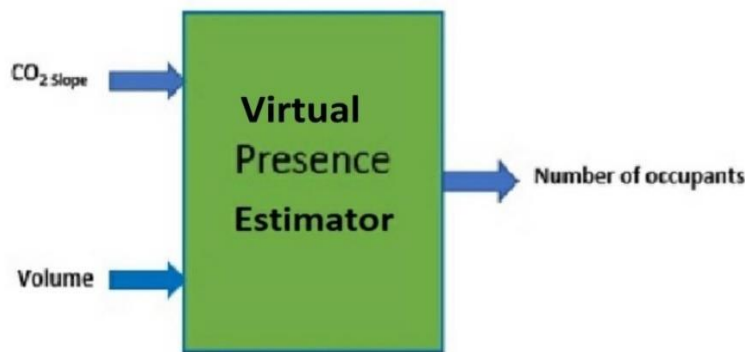
1. The volume of space
2. The Slope of increment part per million (PPM) of carbon dioxide (Equation 23).

$$OCC(t) = f(s(t), v) \tag{22}$$

$$s(t) = \frac{CO_2(t_{k+n}) - CO_2(t_k)}{t_{k+n} - t_k} \tag{23}$$

Where  $OCC(t)$  is the output (number of occupants),  $f(s(t), v)$  is a function based on  $CO_2$  slope in a time interval ( $s(t)$ ) and volume ( $v$ ).

The proposed model is estimating the number of occupants based on MAMDANI fuzzy inference techniques. Figure 90 proposed the block diagram of MAMDANI fuzzy inference for presence estimation.



*Figure 90. Virtual presence estimator based on MAMDANI fuzzy interface technique*

The  $CO_2$  slope has 9 Gaussian membership functions: Small Small (SS), Medium Small (MS), Large Small (LS), Small Medium (SM), Medium Medium (MM), Large Medium (LM), Small Large (SL), Medium Large (ML), Large Large (LL) (Figure 91).

Volume has three Gaussian membership functions: Small, Medium, Large (Figure 66).

And the number of occupants has 6 Gaussian membership functions: Very Small (VS), Small (S), Medium (M), Large (L), Very Large (VL), Very Very Large (VVL) (Figure 92).

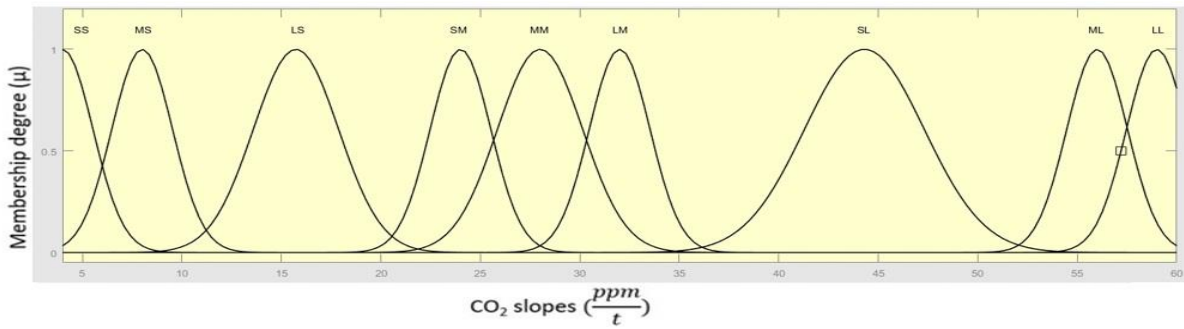


Figure 91. Membership functions of CO<sub>2</sub> slopes

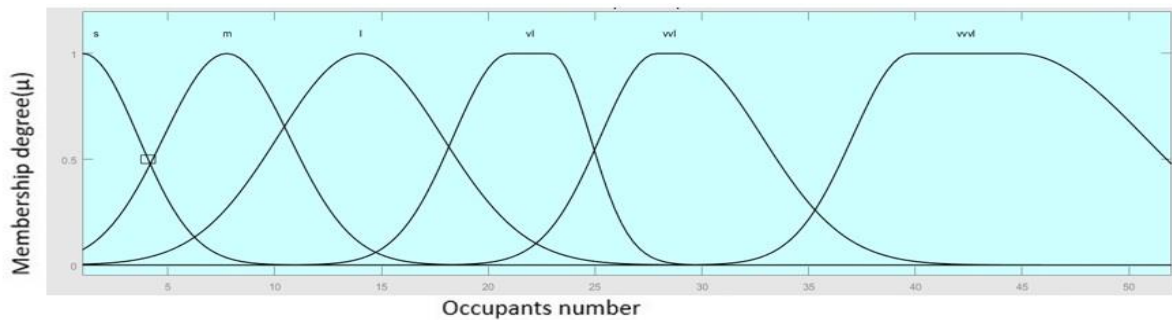


Figure 92. Membership functions of the number of occupants

According to CO<sub>2</sub> slopes and volume of the room that are the input of the fuzzy estimator, the number of people can be approximated. In fact, CO<sub>2</sub> slopes and volumes are the inputs to fuzzifier and estimation of the occupants is the output of the defuzzifier. The fuzzy knowledge base and relating inference engine of the fuzzy model is constructed according to several rules that are defined based on obtained recorded data. These data are recorded by several experiments that we are going to explain in the following sections.

#### 4.4.3. Implementation of the proposed presence estimator in building A of SENART campus

The basis of the proposed virtual presence estimator is on the CO<sub>2</sub> sensor and PD on DALI network. Regarding the aforesaid SBEMS platform, the CO<sub>2</sub> sensor is added to the physical layer that would be monitored in the supervision layer through the PLC in the control layer. The co-operation between CO<sub>2</sub> sensor and DALI network leads to estimating the number of people in a room. Figure 93 shows the implementation of the presence estimator in SBEMS.

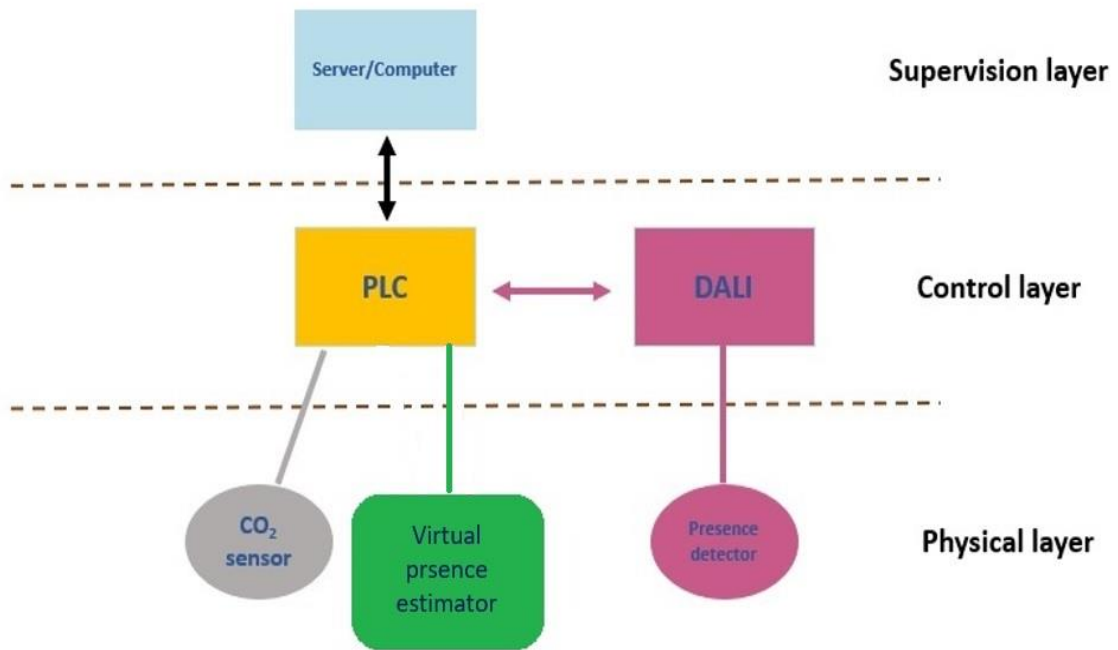


Figure 93. The implementation of virtual presence estimator in SBEMS

As aforementioned, the virtual presence estimator with the co-operation of DALI and CO<sub>2</sub> sensor is able to estimate the number of people. When PD detects the presence of the user through the DALI network, it will transfer the data to PLC and the function relating to the slope calculator will activate in PLC. After activation of the related function, PLC will start to record the Part Per notation of CO<sub>2</sub> (In PPM) from the CO<sub>2</sub> sensor in the specified time interval in order to compute the corresponding slope. Finally, according to computed slopes and pre-defined room size, the number of people will be estimated.

#### 4.4.4. experimentation, result, and evaluation of virtual presence estimator

Several experiments are executed in order to implement the proposed presence estimator and evaluate the model. Plenty of rooms with different sizes are selected. The data relating to CO<sub>2</sub> density(concentration) are recorded based on a pre-defined protocol when the rooms were occupied by users. Concerning the experimentation, Four various rooms are chosen with different sizes: 100m<sup>3</sup>, 106m<sup>3</sup>, 162m<sup>3</sup>, 200m<sup>3</sup>. The recording of data has been done two times for each room on different days randomly. During the experimentation, windows are kept closed(see appendix B). The concerned building has natural ventilation through windows trickle. Indeed, each individual window is equipped by trickle vent.

Table 17 shows the size of rooms, relating occupations during the data collection, and corresponding slopes after 30 minutes of people's presence for two experiments of each room. The recorded data illustrates the number of people in a room and relating volume has a linear relation with CO<sub>2</sub> part per million increasing. The relation between volume, occupation, and relating slopes can be defined as below:

$$\frac{S_1}{S_2} = \frac{V_2}{V_1} \times \frac{P_1}{P_2} \quad (24)$$

Where: S<sub>1</sub> and S<sub>2</sub> are relating slopes

V<sub>1</sub> and V<sub>2</sub> are volumes (m<sup>3</sup>),

P<sub>1</sub> and P<sub>2</sub> are the numbers of people in the rooms.

According to this facts, the rule-based part of MAMDANI fuzzy presence estimator and relating above membership functions are constructed. Table 18 shows the rule-based part of the virtual presence estimator.

Volume of the room (m <sup>3</sup> )	Occupation (Number of people)	Slopes in 30 minutes of a time interval ( $\frac{ppm}{t}$ )
100	27	58-60
106	30	54-55
162	15	18.6-20
200	15	16-17.3

*Table 17. Size of the room (m<sup>3</sup>), Number of people and slope in the first 30 minutes of the data collection*

Slopes \ Volume	SS	MS	LS	SM	MM	LM	SL	ML	LL
S	S	S	S	M	M	M	M	L	L
M	S	S	M	M	L	L	VL	VVL	VVL
L	S	M	L	VL	VL	VVL	VVVL	VVVL	VVVL

*Table 18. Fuzzy rules of virtual presence estimator*



Concerning testing the model, after constructing the model, the simulation result of the model is compared with ground truth data for testing that is illustrated in Table 17. The error relating to each case are computed considering the following equation:

$$Error = \left| 1 - \frac{P_s}{P_g} \times 100 \right| \quad (25)$$

Where the  $P_s$  is the presence estimated by the fuzzy estimator,

And  $P_g$  is the presence of data relating to the ground truth.

Table 19 presents the result relating to the error of the model:

The comparison of presence estimation by virtual presence estimator with grounded truth results shows the virtual presence estimator is able to estimate the number of people with a low error. As it is clear on the table, in worst case, there is an error of 6%. In fact, the proposed fuzzy approach estimator within a presence detector sensor and a CO<sub>2</sub> sensor shows its effectiveness for estimating the number of people virtually.

Rooms sizes (m <sup>3</sup> )	Average of errors (%)	Interval of errors (%)
100	3	3
106	4.5	4-5
162	3.5	1-6
200	6	6

*Table 19. The error of the fuzzy presence estimator in different room sizes*

#### **4.5. The architecture and evaluation of SBEMS regarding the heating fuzzy controller with presence estimator**

Regarding the new approach for controlling the heating space system: A fuzzy controller and virtual presence estimator; the proposed architecture of SBEMS in chapter 2, section 2.3 has to be updated. Figure 94 presents the software block diagram of the heating system controller within the presence estimator and the following Figure 95 shows the updated block diagram architecture of the SBEMS.

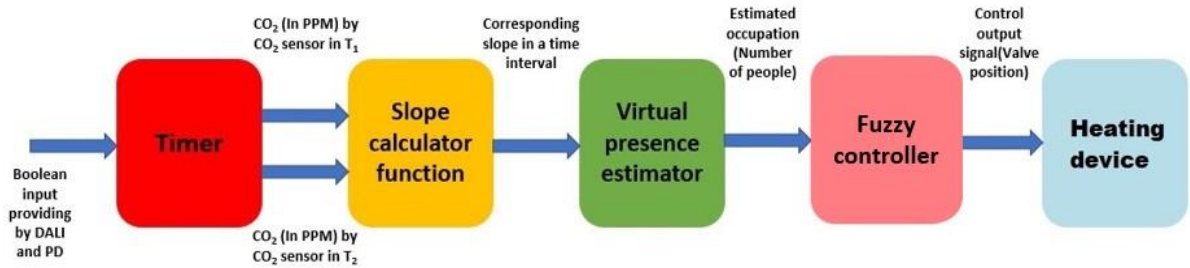


Figure 94. Software block diagram of the heating space controller

The proposed software architecture of the heating space controller is designed and implemented on PLC by MATLAB FUZZY logic toolbox, Simulink, and PLC coder. Regarding aforesaid figures, The control functionalities of the heating dynamics of the building's living space are interpretable: The DALI network activates or deactivates the timer function on PLC according to providing data by PD about the presence or absence of people. While it is active, the slope calculator function by considering the pre-defined time interval catch two values of CO<sub>2</sub> PPM and compute the corresponding slope. Then the virtual presence estimator by taking into account, the volume of the room and computed slope, estimate the number of occupants in the room. Finally, the fuzzy controller system by receiving the number of occupants from the virtual presence estimator and other data that is receiving from the temperature sensors (TS) via EnOcean, act on the radiator motor valve which is located in living space.

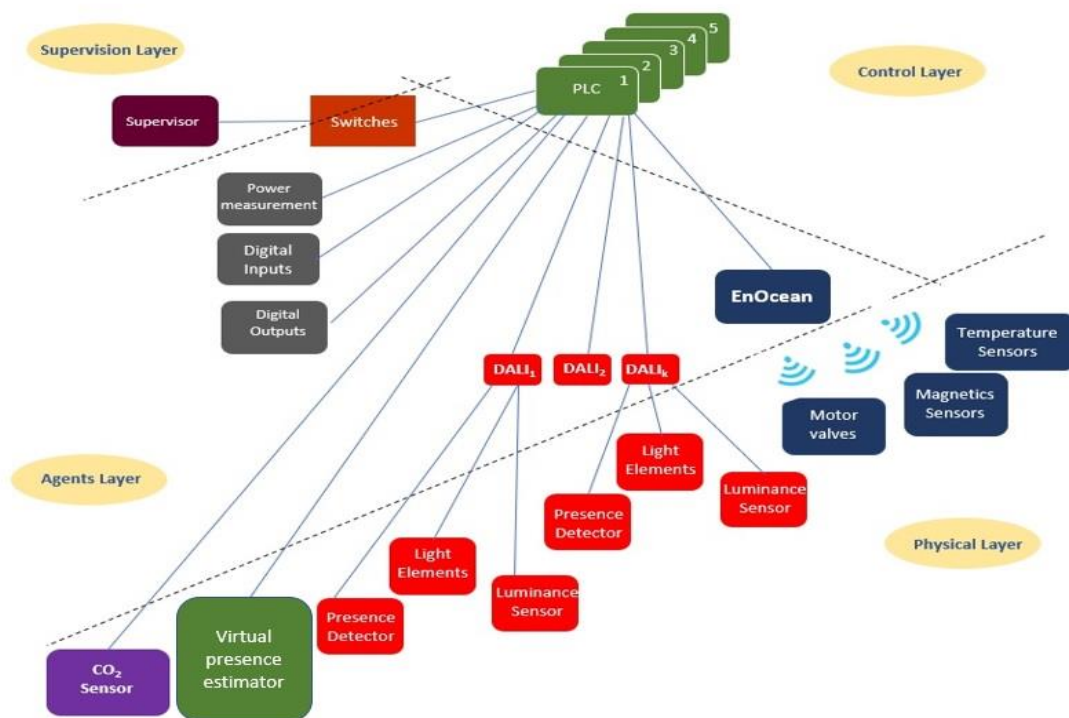


Figure 95. Updated Implementation block diagram showing different layers and related components of the SBEMS

#### 4.6. Simulation, and evaluation of the fuzzy controller with virtual presence estimator as an occupation counter

In order to evaluate the operation of the fuzzy controller with the virtual presence estimator, two simulations are executed. The first simulation is in a theoretical classroom with a medium size ( $V_{LS}^F = \text{Medium}$ ). The relating scenario in this simulation is like the scenario in section 4.3.4.2. The difference between this simulation with the one in section 4.3.4.2 is about the process of people counting. In section 4.3.4.2, a counter immediately estimates the number of people. However, in this section, the responsibility for presence estimation is with the recent proposed virtual presence estimator. Figure 96 and Figure 97 respectively show the operation of valve position by FC while the virtual presence estimator is utilized and relating temperature evaluation in a theoretical classroom with a  $V_{LS}^F = \text{Medium}$  size.

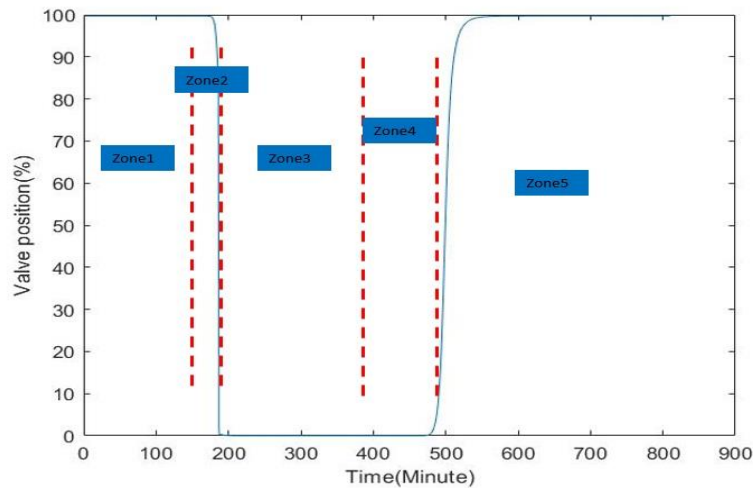


Figure 96. Valve position variations ( $\vartheta_p(t)$ ) for FC with the operation of the virtual presence estimation in a theoretical classroom with medium size

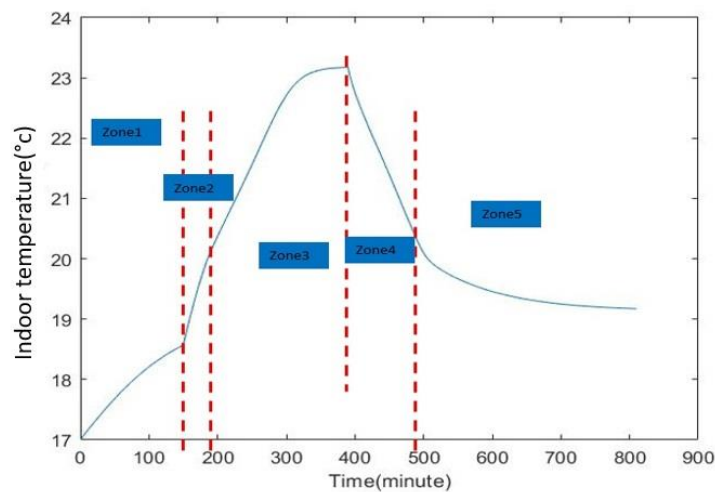


Figure 97. Temperature evolution of the room by FC with the operation of the virtual presence estimator in a theoretical classroom with medium size

The initial indoor temperature is 17°C. In zone 1, there is no occupation (presence of people) and FC adjusts the valve position in 100%. After 150 minutes, the students are entering the classroom, and PD in DALI network detects the presence. It activates the timer and slope calculator function. According to the predefined time interval ( $\Delta t = t_{k+n} - t_k$ ) for the timer, the slope calculator function based on the recorded value of the  $CO_2$  sensor picks the part per notion of  $CO_2$  in  $t_k$  and  $t_{k+n}$ . Considering the picked values, the corresponding slope is calculated. This time interval is 30 minutes. It means it takes 30 minutes to estimate the number of people in the space. In zone 2 there are 15 people in the classroom but the presence estimator still does not estimate the number of peoples and as a consequence, the FC is still keeping the valve position in 100%. In zone 3 after 30 minutes, the virtual presence estimator is estimated the number of occupants (with 3% error) and as a result, the FC declines the valve position. At the beginning of zone 4, the indoor temperature is 23.1°C, and peoples are starting to leave the classroom (the PD does not detect the presence of people). However, because of the higher temperature than setpoint, the FC keeps the valve position in 0% until the end of zone 4. At the beginning of zone 5, the indoor temperature is less than setpoint temperature and the PD still does not detect occupation and as a reason, the FC increases the valve position.

The next simulation is regarding the practical room with a large size  $V_{LS}^F = Large$ . The same scenario as 4.3.4.4 is utilized for simulation here but for counting the number of the occupant, the virtual presence estimator is utilized. Figure 98 and Figure 99 respectively show the operation of valve position by FC while the virtual presence estimator is utilized and relating temperature evaluation in a practical classroom with a  $V_{LS}^F = Large$  size.

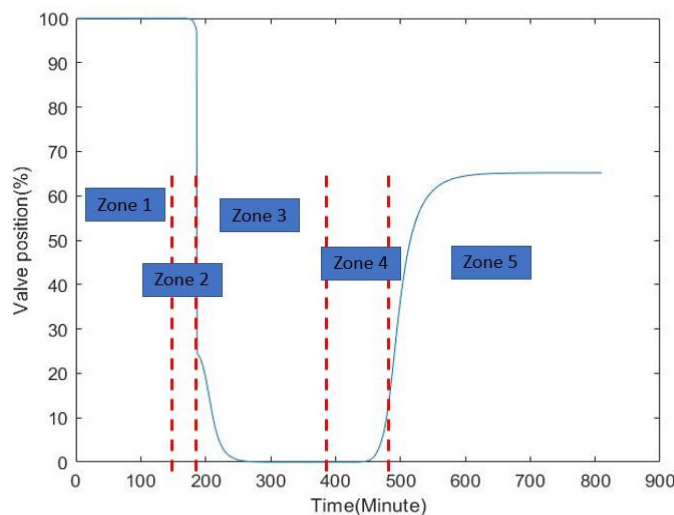


Figure 98. Valve position variations ( $\vartheta_p(t)$ ) for FC with the operation of the virtual presence estimation in a practical classroom with large size

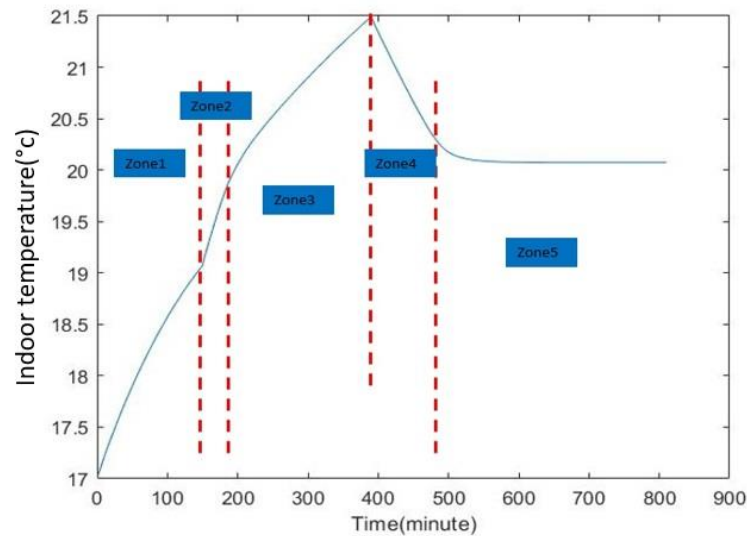


Figure 99. Temperature evolution of the room by FC with the operation of the virtual presence estimator in a practical classroom with large size

In zone 1, the initial temperature is 17°C, and the number of occupations is 0. In order to reach setpoint temperature (20°C), the FC set the valve position in nominal power (100%). In zone 2 the classroom is getting full by 15 people. The PD on DALI network detects the presence. It leads to the activation of the timer and slopes calculation function. In the specific time interval (30 minutes), the relating slope like the previous simulation is calculated and the virtual presence estimator estimates the number of occupants (by 6% error). As a consequence in zone 3, the FC adapts the power of the radiator by adjusting the valve position to gain the needed heat from occupants bodies. After the temperature reached to set point in zone 3, the FC closed the valve to 0%. In Zone 4, occupants are starting to leave the classroom, and PD does not detect the presence of people anymore. However, the temperature is higher than the setpoint and as a result, the FC keeps the valve position in 0%. In zone 5, when the temperature is less than setpoint, the FC adjust again the valve position to keep the temperature at 20°C.

The proposed virtual presence estimator can estimate the number of people in a space with a small error. It suits for places that cameras cannot utilize for security reasons or the user does not want to spend money on installing presence estimator sensors. The proposed virtual sensor estimates the number of occupants with a delay. Although in comparison with the presence counters, it has a delay (30 minutes) to estimate the number of occupants but due to the slow dynamic of the heating slopes (temperature evolutions), it does not affect the functionality and energy efficiency of the system in a meaningful way. The comparison of Figure 74 and Figure 79 with Figure 97 and Figure 99, respectively represent this fact. Where the occupancy info was injected to the controller immediately in versus injected with 30 minutes delay. It perfectly can act as an alternative solution for estimating the number of occupants in the heating system control chain. In the proposed approach, one more time the SBEMS as a platform shows its powerfulness for developing the subsystems of the SBEMS. In addition, it illustrates

a flexible environment for integrating different technology with development purposes. The presence detector in lighting system was integrated with a  $CO_2$  sensor in order to construct a virtual presence estimator and serves in the heating controller by using Enocean technology. Indeed, it shows the remarkable flexibility of the SBEMS as a research and development platform.

## 4.7. Conclusion

In this chapter, we focused on designing a heating controller for the heating system of a smart building that is located in SENART campus of University Paris-Est Créteil. Regarding plenty of thermodynamical behavior in living spaces, there is always a simplistic view for designing the heating controllers. The presence or absence of the user in space is one of the most important parameters. It is highly affecting the heating dynamic of the living spaces, due to they can be seen as an additional heating sources. However, because of the unidentified heating dynamic effect of occupants (user) in space, it is always ignored for designing relating controllers (as it is also stated in section 1.6).

Due to these facts, an approach regarding the heating controller design has been done in two steps:

1. Modeling the heating dynamic of the living-spaces taking into account their occupancy by system identification methods
2. Designing adaptive controller based on analyzing the heating dynamics model of living spaces and constructing the knowledge-base part of the controller

The methods relating to identification tools demonstrate its ability for discovering and modeling the dynamic behavior of the building's living space heating system in different conditions (presence and absence of the people). The relating approach in identification is on the basis of time-series prediction providing by NARX model that is profiting from multi-layer perceptron learning and generalization. The relating results, as mentioned in section 4.2.5 illustrate the ability of NARX model for identification of the living space's behaviors. The obtained MAE and MSE results show a high accuracy for the prediction of indoor temperature. The identification approach in this part is offering an interesting application for thermal studies of living spaces where the occupancy of spaces is also taking into consideration.

In the second step, a fuzzy approach with the TAKAGI-SUGENO method is presented to face the control problem of the aforesaid dynamic behavior regarding various conditions. On a basis of the heating dynamic model of the living-spaces that is modeled and analyzed priorly at the first step, the knowledge-based part of the fuzzy controller is constructed (by taking into consideration the additional thermal energy that is generate by human body heat radiation). The construction of the controller knowledge-based part, according to identified dynamic parameters of living spaces, illustrated the effectiveness of the proposed method in contrast with model-free approaches controller

design. The present controller is responsive to dynamic parameters of spaces, especially the occupants as one of the highly dynamic ones. In order to evaluate the effectiveness of FC, it is compared with an On/Off controller that is highly popular for controlling the heating system. Due to this, three different scenarios for simulation are proposed to evaluate the functionality of FC in comparison with the On/Off controller.

The results show the FC in comparison with an On/Off controller is much more energy-efficient. The FC shows the ability of adaptation in different conditions by considering occupants. In all the experiments the FC could save energy in comparison with On/Off controller. In some cases (the experiment in a medium room with 28 occupants), the system did not even use the radiator's power to heat the space and all the needed energy is exploited from occupant's bodies. In all cases, loss of energy declined and where the spaces are occupied by inhabitants, the share of radiator for heat generation is decreased in order to gain the rest of the needed heat from human body heat radiation in spaces. The results also show the FC is respecting the user comfort. In all cases of simulations, the optimal total output power by considering the occupation and output power of heating devices is proposed by FC. It leads to reach the range of the desired temperature at the same time interval in all cases, without involving the user and not later than a specific time. The proposed FC is implemented on PLC for validation in real living space. The results confirm the functional adaptability of FC in order to face the dynamical behavior of the living spaces in reality.

Finally, confirming with the imperative role of occupation in the functionality of the FC, a virtual presence estimator is proposed. The VPE is on the basis of the fuzzy inference system with the MAMDANI method. The results show a small error between estimation numbers and grounded truth values. The error in the worst case is 6%. In the last part of this chapter, we evaluated the operation of the fuzzy controller while the virtual presence estimator was responsible for estimating the number of occupants. It shows the virtual presence estimator can perfectly estimate the number of occupants with a small error and it can utilize as an alternative solution for estimating the number of occupants.

## General conclusion and perspective

Nowadays because of energy consumption trends and limitation of resources for generating energy, the proper attitude toward it is valuable. The Ministry of Ecological and Inclusive Transition of France set a goal by 2030 and planned several policies and strategies (Multi-Annual Energy Plan (MAEP)) in order to develop energy consumption and production. One of the proposed solutions by the aforesaid ministry is an increment in energy efficiency. The advancement in IoT technologies and computational supports enormously are assisting investigators to enhance the energy efficiency of high consuming parts. As it is emphasized in this investigation, the buildings are one of the high energy-consuming parts and the related technologies to SBEMS are highly under development. Due to this fact, the focus of this thesis was on the development of smart building energy management systems by ambient intelligence techniques and technologies. In this work, we were dealing with a SBEMS which is located on a building of a campus SENART of UPEC (building A).

This investigation can be summarized in three main sections:

The architecture of the Smart building energy management system:

In chapter two, we are discussing architecture for SBEMS. The proposed architecture is taking advantage of the multi-layer system architecture. The presented system benefits from plenty of a number of high-level technologies in each layer. In the top layer (supervision), it is taking advantage of the best existing software in the market for monitoring, controlling, and programming. The SBEMS of SENART campus in this layer is taking advantage of two high-level monitoring and controlling software: TopKapi and Codesys. In the second layer (control layer), it benefits from Wago programmable logic controllers. It is a powerful PLC that is open to a wide range of hardware and technologies and plenty of communication protocols. In the third layer, there are EnOcean technology and DALI technology which are taking care of heating and lighting systems. As mentioned in chapter two, EnOcean is an energy harvesting wireless technology that is highly energy-efficient and DALI is a powerful protocol for lighting ballast that we obtained its remarkable functionalities in chapter 3. Finally, in the last layer, there are several sensors and actuator which are providing data about the ambient through the layer three to two and one.

The designed architecture is highly flexible and open to the most available technologies and software in the market. The implemented architecture illustrates the high performance of monitoring and data collection and serves not only as an automated system for managing the building but also as a powerful platform for investigation purposes. The utilization of this platform is illustrating in chapters 3 and 4. We showed the proposed SBEMS as a research platform provides a remarkable flexible environment for developing different subsystems of the SBEMS.

The perspective regarding the architectural design of the SBEMS can be focused on the hardware and development of the architecture. The presented system easily can integrate



with plenty of recent software and hardware, as illustrated during this Ph.D. For instance, the monitoring and awareness system can be enhanced, by equipping the physical layer of the proposed architecture with some sensors. These sensors can be virtual sensors or physical sensors. Improvement of the aforesaid system can lead to the advancement of AmI level in the future. The integration of SBEMS with renewable energy sources for self-energy production is another interesting topic that can be studied in the future. As it is mentioned in MAEP in near future the buildings should act the role of local producers of energy.

Smart lighting system design:

In chapter three, an adaptive and smart lighting system on the basis of the Lumen method, DIALux simulation software, and relating technologies to lighting systems are proposed. The lighting system in SENART campus is taking advantage of DALI technology which is specialized for controlling lighting in the buildings. DALI in the architecture of SBEMS is serving as a stand-alone subsystem as noted in section 3.2.

Within the Lumen method and DIALux simulation, the proper number of lighting elements, and the architecture of placing them in the space is discovered. By Lumen method, the proper number of lighting elements is calculated. According to the result of Lumen method, several simulations are executed in DIALux in order to find the best architecture of LE placement in spaces. The provided simulations are based on the different architecture of LE placement in various outdoor lighting conditions (no daylight, overcast daylight, and average daylight) in order to satisfy user comfort. Before validation of the approach on the building, the simulation is validated based on an experiment due to give a basis of elaboration versus reality. The result in this part shows the confirmation of elaboration between simulation and reality.

Finally, the proposed lighting system is validated and evaluated according to several experiments based on several protocols. The results show within the aforementioned approach, the energy-saving of electrical consumption in the lighting section on average is 42.95%. In some cases, the energy-saving reach 80% and in the worst case, it is about 28%. The presented lighting system is covering the drawbacks of the existing lighting systems that we discussed in chapter 1. We showed this approach for designing a lighting system can be generalized in different spaces and decrease energy consumption, and the cost of energy for lighting systems. The intended approach shows the lighting system can adapt its control functionalities in different lighting conditions in order to provide the user, satisfaction, and also decrease the energy consumption of the lighting system.

The integration of the intended lighting system with recent technologies regarding the batteries and solar cells can highly increase the efficiency of the lighting system. It can be studied as the future work of the lighting system.

The heating controller in smart building energy management system:

The most consuming part of a building is the heating system. In chapter four of this thesis, we are dealing with the heating system. We have tried to provide a solution in

order to decrease energy consumption in this part. The basis of this chapter is on the ambient intelligence which is provided by the SBEMS and exploiting energy from thermal radiation energy that is emitting from the user's bodies in order to decrease the generating heat by the heating devices. At the beginning of this chapter, an approach regarding the modeling of the heating dynamics of the working spaces is provided in order to study the dynamical thermal behavior of the working spaces in the absence and presence of the user. The modeling in this part has been done by black-box modeling. It is done by time series prediction according to NARX method and Multilayer perceptron learning. The results regarding the identification of the heating dynamics of living spaces illustrate a high accuracy model for the prediction of indoor temperature. It also reveals the great performance of the approach for modeling the heating dynamic of living spaces considering the effect of occupants as an additional heating source in spaces. It serves as an application for studying the heating dynamics of space with the purpose of designing the heating controller based on knowledge (model-based approach). In the next step of this chapter, a fuzzy controller with Takagi-Sugeno method is presented for facing the heating controller challenges of spaces. The knowledge-based part of the fuzzy controller is constructed based on analyzed heating dynamic model of living spaces that are priorly presented. It considers the influence of occupants as an additional heating source in the control loop. The fuzzy controller is compared with a thermostatic (On/Off) controller in order to evaluate and illustrate the its advantages. Several simulations are executed according to various scenarios. The scenarios are designed in order to reveal the ability of FC in different conditions; Various volumes of spaces with a different number of occupants. The result in this part is remarkable. In all scenarios, the loss of energy is decreased. In the room with medium size while there are 28 occupants the heating gain is provided just by occupants and FC turned off the radiator however with On/Off controller the radiator is still working (100% saving energy in comparison with On/Off control while there were people in the space). In large and office room also the results illustrate the share of radiators for generating heat are decreasing in the presence of users and space gain a part of the needed heat from user's bodies (4.86% and 44% saving energy in comparison with On/Off control while there were people in the space, respectively).

Considering the importance of the number of users in working spaces, A virtual people counter is introduced. The virtual presence estimator (VPE) is based on the Fuzzy logic approach with MAMDANI algorithm. It estimates the number of people in a space according to provided data by Carbon dioxide sensor and presence detector on DALI network. The comparison between estimation results of the virtual presence estimator model and the grounded truth results illustrate a small error (1% in the best case and 6% in the worst case). Finally, two simulations are executed regarding the functionalities of the fuzzy controller where the VPE is in charge of occupants number estimations. The result in this part shows the VPE can be utilized as an alternative solution in places that there are restrictions about camera installation for counting the number of people or where there are no specialized presence counter sensors.

The proposed approach shows the heating controller effectively can adapt its functionalities according to the presence and absence of the user. Indeed, it illustrates

its ability in order to optimize the output power of heating devices according to the occupations of spaces. It shows for controlling the heating devices in spaces, some parts of the needed energy for heating the spaces can be supplied by occupations. It leads to decreased thermal energy consumption without interruption of user comfort. With the proposed method, the drawbacks of the heating controllers design which mostly are based on model-free approaches and it is remarked in chapter one is covered.

The perspective of this chapter is extremely bright. By considering different dynamical parameters that can affect the behavior of the heating system, the identification of the heating dynamics of living spaces can be improved. For instance, the irradiance of the sun is one of the dynamical parameters that can take into consideration as a dynamical phenomenon that affects the behavior of heating spaces. Considering the restriction over data collection (just in the cold time of the year), more experiments can be done in order to construct better time-series data set for the training phase of NARX. In parallel, other methods for time-series prediction can individually study deeper, like Long short-term memory (LSTM) neural network, NARX by radial basis function (RBF) neural network, etc. Regarding the fuzzy controller, the performance can be improved if other new parameters take into consideration in control strategies. As an example, the energy label as an input feature to the fuzzy controller can help to enhance the performance of the fuzzy controller. It will lead to functionality enhancement of the fuzzy controller for its generalization in various spaces. In fact, the fuzzy logic approach with powerful architecture and functionalities of SBEMS provides this capacity to enhance the performance of ambient intelligence and heating controller. Regarding the virtual presence estimator, it can be developed for faster response time for estimation of occupants number. Its functionalities also should enhance for places that buildings are equipped by ventilation systems.

Finally, regarding the user comfort in the abovementioned subsystems, the developments of SBEMS enhance user comfort. In the case of the lighting system, the visual satisfaction was achieved by respecting the needed light intensity on the working plane, and in the case of the control heating system always the optimized total output power was used to reach the desired temperature in a specific time. The adaptive functionalities and monitoring part of the SBEMS in all the subsystems lets the user be aware of actual conditions and reach the involvement of the user for controlling the subsystems to a minimum. However, in parallel because of the powerful user interface users always have the possibility to interact with the system and set their desired parameters easily.

The SBEMS architecture and its related technologies show its powerful abilities as a research platform. Regarding the development of the lighting system and designing the heating controller, we are taking advantage of its powerful monitoring and user awareness systems, data collection, integration abilities of software and hardware technologies, and easy implementation of proposed approaches.

## Appendices

### Appendix A

Here you can find an example of a time series dataset that is collected and utilized for the identification of heating dynamics of living spaces. Figure 100 to Figure 103, respectively shows the time series dataset regarding the operation of the valve position of the radiator, outdoor temperature, indoor temperature, and information of occupants, during sampling.

The data collection protocol and approach is the same as what is defined in the context of the thesis however the time of data collection is longer (longer time series) that provides more information. During the data collection, the valve position is operated in various middle positions (between 0 to 100%) in the presence and absence of the occupants. Also, the number of occupants is changing between the minimum ( $OCC=0$ ) and maximum (in this case  $OCC_{max}=28$ ).

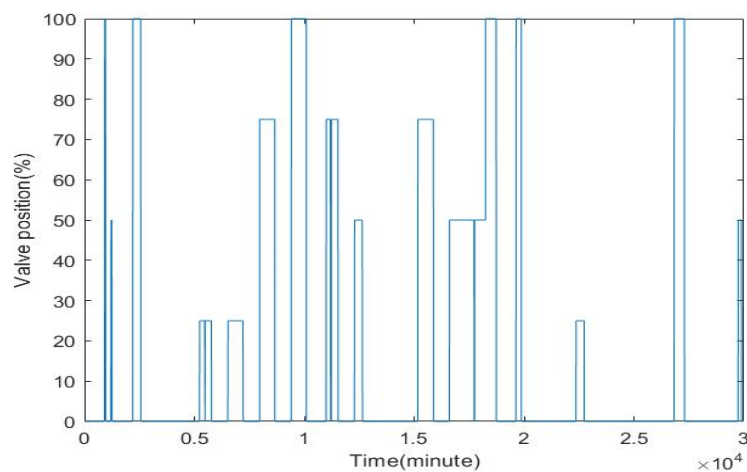


Figure 100. Valve position time series dataset

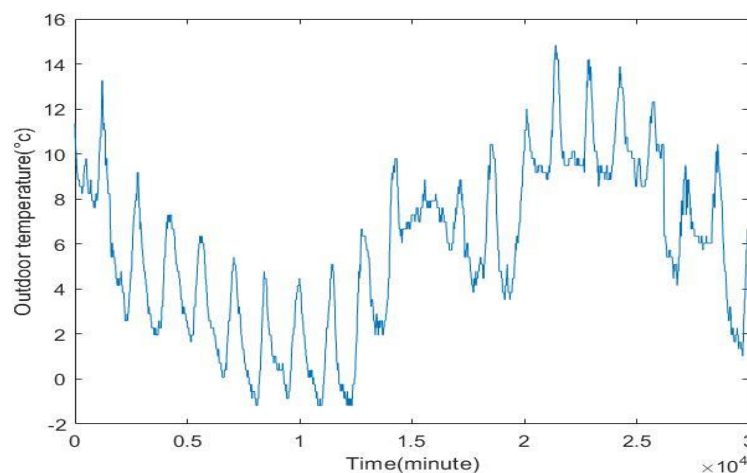


Figure 101. Outdoor temperature time series dataset

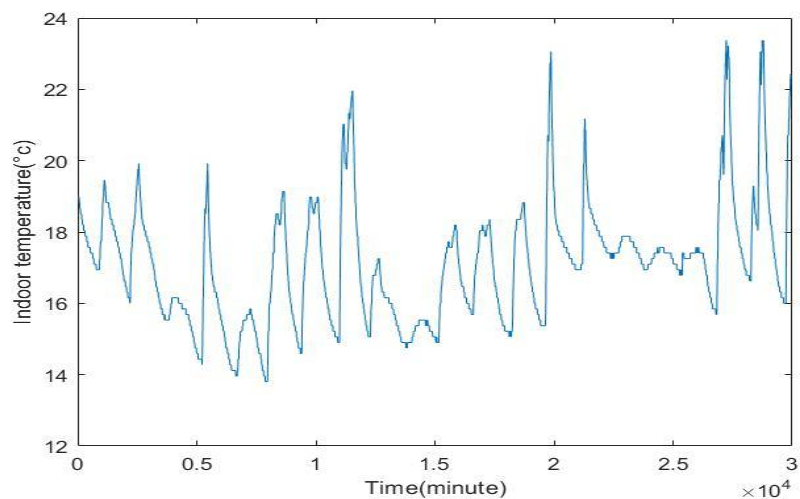


Figure 102. Indoor temperature time series dataset

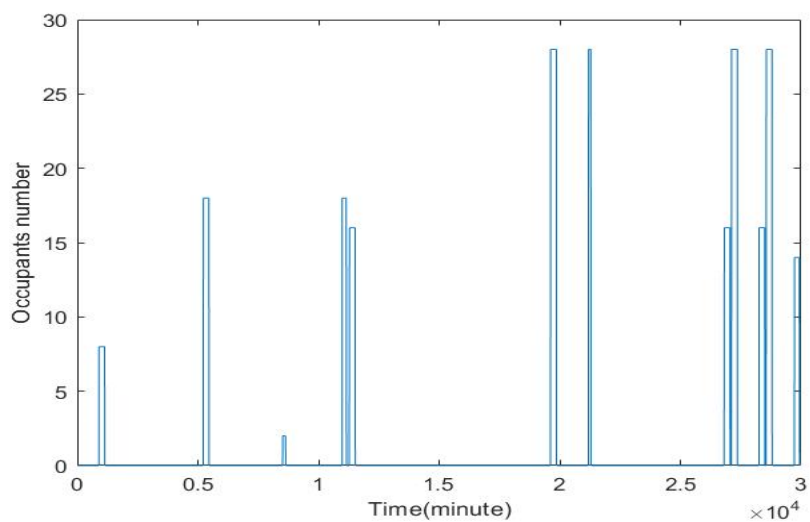


Figure 103. Occupants number time series dataset

## Appendix B

Here you can see an example of time series relating to the concentration of CO<sub>2</sub>. Figure 104 and Figure 105, respectively show the information about the number of occupants during data collection and the recorded data regarding the CO<sub>2</sub> concentration.

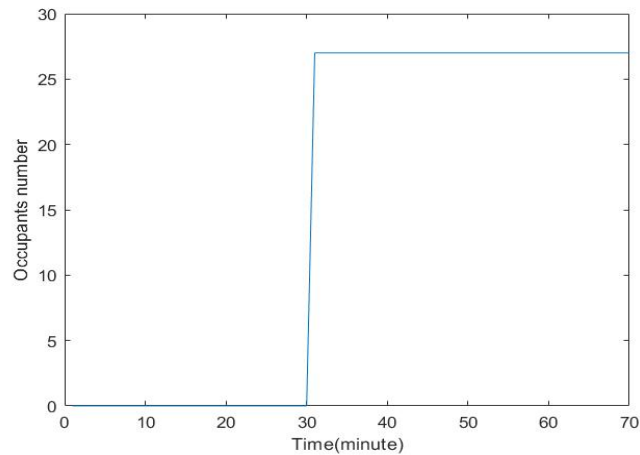


Figure 104. Occupants number time series relating to CO<sub>2</sub> dataset

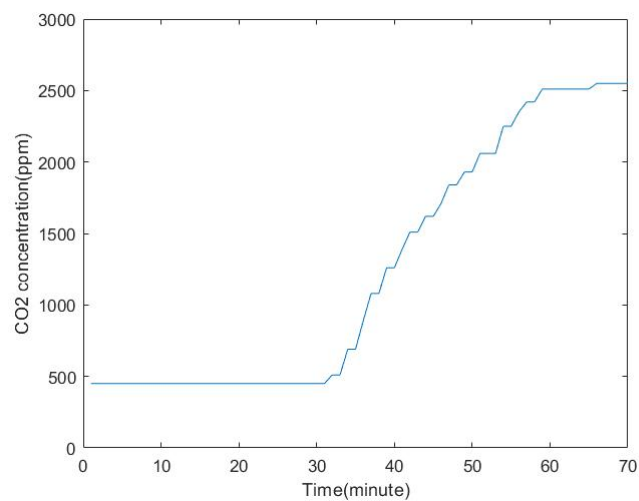


Figure 105. CO<sub>2</sub> concentration time series

## Publications

### Conference:

R. S. Broujeny, K. Madani, A. Chebira and L. Hurtard, "A multi-layer system for smart-buildings' functional and energy-efficiency awareness: Implementation on a real five-floors building," *2017 IEEE 8th International Conference on Awareness Science and Technology (iCAST)*, Taichung, 2017, pp. 87-92, doi: 10.1109/ICAwST.2017.8256529.

R. S. Broujeny, K. Madani, A. Chebira, V. Amarger and L. Hurtard, "A Machine-Learning Based Approach for Data-Driven Identification of Heating Dynamics of Buildings' Living-Spaces," *2019 10th IEEE International Conference on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications (IDAACS)*, Metz, France, 2019, pp. 197-202, doi: 10.1109/IDAACS.2019.8924329.

### Journal:

R. Sadeghian Broujeny, K. Madani, A. Chebira, V. Amarger, and L. Hurtard, "Data-Driven Living Spaces' Heating Dynamics Modeling in Smart Buildings using Machine Learning-Based Identification," *Sensors*, vol. 20, no. 4, p. 1071, Feb. 2020.

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