



POLITEHNICA University of Bucharest Faculty of Power Engineering

Doctoral Thesis - Abstract

Optimization of energy efficiency for residential buildings by using artificial intelligence



Author:

Ing. Andrei Liviu NEGREA

Directors:

Prof. Dr. Ing. Adrian BADEA Prof. Dr. Ing. Christian GHIAUS

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Negrea LIVIU ANDREI

Optimization of energy efficiency for residential buildings by using artificial intelligence

Devant le jury composé de :

Professeur	George DARIE (Université POLITEHNICA de Bucarest)	Examinateur	
Professeur Professeur	Frank TILLENKAMP (ZHAW, Suisse) Florica COLDA (UTCB, Roumanie)	Rapporteur Rapporteur	
Professeur	Ion Hazyuk (INSA Toulouse, France)	Rapporteur	
Professeur Professeur	Christian GHIAUS (INSA Lyon, France) Adrian BADEA (UPB, Roumanie	Co-directeur de thèse Directeur de thèse	

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Introduction

The world's energy consumption problem has become one of the most appealing subjects in 2020 because of the progress in urbanization and advancement of networking society [1]. The planet is under serious threat due to energy crisis because of fossil energy depletion and global warming determined by harmful gases. Therefore, ideas and projects on "how to save energy", are among the most common subjects on every social debate. New ways of producing energy must be found in order to combat energy crisis.

The subject proposed in this thesis responds to nowadays concerns and to the necessity to decrease the generated power consumption in buildings, especially in the residential sector. A data report regarding energy efficiency in buildings, realized by ENERGDATA in 2014, shows that the energy price grew with 64 % from 2004 to present. The energy costs of residential sector reached a peak of 40 % consumption for the entire Europe, while in Romania the prices were close to 44.4 % of the electricity price tag [2].

Due to a strategic energy action plan approved by Romania for 2007-2020 period, a potential reduction in energy consumption was identified for the residential sector. After a statistical analysis, the potential of energy reduction in Romania is estimated, depending on the sector they belong, to 30 - 50 % for residential and 13 - 19 % for tertiary sector. The consumption for space heating in buildings in Europe represents 67 % of the total energy consumed in buildings (Romania has a total consumption of 50 %), dragging attention to the potential energy savings that can be done.

This thesis focuses on the usage of artificial intelligence to optimize the energy performances of residential buildings, emphasizing a huge impact on sustainable development from two standpoints. The first angle is the energy management optimization for residential buildings, representing an increase in energy efficiency that leads to sustainable development and draining renewable energy from unlimited sources.

The second angle is the integration of clean technologies through the usage of artificial intelligence to increase the energy performances in buildings. The adoption of this type of technology reduces the incidence of industrial leftovers on the environment by preventing pollution and by savings money [3]. In general, through energy efficiency we obtain:

- reduction in usage of raw materials,
- reduction in pollutant emission,
- reduction in waste,
- financial savings,
- lower interest on gas imports
- power consumption reduction
- improved air quality
- improved living conditions

Therefore, the prediction of energy demand for heating and cooling loads, presents the main factors in identifying measures to lower energy consumption. The thesis aims to develop a set of services that allows modeling, verification, and control of equipment of testing laboratory. In order to create specific conditions of thermal comfort, certain methods can be applied. These methods imply having as inputs a set of measured parameters (indoor temperature, outdoor temperature, energy consumption, solar radiation, humidity or generated energy from renewable energy sources, energy flux) and a set of building characteristics (construction material) to provide an energy prediction with low errors to lower the utilization of energy in buildings.

It is important to notice that thermal comfort has always been the highest consumer when talking about human needs. "A state in which there are no driving impulses to correct the environment by the behavior" is the characterization of thermal comfort as Hensen explained [4]. To complete the sentence, ASHRAE outlined this phenomenon as "the condition of mind in which satisfaction is expressed with the thermal environment" [5]. Based on the above interpretations, thermal comfort could be identified as a state of mind, body, cognitive process, and not referring to a state of condition. Among people, thermal perception may differ radically, even if they are situated in the same environment. A more reliable explanation about thermal comfort methods, physiological comfort, mathematical modeling on energy transfer between human organism and surroundings can be found on N. Djongyang paper [6].

Thesis outline

A mathematical model based on experimental measurements to simulate the behavior of the building was developed. The system was implemented in a passive house from UPB, with a development perspective to a student campus or to a residential district.

The experimental protocol was implemented by following certain steps:

- Build the input parameter's database indicating the system sensors.
- Collect weather data (solar intake, wind, humidity, cloud coverage) for example, solar intake performs an important aspect for the laboratory, as external parameters influence the thermal comportment of the house.
- Intake of auxiliary flows (the flow injected by the HVAC system
- Control the house temperature.

The model for the system inputs and outputs, consists of three significant areas. The first part contains information about input data of the system such as weather data and auxiliary heat flow rates. The second part represents a mathematical model able to process the input data and to predict the future input data in order to respond with a precise output. The model is responsible for the connection between inputs and outputs. The third part is the output calculation that has double role. The output is used for:

- Harvest the necessary variables for the system (such as interior temperature or energy consumption).
- Providing the inputs for the transfer function (outputs become inputs for the function).

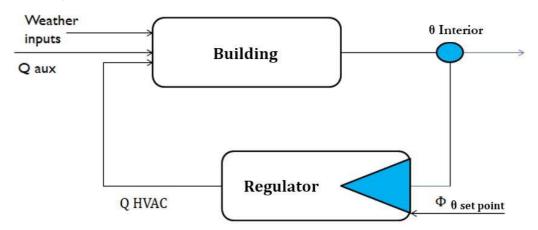


Fig. 1 Diagram for mathematical model in-use

The system model for entries and outputs is exemplified in Fig. 11 with the implementation of a control system into the model. The HVAC heat flow rate is computed as a new input for the mathematical model to control inside temperature. Another modification to the system is the implementation of set-point temperature, as a control system for the mathematical model to receive a new input

To obtain the numerical model, a full analysis of a physical phenomenon of the house is required. To solve and analyze the mathematical model, we can use several models:

- white box full knowledge about the implemented system,
- black box zero knowledge about the implemented system,
- grey box some knowledge about the implemented system, physical and statistical.

In thesis a grey box model is used, as a hybrid method that can help solving a system in a fast manner, because it is capable to simulate the house's thermal behavior and to optimize the input parameters. Using this method, the prediction of energy consumption can be scientifically justified. Typically, a grey box model is needed when a physical appearance of the residential house is realized, when it is incomplete or does not provide enough details about the system.

As a conclusion, it is fundamental to acknowledge the energy consumption of the house due to the following perspectives [7]:

- Estimation and parameters calculation of a building (sizing of thermal installation and cooling systems).
- Calculation of consumer costs.
- Optimization for reduction of costs.

Short presentation of the thesis chapters

Chapter one's purpose is to present the problem of world's energy consumption, especially in urban area. This thesis responds to nowadays concerns and to the necessity to decrease the energy consumption in buildings. The potential reduction in energy consumption in Romania shows increased potential as the statistics from EU display. The thesis outline is covered in the upcoming section, along with the control algorithms presentation. This part gives attention to relevant data, suitable to the achievement provided in this essay.

Chapter two details the basic characteristics about testing facility from University POLITEHNICA Bucharest. Basic properties include knowledge about construction materials, cooling, and heating system (HVAC), off grid system, smart solution implementation, or PV panel power. This section gives special attention to essential information, related to passive house requirements and concept, with preponderation on surveillance system.

Chapter three's objective is to emphasize how data and measurements have been acquired for the thesis purposes. With a short introduction on the devices that gather real time data, smart meters, this chapter presents the interaction between user and smart meters through an HMI software. Different modules of the SMXcore are described as a solution for data collection. Moreover, physical, and electrical acquisition data are underlined with a statistical analysis of weather inputs. For the relevance for this thesis, examples and interpretation of results are being presented as a conclusion of this chapter.

Chapter four presents energy predictions based on degree-day and grey-box methods. These methods are estimating energy consumption of the testing laboratory, while using a very low quantity of data while chapter five energy monitoring and control are being highlighted withing the thesis goal. Small introduction about energy control and energy generated inside the Passive House are presented as a solution for controlling and optimizing the buildings energy consumption. To attain good thermal comfort inside the house, fuzzy logic technique is used. The proposed target is measured by percentages of logic assumptions. MATLAB software was used to simulated and validate the process in accordance with a policy management system.

Chapter six concludes thesis goal to optimize residential buildings energy efficiency by using artificial intelligence techniques. Energy consumption depends on three different things: buildings energy efficiency, systems energy efficiency and how the energy is being exploited (human behavior and control algorithms) which corresponds to nowadays needs. Thesis contribution includes development and implementation on a real house of a fuzzy controller. Furthermore, this chapter emphasize the thesis perspectives about an introduction in human behavior and a detailed weather algorithm implementation. Last appendices and bibliography are submitted.

General presentation of control algorithms

PID - classic

Buildings control strategies and experience, multiple domestic and outdoor disturbances have been claimed to affect the thermal behavior of any system. Thus, the main task of a controller is to adjust thermal conditions [8]. A PID controller is composed of:

- P, proportional controller,
- I, integrator and,
- D, differential action.

The proportional part adjusts the error through multiplication of the deviation between the set-point and the measurement with a constant. The Integrator (I) corrects the control signal by integrating the error in time. By including the integral to the systems activity, it dispels the offset but decreases the system stability. In order to combat this situation, the Differential (D) operations further introduced, rectifies the low frequency flaws collected by the Integrator. The benefit of using the Differential action is due to its ability to quickly modify errors values, disregarding the delayed values. For the purpose of getting optimal and accurate results out of a PID control, specific configuration and constant setup must be taken into account.

The PID interacts with system that is controlled. The system has input and output variables. Inputs are presented as the actual signal delivered to the ecosystem as long as output result are the controlled variables. The basic idea of the control system is to understand how to generate the input signal in order for the system to produce the required variable, inside temperature — meaning the output.

State-space representation

The previous paragraphs presented a classical PID controller while this subchapter focuses on the modern state-space representation and optimal control. One of the benefits of using state-space representation is the fact that dynamic systems can be modelled by differential equations [9]. The system property of changing at any given time is a function of its current state. For example, the way the system is changing due to acceleration it's a function of its position [10].

For an arbitrary dynamic system, we can calculate how the energy is changing by analyzing the relation between its states and derivatives [11], [12]. As an example, if the energy of the system is being dissipated over time, then we can claim the fact that the current system is stable. Moreover, the faster the energy is dissipated, the systems becomes stable. As mentioned before, the stability is the property of the system that the states and the derivatives are linked to each other:

$$\dot{x} = f(x) \tag{1}$$

where,

 \dot{x} – time derivatives and

f(x) – function of the states.

To be noted that any system can be moved and influenced by external energy, like additional inputs. Hence, the derivates of dynamic system is a function of its current states and external inputs as presented by Tashtoush [13]:

$$\dot{x} = f(x, u) \tag{2}$$

where u - inputs.

A key role is played by the state variable due to its numerous apparitions in the state-space equations. They are conceived as the minimum set of variables that describes the entire structure in order to accurately predict the future behavior of the system.

To conclude, a good description of the state-space representation is done by Nijsse [14], who compares the results obtained with finite impulse responses from finite impulse response models (FIRM) in air conditioning structures.

Intelligent control: fuzzy logic

Fuzzy logic algorithms are constituted by IF-THEN rules representing a closer knowledge of human behavior within the interaction with the HVAC system. For instance, a fuzzy rule may be, if interior temperature is lower than your standard comfort and decreases rapidly, then turn the heating system on. Fuzzy algorithms are considered to be complicated code programming system in the cooperation with the user, leading to nonlinear control algorithm. Rules are made of qualitative values while nonlinear algorithms depend on quantitative variables, causing important lack of information. The benefit of using fuzzy algorithms is the ability to model complex control strategies and to transform quantitative variables into real number. Thus, a fuzzy control algorithm is a nonlinear static function. In addition, depending on the pre-setup nonlinear rules, the algorithm may be robust on not. Equally important, when knowing the variation of the parameters of the system, a fuzzy control algorithm may be developed, which can be less sensible to variations than a robust linear algorithm. Such algorithm can be compared with the theory presented by Astrom and Wittenmark [15], specifying that fuzzy control algorithm are more robust when having knowledge about the variation of process parameters.

The fact that fuzzy algorithms are suitable to nonlinear processes lies in the dependency on the chosen input variables. For example, a PID algorithm running on fuzzy logic is superior to a linear PID algorithm in tackling with the nonlinear processes, as long as the system nonlinearities are known.

Fuzzy control systems can be approached from two perspectives: theoretically and pragmatically. This thesis will focus on pragmatically standpoint, due to local interference of fuzzy rules. A fuzzy control algorithm is considered to be a nonlinear static relation between inputs and outputs, no matter of their variation in time.

In fuzzy control system, there are two types of rules exemplified by: Mamdani (linguistic fuzzy models) and Sugeno (linear fuzzy models). The difference is made by the rule consequences. The Mamdani fuzzy rules are the first rules used in control fuzzy application systems, noted as a general form as (3) [16]:

$$r_k$$
: IF a_1 is A_1^k and a_n is A_1^n THEN b_1 is B_1^k and ... b_w is B_w^k (3)

In spite of the use of *max-min* inference method, limitations are present into the system because of the usage of rule consequences of only one fuzzy set defined on the output sets.

At the same time, Takagi and Sugeno introduced another fuzzy controller having as general form (4) [17][18]:

$$r_k$$
: IF a_1 is A_1^k and a_n is A_1^n (4)

$$b_1 = f_{1,k} (a_1 \dots a_n) , \dots, y_w = f_{w,k} (a_1 \dots a_n)$$
 (5)

Output rule consequence are membership functions, where Sugeno utilized linear function that can be interpreted as a set of linear local function where the switch from a local control algorithm to another one happens very easily. Another interpretation of Sugeno rules is the modification of linear control algorithm parameters by a fuzzy supervisor. In fact, the Sugeno controller computes a weighted output average of different local functions.

The applicability of fuzzy control algorithms is large: cameras, washing machines, color TV, car's transmission control, climatization or even heating, ventilation, or air conditioning.

Testing facility

The experimental house of UPB was built as a standard duplex house with one floor. It is divided into two houses, East and West wing. The East wing of the house serves as a student research laboratory running an EAHX system, which uses ground temperature to preserve a constant temperature inside the house. The West wing has the same thermal properties as the East wing, running on a different HVAC system: air to air heat recovery unit plus a geothermal heat pump.

The building was designed as a passive house in order to reduce the thermal load through efficient insulation and air tightness. Each wall has a minimum of three distinctive layers characterized by good thermal conductivity level. Triple glazed windows are positioned on the southern part of the building.

In order to increase the efficiency of the HVAC system, a Canadian well was used, because of soil constant temperature. A pump takes the air from the environment and introduces it into the heating recovery unit through a 40 m u-shape tube.

None of this can happen without the solid monitoring system implemented into the experimental house by a team of researchers and engineers, testing the HVAC efficiency and digital technologies. The monitoring system collects information such as: temperature, air quality and electrical power. Being equipped with both software and hardware solutions, the monitoring system offers a low-energy consumption policy accordingly to user's needs. The monitoring system is composed of multiple wired and wireless sensors, spread inside the building, providing useful information data about selected parameters. For this reason, a Policy Editor is running as a desktop application where html code is needed to control the HVAC system and electrical resistance.

The passive house laboratory from UPB, as presented in below picture, delivers optimal conditions for measuring and data acquisition, especially connecting smart meters to the grid. In the upcoming chapter, more information about the data collection and information flow is provided.



Measurements and data acquisition

In the upcoming section, information about data acquisition methods as well as different measurements techniques are being detailed. A smart meter system is needed to measure how much electricity and energy is used. They are the newest engineering products that aim to replace the regular meters of gas and electricity systems by 2020 according to European Commission [19]. This system is necessary to measure the energy consumption and the use of the buildings 24/7 while sending data to service supplier, wirelessly. The use of the smart meter system saves plenty of time due to no manual reading and incorrect estimation bills. With smart meters, instant data are sent to a supplier, having precise energy data such as the system implemented in the experimental house. The difference between the supplier and the experimental house is that all the data from the testing laboratory is gathered to a specific server and maintained under constant observation.

The smart meter passive house system can gather three distinct types of data: real-time data, persistent data and archived data. Each data is linked to a smart meter equipped with an SD slot card where a Raspbian operation system is installed.

Multiple applications are running on the system proving constant data collection. The interaction between the SMX and the HMI is made via a remote computer connected to the internet. Numerous modules are operating within the smart meter, creating a fluent workflow with the system.

Systems energy requirements and consumption precisely influence any building's performance in terms of costs and comfort. In this chapter, two methods for estimating the energy usage will be presented:

- 1. forward modeling
- 2. data-driven modeling.

Two basic procedures might be applied to any mathematical model, in the interest of determining the 3rd component or the output:

- 1. forward approach,
- 2. data-driven approach.

The forward approach is employed to forecast the output parameters of a stated prototype, taking into consideration the knowledge about architecture and parameters when subject name the inputs. Forward approaches employ a physical characterization of structure's system or element of concern. In other words, location, building's properties, house's position, HVAC system or construction's material are known.

The data-driven approach implies knowing a big amount of data on entries and outputs. The major advantage of this method is the easiness of implementation of the system that does not require physical characteristics to forecast building behavior. This type of method performs in optimal condition when information is accessible for analyzation. To sum up, the second approach identifies system prototype with rigorous prediction of structure efficiency.

The difference between approaches consists into the number of gathered parameters due to reduced and recurrent data enclosed into database. Generally, forward approaches are more permissive than data-driven methods when it comes to energy estimation of building characteristics.

A recent development of smart meter system made possible the connectivity of every device to the IoT system, as long as the system is connected to the internet. Moreover, the IoT ecosystem can exchange information with any device connected, at any time or location via a unique platform.

A smart meter indicates the total amount of energy use, in real time, plus the total costs of the situation in country currency. One of the major advantages of using a SMX platform is the remote communication every device can have, due to the fact that, as long as mobile data connection is available, actions can be taken with a third-party application. Payments and house balances can be seen directly through a remote connection to the smart meter saving time and resources. The management usage can be registered and setup according to user preferences, implementing a better control on the energy consumption.

For the purpose of this thesis, weather data has been directly gathered from the external sensors, as well as confronting daily updates from the forecast website: Accuweather, Wunderground, Weather-forecast or Ventusky. Complex database was created by monitoring several cities from Europe (Lyon, Rome, Berlin, Bucharest) including 30 days forecast data. Additionally, Energy Plus website was used to identify weather inputs.

The weather prediction is as important issue of the thesis because of the direct impact on the building. Taking into consideration the weather aspects, any building is subject to temperature modifications, thus energy consumption losses may appear. The environmental parameters are directly impacting the consumption of any residential structure being able to increase the temperatures in rooms, cooling the inside air temperature or even triggering the system for unnecessary heating.

For the data prediction with the algorithm proposed, two distinct methods must be acknowledged. The grey box algorithm is specific for its ability to output certain parameters, as well as multiple inputs. For the purpose of this thesis, we propose two algorithms that are based on Grey Box models, that are able to gather and to predict both physical and statistical parameters.

The first algorithm is referring to the physical part of the building as: materials used for building construction, shape of the house, orientation, multiple layers of building components or energy losses from thermal bridges.

The second algorithm is a statistical algorithm used to create a database of the input data in terms of weather selected parameters. Weather data can be downloaded from various authorized websites such as: Accuweather, Wunderground, Weatherforecast or a complex solution, Ventusky.

For the development of the weather database, certain parameters such as: temperature, humidity, precipitation, wind speed, cloud cover, pressure, time stamp (date, hour) had been chosen. The period of the year is very important because the weather parameters can vary from January to August. In order to prove good accuracy of the data acquisition, tests were done for a specific period of the selected months.

Taking into consideration that the weather prediction algorithm is reading the inputs and submits the outputs for a period of 30 days in advance, multiple input parameters were gathered from the following websites:

- www.accuweather.com [20]
- https://www.wunderground.com [21]
- http://www.weather-forecast.com[22]

Four cities were monitored for the input database by taking into consideration geographic position. The cities were chosen between a distance range of 1000 km with the condition of having opposite weather climate. For a better understanding of the weather prediction algorithm, for a period of two months four cities were monitored: Bucharest (as reference), Lyon, Rome, Berlin.

Hourly weather parameters are collected as inputs for the algorithm computation. During a 24-hour period, the following parameters have been selected following parameters in order to achieve a superior accuracy: outside temperature, real feel temperature, humidity level, condition (clear sky or cloudy), precipitation level, wind Speed, cloud cover, pressure.

The objective of the proposed algorithm, is to identify the inputs weather from Energy Plus website [23] and to create a file able to convert the weather-data in a readable format. Moreover, the algorithm can find the solar radiation on a titled surface displaying and visualizing the data. Additionally, physical analysis and state-space models identify the stability and precision of the analyzed system.

An EPW file has multiple unnecessary text and needs to be suitable for the readout of algorithm. On the first row of the EPW file, location and the exact time-data are displayed, followed by parameters such as: max temperature, min temperature, average temperature, ground temperature, relative humidity etc.

With the conversion of the EPW file into CSV file, a MATLAB algorithm is able read and take as inputs only the desire values. The CSV file is organized in 15 columns starting from year, month, day, hour, minute and finishing with global radiation, diffuse radiation, or atmospheric pressure.

SMX (smart meter extension)

Smart Meter Extension (SMX) is a system implemented on a Raspberry Pi2 board, having a concentric data base architecture [24]. Within the data base, the communication with the application is not directly but through specific channels. This type of system protects the data with a RBAC (Role Based Access Control) software, allowing the information transfer to be done without interruption.

The first step in creating a SMX architecture based on a Raspberry PI2 single board computer is to create an image with the necessary files to allow application execution. The image consists of a package and a REST-Api for the Mongo data base. To be noted that the image for the open-source SMX has all the essential programs already installed in a previous configuration. Thus, it allows the user to develop his own modules and to interact with the system according to his needs.

From a dynamic point of view, the SMX is able to detect three different types of data:

- 1) **Real-time data**, which is non-persistent data, and which is expected to be frequently modified (such as reactive power P and Q, voltage U or currents I)
- 2) **Persistent data**, which are memorized after the system turns on/off. The process of data written on the storage is assured by the SMX solution. On the other hand, the persistent data is used to create the Mongo database. If the user is not familiar with the MongoDB solution, NoSQL is proposed for storing this kind of data. In communication with certain apps, the data can be exchanged as follows:
 - the real-time communication with the SMXCore can be realized through a MongoDB module of the SMX.
 - the communication between the REST Api and the MongoBD can be established with any application trusted by the system. The benefit of using this sort of communication is the data-privacy, as well as for designing security policies.
- 3) Achieved data, which is very related to persistent data. This type of data has a time step interval from 1 to 60 seconds, depending on the user's needs. A considerable advantage of using this technique is the data-retrieval through offline readouts on separate files. Files are classified as: 1) daily; 2) weekly or 3) monthly files.

Valuable parameters such as P, Q, U, I or energy registers A+, A-, R+, R- can be seen into the database. Additionally, the evolution of data can be displayed using the SMX method. The SMX is equipped with a SD slot card for multiple purposes. One of the advantages of using a SD card is the installation of a free *raspbian-jessie-lite-16-11-image*. Multiple modules are set to be turned on, once the connection SMX - SDcard is established:

- **Set of modules** - which are installed in the TZ (trusted zone). An important asset is the "MQTT Client" (Message Queuing Telemetry Transport) which can communicate with any external device. The client uses a Mosquitto MQTT broker and two Dockers: #0 and #2.

To be noted that any Docker "#x" is a group of Docker applications which can interact, even if they work under Docker restrictions, with the Trusted Zone through the REST Api of MongoDB or through an MQTT client of SMXCore. For security and privacy reason both will have RBAC system implemented.

- **MongoDB package** available on the internet as an open-source package and is installed in TZ. This broker allows the connection of trusted applications to the real-time database.
- **REST API** responsible for the direct connection between Apps and MongoDB. By using a token, only permitted data is allowed to be exchanged within the communication with the database. Each user must have a mandatory PP (privacy profile) and an RBAC system installed.
- **Web-Server app** running on a web-oriented Human Machine Interface (HMI) for local readout of SMX data. The App has Java script language-code, creating a powerful and stable NOD-JS web server. In particular, the image having the Basic-SMX-HMI woks with two instances: 1) docker environment; 2) trusted zone. Both instances have two different ports, working complementarily.
- **OpenVPN** strictly installed for the purpose of creating a safe remote connection to the server. As long as the network administrator is connected to the internet, it can access the system through the VPN connection.

Under these circumstances, a huge advantage of the SMX implementation is the further development of HMI applications in accordance with user's needs.

Data collection and integration through IoT

An ongoing dispute on the energy sector is the implementation of Internet of Things (IoT) within any eco-system or residential buildings. Sustaining the modernization of IoT direction, there was a constant struggle between gathering data and providing the best solution to secure this information acquisition.

The prediction of input data is related to the newest technologies recently implemented into the testing facility form UPB, which is running on an IoT working module. The goal of the chosen purpose is to understand the behavior of the people living inside the building. The system is programmed to analyze and monitor input data, especially the comfort parameters in any kind of residential constructions. Moreover, a platform has been created to investigate the data collected and to assimilate it with current technology in order to save energy as much as possible. In addition, by connecting 3rd-party apps to the IoT system model, the experience level for each individual is adequate to a friendly and easy utilization. The experimental design is working under wireless network sensors capable of sending instant data to the IoT system. IoT comes with a solution providing full connection to any kind of object linked to the internet. In the testing facility from UPB, each user has a specific profile created.

The purpose is to enhance the system evaluation and of the information accumulated from the smart devices. IoT can be outlined as global framework that harvest important information about specific data, including input data for mathematic models. This type of knowledge is analyzed through distinct parts relying on three dimensional states: time, place and device.

When it comes to IoT ecosystem, one of the most important elements of the system is the device. The devices can be found as physical equipment (things/objects) working as collector information. Every device can exchange information with another device, no matter the time or the place, via a particular platform. Depending on the user needs, each device may be programmed to save information on a specific database with a pre-setup time step.

All the dimensional states are communicating with each other through stable protocols, making the IoT infrastructure a good solution for analyzing and data awareness. Intelligent tools or controllers can be recognized as physical sensors able to transmit useful parameters about the surroundings.

Every sensor has in its componence a small motherboard. Taking into consideration that most of the devices have a software routine, it implies a hardware entity that needs to be present all the time. Hardware solution for the IoT infra-structure is cost effective and functionality wise. In Table 1., the main elements of an IoT structure are presented. Each layer of the structure has an important role, inflicting directly the energy consumption of the testing laboratory. The devices are responsible with the connection with the system and prepared for monitor and organization.

Table 1. 101 ecosystem – important elements					
Device	Data collection	Data analysis	Application		
		•	11		
0 1.1	G' 1	D (1 11 1 1)	T , 1		
One or multiple	Signal	Data handling, data	Interchange		
objects that are	conversion	analytics, cloud-	information between		
controlled and	(input analog	based computing.	3rd party application		
monitored	output digital)		and user synergy		
Safety or protection manners					

Table 1. IoT ecosystem – important elements

The 2nd layer of the IoT eco-system is responsible for the data collection implying the signal conversion from an input analog into an output digital signal. The transformation of signals depends on the following:

- Measured physical signal
- Diversity of sensor type
- Time period of data compilation

The 3rd layer analyzes and processes the filtered data within the cloud computing files. The end user receives only the most relevant information as graphics or statistical documents. After a complex analysis of the processed data, this layer provides only the necessary information for the inhabitant to evaluate.

The final layer is dedicated to the application center, connecting the upper layers with the party system via all sorts of protocols. In **Error! Reference source not found.**, a technical communication model is provided, showing the operational assumption of data access to the network gateways. This type of communication is done through

multiple secured VPN channels, being controlled by a set of procedure that authorizes security guidelines.

The testing laboratory is running on an IoT working module that is structured in multiple sparrow sensors suppliers that are in strong correlation with an acquisition center (working on IEEE 802.15.4 standard). Built up for development a purpose, a *Sparrow* is a wireless sensor network (WSN) operating on different standards for testing wireless applications. One *Sparrow* wireless node is composed of various elements with small dimensions, low-power consumption and low-cost sensors. Those sensors are systematized in a regular structure able to gather data from the environment and to connect to nearby networks over a specific gateway

The principal source of energy for the sensor is the battery pack, which is composed of 2 x AA 1.5V CR2477N batteries that stores an average amount of energy (950 mAh). For monitoring the energy consumption rate of the battery pack, an energy management sensor was preferred to be part of the *Sparrow* node sensor.

By transforming analog into digital signal, the blocks functionality gathers information about important parameters of the testing facility:

- indoor air pollutants: dust particles (1 to 10 μm),
- leaks of combustible gas such as: methane, propane or carbon monoxide,
- ammonia,
- sulfide,
- benzene steam,
- temperature or humidity.

Energy prediction based on small amount of information: degree-day and grey-box models

Heating Degree-Day (HDD) is a common procedure for estimating energy consumption of any residential buildings. Carbon dioxide emissions can also be estimated by using HDD method because of the collected data during a selected period. In case of major building refurbishments, the user can set the energy levels according to the analysis of the system [25].

Energy savings and consumption of residential building are computed by multiplying analogous hour number with outside temperature value. Thus, steady-state models should not be used because of the variation of interior gains and temperature. The degree-day method can bring estimation of annual loads with, or without, any difficulties (if the internal gains and inside temperature are constant).

In case of changes in free loads and temperature set points of buildings, energy consumption is affected. Considering the system improvement, temperature involved in the system can be balanced by using heating degree-day method. As accuracy is one of the main keys of a perfect system functionality, a reference temperature needs to be calculated. The default temperature is equal to the base temperature where building is at equilibrium point. After identifying this step, a difference between outdoor and base temperature needs to be determined. When thermal comfort conditions are fulfilled and system is not working, the building is in balance point [26].

For achieving a good thermal comfort, many users use different heating or cooling systems. Moreover, the testing laboratory from UPB is running the HVAC system, taking into consideration the balance point of the house. The difference between the base and outside temperature, according to HDD methods, is supported by the HVAC system. The degree-days method works if applied on a period of 24 hours. For a better accuracy of the targeted temperature, it is recommended to divide in hourly intervals. Despite this advantage, several detrimental aspects can be are present in the degree-day method:

- the 1st problem of using degree-day method is parameter estimation such as overall heat loss coefficient and base temperature (presenting a slight error for the output calculation),
- the 2nd issue consists of identifying the buildings energy efficiency approach (the analysis is done only for certain parameters).

Firstly, a hypothesis needs to be done before calculating the output – the residential heating energy consumption. Secondly, any statistical references can deliver approximate results at the beginning of the analysis. The best fit for the energy appliances relates to the use of internal and external temperatures, constant gains, energy consumption or air infiltration. For example, having an assumption on suggested parameters such as base temperature, average of a day's high and low temperatures,

hourly temperature reading, an accurate approximation of the building's energy efficiency can be done.

Simplified methods use mean outdoor input parameters to measure the energy demands. The fluctuation of indoor and outdoor temperatures of degree-day procedure excludes periods when HVAC system is turned off. Duration and magnitude perfectly describe the degree-day technique, while estimating the energy consumption of any building.

For a better understanding of the working principal, the degree-day method is demonstrating the importance of base temperatures and time-period. As mentioned before, the difference between the 1^{st} and the 2^{nd} day is made by the method used to describe temperatures:

- 1) Day 1 Mean daily temperature.
- 2) Day 2- Degree-day.

Base temperature (balance point)

The base temperature is set-up at the beginning of calculus, while the degree necessary to turn on the system is hourly determined. Even if the heat gains inflict difficulties on the system by not recognizing the right base temperature, additional adjustments can be done with the HVAC to achieve a comfort inside temperature. To deliver correct explanation of the default temperature, multiple thermal aspects must be taken into consideration as follows: thermal capacity, heat loss, air infiltration rate, heat loss coefficient, building orientation.

To conclude, since outside sensor detected a lower temperature than normal, the HVAC system consumption was higher than usual (due to accumulation of degree-days points). Important to realize is that the accuracy of this type of method is not very high but the rapidity of the analysis provides a result in no time.

Specific annual heat demand for the building is being calculated monthly, showing good response of the system. After running PHPP file Fig. 2 is obtained as being the specific losses, gains and heating demand of the testing laboratory marked with different colors. During the warm season, the specific losses are on a minimum trail while the specific solar gains are at maximum potential, implying no specific heat demand for the HVAC system.

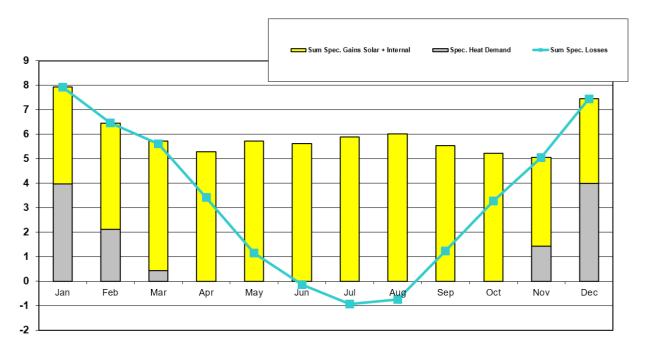


Fig. 2 Specific losses, gains, heating demand (kWh/m2 month)

During winter season, specific heat demand is growing due to weather conditions. Despite this behavior, testing laboratory is running on good reference range intervals because average mean is kept below 12 kWh/m²y.

When using cooling degree-day, buildings energy estimation can be systematized by showing the exact amount of day-points needed to minimize the inside temperature. Due to high solar gains, the HVAC system needs to bypass the electrical resistance, injecting fresh ground temperature inside the building. Fig. 7 shows the graphical representation of specific losses, loads and cooling demand of the HVAC system, monthly.

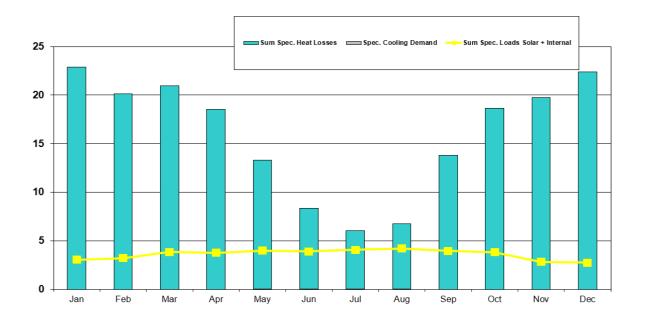


Fig. 7 Specific losses, loads and cooling demand (kWh/m2 month)

The HVAC system is organized to implement an indoor temperature of 25 $^{\circ}$ C during summer period, inside each room of the building.

In terms of energy consumption and cost reduction, energy estimation is one of the most important characteristics. With a precise energy estimation, multiple detrimentally issues can be overcome, such as: financial problems, ineffective energy usage or energy savings. Although system simulations help to predict energy use, the accuracy may not be so precise due to software errors. Even though the investigation can be made on a high level, the biggest concern is the time-consuming process. The advantage provided by degree-day method is the simplicity for estimating building's energy consumption when it comes to heating or cooling. It is required only few input data to run a complete analysis to predict energy consumption or, briefly, to identify factors influencing the consumption.

Grey-box models

A grey-box model equation is used to describe the dynamic system. The stochastic differential equations (SDE) are the basic equation from where the system drags its inputs:

$$dT_1 = \left(\frac{1}{C_1 R_1} (T_e - T_1) + \frac{1}{C_1 R_2} (T_i - T_1)\right) dt + \sigma_1 dw_1 \tag{6}$$

$$Q_{i,k} = \frac{1}{R_2} \left(T_{i,k} - T_{1,k} \right) + e_k \tag{7}$$

where.

- Q_i output is the observed heat flux
- T_i ambient temperature
- T_e. indoor temperature
- T_1 state variable in equation (6), together with the observation equation (7).
- k is the k^{th} observed value at time point T_k .

Parameters are:

- C_1 wall heat capacity
- R₁ thermal resistance from the ambient into the lumped state in the wall
- R₂ i- thermal resistance from the lumped state to the interior
- $\omega 1$ is assumed to be a Wiener process, which is a continuous time noise process that has the property ω_1 , $T_k \omega_1$, $T_{k1} \sim N(0, (T_{k-1} T_k)^2))$. The unit is here \sqrt{s} . The variance of the system noise is thus σ_1^2 .
- the observation noise $e_k \sim N(0, \sigma^2)$ is presumed to be white noise, hence, normal distributed variance σ^2 .

Grey-box identification model

The model used in the system is illustrated with the RC-diagram in Fig. . CTSM (Continuous Time Stochastic Modelling) is utilized in estimation parameters with SDE (prediction error) and is available as an R package named CTSM-R. The R software was used to simulate the identification parameters and to transform the analyzed wall into a nodal circuit:

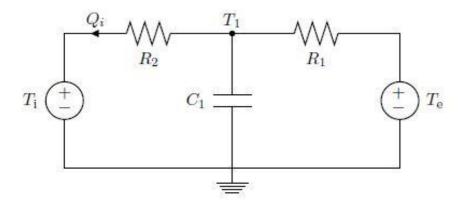


Fig. 6 RC diagram

Given these points, a short report was made with concise answers illustrating the plots for the system. The steps of coming up to the displayed parameters started by running the script programmed in the R software.

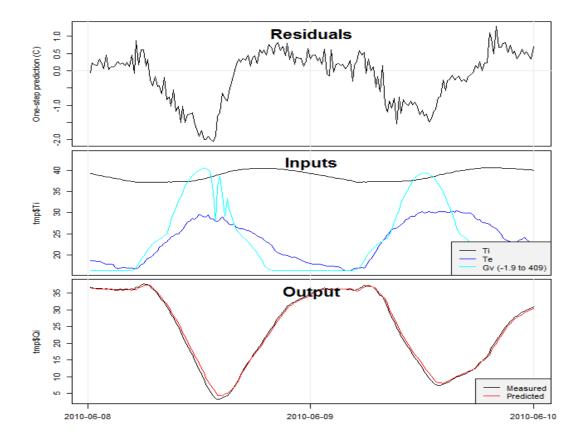


Fig. 7 Residuals, inputs and outputs of the system

Starting with relieving of inputs system, we identify the inside temperature marked with black line, the environmental temperature outlined with purple line and the solar gains noted with cyan. On the other hand, outputs model are specified in the bottom of the Fig. 7, subplot with measured energy flux as black line and the prediction of energy consumption, draw with red line. Thereupon, the residuals variation is presented.

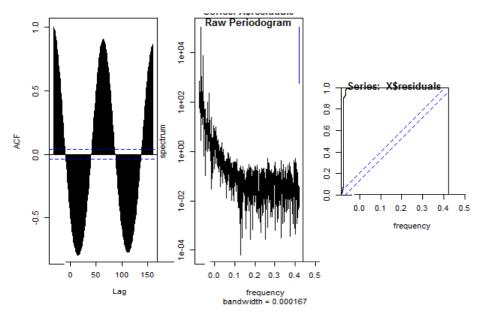


Fig. 8 The correlation of residuals and white noise

As presented above in Fig.8, residuals correlation has been calculated using R software while result was plotted in a bandwidth image. In the first place, residuals are correlated, following a precise path, underling the fact that there is no white noise (in our case error). The analyzed spectrum has low values when comparing to a different frequency, which indicates that some parts of our implemented system, even different inputs, have small values. On the other hand, looking at the right side of Fig. 8 we can point out the incertitude of residuals that are not in the confidence band, not even 5%, implying that the model is still on working phase. Due to this incertitude the model is classified as not feasible and the perfect fit was not yet discovered.

Moving further on the technical survey, if we examine Fig. 8, we can affirm that the system is precise, it follows a good track, but the residuals does not have sustainable values. A good observation would be that there is an enormous influence upon the system that is similar to a solar gain and is influencing the heat flux. By looking at graph and also by checking the elements of equation (6), the "GV" term (solar radiation) is missing completely from the mathematic model. In addition, the solar radiation is impacting directly the house, having a major effect on energy consumption, where g is a coefficient describing the ratio of the vertical radiation absorbed by the wall.

System enhancement can be made by implementing the solar radiation in the simple grey-box model as follows:

$$dT_1 = \left(\frac{1}{C_1 R_1} (T_e - T_1) + \frac{1}{C_1 R_2} (T_i - T_1) + \frac{g}{C_1} G_v\right) dt + \sigma_1 dw_1 \tag{8}$$

In other words, the system can be summarized as an RC nodal model with 2R (resistance), 1C (capacity), 1Gv (solar gain) and the T (temperatures) from the borders, inside and outside. The flux moves towards the interior temperature with the summation between the outside temperature and solar radiation, as exemplified in Fig. .

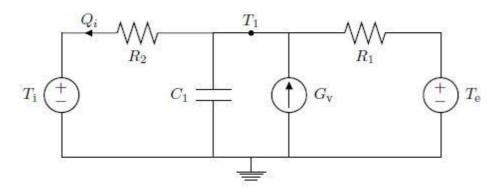


Fig. 9 Nodal form with solar radiation

After the calculations has been made, results are presented in Fig. 10 where and improvement of the previous version of the system is displayed. As mentioned before residuals are being plotted, while on the middle section, input parameters are shown. The difference is made by the G_v term which represents the solar gains of the system. Results presents constant residuals, enhanced inputs and a serisous upgrade of outputs (predication and measured) as mentioned in the bottom of the picture.

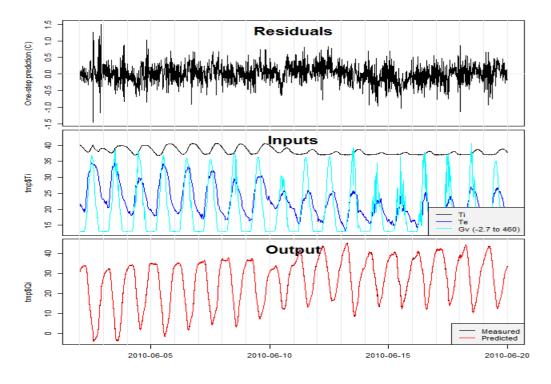


Fig. 10 The system with solar radiation implementation

With the intention of achieving better results, solar radiation has been integrated into the system and enhanced a progress in outputs. One of the fastest changes of the

system can be seen by looking at high values from Fig. , pointing that solar radiation is strongly related and directly proportional with the inputs. At the same time, energy flux switches constantly, demonstrating a solid relationship with solar radiation. Taking into consideration results from the above exemplification (model without solar radiation), residuals decreased significantly. Additionally, the system tends to move towards small residual values showing new improvement opportunities.

Last, but not the least, the 3rd example of a system was designed. Thus, steady point (T2) and new capacity were brought in accordance with the solar radiation, reminding the fact that capacities are helpful for storing excess energy from the system. Therefore, a new mathematical model was created having the subsequent equations:

$$dT_1 = \left(\frac{1}{C_1 R_1} (T_e - T_1) + \frac{1}{C_1 R_2} (T_2 - T_1) + \frac{g}{C_1} G_v\right) dt + \sigma_1 dw_1 \tag{8}$$

$$dT_2 = \left(\frac{1}{C_2 R_2} (T_1 - T_2) + \frac{1}{C_2 R_3} (T_i - T_2)\right) dt + \sigma_2 dw_2 \tag{9}$$

The analytical structure of new model is different from equation (6) because of the implementation of additional capacitance (C_2) , resistance (R_3) and steady point (T_2) as displayed in Fig. 1111:

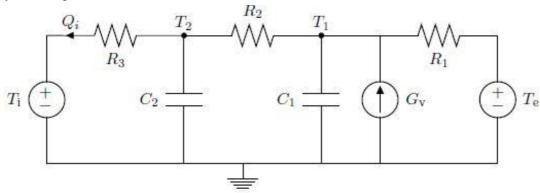


Fig. 11 Mathematical model with solar radiation and steady point

The results obtained is an improvement asset to the system, being exemplified in Fig. , where a substantial residuals difference can be noticed. The residuals are maintained in the confidential bandwidth, with more than 95% of the scenarios showing good enhancement. None of the less, the most important value is the other 5% of the percentage, which is considered to be the systematically error.

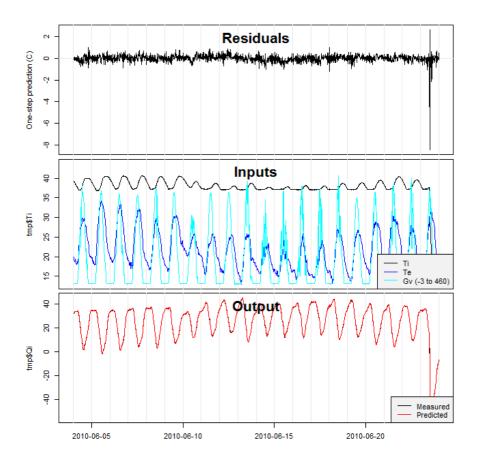


Fig. 12 Reports and results for the last model

As Fig. 1313 presents, inputs are following a favorable trend, being equivalent to solar rays gathered from ambient. Unlike inputs, output parameters have a systematic error at the analysis conclusion. Moreover, the time step for the simulated system was chosen to differ from step to step, having as time step: 2, 5, 10, 15, 20 and 30 minutes. Data were gathered in series to comprehend the link between residuals and estimation error prediction.

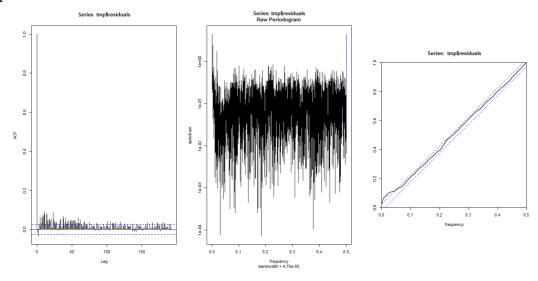


Fig. 13 Residuals and results

In closing, the more we reduce time step of the analysis, the more the accuracy is growing, and residuals becomes higher, providing the opportunity to control them easily. The slightest change of inside temperature has a major effect upon residuals, forcing the systems output to change its value. As displayed in Fig. 114, residuals present a huge modification at the analysis outcome which was caused by a malfunction of the system. To be noted that residuals are maintained in the band of confidence more than 96%, proving the algorithm efficiency in cause.

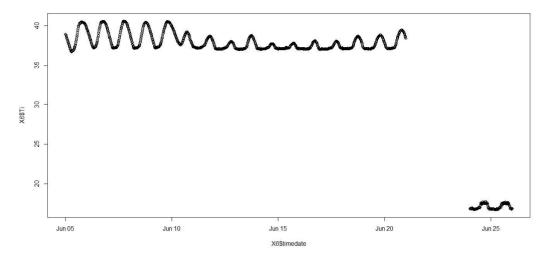


Fig. 14 Dropdown in residuals due to systhematic error

Moreover, the dropdown seen in Fig. 114, cause by the system malfunction residuals are beginning to stabilize at a certain point, on 25th of July. As a conclusion, by seeing the results of residuals, we can acknowledge the fact that this model is an improvement, because residuals are following a constant pattern, being contained in the band of confidence with high precision. The model is sensible to inputs, especially when initial parameters suffer modification. To cover this issue and improvement is necessary since radiation from sun is strongly related to systems resistances.

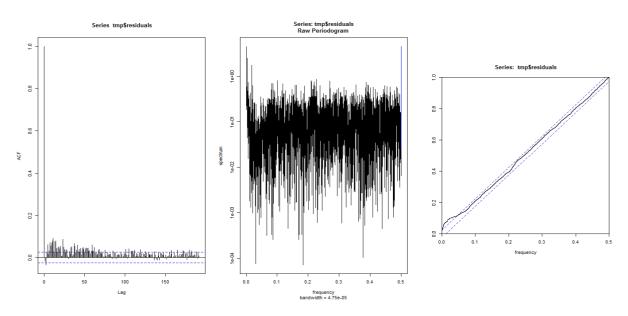


Fig. 15 Residuals and results

Model approach number 3rd has the best fit for the system analyzed which can further be improved, by taking into consideration larger inputs data, weather aspects or human behavior patterns. The residuals are maintained in the band of confidence with an efficiency of more than 97% as display in Fig. 5.

Energy monitoring and control

In this chapter energy control and monitoring are presented, as a solution for optimizing buildings energy consumption. Energy monitoring involves capturing the overall power consumption of testing laboratory or recording the consumption of each device from the building. Nowadays, monitoring energy can be acquired through several means such as: thermostats, system feedback, smart meters, administrative data, statistical models' surveys, specific sensors [27].

Energy monitoring is helpful if control is required. The importance of using fuzzy logic in automatic control is related to the fact that the user does not need much system knowledge and the controlled usage is determined by linguistic rules. The system doesn't need to be reduced to develop a working fuzzy logic controller while the conditions are robust, because of variability in inputs [28][29]

Thermal comfort using fuzzy logic

The fuzzy logic technique is an approach of attaining a reliable thermal comfort. This method implies controlling the energy system by heating and cooling the building. Whether to start, or to shut down the HVAC system depends on policies and human behavior. Fuzzy logic suggests two realistic mechanisms to identify whether energy is saved or lost.

The first mechanism is recognized as being part of the Boolean logic system, meaning that any object can be described by either "True" or "False" value. The interpretation values define static values such as 1 or 0; 1 - is assigned to "True" value while 0 - is allocated to the "False" value.

On the other hand, second mechanism receives values between a specific reference range. The controller analyzes data gathered from sensors and correlates them with values from 0 to 1. Hence, when receiving 0.7 grade of value, it's not completely true, but partially true, while False or mainly false, is pointing to 0.3 grades of value.

Any system equipped with fuzzy logic, can take crucial decisions, improving energy effectiveness and energy savings. The implementation of a fuzzy logic system into the testing laboratory proved higher efficiency when modeled with HVAC system [30][31].

The software implemented into the testing laboratory is a (SBC) Smart Building Controller, able to reduce buildings energy consumption. The monitoring infrastructure collects surrounding inputs and creates a database for further analysis. In the light of achieving a good temperature level, SBC enables the possibility to modify policies, to control the HVAC equipment. Additionally, the SBC software has a couple of benefits, including the electrical resistance management or real time feedback. Each system feedback is useful for predicting energy consumption, due to a detailed information

about database. Hence, the user can interact with the system by configuring each part of the SBC software

Fuzzy control is based on applied engineering methods, following strict standards without taking into consideration values such as true or false. A fuzzy logic system consists of taking non-linear INPUT data and transforming to scalar OUTPUT data as in

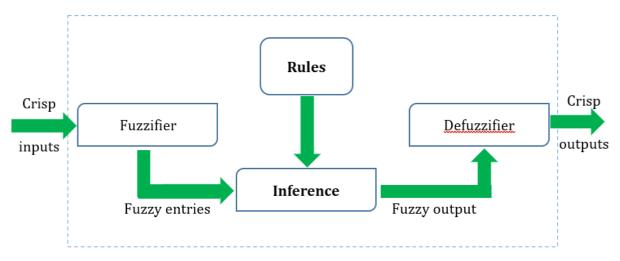


Fig. 17 Structure of fuzzy implementation

The structure of fuzzy algorithm from Fig. image, details the basic method of analyzing input data and providing requested output. The fuzzifier receives the input data gathered from sensors and transforms it into dependency grades, starting from 0 to 1. After transformation takes place, a fuzzy input set is being created and prepared for the upcoming process. The afterwards process is the inference step, where the acquired set is put under a set of regulation which are created by the user to generate fuzzy output sets. The inference level has every input evaluated by each rule, generating output sets based on feedback. The final process relies on the transformation of fuzzy output set into input set to the "defuzzifier", which accepts the data and models them into numerical values, thus non-fuzzy.

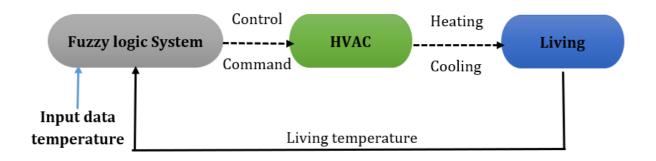


Fig. 17 Fuzzy system appliance

Fig. presents an approach of UPB testing laboratory fuzzy system. The diagram starts from the left part, as it gathers set of inputs data (degrees) from the environment. After the fuzzification takes places, the HVAC system, depending on the commands he receives from the algorithm, knows what action to take. The HVAC system can heat or cool, the inside temperature, influencing the buildings energy consumption, but not before confronting with initial value of indoor temperature.

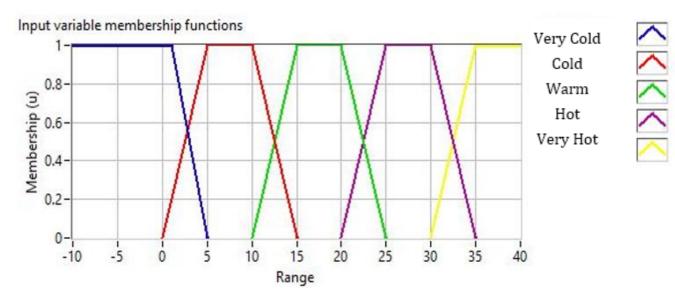


Fig. 18 Membership level of fuzzy logic algorithm

Returning to the dependency set, input data is submitted to a specific set of rules and classified as being either HOT or COLD. The classification is made relying on a dependency level as presented in **Error! Reference source not found.**2. If external sensor detects 18 °C beneath room temperature, the HVAC will receive a dependency level of 0.95 HOT and 0.05 COLD, meaning the system must turn on.

Temperature	Very Cold	Cold	Warm	Hot	Very Hot
			Heat up	Heat up	Heat up
Very Cold	Don't change	Heat up			
			Heat up	Heat up	Heat up
Cold	Cool down	Don't change			
	Cool down	Cool down		Heat up	Heat up
Warm			Don't change		
	Cool down	Cool down	Cool down		
Hot				Don't change	Heat up
	Cool down	Cool down	Cool down	Cool down	
Very Hot					Don't change

To simplify the equation, the dependency levels can be kept as a matrix form, improving accuracy and triggering HVAC system. **Error! Reference source not found.**1 is defining the matrix from where the system chooses what to trigger.

Fuzzy algorithm

For a better explanation of the membership level, a set of fuzzy inputs has been uploaded into the LABVIEW software, as presented in Fig. to observe output results. The dependency levels are described as fuzzy function, that can transform fuzzy values into non-fuzzy values (numerical values). In a fuzzy logic system, the most substantial variable is the output. As long as the control output is stable and doesn't fluctuate, a good thermal condition is obtained. The software includes a three-tab panels where input, rules and testing system are selected. Firstly, the input was assessed to temperature variable which is represented by outdoor temperature.

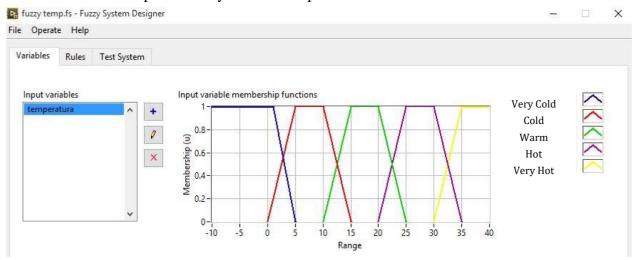


Fig. 19 Fuzzy membership functions

The fuzzy system software-designer from LABVIEW allows users to examine when, and in what manner, the HVAC system will be triggered. User can select the Defuzzification method concerning multiple inputs with a suggested consequent. Second step consists of the construction of the logical conditions for each time-step of the system, as displayed in Fig. 20

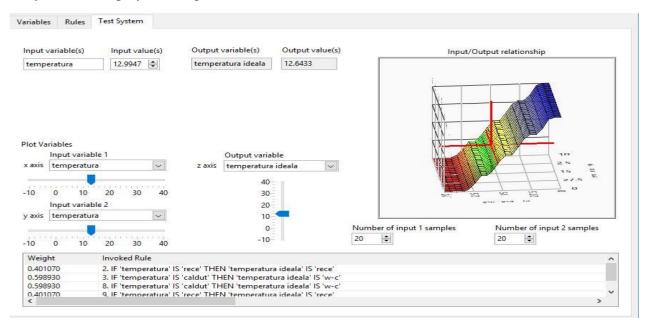


Fig. 20 Implementation of fuzzy rules

One of the advantages of using this technique is the easy implementation of any logical condition such as: CASE, IF-THEN, IF-THEN-ELSE, FOR. Rules are built strategically to understand the next execution. On the lower part of the image, multiple inputs can be selected and subjected to a specific rule. The action is mentioned on the right part where the HVAC system is triggered.

Third step described in Fig. , is the plotting of bonding between input/output relationship. Readout of input variable is shown in left side while the outputting is mentioned on the top of the image. Interested to note that the output variable can be modified depending on the thermal comfort and the interference set up.

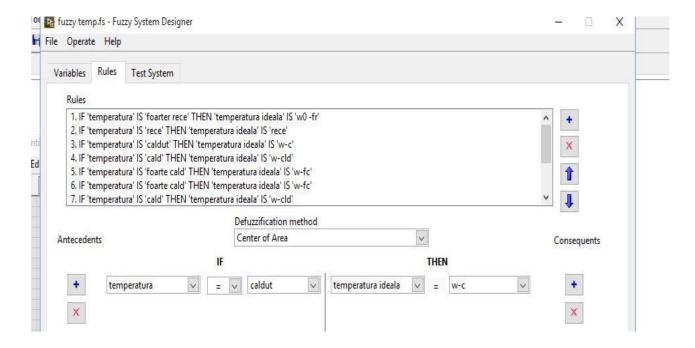


Fig. 21 Fuzzy logic testing system

As literature presents, fuzzy logic method has been tested in strong relationship with artificial intelligence, resulting in achieving good thermal comfort with optimized energy consumption[32]. Taking into consideration that temperature is classified as the most compelling element of thermal condition, by attaining it, involves keeping inside temperature between 20 °C and 28 °C.

To achieve and to preserve a favorable degree of comfort, the implementation of a policy that commands the ventilation flow rate was developed. The policy was created depending on two inputs, outdoor temperature and ground temperature. In addition, policy was set up with two regulations, one to identify and one to validate outside temperature. Outside temperature is directly impacting energy consumption of the house, which leads triggering the HVAC system and energy usage.

These rules are applied during daytime and nighttime, once per minute, calculating an average with inside temperature, as illustrated in Fig. 22. When dropping below or above 20 °C of the average outside temperature, the fuzzy-logic algorithm changes the flow rate and increases the fan capacity, to equilibrate with the inside

temperature. Moreover, due to strict guideline, the rate flow raises with 20 % when temperature is below 20 °C and reduces to 7 % when temperature is above the reference.

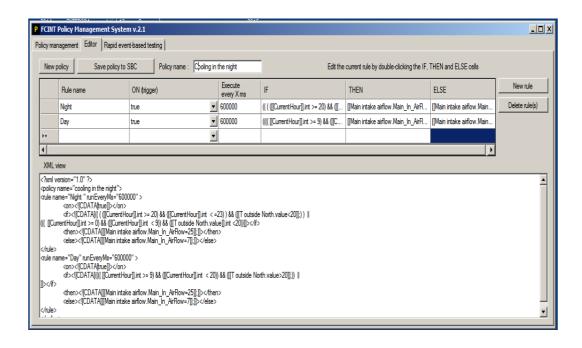


Fig. 22 Policy line code

The policy management has multiple tabs which can be customized without difficulty. In order to personalize the algorithm, XML code must be written under the Editor tab. The Rapid Event tab can set up collecting time-step data, preciseness of activating HVAC equipment and interpretation of power spent, within the house necessities.

Results of fuzzy logic control

With a view on the energy consumption, data is plotted for 6 months (as presented in Fig. :

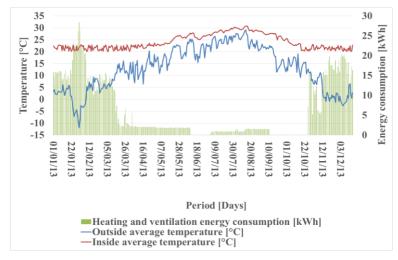


Fig. 23 Variation of heating and ventilation energy consumption [90]

During summer period, temperatures are elevated and the request from HVAC system to ventilate inside rooms was high, but with minimum energy consumption. The variation of indoor temperature between 18.73 °C and 30.96 °C is exemplified with 166.08 kWh energy demanded for ventilation. Furthermore, the average temperature for selected period was 26.46 °C taking into consideration solar radiation input. Displaying a value of 406.53 W/m², the mean solar radiation had a big impact on the indoor temperature who was kept under 27 °C, due to exchange air-cooling with ground temperature. For instance, Fig. 24 relates the variation of outdoor temperature during the daytime (from 08:00 AM until 20:00 PM). Each colored line exemplifies a specific zone of the house, while solar radiation is represented as a scale on the graph, as Fig. displays:

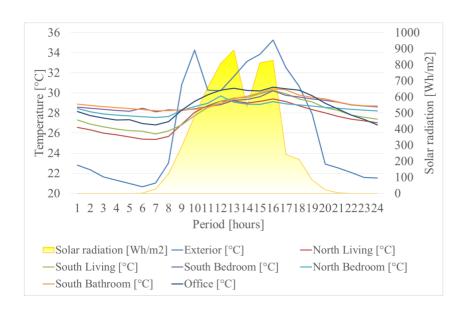


Fig. 24 Evolution of indoor and outdoor temperature

Equally important is the exemplification of temperature evolution within a selected day, underlining the inactivity of airflow rate, while inside temperature is constant. As Fig. 20 illustrates, marked with orange line, the air temperature injected into the house has a lower value than the actual temperature. This process appears when an exchange between outdoor air and ground temperature occurs.

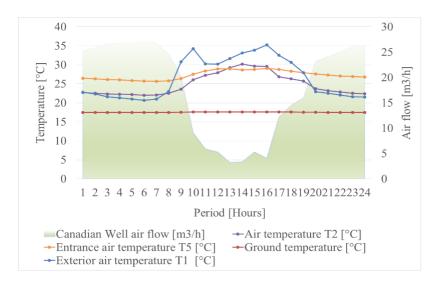


Fig. 20 Evolution of the HVAC temperatures on 22nd of July 2014

To be mentioned that the above image exemplifies multiple temperatures, colored with different markers, emphasizing the achievement of a good thermal comfort. The working procedure of the system relies on a Canadian Well method, as presented in Chapter 2 within the testing facility HVAC system. Outside air is dragged into U-shape pipelines, while exchanging temperature with ground temperature, and injecting into the "air to air heat recovery unit". From this point, the cold air is introduced inside building and ventilated constantly to maintain a stable thermal behavior.

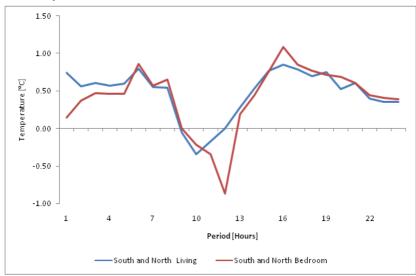


Fig. 26 Temperatures variation between N and South [109]

A comparison between the rooms positioning was made. As Fig. shows, the orientation of the house impacts the energy consumption directly, having a variation between North and South.

To conclude with, by developing and testing the fuzzy logic technique, inside temperature of the testing laboratory has been kept under good thermal level, with maximum energy savings. The system has been implemented in LabView software and tested on the laboratory to manage production of energy in an effective way.

Conclusion

Thermal condition improvement is considerably achieved through fuzzy logic control and policy management. Even if human behavior presents a reliable solution for reducing energy consumption, a greater result is obtained while running intelligent control systems.

If-then-else scripts are developed within policy management system which can adjust the HVAC system to save energy. Inputs are passing through a "fuzzifier" filter, applied to certain rules and then outputted into a "defuzzifier" filter. Crisp outputs are being displayed to a web platform created for monitoring interior parameters.

As the fuzzy control is based on following precise commands, real data are being transmitted to the platform for constant evaluation of energy usage. System reacts to temperature fluctuation, where a dependency matrix tells the system when to trigger on or off. Given these points, several sets of fuzzy inputs have been uploaded to a computer, to exemplify the dependency matrix and the observation of output results.

As long as control outputs are stable and don't vary often, good thermal condition is acquired with minimum energy consumption. The occupants can anytime examine the HVAC status and changes brought to the system. A reliable comfort degree was successfully met by implementing policy editor that controls buildings ventilation flow rate. These set of rules are working on day-night routine, calculating average inside temperature, in order for the system to start working or not.

As has been noted, temperature and ventilation control are improving air quality rate and reducing energy consumption for UPB testing laboratory. The system implemented in the building permits measurements and acquisition of real-time data, later used in estimating energy consumption, and controlling buildings temperature

Artificial intelligence approaches have been proven to optimize the energy efficiency of residential buildings to accomplish thesis goals, especially for the testing laboratory from UPB. The knowledge about different degree levels, times scale, inputs collection or output computing time have been presented as a solution to reduce energy consumption in residential buildings.

Taking into consideration the above facts, several sets of fuzzy inputs have been uploaded into the system to exemplify the dependency matrix and the observation of output results in a Labview software. Minimum energy consumption is acquired using fuzzy control while obtaining good and constant inside thermal condition. A customized level of comfort can be obtained due to policy editor implementation, that controls the buildings ventilation flow rate. Thus, controlling temperature and ventilation an improvement of comfort and energy savings within UPBs testing laboratory can be acquired.

Heat and mass transfer are used to model thermal behavior of building, while degree-day method estimate energy consumption based on historical data. For creating

the weather algorithm, heating and cooling degree calculation are determined. Briefly, the system behaves consequently to outside temperature.

Mathematical models are used to describe any running system to obtain specific output. Every mathematical model composition is made of three elements: input variables, system function, and output variables. On a basic process, output variables are obtained in different ways in conformity with forward or data-driven approach, as well as state-space models.

To validate the system, couple of estimation approaches that use several parameters were brought to predict energy consumption and to lower buildings energy usage. A grey-box modeling estimates parameter by establishing a bond between inputs and outputs. A rigorous analysis was made using R software, based on weather influence over the inputs. Solar radiation utilization, proven to be helpful into the mathematical model, leading to less energy consumption. The system exemplification is made using data readout, while a mathematical model clarifies the correlation between output and residuals. As mentioned above, CTSM-R software was used to plot the results in a bandwidth image explaining the incertitude of residuals and their belonging to allowed bandwidth.

Result interpretation of both physical and electrical data leads to an improvement on the energy usage and consumption rate, while different voltage evolution underlines the existence of consumers inside the house. Moreover, the energy losses from the building are compensated by the energy produced by the PV system, helping in the reduction of overall energy consumption. The results shown through the IoT system can be used to create policies/routines to save or to lower buildings energy, reducing energy consumption.

In closing, by developing these approaches, UPB testing laboratory was kept under optimal thermal comfort, using minimum energy consumption and the aim of the thesis is considered to be achieved

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Appendices

The Appendix 1 presents the testing facility structure while the 2nd appendix is related to the code implemented in MATLAB for the house's walls. Appendix 3 explains

the policies implemented while appendix 4 brings the modules for starting the SMX platform for data acquisition. To conclude with, appendix 5 describes the weather data algorithm and its implementation.

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