Hybrid AI Energy Distribution Improvements in Domestic Electrical Heating Systems

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Abstract

This research presents a hybrid artificial intelligent procedure for electrical energy distribution and set point temperature tracking in electrical domestic heating systems, which accomplishes with the Spanish Regulations for Heating Systems in Buildings considering the five different climate zones in Spain. The procedure is a multi-objective solution to train Fuzzy Controllers (FC) for maintaining the set point temperature while distributing the available electrical energy between the heaters in the building. There exists a FC for each climate zone, therefore, a different data set is gathered for each one considering the specific environmental conditions, the required building materials, and so on, accordingly to the climate zone. The research results and the developed prototype are to be integrated in a new device in the electrical dry heaters catalogue of a local company. This new device, which represents an energy rationaliser and a temperature controller in one device, will allow users to efficiently control their electrical energy consumption due to the heating system.

Keywords: Hybrid Artificial Intelligence Systems, Energy Efficiency, Electrical Energy Rationalization, Electrical Heating Systems

1. Introduction

The greater the society prosperity the greater the required comfort in the houses and the higher the amount of electrical energy requirements. A direct consequence is the policies to promote the reduction of energy consumption. In buildings, heating systems represent the main energy consumption source. Consequently, a reduction in the electrical energy consumption in electrical heating systems represents a step towards the global sustainability.

Spanish regulations changed in 2007 so that new building constraints for materials and isolation covering dimensions arise. Indeed, a Spanish Regulation was introduced which establishes the dimensions for the heating systems according to the corresponding climate zone in Spain, RITE[1] [1].

A heating system in a building could integrate dry electrical heaters, which induces a higher electrical energy consumption than conventional hot water based heaters. As a result, the electrical energy fee will be expensive and it would be necessary to install energy sharing device to limit the electrical energy consumption. In previous works, a wireless multi-agent hybrid fuzzy system has been proposed [2, 3] and the development of such device has been analyzed. An in depth study of the energy efficiency in buildings has also been carried out, [4] [5].

In this work, two main contributions in energy sharing between electrical

[1]Reglamento de Instalaciones Térmicas de los Edificios = Regulations for thermal installations in Buildings

heaters are presented. On the one hand, the application of multiobjective hybrid intelligent systems in the learning of energy sharing controllers, which makes the use of the concept of energy balance, is described. On the other hand, the learning and optimizing of an energy sharing controller for each of the five different climate zones defined in the RITE. This second contribution makes the new approach fulfills with the Spanish Regulations. Finally, the energy sharing controller is designed as a Fuzzy Controller (FC).

This paper deals with the description of the whole multiobjective rationaliser system including the latest improvements and the energy balance distribution algorithm. In Section 2 the context information is given, including the Spanish Regulations and the problem description. Related work is also detailed. In Section 3 the intelligent energy distribution and each design decision are detailed, while in Section 4 the experiments and results are commented. Finally, conclusions are included.

2. Preliminaries

This section deals with the contextual information needed to understand the design decisions. Next subsection summarizes the Spanish Regulations. Then, the problem description is detailed. Finally, related work is analysed.

2.1. The Spanish Regulations for domestic heating system installations

In the first quarter of 2007, the Spanish Parliament approved a new building regulation -in what follows, RITE [1]-. As a result, building methods have been updated [6]. This new regulation had many consequences, as it determined how new buildings must be accomplished [7]: materials, insulation, etc. In Spain, the LIDER software has been developed and should be used to calculate the heating installation in a building [8]: the number of heaters and their nominal power are fixed.

The RITE establishes 5 climate winter zones, named with a letter from A to E, where E represents the maximum in weather severity. A peculiar fact is that in Spain only 3 of the 5 winter zones defined in the RITE are considered [1]. Moreover, a number between 1 and 5, related with the summer weather severity, is also given. The combination of winter and summer severities determines the *climate zone* for each location in Spain.

Furthermore, the constructors build many different kinds of buildings: condominiums -each apartment includes 2, 3 or 4 bedrooms-, detached and terraced houses, etc. All of them can have an electrical heating system installed, so the design of an energy distribution device must consider all the possible cases. The term *building topologies*, which refers to all of the building parameters that influence the heating system, have been extracted from the analysis of the building market, and have been reported in [2, 3]. These building topologies are included in Table 1 for the sake of readability.

2.2. A formal description of the problem

On the other hand a local company intends to extend its catalogue of heating systems with a new complementary device to share the available electric energy among the installed heaters allowing to set an upper bound for the electric energy consumption due to the heating system.

In sharing the available electric energy, the new device should take into account the active heaters and the user predefined temperature settings and profiles. Therefore, the energy sharing should consider, firstly, the differences between the in-rooms temperature and the corresponding temperature

Table 1: The building topologies considered representative of the building market.

Topology type	Topology name	N^o of Bedrooms	Area in m^2	Description
1	Condo	3	85–95	A house in a condominium
2	House	4	220–250	An individual isolated house, a cottage or a lodge
3	Office	-	85–130	An office in an office building

set points and, secondly, the deficit of energy in the rooms. The energy deficit in a room is calculated as the difference between the electrical energy required to reach the temperature balance and that actual spent in heating. Consequently, if the same temperature error is measured, the higher the energy deficit the higher the assigned heating electrical energy. Finally, the device must allow users to set an upper bound for the electric energy consumption so the electrical energy fee is limited.

2.3. Related work

Although there exists literature background related with the improvement of the heating systems, the most part of it only considers the optimisation of the whole Heating and Ventilation Automated Control (HVAC). The solutions consider the minimising of the energy consumption [9] or the minimisation of the temperature error [10]. Many different techniques have been employed including evolutionary algorithms [11], ANFIS and neural networks [12], genetic fuzzy systems [13], Fuzzy controllers [14, 15, 16], among others. Nevertheless, domestic heating systems are rarely studied and analysed [17, 2].

As stated in [18], the relevance of measuring the energy consumption and the comfort variables would help to improve the comfort in the buildings, inducing a multi-objective optimisation problem. Only a few researchers had considered the multi-objective issues in heating system [19, 20, 21]. This latter trains a FC to control the position of the blinds using two objectives: the energy consumption minimisation and the optimisation of the thermal comfort. Notwithstanding, bounding the energy consumption has never been considered in controlling heating systems.

On the other hand, [22] shows the relevance of different variables, such as seasonal aspects, role and occupational aspects, etc., in the indoor temperature and the set point temperature in the spaces. Comfort in buildings should be faced in different areas. One of those areas is the insulation reinforcement and testing. Studies concerning the improvement in the energy saving attending to the building insulation in Spain and in Greece are presented in [23] and [24], respectively. Nevertheless, the technical issues related with measuring the energy efficiency in houses and in buildings represent a challenge that have not been solved yet. Both comfort variables and energy measurements are to be considered, but how to merge these different measures is not a simple task. Perhaps more than one index should be used [25], so multiobjective techniques should be employed to evaluate building and insulation designs. To our knowledge, single objective techniques have been considered for insulation and building design computer aided tools [26].

3. An Intelligent Electrical Energy Distribution and Control System

Here a new an hybrid artificial intelligent system for energy distribution is presented (see Fig. 1). The electrical heating installation is compound of electrical heaters (1) that collaborate with the CCU (2). A wireless connection -a Zigbee network- is used so the installation cost is reduced. A two step procedure has been designed. The first stage, called the Design Stage, is the responsible of learning a Fuzzy Controller (FC) for each configuration[2] (see Fig. 2). The Run Stage is the operational stage, where the specific FC corresponding to the current configuration is used to distribute the AEP between the collaborative heaters in Fig. 3.

Some definitions are used in the description that follows. We shall call *available electrical power (AEP for short)* the amount of power that is currently available for the heating system that the CCU can distribute among all the installed heaters. The *required power (RP)* is the estimated amount of electrical power the heaters should consume in order to keep the set point temperature in each room of the house. Analogously, the instantaneous electrical power consumed by the heaters represents the *heating power (HP)*. Both RP and HP are measured for each heater and room and also accumulated for the building.

The *required energy (RE)* is the integral in the time of the RP, while the *heating energy (HE)* is the integral in the time of the HP. Finally, the *energy*

[2]In what follows, each pair of climate zone defined in RITE and building topology will be referred to as *configuration* for the sake of simplicity.

deficit (ΔE) is the difference between the RE and the HE. Also, each space in a building will be referred to as *room*.

The procedure will distribute the instantaneous heating power among the collaborative heaters considering two objectives. The first objective is to minimize the temperature error in the room, measured as the difference between the room temperature set point and the current room temperature. The second objective is to minimize the energy deficit in the room. The reasons of using the energy deficit ΔE is twofold. Firstly, if a room is cold, the lower the HP assigned to the room the higher its ΔE. Secondly, the higher the inertia of the room -that is, the bigger the volume of the room is- the higher the ΔE if the HP is bounded. With this two objectives the criteria for energy distributing in the problem definition is accomplished.

The heaters can collaborate in the network or act as stand alone devices. In the collaboration mode, the CCU drives the distribution of the AEP among the remaining collaborative heaters. In the latter case, the heaters HMI is used to set the temperature set point and a operational program and the heaters do not communicate with the CCU.The heaters can change their mode from collaborative to stand alone if the CCU becomes unavailable. In the left of this work, the terms local behaviour, local mode or stand alone mode are considered totally equivalent.

A multi-agent system architecture was designed to introduce the intelligent behaviour and robustness to the system. An FC is learned for each configuration and, when tuned the CCU, the current configuration's FC is copied for each room in the building. In operation, the CCU will distribute the AEP according to the room FC output. To distribute the AEP between the heaters, the CCU arranges the time in periods of 10 minutes. In each period, the CCU establishes the instantaneous power rate of each collaborative heater during the whole period. The heaters are ON/OFF devices, so they can not heat at any rate but 0 W or nominal power. Then, a time interval is calculated as the time needed for the heater in the ON state -at its nominal power- so the same amount of energy is spent in heating, as shown in Fig. 4.

For this purpose, the 10 minute period is divided in 24 slots of time. In a slot, each heater is assigned with the ON or OFF stated. The CCU guarantees that the AEP is never surpassed for all the slots. The length of each period, fixed in design to 10 minutes, is considered suitable to evaluate the thermal dynamic in each room. The number of bits in the period has been set to 24 because, in this manner, with just 3 bytes, the ON/OFF profile of each heater can be completely defined, but also because the implicit bit time length is suitable to avoid heater fatigue.

For the sake of robustness, the heaters detect system collapses so they can automatically change to the local behaviour. A heater establishes the system is collapsed if during a period of time it can not communicate with the CCU. In this case, the heater changes to the local control state until the communication with the CCU is recovered. Moreover, users can activate, deactivate or switch to local mode as many heaters as desired. The CCU will only consider the collaborative heaters in the distribution of the AEP, which is decreased by sum the nominal power of all the local mode heaters. Indeed, the comfort settings introduced in the CCU are shared with the heaters, so in local mode the heater comfort settings remain the same if the user does not change them through its human-machine interface.

The CCU is responsible for distributing the AEP among the collaborative heaters according to the following two objectives: the temperature error ΔT and the energy deficit ΔE. The former is calculated as the difference between the set point temperature and the instantaneous room temperature. Both objectives should be minimised for all the rooms in the building. As stated before, the ΔE is the difference between the RE and the HE.

To accomplish both objectives the following procedure is carried out. Each heater sends to the CCU the room mean temperature and the room ΔE according to its knowledge. Both measurements are introduced as inputs to the room's FC, which estimates the power rate the heater should perform during the next period in order to reach both objectives. Then the power rate for each heater is prorated to avoid surpassing the AEP, so the HP for each of the bits of the next period and for each heater is calculated.

A two steps procedure is designed to train the FC and to carry out the energy distribution algorithm in the CCU. The first step is called the *design stage*, which is responsible for the learning and training of the FCs for each topology, and is shown in Fig. 2. The FC is a Mamdani FC and it is specific for the configuration, so it has to be trained to accomplish with the two objectives. Correspondingly, the AEP distribution using such FC is also optimised. The FC design and training descriptions are detailed in Subsection 3.1, and are included in the design stage detailed in Subsection 3.2. The second stage is called the *run stage*, and can be seen in Fig. 3. In the run stage the energy distribution is carried out once the CCU is configured and the heater network is up. The run stage is described in Subsection 3.3.

3.1. The Fuzzy Logic Controller

The Fuzzy Controller is a Mamdani fuzzy system initially designed by experts [27]. The FC was designed using the Matlab Fuzzy Toolbox [28], and the experts chose the FC characteristics graphically. In this way, the following design decisions were made. Firstly, for all the fuzzy operations aggregation of antecedents and implication the product is the t-norm used in the FC, while for the aggregation of rules the t-conorm used is the maximum. All rules have the same weight (1.0). The defuzzyfication method is the mean of the maximums.

Each variable, either it can be input or output, is defined with three uniform and normalised linguistic variables called LOW, MEDIUM, HIGH. The LOW and HIGH linguistic variable have trapezoidal membership functions while the MEDIUM one has a triangular membership function.

For each heater installed in a room the FC associated to that room is evaluated. The FC inputs are the room temperature error (ΔT) and the energy deficit in that room (ΔE). The temperature error is calculated as the difference between the temperature set point -as given in the timetable profiles for that room- and the room mean temperature measured by the heaters. The ΔE is calculated in each heater as the difference between its RE and its HE. The FC output is the percentage of the heater nominal power needed for the room to reach the set point temperature during the next 10 minute period. The output of every heater installed in the building is then normalised. In Table 2 the membership functions for the linguistic variables of each variable set by the experts are shown.

The FC should be initially learned and trained as detailed in the following subsection. Although the rule set is learned, the best suite rule set is chosen for all the FCs for the sake of minimising the memory requirements of the micro-controller devices in which the FCs are to be deployed. It is worth noting that, while in operation, any FC can be tuned up to fit the specific room to which it is associated. In this case, only the consequences of the rules, that is, the three fuzzy sets are to be tuned up using fuzzy set classical local tuning methods [29, 30, 31, 32, 33, 34]. As it is desired to keep the variables uniform and normalised, tuning up an FC only modifies the three values {A, B, C} given in Table 2.

Table 2: The Fuzzy Controller designed by the experts, the initial values for A, B, and C are 0.25, 0.5 and 0.75, respectively.

Membership Function	Temperature Error	ΔE	output
LOW	trap(0, 0, 0.5, 1)	trap(0, 0, 0.25, 0.5)	trap(0, 0,A, B)
MEDIUM	trap(0.5, 1, 1.5, 2)	triang(0.25, 0.5, 0.75)	triang(A, B, C)
HIGH	trap(1.5, 2, 10, 10)	trap(0.5, 0.75, 1, 1)	trap(B, C, 1, 1)

3.2. The design and learning of the FCs

The design stage starts when the configurations have been completely defined. For each configuration several steps are carried out. Firstly, the historical meteorological data for a climate zone has to be gathered. Specifically, the outdoor temperature, the humidity percentage and the solar radiation must be harvested. Moreover, the building topology -its dimensions and characteristics- should be exactly modelled as detailed in advance. Therefore, the building materials and their properties -trasmittance, emissivity,etc.-

should be given. At the same time, all the relevant profiles should be fixed: i.e. the building dimensions and orientation, the heating profiles, the electric consumption profiles or the occupancy profiles. The HTB2 software is then run with all the gathered data to calculate the thermal dynamics in every room of the building and also the instantaneous heating power required to reach the set point temperature. The HTB2 is a publicly available software that can be obtained from [35].

The outcome of the HTB2 is a high dimensional data set which must be post-processed so two data sets are generated. The first one is used to estimate the thermal parameters of each room in the building, while the second data set is used to train an FC for the current topology. When training the FC for a configuration with the latter data set the two electric power distribution objectives -the energy deficit and the temperature error- should be considered, so a multi-objective should be used. In this research, the simulated annealing technique is used [36].

In order to train the FCs and to evaluate how the heating system performs, the estimation of the thermal dynamics of each room in the building is needed. For each configuration, the step response of the building is simulated with the HTB2. The building thermal dynamics is analysed both when the heater changes from OFF to ON and from ON to OFF. From the HTB2 output data set only the relevant information is used, that is, the transitions between steady states in order to extract the dynamics.

The use of Artificial Neural Network (ANN) to define prediction models for building variables as indoor temperature or relative humidity, has grown in last years [37, 38]. In this research, a two-layer network of fast-forward type, with tan-sigmoid transfer function in the hidden layer and a linear transfer function in the output layer. This is a useful structure for function approximation (or regression) problems. The ANN inputs are the indoor temperature (T_x), the outdoor temperature (T_{out}) and the heating power spent in the room (P_x). Thirty neurons are used in the hidden layer. The network should have one output neuron since there is only one target, the indoor temperature in the next period. We will use the Levenberg-Marquardt [39, 40] algorithm for training, and an ANN is found for each room. We propose the use of train-test procedure that will be repeated until the validation error stops decreasing or 100 epochs, whichever occurs first. The train, the test and the validation data sets are chosen as the first half of the input data set, the second half of the input data set and the whole input data set, correspondently.

Once the thermal dynamics of all rooms of the configuration are defined, the learning and training of the FCs is carried out. As detailed in the previous Subsection, the basic FC established by the experts is optimised. The objective to be accomplished is to minimise both the ΔE and the ΔT for each room in the building. This is a multi-objective problem, and the multi-objective simulated annealing algorithm presented in [36] is used. This multi-objective algorithm is a Pareto based approach and is shown in Fig. 5.

Each individual represents an FC. The MOSA should optimise both the rule set and the parameters set. As stated before, the rule set is only to be optimised for the first configuration considered, while in the left configurations the rule set remains unchanged and only the consequences are evolved. Consequently, all the FCs have the same rule set. In this way, the memory requirements of the micro-controller is minimised and so the cost of the device. When no rule set optimisation is to be carried out the individual is represented only by means of a parameter set. The rule set is represented as a vector of integers, each one is an index on the membership function used in the rule for the corresponding variable. The parameters set is a vector of float, a float for each membership function of all the variables -ΔT, ΔE and the output-. The reader should recall that only three uniform and normalised membership functions are used for all variables, the inner one is a triangular membership function, while the others are trapezoid functions. In this case, only the three parameters of the triangular membership functions are to be optimised, [20]. Therefore, the integers are in the range $[0, 2]$. The floats are in the range $[0, 2]$, $[0, 1]$ and $[0, 1]$ for the temperature error, energy deficit and the output variable, respectively. Also, restrictions related with the semantic of each linguistic label are included, i.e. the parameter for the LOW label should be lower than the parameter for the MEDIUM label.

The mutation randomly changes the values of the individual parameters according to the restrictions mentioned above. The distance between individuals is calculated as the square root of the squares of the difference between the parameters. The multi-objective fitness function includes the sum of the ΔE and mean square error in the ΔT input for all the rooms in the building. To evaluate each individual, which in fact is an FC for the current configuration being analysed, the electrical energy distribution algorithm detailed in the following Subsection is used. The evaluation of each individual is done using the post-processed HTB2 output data set, with only the relevant information from the data set for each room. This data set includes the outdoor temperature, the temperature in each room, the temperature set point for each room and the power requirement for each room. The corresponding thermal model is used to calculate the temperature in each step according to the FC and the electrical energy distribution. From the individuals in the elite population the best suite FC is chosen, the one nearest to the identity line in a plot of ΔE against ΔT.

3.3. The rationaliser algorithm and the system operation

The Run Stage represents the algorithm carried out in the CCU to distribute the electrical energy, called Energy Distribution Algorithm (EDA), shown in Fig. 3. The EDA is responsible for the energy distribution, and it is assumed that the CCU has been configured according to the configuration and current heating system -all the rooms in the building have been defined and also the associations between heaters and rooms-.

According to the configuration, the CCU chooses the corresponding FC and makes a copy for each defined room. The CCU stores in ROM the best suite controllers obtained in the previous stage, an FC for each configuration. Every 10 minutes the EDA is run in the CCU to distribute the AEE for the next period, that is, to fix the 24 bits for all collaborative heaters.

The inputs of the EDA are the instantaneous electrical consumption in the building, the set point temperature timetable, the mean temperature and the ΔE measured in each heater. The instantaneous electrical consumption is used to calculate the instantaneous AEP and, thus, the AEE. The mean temperature and the ΔE are obtained from the heaters, the former is measured through the temperature sensor built in each heater.

The ΔE is calculated as the difference between the RE and the HE.

Both the RE and the HE are calculated as the integral in the time of the RP and the HP, respectively. As the heaters are ON/OFF devices, some simplification can be assumed. The instantaneous power in a heater can be zero or its whole nominal power. So the RE is linear with the number of bits that the heater considers should be ON divided by the total number of bits in a period of 10 minutes, that is, 24 bits. In the same way, the HE is linear with the number of bits the CCU sets the heater to be in the ON state divided by the total number of bits in a period of 10 minutes, that is, 24 bits.

Consequently, the ΔE is calculated as follows: for each bit, if the remote heater considers that in the local behaviour it should be ON but the CCU has established the state of OFF then ΔE is incremented in 1 (the 100% of the nominal power of the heater can't be used). Conversely, if the remote heater considers it should be OFF but the CCU has given the ON state then ΔE is decremented in 1. In any other case ΔE remains unchanged. The accumulation of the ΔE of the heaters installed in the same room is proportional to the nominal power of each one divided by the sum of installed power in the room.

The data gathered from each heater are the inputs to the FC of the associated room. The outcome of the FC is the proposal of heating energy for the next period of 10 minutes. So for each heater with a temperature error higher than 0 a proposal of heating energy (PHE) according to the corresponding FC is obtained. Let TPHE be the accumulative of the proposal of heating energy for each heater.

The CCU assigns the HE for each heater as the percentage of AEE corresponding to its PHE and the TPHE. Once the HE has been assigned for each heater, then it is distributed among the 24 intervals in the period according to: a) the AEP must not be reached in any interval, and b) the HE should be assigned in consecutive intervals so that the number of transitions between the ON and OFF states in the heaters is minimised. The shorter the number of transitions the longer the heater life will be.

3.4. Some extra improvements in the Electrical Energy Rationalization

Several improvements have been included in the energy distribution system. First, the CCU is able to learn from the environment by tuning the FC associated to a room in the building. To achieve that, the CCU expands or contracts the membership functions of the FC output variable linguistic labels. In other words, the CCU expands or contracts the values of the parameters $\{ A, B, C \}$ in Table 2.

The new set of parameters is obtained as $\{ A^p, B^p, C^p \}$. To obtain p, the CCU does as follows. When the user sets the auto-tuning option for a room, the CCU requests the associated heaters the ΔE_{lt} value. This is the long term energy deficit in a heater. This value is calculated in the same way as the ΔE but for a period of a week, that is, 7 days.

If the heater gets into LOCAL mode, the ΔE_{lt} is fixed to 0. When more than one heater is associated to the room which is to be tuned, the ΔE_{lt} is rated according to the nominal power of the heaters. Once the CCU receives information from each heater the value of p is calculated with Eq. 1, where the functions f_x are shown in Table 3.4 with trap referring to trapezoidal membership functions.

$$p = 0.9f_{0.9}(\Delta E_{lt}) + 0.95f_{0.95}(\Delta E_{lt}) + 1f_1(\Delta E_{lt}) + 1.05f_{1.05}(\Delta E_{lt}) + 1.1f_{1.1}(\Delta E_{lt}) \tag{1}$$

Name	Function
$f_{0.9}$	$\mathrm{trap}(-\infty, -\infty, -0.6, -0.35)$
$f_{0.95}$	$\mathrm{trap}(-0.6, -0.35, -0.35, -0.25)$
f_1	$\mathrm{trap}(-0.35, -0.25, 0.25, 0.35)$
$f_{1.05}$	$\mathrm{trap}(0.25, 0.35, 0.35, 0.6)$
$f_{1.1}$	$\mathrm{trap}(0.35, 0.6, \infty, \infty)$

A second improvement of the proposal is the synchronisation algorithm that has been integrated so the heaters and the CCU always have approximately the same time. The algorithm to synchronise the heaters and the CCU is the well-known Berkeley algorithm. Finally, the CCU and the heaters also interchange messages in order to keep a better knowledge of the state of the system. Each time a heater changes from local mode to remote mode or viceversa it sends a message to the CCU. If the CCU has not received messages from a heater then it sends a message to request its state. If no response is received then the heater is believed to be in local mode. If a heater does not receive messages from the CCU, then it requests its state, and if no answer is received it changes to local mode.

4. Experiments and Results

In this section, the results obtained from the Design stage are presented and the energy distribution approach is evaluated in physical prototype to validate it (the Run stage).

The decisions taken in this section to obtaint the numerical results are the following:

1. Choose the configuration to avoid the high number of experiments in the prototype phase.
2. Learn a suboptimal fuzzy controller for the chosen configuration (Design phase).
3. Learn a thermaldynamical model for the configuration chosen in step one (Design phase).
4. Test the fuzzy controller obtained in step two for the chosen configuration (Design phase).
5. Test the chosen fuzzy controller obtained in step two with a phisical prototype for a simple configuration (Run phase).

4.1. Configuration selection

The Design stage has been carried out for each pair of building topology and climate zone, specifically, for the same climate zone mentioned above. The apartment belongs to the building topology of Condo (see Table 1). Then, the Design stage was run from the data gathered for the E1 zone, the realistic profiles and the Condo topology (Fig. 11)). For validation purposes an example of a real installation is considered: an apartment in the city of Ávila is the building to be tested (Fig. 12). Ávila is the capital city of the province of the same name in centre of Spain. The climate zone is E1 according to the Spanish Regulations. The nominal powers of the electrical heaters are also calculated as the corresponding Spanish Regulations state: 1000 W, 1000 W, 500 W and 500 W are the nominal powers of the electrical heaters to be installed in the living room, in the bedroom, in the kitchen and in the bathroom, respectively.

4.2. Fuzzy controller learning and Thermodinamical model

The aim was to learn the FC for the pair <Condo, E1 climate zone>. The installed power in the selected building for design phase is 10500 W. So, to validate the proposal two experiments have been carried out: one with a AEB of 5500 W (below the installed power) and another one with a AEB of 12000 W (above the installed power). Both fuzzy controllers are shown in tables 3 and 3 respectively.

Table 3: Membership functions for the linguistic variables of each input-output variable for a AEB of 5500 W

Membership Function	$\Delta Temperature$ Error	ΔE	output
LOW	trap(-0.5, 0, 0.5)	triang(-0.5, 0, 0.05)	trap(-0.5, 0, 0, 0.0560, 0.3936)
MEDIUM	trap(0.0, 0.5, 1.0)	triang(0.0, 0.05, 0.1)	triang(0.0560, 0.3936, 0.7371)
HIGH	trap(0.5, 1, 2, 2.5)	trap(0.05, 0.1, 1.0, 1.2)	trap(0.3936, 0.7371, 1, 1)

Table 4: Membership functions for the linguistic variables of each input-output variable for a AEB of 12000 W

Membership Function	$\Delta Temperature$ Error	ΔE	output
LOW	trap(-0.5, 0, 0.5)	trap(-0.5, 0, 0.05)	trap(-0.5, 0, 0, 0.5111, 0.5336)
MEDIUM	trap(0.0, 0.5, 1.0)	triang(0.0, 0.05, 0.1)	triang(0.5111, 0.5336, 0.9585)
HIGH	trap(0.5, 1, 2, 2.5)	trap(0.05, 0.1, 1.0, 1.2)	trap(0.5336, 0.9585, 1, 1)

The error evolution for the ANN to learn the thermal dynamics of a room in a house for a Condo building type and the E1 climate zone is presented in Fig. 6.

4.3. Design stage - fuzzy controller results

In Fig. 7 the evolution of the power distribution for the Condo is presented for a period of three and a half days when the AEP is equal or higher to the total installed power. The upper part is the evolution of the total heating power compared with the obtained from HTPB, while the lower part is its extension for showing a higher level of detail. The corresponding signals evolution when the AEP is lower than the total installed power can be seen in Fig. 8. It is worth noting that the heating power surpasses the neither the AEP not the CPL.

The indoor temperature and the heating power evolution in the living room of the Condo with no AEP limit set is shown in Fig. 9 . Both variables are presented as the percentage of the temperature set point and the heater's nominal power, respectively. In Fig. 10, the same graphic is shown for a bedroom. In this case, the temperature reaches the set point and the ΔE is kept low. The outcome of the Design stage, as stated before, are the FCs for all the configurations.

4.4. Run stage - Results

The system is implemented in a prototype using the RZ200 Zigbee Evaluation Kit from Atmel [41], which is shown in Fig. 13. The building has been built in the laboratory -scale 3/50, and the electrical heaters have been simulated by means of resistors of the corresponding rate. A realistic heating profile has been used, and two different electrical energy scenarios are tested: when there is no bound and with an upper bound for the electrical energy consumption. In the former, the building should reach the equilibrium temperature, while in the latter the electrical energy consumption should not surpass such limit. In this second case, no set point temperature can be reached if the RE is higher than the HE.

Results gathered from the prototype are shown in Fig. 14 to Fig. 17. In Fig. 14, it is shown the evolution of the heating power with a reduced heating power limit of 4kWh and 3.2 kWh, respectively. It can be seen that there is a higher energy consumption when there is no upper limit, allowing a better heating of the house. In this Figure, the effect of the FC attending both the energy deficit and the error temperature, reducing the energy consumption. Perhaps, the FC should be less conservative that it is, and a better training should be carried out in order to increase the heating power output.

The evolution of the heating power and the temperature for the living room and the bathroom in the apartment when there is no electrical power limit set is shown in Fig. 15. Both variables, indoor temperature and heating power, are presented in percentages with respect to the set point temperature and with the heater power rate, correspondently. In this case, the house is little cold, and the heating system manages to reach the temperature set point.

The same variables evolution for the case of an electrical power limit set to 3.2 kWh is shown in Fig. 16. In this experiment, the house is in thermal equilibrium state, and the heating system manages to keep the house in such state. Finally, in Fig. 17 shows the evolution of the total heating power for the same experiment in the apartment.

4.5. Analysis

Analysing the results it can be said that the FC should be improved as it behaves conservative. This behaviour should be avoided because if the house is too cold it will take a quite long time to reach the set point temperature. It is thought that the training should be larger, using a higher number of iterations in order to choose a better fit FC. Also, it should be analysed if both objectives have the same relevance or not. Recall that the same relevance was given to both objective, and that the FC was chosen as the intersection between the Pareto front and the identity line. If this is not desired, then the FC is to be chosen as the intersection between the Pareto front and the corresponding line representing the relevance ratio.

The approach here detailed is now under the load test. Three scale models are being analysed. Each test is run for different electrical energy consumption bounds and for different outdoor temperatures. Also, the analysis of all the different scenarios are tested. It is estimated that by the end of this year the approach will be accepted and the final product can be designed.

5. Conclusions

In this work, a multi-agent system for the energy management of domestic electrical heating systems accomplishing the Spanish Regulations is detailed. In order to consider the efficiency of the heating system in any possible location in Spain according to the current Regulations, uncertainty in the process is dealt with by fuzzy controllers. The proposal includes a two steps procedure. The first step includes a hybrid artificial intelligent system to train the thermal dynamics and a fuzzy controller for each pair of climate zone and building topology. The second step includes the energy distribution algorithm, the multi-agent interaction, etc., in order to distribute the available electrical energy among the collaborative electrical heaters. Although the FC needs some extra adjustment, this approach has been found valid for domestic heating installations in Spain, and is expected to be included in a local company's catalogue.

An exhaustive study of the Spanish Regulations was carried out and the most severe cities have been chosen to train the fuzzy controllers. Then the historical real data was gathered and a multi-objective algorithm was used. The multi-agent system application and the different refinements included in the final solution make this approach interesting.

Acknowledgement

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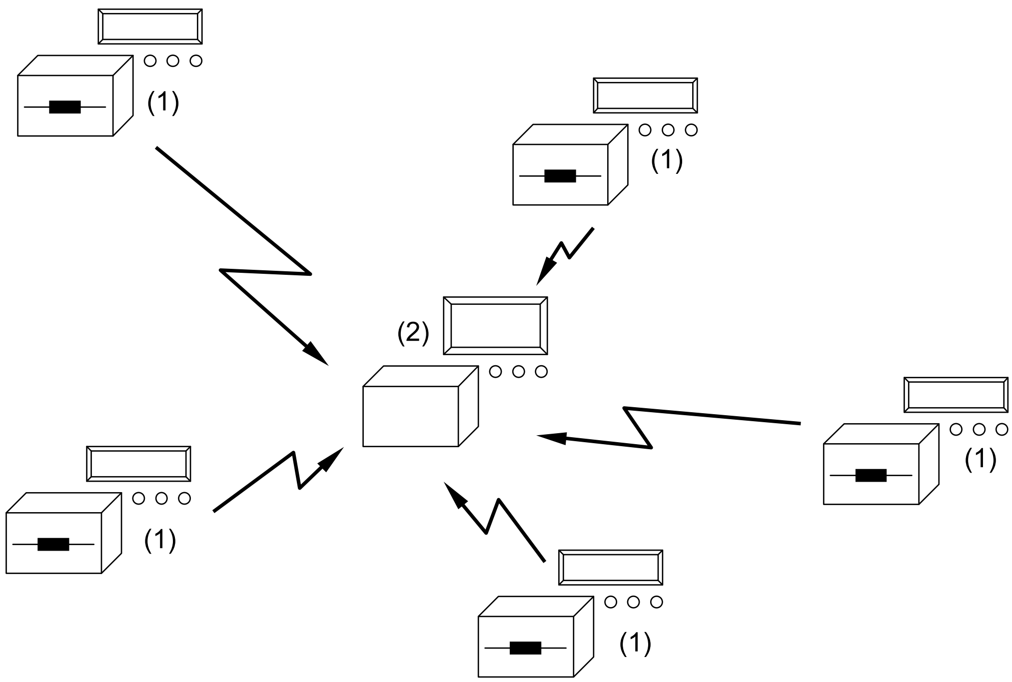


Figure 1: The EHEID schema. The heaters (1) collaborate with the CCU (2) to distribute the AEP and to keep the set point temperature profiles in the house.

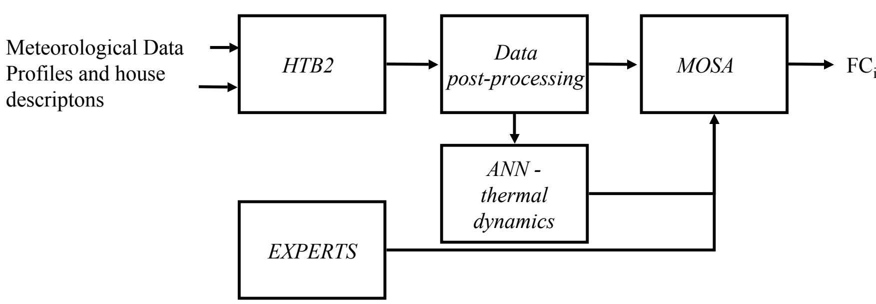


Figure 2: The Design Stage: an FC for each configuration is obtained.

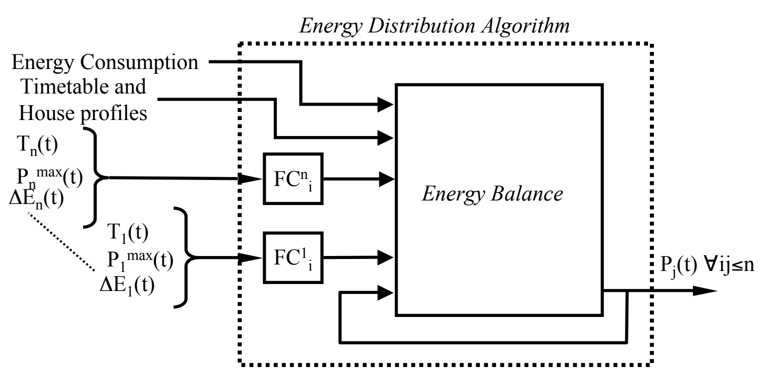


Figure 3: The Run Stage: the EHEID algorithm sets the energy restrictions while attempting to maintain the set point temperature profiles in the building.

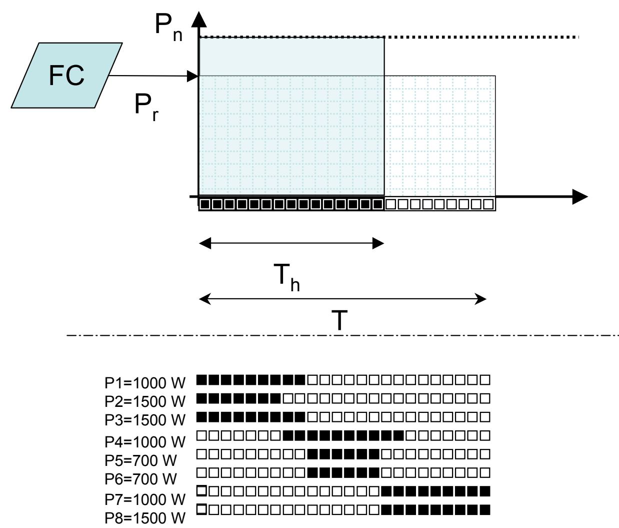


Figure 4: upper figure) Determining ON state interval for each heater. The FC output for a heater is a power rate (Pr) during T=10 minutes period, an amount of energy E is spent. The equivalent energy is spent in Th seconds at nominal power (Pn). Thus, the heater will be ON Th seconds in the next 10 minute period. A black square represents a heater in ON state. lower figure) Time slots distribution between heaters. For each slot, the sum of the nominal power Of all the heaters in ON state is lower than the AEP. A black square represents a heater in ON state.

Needs:

Initial and final temperatures: $T_{initial}$, T_{final}

Cooling factor : C

Produces:

A set of nondominated models: PARETO

```
Initialize the population of models:  X = {x_0}
Initialize the set of elites :  PARETO = X
T ← T_initial
while T ≥ T_final
   // X' is the intermediate population
   X' ← ∅
   for each x ∈ X
      x_mutated ← mutation(x)
      if x_mutated ≺ x then
         X' = X' ∪ {x_mutated}
      else if x ≺ x_mutated then
         if rnd() < exp(-distance(x, x_mutated)/T) then
            X' = X' ∪ {x_mutated}
         else X' = X' ∪ {x}
      else
         X' ← X' ∪ {x, x_mutated}
      end if
   end for
   PARETO ← nondominated models of the joint set PARETO ∪ X'
   X ← selection(X')
   T ← T · C
end while
```

Figure 5: Pseudocode of the MOSA algorithm

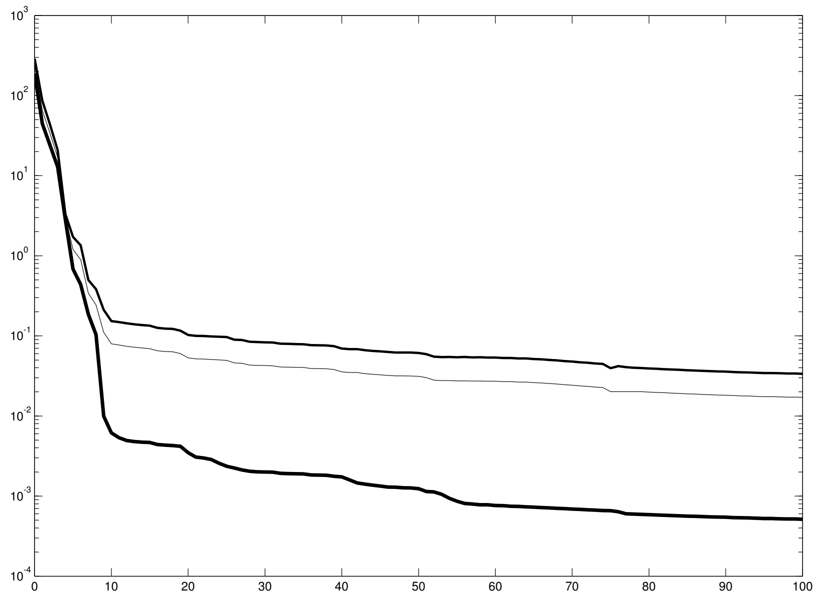


Figure 6: Evolution of the ANN error: the thick line is the training error, the intermediate width line is the test error and the thin line is the validation error.

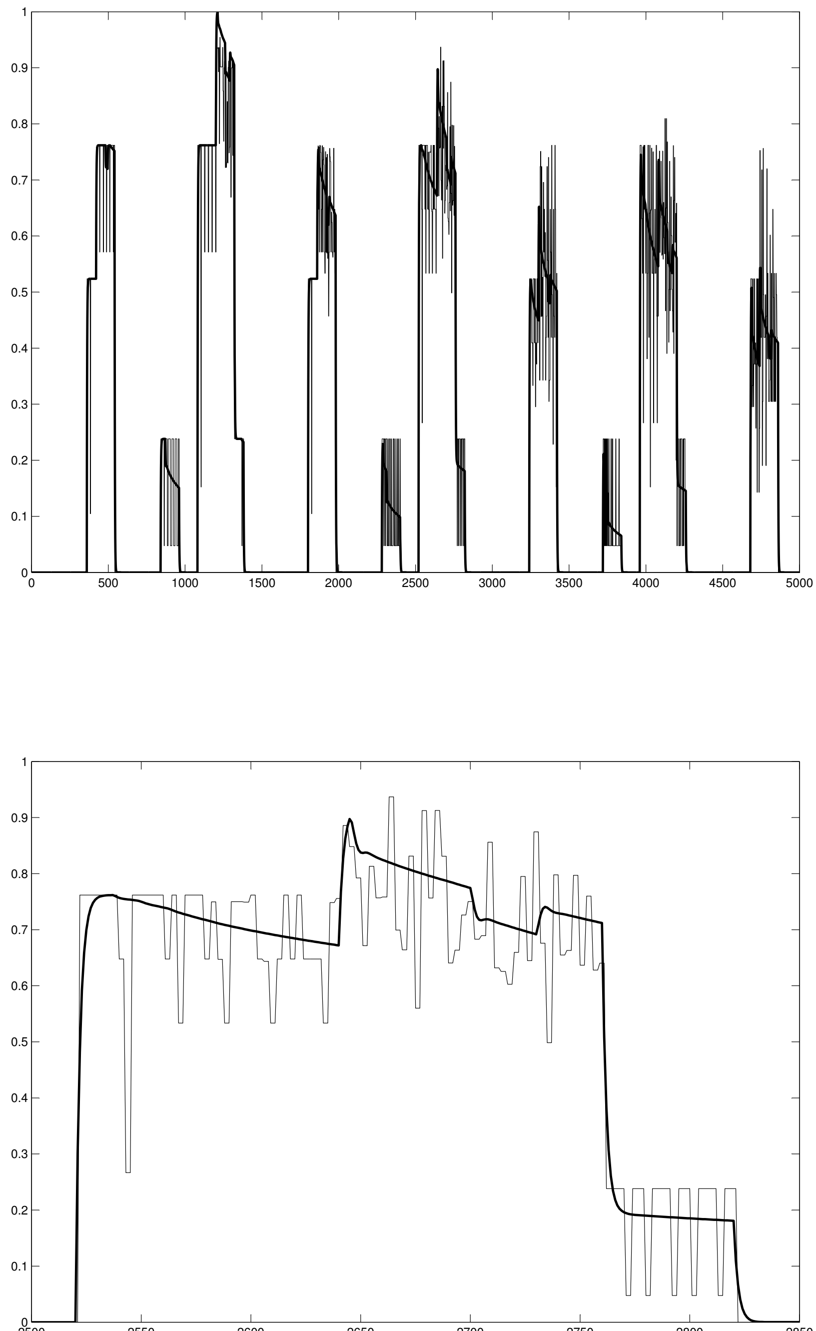


Figure 7: Evolution of the heating required power calculated by HTB2 -the thick line- and the heating power propose by the distribution algorithm -the thin line- after the FC has been trained. The upper figure corresponds with the unlimited AEP, the lower figure is an extension of a interval included in the upper one.

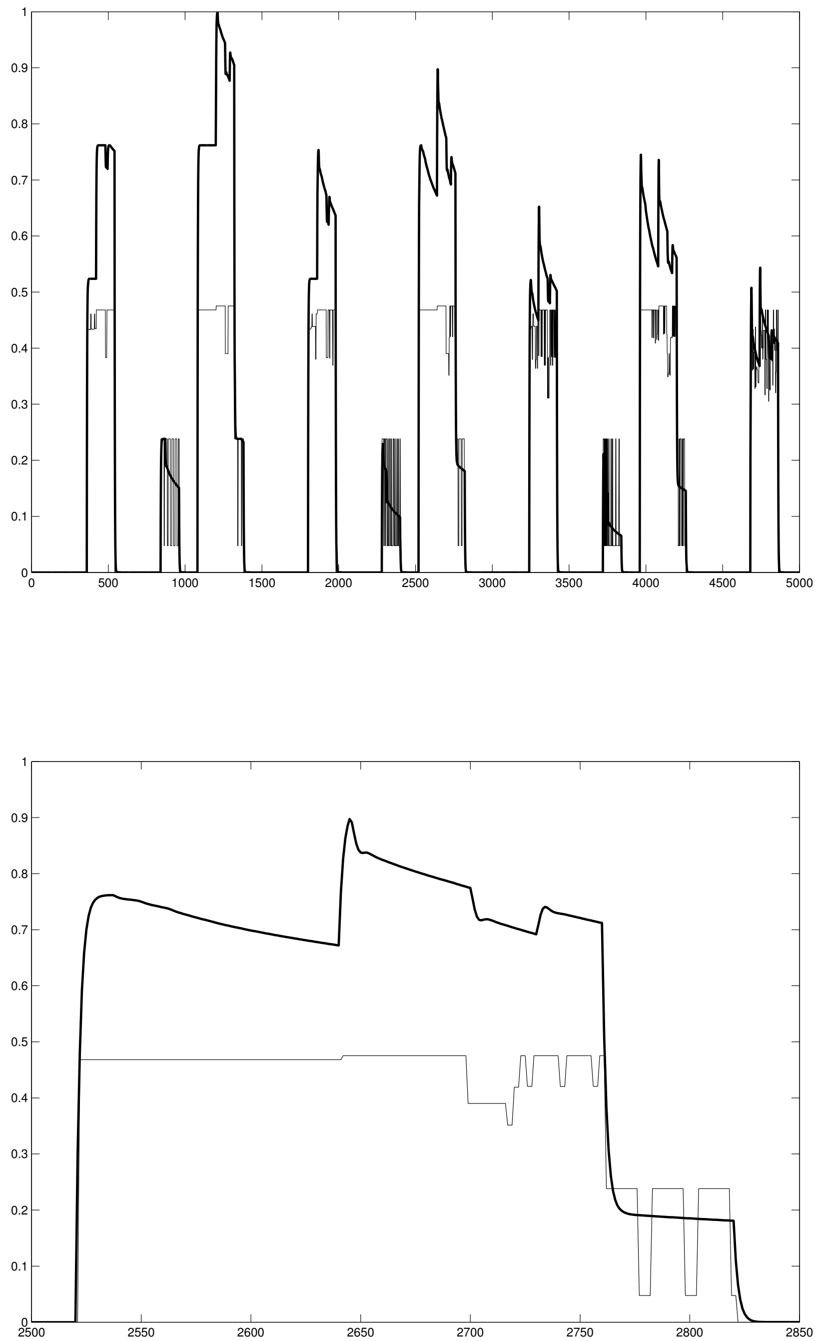


Figure 8: Evolution of the heating required power calculated by HTB2 -the thick line- and the heating power propose by the distribution algorithm -the thin line- after the FC has been trained. The upper figure corresponds with the limited AEP (AEP equals to 5500 kW), the lower figure is an extension of an interval included in the upper one.

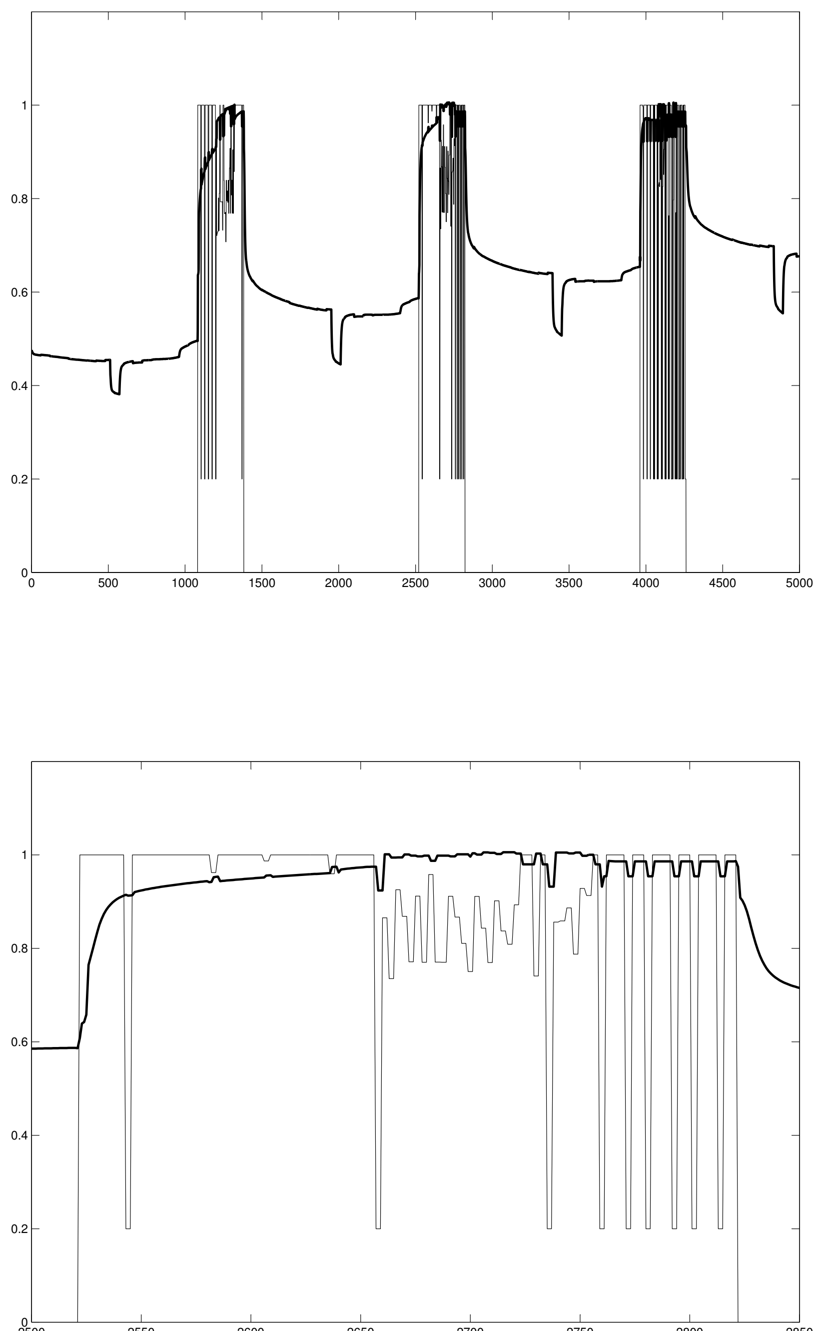
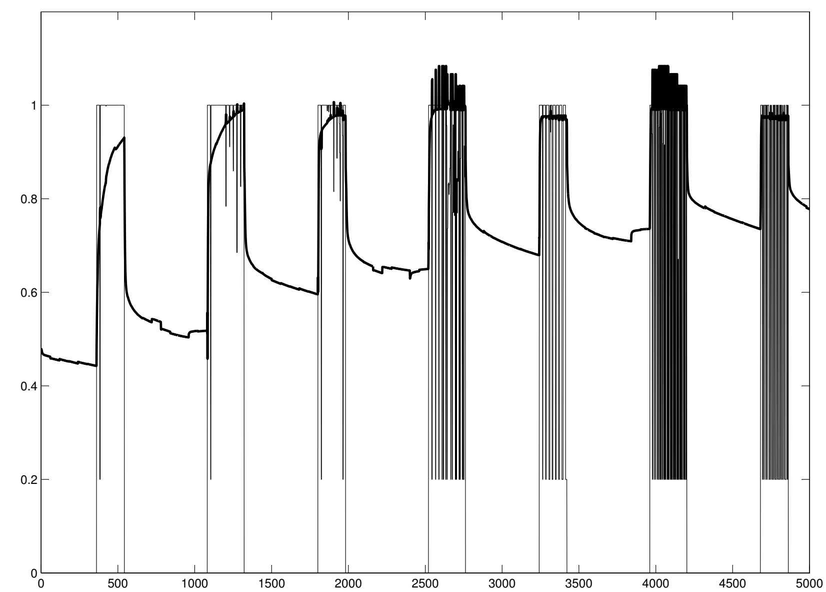


Figure 9: Evolution of the heating power -the thin line- and the in-room temperature -the thick line- for the living room of the Condo an unlimited AEP is used. The upper figure is the evolution of both signals in a long period. The lower one is an extension of an interval included in the upper one.



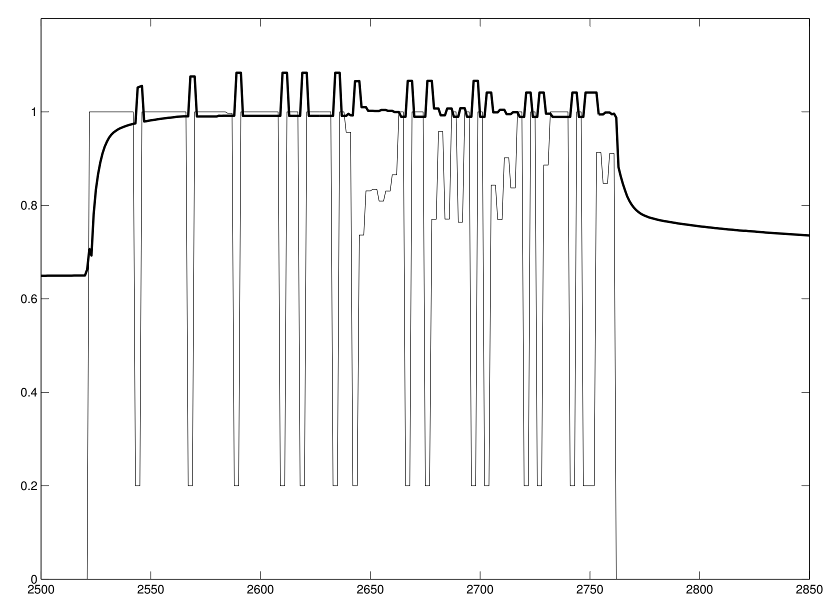


Figure 10: Evolution of the heating power -the thin line- and the in-room temperature -the thick line- for a bedroom of the Condo an unlimited AEP is used. The upper figure is the evolution of both signals in a long period. The lower one is an extension of an interval included in the upper one.

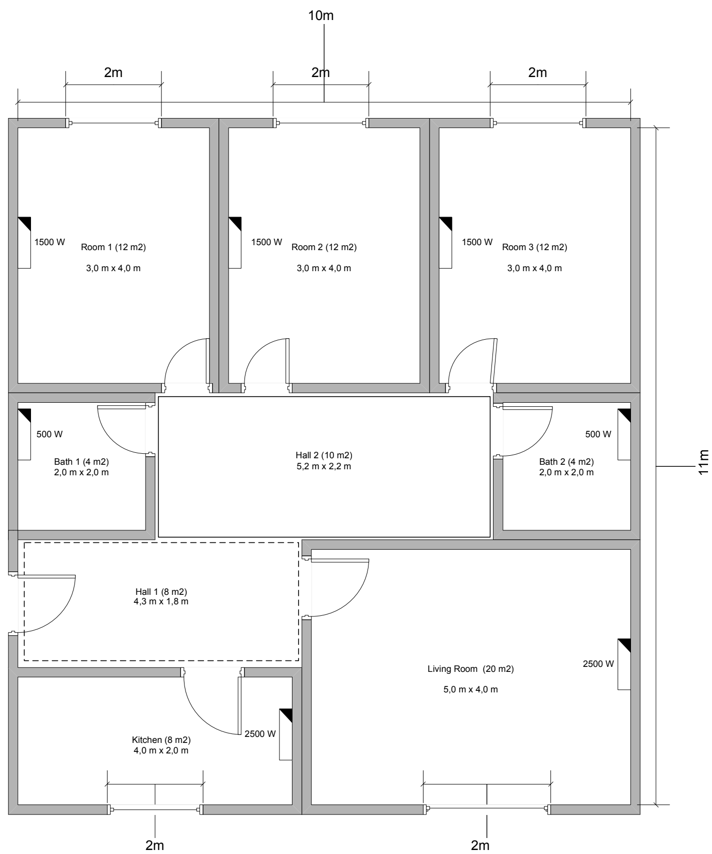


Figure 11: The apartment in the city of Avila for the Design phase, in the E1 climate zone.

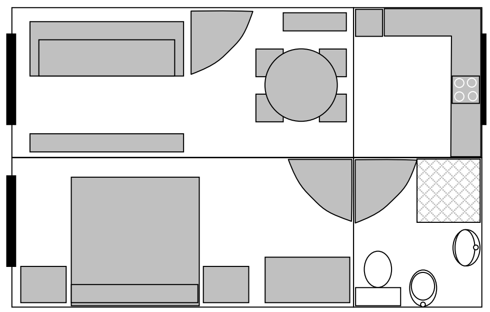


Figure 12: The apartment in the city of Avila for the Run phase, in the E1 climate zone.

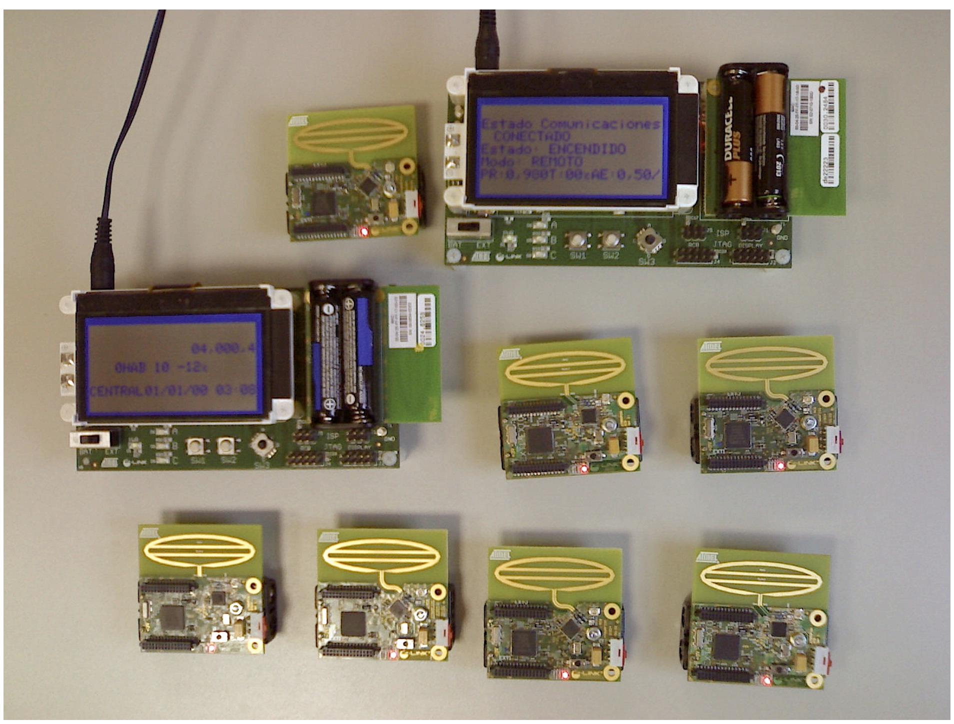
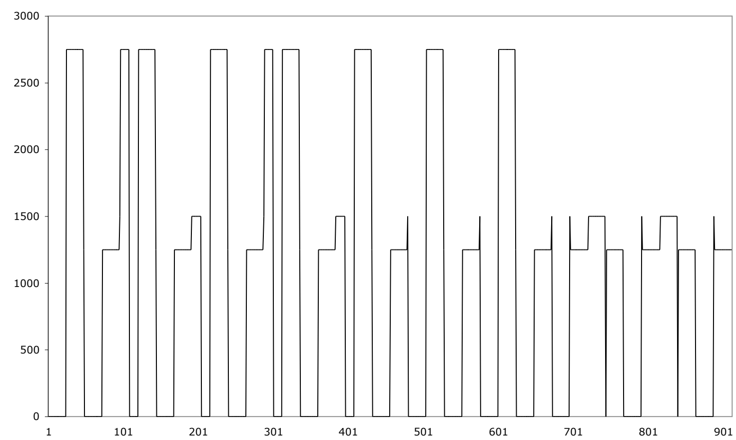


Figure 13: The prototype boards for testing and validating the approach.



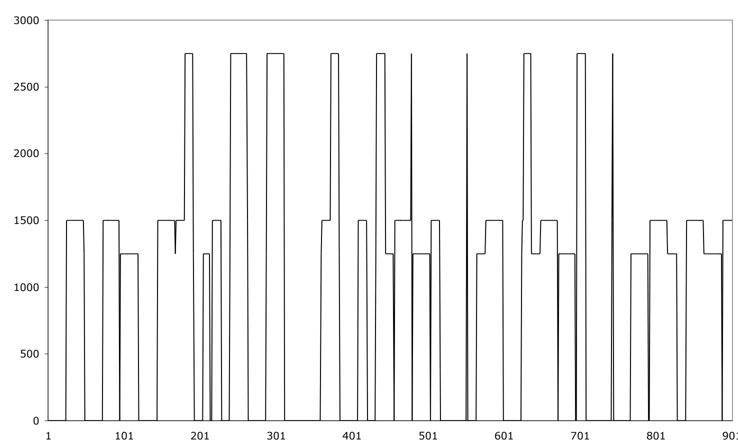


Figure 14: Evolution of the total heating system in the apartment. The upper part of the figure corresponds with the evolution of the total HP in the apartment when the electrical power upper limit is the same the installed heating power. The lower part corresponds with a power limit of 3.2 kWh.

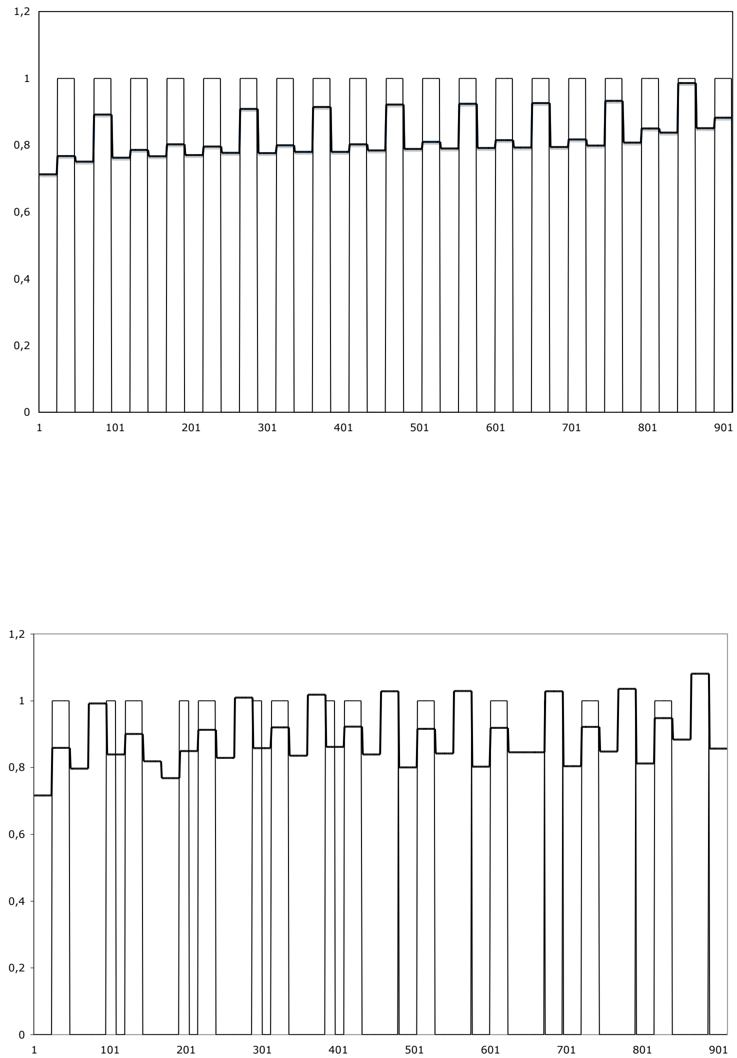
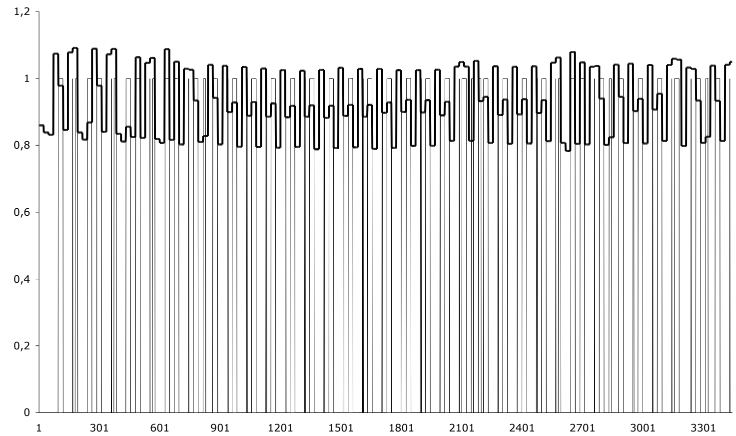


Figure 15: Evolution of the heating power and the indoor temperature for the living room and the bathroom on the apartment is shown. In this case, no upper power limit is set. The thick line corresponds with the indoor temperature, while the thinner one corresponds with the heating power evolution.



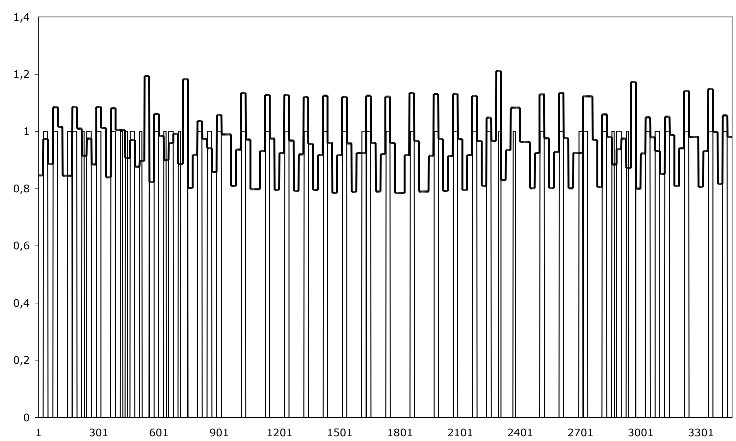


Figure 16: Evolution of the heating power and the indoor temperature for the living room and the bathroom on the apartment is shown. In this case, the upper power limit is set to 3.2 kWh. The thick line corresponds with the indoor temperature, while the thinner one corresponds with the heating power evolution.

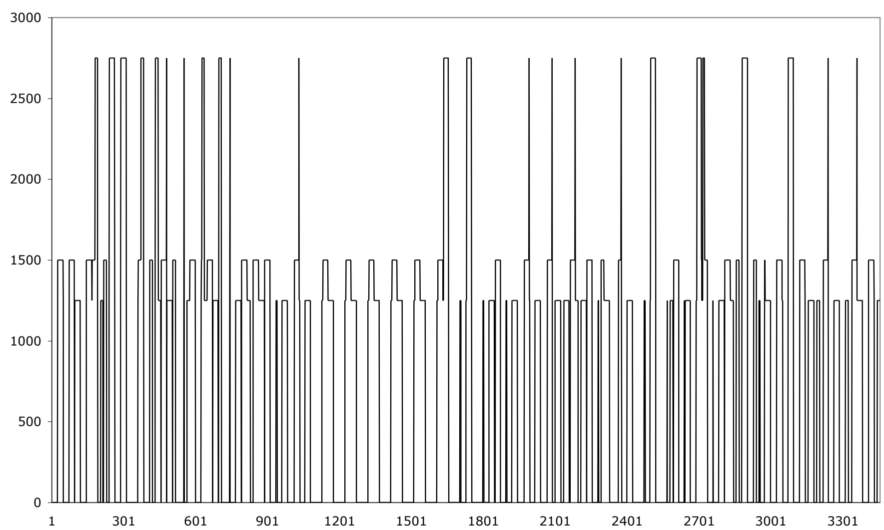


Figure 17: Evolution of the total heating power for the validation Condo when the energy is limited to 3.2 kWh.