



# A low-complexity control mechanism targeting smart thermostats



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## ABSTRACT

This paper introduces a low-cost, high-quality Decision Making Mechanism for supporting the tasks of temperature regulation of existing HVAC installations in a smart building environment. It incorporates Artificial Neural Networks and Fuzzy Logic in order to improve the occupants' thermal comfort while maintaining the total energy consumption. Contrary to existing approaches, it focuses in achieving significantly low computational complexity, which in turn enables its hardware implementation onto low-cost embedded platforms, such the ones used in smart thermostats. Both the software components and hardware implantation are described in detail. To demonstrate its effectiveness, the proposed method was compared to ruled-based controllers, as well as state-of-the-art control techniques. A simulation model was developed using the EnergyPlus building simulation suite, a detailed modeled micro-grid environment of buildings located in Chania Greece and historic weather and energy pricing data. Simulation results validate the effectiveness of our approach.

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## 1. Introduction

Buildings are immensely energy-demanding and are expected to consume even more in the near future. It has been estimated that the amount of energy consumed in European Union's (EU) buildings reaches around 40–45% of the total energy consumption, whereof two-thirds of which is used in dwellings [1]. More thoroughly, in the current decade the energy demand of the tertiary and residential sectors has increased by 1.2% and 1.0% per annum respectively [2]. As a result energy usage in the above sectors is responsible for approximately 50% of the greenhouse gas emissions [3]. Hence solutions that promise to alleviate these drawbacks are a prerequisite of next-generation's buildings' infrastructure.

There are a number of ways to reduce the energy consumption, and subsequently the ecological footprint, of a building. Among others, buildings can be designed more efficiently at the planning stage which, whilst ideal, is not always an option. Existing buildings can be retrofitted to improve energy efficiency – although that can be financially prohibited and disruptive, taking into account that building components are often slowly replaced, mainly due to their increased cost. A more practical approach is to use software-based

solutions to ensure efficient management of energy consumption. For instance, Building Energy Management Systems (BEMS) are computerized platforms that enable building operators to monitor and control at real-time different systems including heating, ventilation and air conditioning (HVAC).

The problem of deciding upon a HVAC configuration is a well-established challenge that has been attracting the interest of many researchers over the years. Based on relevant literature, there are two mainstream ways of controlling an HVAC system. The first one corresponds to systems that support online decision making. These systems are reactive to climatic conditions, building operation as well as occupancy variation [4]. On the other hand, the second approach refers to a Model Predictive Control (MPC) which estimates the optimum decision making strategy to be implemented [5]. Both of these approaches exhibit advantages and disadvantages. For instance the online control systems can react only to the actual building conditions, while an MPC can move forward in time to simulate the impact of alternative control operating scenarios.

Despite the significant progress made in optimal nonlinear control theory [6,7], the existing methods are not, in general, applicable to large scale system (LSS) because of the computational difficulties associated with the solution of the Hamilton–Jacobi partial differential equations. Similarly, although MPC for nonlinear systems has been extensively analyzed and successfully applied in industrial plants during the recent decades [8,9], it likewise

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## Nomenclature

BEMS	building energy management system
HVAC	heating, ventilation, air conditioning
MPC	model predictive control
LSS	large-scale system
PV	photovoltaic
DMM	decision making mechanism
RBC	ruled based controller
PPD	predicted percentage of dissatisfied
ANN	artificial neural network
FIS	fuzzy inference system
FIE	fuzzy inference engine
MF	membership function
$k$	number of buildings found in smart-grid environment
$E_i(t)$	energy consumption for building $i$ at time-step $t$
$C_i(t)$	thermal comfort for building $i$ at time-step $t$
$E_i^{PV}(t)$	energy production from PV panels for building $i$ at time-step $t$
$E_i^B(t)$	energy provided by batteries for building $i$ at time-step $t$
$E_i^G(t)$	energy purchased from the grid for building $i$ at time-step $t$
$E^{PV}(t)$	total energy production from PV panels at time-step $t$
$E^B(t)$	total energy provided by batteries at time-step $t$
$P(t)$	price for purchased energy from grid at time-step $t$
$\alpha$	aggressiveness for optimizing energy cost or thermal comfort
$AF$	available funds for buying energy
$P^E(t)$	current energy price at time-step $t$
$A^E(t)$	availability of energy at time-step $t$
$D^E(t)$	demand for energy consumption at time-step $t$

encounters dimensionality issues: in most cases, predictive control computations for nonlinear systems amount to numerically solving a non-convex high-dimensional mathematical problem whose solution may require formidable computational power if online solutions are required.

The increased computational cost of the aforementioned solutions make them affordable only to enterprise environments (as part of a BEM or HVAC system). As a result, there is an emerging need the last few years for techniques of lower computational complexity that are able to accommodate residential buildings as well. This necessity has already been identified by the industry, as it is portrayed by the expanding market of smart thermostats. Even though the market is still at its nascent stage, analysts expect it to grow exponentially, as consumers become more aware of the advantages and features of such an advanced decision making mechanisms for heating/cooling. According to a recent report by Sandler Research, the global smart thermostat market is projected to generate revenue of more than \$1.3 billion by 2019 [10].

In order to handle the increased complexity, various heuristic methods, such as the stochastic dynamic programming [11] or the genetic algorithms [12], have been proposed, which balance the derived solution's quality with the problem's complexity. Furthermore, the optimization of the building's systems control can also be supported by methods that rely on empirical models [13], simulation optimization [14], artificial neural networks (ANNs) [15], and weighted linguistic fuzzy rules [16–18]. Even so, besides the major drawbacks that these methods exhibit, such as the need for excessive training or customization which

results in lacking of a general-purpose final solution, none of the aforementioned studies investigate the designing of a lightweight solution, able to run onto a low-performance embedded processor.

In accordance to this trend, throughout this paper we introduce a low-complexity control mechanism targeting to support the decision making at HVACs found in a micro-grid environment. More precisely, we introduce a novel decision making framework for supporting the building's cooling/heating control. For this purpose, multiple power sources (PV panels, batteries and the main grid) are employed and their optimum combination is discussed in a systematic way. In order to support the task of decision making at this environment, a fast yet accurate mechanism for computing the temperature set-points based on an Artificial Neural Network (ANN), is also proposed. The proper design of such a mechanism, both in terms of the ANN's architecture and training, makes it feasible to compute the optimum thermostat's set-points with increased accuracy according to weather conditions. Then, we enhance the aforementioned decisions in order to take into account inherent constraints posed at real-time (e.g. trading price of energy, available funds for a given period, etc). This feature is feasible by appropriately adjusting the previously computed (by the ANN) temperature set-points with a component that relies on Fuzzy Logic. Such a component aims to redistribute a given amount of funds over time in a way that significantly improves the occupants' thermal comfort with a negligible impact on energy consumption. Finally, we have developed a hardware prototype of the proposed decision making mechanism. As an underline platform for this purpose, we employed a low-cost, low-performance embedded device (ATmega640 micro-controller). During the hardware development phase, emphasis was given in minimizing the computational and storage complexity of the employed algorithms which realize the decision making process. Towards this direction, a number of well-established methods for designing embedded software was also taken into account. According to our analysis, the introduced solution achieves comparable performance (in terms of the computed temperature set-points) compared to relevant state-of-the-art approaches but with significantly lower computational complexity.

The main contributions of this work, can be summarized as follows:

- Introduction of a novel decision-making mechanism for improving the occupants thermal comfort while maintaining the total energy consumption in smart buildings environment. The introduced solution, which relies on an ANN and Fuzzy Logic, exhibits remarkably low computational/space complexity, which in turn enables its hardware implementation onto low-cost embedded platforms.
- Evaluation of the introduced solution by a detailed modeled simulation of a micro-grid environment of buildings located in Chania (Greece) and historic weather and energy pricing data.
- Development of a hardware prototype of the proposed decision making mechanism.

The rest of the paper is organized as follows: Section 2 formulates the problem at hand, while Section 3 describes the introduced decision making framework. Section 4 presents the two main facilitators of our framework, namely the Artificial Neural Network and the Fuzzy Inference System. Experimental results and comparisons that highlight the efficiency of our proposed solution against relevant control techniques are discussed in Section 5. Finally Section 6 concludes the paper.

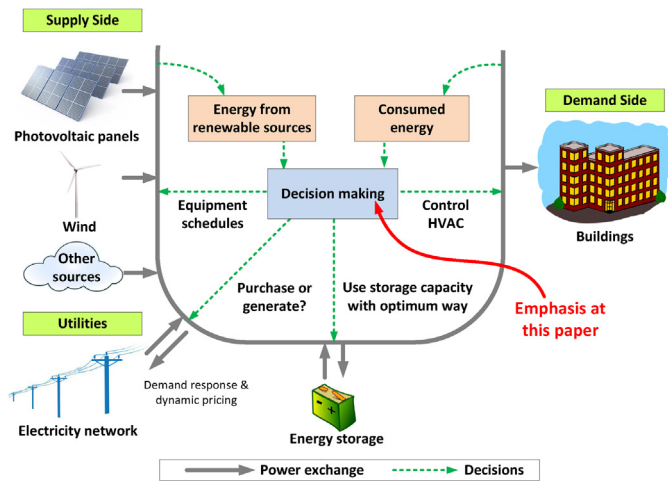


Fig. 1. Overview of micro-grid problem formulation.

## 2. Problem formulation

The constant demand for energy efficiency, the deployment of renewable energy sources and the onset of smart grid technologies, foretell that in the near future an increased number of building facilities will become active participants in the energy market. From the system point of view this will lead to autonomous micro-grids with energy trading capabilities and flexibility in regard of shifting or reducing electrical loads as needed.

More thoroughly, the concept of a smart or intelligent grid has been around for many years. This technology enables real-time monitoring and reaction, which allows the system to constantly modify and tune itself to an optimal state. It also has the ability to anticipate, which enables the system to automatically look for vulnerable areas that could trigger larger problems and disturbances. Finally, it has rapid isolation, which allows the system to isolate parts of the network. As we entered the 21st century, a number of electric utilities, such as market-driven pricing, are available. In such a scenario, instead of having a flat-rate pricing scheme for electricity 24 h a day, 7 days a week, variable pricing mechanisms can exist where the cost per kilowatt-hour may change based on the day, time of day, or a more dynamic event, such as the weather conditions or the expected load requirements. Since the grid must remain balanced at all times, this movement toward more flexible pricing schemes left utility companies and government regulators with a challenge to find the means to measure the electricity consumption more accurately so that it could be properly matched with the produced energy. For this purpose, novel techniques that guarantee efficient building-to-microgrid, as well as microgrid-to-grid integration have been studied [19].

Fig. 1 depicts the template of the employed usecase. Assuming that a number of renewable power sources are available (e.g., PV panels, wind turbines, etc.), their usage could reduce the building's energy cost. For this purpose, the AF parameter denotes the available funds for buying energy from the main grid. If the available power from renewable sources is not enough to meet the occupants' demands, additional electricity can be purchased from the grid (which decreases the value of the AF's parameter). Otherwise (i.e. when the availability of renewable sources exceeds the demand), the spare energy can be either stored in batteries, or sold to the grid (which increases the value of the AF's parameter). The selection of the preferred strategy depends on the dynamic pricing, the batteries' capacity, the estimated building's demand in the near future, as well as the maximization of the batteries' life [20]. Both the purchasing and selling of energy from/to the grid is conducted according to different rates.

Table 1  
Summary of building properties.

Building	Surface area	Thermal zones	Operating hours	Warming-up pre-cooling	Random occupancy
#1	350 m <sup>2</sup>	8	6:00 am–9:00 pm	No	Yes
#2	525 m <sup>2</sup>	10	8:00 am–9:00 pm	Yes	Yes
#3	420 m <sup>2</sup>	10	8:00 am–5:00 pm	Yes	Yes
#4	280 m <sup>2</sup>	6	7:00 am–8:00 pm	Yes	Yes
#5	228 m <sup>2</sup>	4	6:00 am–6:00 pm	No	Yes

In our analysis, emphasis was given to the Decision Making Mechanism (DMM), which is responsible for determining the thermostat's set-points. The aforementioned selections are performed fulfilling the objectives of reducing the energy consumption, minimizing the cost of buying energy from the grid, and maximizing the occupants' thermal comfort in regard to the studied micro-grid usecase.

### 2.1. Problem instantiation

The problem we tackle throughout this paper deals with the optimum control of smart thermostats (i.e. heat/cool operating modes) in order to significantly improve the occupants' thermal comfort without affecting the energy consumption. The target usecase corresponds to five neighborhood buildings, as they are summarized in Table 1. Without loss of generality for the introduced solution, we consider that people occupy the buildings only during the operating hours, while the distribution of people per room varies during the day. Each building is equipped with a number of weather sensors that monitor indoor/outdoor air temperature, humidity and radiant temperature values. Furthermore PV panels and rechargeable batteries are also employed in favor of minimizing the energy cost. Depending on the energy requirements the buildings can interact with the main grid in order to purchase or sell energy at different rates (dynamic pricing policy). The problem cannot be considered trivial due to the intermittent behaviour of the solar energy, the uncertain dynamics of the buildings and the need to meet the thermal comfort constraints for the micro-grid occupants.

The efficiency of the introduced framework is evaluated on a micro-grid test case, developed using the EnergyPlus suite [21]. The studied buildings are modeled in a detailed manner<sup>1</sup> [22,21], while the employed weather and pricing data correspond to publicly available information collected in 2010 [23,24]. By configuring the HVAC's set-point in each thermal zone it is feasible to achieve mentioned enhancement at the occupant's thermal comfort with a negligible penalty in energy consumption.

Assuming that our grid consists of  $k$  buildings, the derived solutions are quantified with two orthogonal metrics, namely the energy cost and the occupant's thermal comfort level, according to Eq. (1). Factors  $E_i^G(t)$  and  $C_i(t)$  refer to the energy purchased from the grid and the thermal comfort respectively of building  $i$  at time-step  $t$ . Note that the building's energy cost per time-step  $E_i^G(t)$  differs from the total energy consumption  $E_i(t)$ , since it takes into consideration the power saving from the PV panels ( $E^{PV}(t)$ ) and the batteries ( $E^B(t)$ ).

$$\text{Cost}(t) = \sum_{\forall \text{timestep}} \left( \frac{\alpha \times \sum_{i=1}^{i=k} (E_i^G(t)) + (1 - \alpha) \times \sum_{i=1}^{i=k} (C_i(t))}{k} \right) \quad (1)$$

<sup>1</sup> The modeling of the buildings was part of the PEBBLE FP7 project (<http://www.pebble-fp7.eu>) funded by the European Commission under the grand agreement 248537.

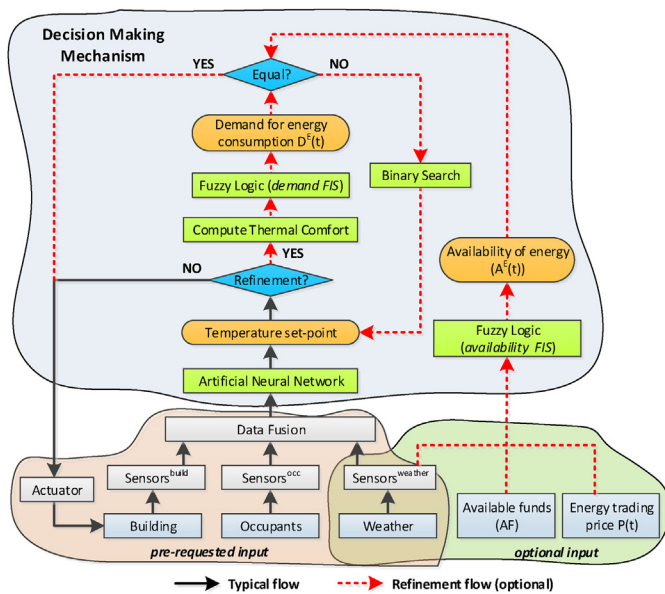


Fig. 2. Proposed methodology for the decision-making mechanism.

The aforementioned energy cost is formulated by Eq. (2). More thoroughly, in case that the building’s energy requirements ( $E_i(t)$ ) exceed the energy provided by the PV panels ( $E_i^{PV}(t)$ ) and the batteries ( $E_i^B(t)$ ), the excessive demand is met by purchasing additional energy from the grid at the current trading rate  $P(t)$ . On the contrary, if the available energy from renewable sources ( $E^{PV}(t)$ ) suffices to meet the desired thermal comfort, the additional energy is stored to batteries (up to their maximum capacity) while the rest of the energy is sold to the grid at the current trading rate.

$$E_i^C(t) = \begin{cases} (E_i(t) - E_i^{PV}(t)) \times P(t), & \text{if } E(t) \geq E^{PV}(t) \\ & \text{without considering } E_i^B(t) \\ (E_i(t) - E^{PV}(t) - E^B(t)) \times P(t), & \text{if } E(t) \geq E^{PV}(t) \\ & \text{considering } E_i^B(t) \\ 0, & \text{if } E^{PV}(t) \geq E(t) \end{cases} \quad (2)$$

Even though the employed control mechanism appears to exploit “as much as possible” the renewable power sources in order to minimize the amount of energy purchased from the grid, this is not always the case. The dynamic pricing, as well as the usage of batteries further complicate the problem at hand, since they enable the operation of the HVAC systems with a low-cost rate.

Even though the energy cost can be easily quantified with metering devices, the occupants’ thermal comfort can only be estimated. Various approaches are available for this purpose; in this work we employ the thermal comfort model developed by Fanger [25,26]. More thoroughly, this model relates environmental and physiological factors in conjunction to the thermal sensation in order to estimate the Predicted Percentage of Dissatisfied people (PPD) in a room.

Finally, the weighing factor  $\alpha$  defines the relative importance of optimizing either the energy cost, or the occupants’ thermal comfort. Since we tackle a multi-objective optimization problem, it is not feasible to find a solution that satisfies simultaneously all the objectives. For instance, the improvement of the occupants’ thermal comfort usually imposes additional energy consumption for cooling/heating the corresponding thermal zone(s). Without loss of generality we assume that both the energy cost and the occupants’ thermal comfort metrics are of equal importance.

### 3. Proposed decision making mechanism for smart thermostats

This section introduces the proposed framework that enables the task of decision making in smart thermostats. This framework, as it is depicted in Fig. 2, consists of two operation modes addressed as *typical* and *refinement* mode. More thoroughly, the first one provides the temperature set-points according to various conditions, whereas the second one refines the already derived set-points through a dynamic energy management process. This dynamism enables the modification of the aggressiveness of the decision making according to the available funds for buying energy AF.

The inputs in this framework are grouped into two categories, depending on the aforementioned operation modes. The *pre-requested* inputs are a set of data acquired from building, occupant and weather sensors. These data refer to the thermal zones’ temperature and humidity values, the number of occupants per room, as well as the current external weather conditions (temperature, humidity and solar radiation). Due to the increased number of distributed sensors that are necessary for monitoring weather and occupants’ conditions, appropriate techniques that support low-level data fusion [27] have also been employed.

Contrary to relevant studies that rely on statistical analysis, the proposed framework derives close to optimal results without taking into account weather forecasts and historical data. Additionally, our approach does not apply any iterative and/or time consuming simulations in order to compute the temperature set-points. In other words, the almost negligible computational complexity imposed by our decision making framework facilitates its implementation as part of a low-cost embedded system (e.g. a smart thermostat).

The second category refers to the *optional* inputs which are the available funds (AF) for a time period, as well as the current energy trading rates (both for purchasing and selling from the grid). These inputs enable a dynamic energy redistribution scheme in a way that balances the overall cost for a certain period of time. Note that such a feature is highly desirable for smart thermostats as it adjusts the aggressiveness of decision making under current weather conditions, occupants’ activity, and market trends.

In the framework’s general form, the temperature set-points per thermal zone are computed by utilizing an Artificial Neural Network (ANN). These networks are widely used in regression analysis to approximate functions that can depend on a large number of (unknown) inputs. Further details about the ANN’s architectural organization as well as the quality of its training can be found in Section 4.1. Even though an effective ANN results to temperature set-points fairly close to the ones derived from existing computational intensive control techniques, it is essentially a “black box” component that does not provide reasoning for either the consumed energy and/or the occupants’ thermal comfort; hence it cannot accurately estimate the building’s dynamic under real-time constraints.

If we abstain from applying the dynamic energy management feature, then the decision making process ends here and the thermostats are configured to the selected temperature set-points. Alternatively, our framework refines the initial temperature set-point by taking into account the available funds (AF) and the current energy trading rate ( $P(t)$ ). The refinement process emphasizes in redistributing the energy cost over time (by appropriately modifying the temperature set-points) in order to improve significantly the occupants’ thermal comfort without affecting the overall energy consumption.

The task of dynamic energy management is supported by a mechanism that relies on two Fuzzy Inference Systems (FIS). The first one (*availability FIS*) assesses the availability of energy ( $A^E(t)$ )

based on the weather data, the available funds ( $AF$ ) and the current market's energy trading rate ( $P(t)$ ), while the second one ( $demand\ FIS$ ) determines the current demand for energy consumption ( $D^E(t)$ ) according to the computed occupants' thermal comfort and the already derived (by the ANN) thermostat's set-point.<sup>2</sup> The availability of energy  $A^E(t)$  remains constant during a time-step, since this value depends only on the available amount of money, the trading rate of energy and the current month.<sup>3</sup>

The solution to the aforementioned problem is reached when  $A^E(t) \leq D^E(t)$ , i.e. being able to afford to spend the required energy (through the appropriate modification at the thermostat's set-point) while taking into account restrictions posed by the available energy and/or by the occupants' thermal comfort violation. For this purpose, the refinement process performs a binary search within the accepted temperature range and appropriately configures the thermostat's operational set-point. Additional details about the employed FIS can be found in Section 4.2.

#### 4. Engine for computing temperature set-points

This section introduces the employed engines, namely the Artificial Neural Network (ANN) and the Fuzzy Inference System (FIS), to address the problems of determining temperature set-points per thermal zone, as well as their dynamic refinement.

##### 4.1. Artificial neural network

The initial temperature set-points per thermal zone are computed by an Artificial Neural Network (ANN). An ANN is a massively parallel distributed system composed of simple processing units called neurons that mimics the biological neural networks in regard of their ability to learn through experience (also known as *supervised learning*). Knowledge is accumulated by the network from its environment through a special learning process called *training* and it is stored as inter-neuron connection strengths known as *synaptic weights*. The efficiency of an ANN depends highly on those synaptic weights, hence the idea behind the training process is to adjust the synaptic weights so that the network exhibits the desired behaviour.

The architecture of our ANN consists of an input layer, a number of hidden layers and an output layer. Typically each layer receives input(s) from the previous layer and forwards its output(s) to the next layer (feed-forward architecture). Consequently, designing an ANN comes down to determining the number of hidden layers as well as their internal organization. The role of hidden layers is to capture non-linear dependencies between the input data and the variables that we are trying to predict. Additional layers of hidden neurons enable greater processing power and system flexibility (i.e. model more complex functions) but they come at the cost of higher complexity for training. The number of neurons per hidden layer considerably affects the quality of derived solution as well. By having too many hidden neurons the system becomes over specified and is incapable of generalization. On the other hand, having too few hidden neurons prevents the system from properly fitting the input data, and thus, it reduces the system's robustness. Thus, a proper balance between these two border solutions is necessary. Our detailed analysis indicated that the optimal ANN's architecture consists of three hidden layers with 30 neurons each.

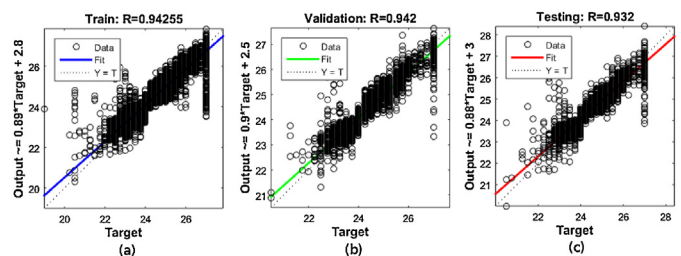


Fig. 3. Regression for the employed ANN's (a) training, (b) validation and (c) testing data sets.

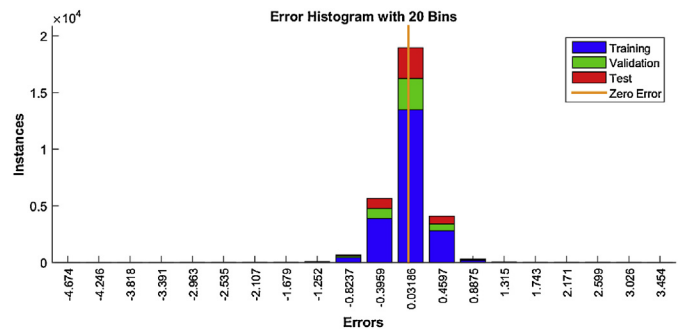


Fig. 4. Error analysis for the employed ANN.

Apart from the architectural organization, the efficiency of an ANN is tightly coupled with the applied training procedure. In our case we utilize the *Levenberg–Marquardt* back-propagation algorithm due to its increased performance, especially for non-linear regression problems [28]. As training inputs we applied a series of mappings between weather conditions (air and radiant temperature, as well as humidity) and the corresponding optimal (in terms of Eq. (1)) temperature set-point, as they were derived from a detailed design space exploration. The training data sets were randomly divided into three categories, namely *training*, *validation* and *testing*, each of which contains 70%, 15% and 15% of the input data sets respectively.

A major concern when utilizing an ANN is to achieve good generalization, that means to produce a correct mapping to the output space for unknown input values. Even though one might think that such a goal can be achieved with a big enough training set, this is not always the case mainly due to the *over-fitting* phenomenon where the ANN ends up memorizing the training data or learns the underlying noise. To overcome this problem we employ two complementary well-established techniques, namely the *early-stopping* and *re-training* [29]. Fig. 3 evaluates the efficiency of the applied training procedure. More thoroughly, this figure depicts the ANN's regression plot regarding the training, validation and testing data sets. The regression plot shows the relationship between the outputs of the ANN and the target (optimal) values as they were derived from our detailed design space exploration. Based on this analysis we can conclude that our implementation achieves a regression value of more than 93% for all the sets.

Complementary to that, Fig. 4 plots a histogram of error values in regard to the aforementioned data sets (each data set is plotted in a different color). The horizontal axis at this figure depicts the distribution of error between the ANN's outputs and the target values. This analysis indicates that the ANN's outputs achieve almost a negligible error for the majority of studied cases, which in turn highlights a satisfactory generalization for the introduced ANN.

<sup>2</sup> By modifying the thermostat's set-point we change the predicted percentage of dissatisfied people per room and consequently the demand for energy consumption ( $D^E(t)$ ).

<sup>3</sup> We spend a greater amount of money during the colder (December–February) and hotter (June–August) months of the year in order to minimize the thermal comfort violations.

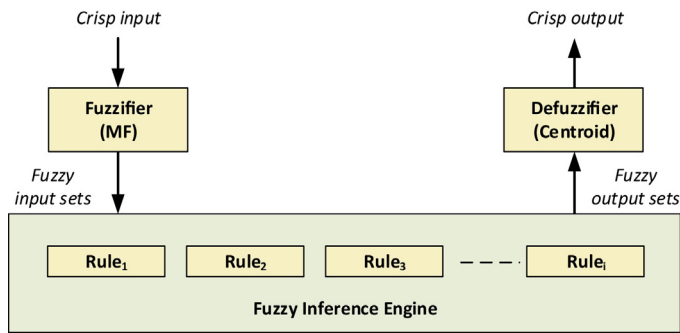


Fig. 5. Architectural organization of the employed FIS.

#### 4.2. Dynamic energy management

In addition to the aforementioned decision making mechanism, the introduced framework supports a dynamic energy management scheme. Such a scheme adjusts the already derived (by the ANN) temperature set-points, having as a goal to improve the occupants' thermal comfort without increasing the energy cost.

This dynamism is achieved by utilizing two Fuzzy Inference Systems (FIS) which rely on fuzzy logic to formulate a mapping between an input and output space. The term “fuzzy” refers to the fact that the logic involved extends the classical Boolean logic in order to handle the concept of partial truth. Fuzzy logic is a form of many-valued logic where the truth value of a variable may be any real number ranging between 0 and 1, in accordance to the observation that humans think using linguistic terms such as “slightly” or “too much” and “degrees of truth” instead of absolute values. In essence, in fuzzy logic the truth of any statement becomes a matter of degree; thus, a FIS is a way to create a flexible model for a complex system that is tolerant to imprecise data.

Fig. 5 depicts the architectural organization of the employed FIS which consists of three stages, namely the *fuzzifier*, the *fuzzy interface engine* (FIE) and the *defuzzifier*. Specifically, the fuzzification mechanism implemented within fuzzifier uses membership functions (MF) to map the input space (universe of discourse, X) to fuzzy sets ( $\mu_A : X \rightarrow [0, 1]$ ). On contrast, the defuzzification mechanism performs the reverse procedure and transforms the fuzzy sets obtained by the inference engine to crisp values, on the range of the output space, by using the centroid<sup>4</sup> method. Selecting suitable membership functions is of paramount importance, as an inaccurate MF might lead to divergence from the desired output. A widely acceptable approach is to start with a simple model that formulates the knowledge at hand and gradually elaborate the membership functions.

Apart from the input/output components, a FIS incorporates a rule base and a reasoning mechanism called *fuzzy inference engine* (FIE). The rule base is a collection of *if-then* rules enforced to the fuzzy sets in order to formulate the expert's knowledge. These rules are appropriately applied using fuzzy reasoning by the FIE in order to perform the mapping from the input to the output space.

The aforementioned process is visualized at Fig. 6. More thoroughly, this analysis depicts the mapping from the input to the output space regarding the *availability* FIS. The horizontal axes represent the inputs of the FIS while the vertical axis gives the FIS' output (availability of energy  $A^E(t)$ ). Note that in order to derive this surface, the entire rule base of the *availability* FIS was taken into account. For instance, during the colder (December–February) and hotter (June–August) months of the year the availability of energy

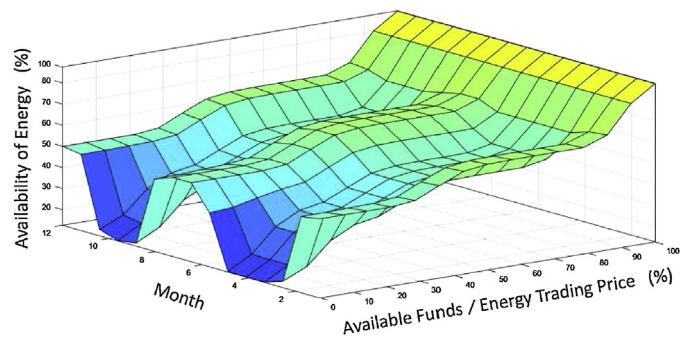


Fig. 6. Graphical representation of the input/output mapping regarding the *availability* FIS.

Table 2  
Rule base employed for the two studied FIS.

FIS	Premise	Consequent
Availability	High $AF/P(t)$	Higher availability of energy ( $A^E(t)$ )
	Medium $AF/P(t)$	Medium availability of energy ( $A^E(t)$ )
	Low $AF/P(t)$	Lower availability of energy ( $A^E(t)$ )
Demand	Rough weather conditions	Higher availability of energy ( $A^E(t)$ )
	Low PPD	Higher demand for energy consumption ( $D^E(t)$ )
	Medium PPD	Medium demand for energy consumption ( $D^E(t)$ )
	High PPD	Lower demand for energy consumption ( $D^E(t)$ )

$A^E(t)$  is high in order to cope with the extreme weather conditions. On contrast, regarding the cases where we are low on funds (AF) or when the trading rate for purchasing energy ( $P(t)$ ) is high then the availability of energy  $A^E(t)$  is low in order to counteract our inability of purchasing energy from the grid.

##### 4.2.1. Details regarding the employed FIS

The rule base of the two studied FIS (*availability* and *demand*) is summarized in Table 2. As mentioned, the availability of energy  $A^E(t)$  remains constant during a time-step, and according to Table 2, the lower the PPD the more energy we demand. Hence, in order to improve the occupants' thermal comfort, we need to either have more funds and/or a low energy trading price (high  $AF/P(t)$  ratio), or experience rough weather conditions (during the colder (December–February) and hotter (June–August) months of the year). By modifying the thermostat's set-points we change the PPD per thermal zone and consequently the demand for energy consumption ( $D^E(t)$ ). When the demand for energy ( $D^E(t)$ ) is less or approximately equal to the available energy ( $D^E(t) \leq A^E(t)$ ), the two FIS reach a consensus, and we set the thermostat to the resulted set-points.

Evaluating a fuzzy rule involves the fuzzification of the premise, the application of any fuzzy operators and finally the applications of the implication operator that gives the consequent of the rule. Aggregating the consequent part of all the rules creates the final output fuzzy set which, after the defuzzification process, provides the final desired output. The employed operators for adjusting the fuzzy inference functions, such as the defuzzification method, are summarized in Table 3. Regarding the input variables, we used Gaussian combination membership functions, while for the output variables we used triangular-shaped membership functions.

<sup>4</sup> The centroid or geometric center of a plane figure is the arithmetic mean (“average”) position of all the points in the shape.

**Table 3**  
Employed operators for adjusting the fuzzy inference functions.

Task	Conjunction (AND)	Disjunction (OR)	Implication	Aggregation
Operator	<i>min</i>	<i>max</i>	<i>min</i>	<i>max</i>

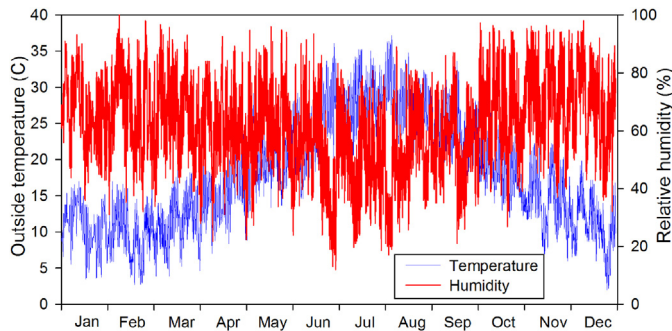


Fig. 7. Annual variation of environment temperature and humidity.

## 5. Experimental results

This section provides a number of experimental results that quantify the efficiency of the introduced framework. By appropriately computing the temperature set-points per thermal zone it is feasible to considerably improve the energy consumption and the occupants' thermal comfort. The experimental setup for our analysis consists of five buildings, as it was presented in Section 2.1. Without loss of generality both the proposed implementation, as well as the reference control solutions, adopt a 10 min time-step, i.e. each thermostat is configured once per 10 min.

The optimal operation for HVAC systems is not an easy task since the increased number of thermal zones and cooling/heating strategies in large scale buildings have to be closely coupled. This is a typical multi-objective problem, where the reduction of energy cost and the maximization of thermal comfort are in conflict with each other. Therefore, no single optimal solution can be found in these problems. Instead, a set of trade-offs that represent the best possible compromises among the objectives have to be computed. Regarding our experimentation, we consider that each of these cost metrics are of equal importance ( $\alpha = 0.50$ ).

The energy consumed by an HVAC system, and thus the energy cost, is a nonlinear function which depends on the thermostat's set-point, the zone temperature, the current external environment conditions, as well as on factors related to the particular unit (e.g. its capacity, efficiency and other inherent factors). As mentioned, we assume that the HVAC systems operate only during the occupancy hours of the buildings, as denoted in Table 1. Additionally, similar to the real world scenarios, the indoor environment of the buildings under consideration is quite sensitive to the variations of the external weather conditions. In other words, the indoor building environment closely follows the change of outdoor environment if no control is applied.

The target buildings are located in Crete (Greece), whereas our experimentation relies on real weather and energy pricing data for 2010 [23,24]. Fig. 7 plots the variation of the external air temperature and humidity values, as they have been acquired by the building's sensors. According to this figure, the variation of the external air temperature ranges between 2 °C and 37 °C, while the corresponding range for the external relative humidity and radiant temperature are 12–100% and 0–47 kW/m<sup>2</sup> respectively. Therefore, proper selections of temperature set-points per thermal zone are absolutely necessary in order to minimize overall cost.

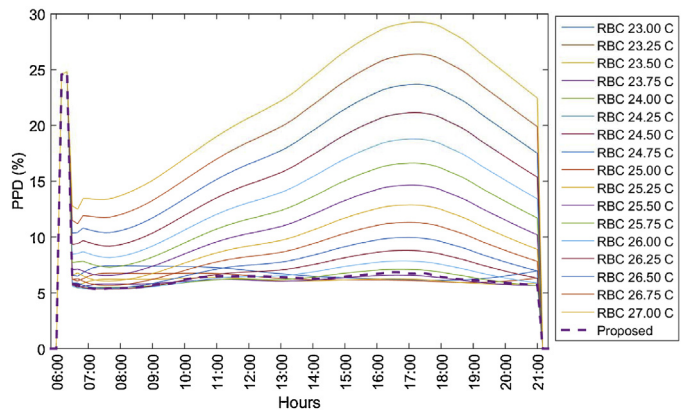


Fig. 8. Variation of thermal comfort during an August's day.

### 5.1. Comparison versus ruled based controller's temperature set-points

The first part of our experimentation evaluates the static flavour of the proposed decision making mechanism, as it is computed by the ANN, against the ruled based controller's (RBC) temperature set-points. For demonstration purposes, the results depicted at this subsection affect a typical August day and the upcoming figures plot the corresponding values regarding only the operational hours of the buildings, during which the buildings are occupied and the HVAC systems are operational.

A well-established metric for quantifying the efficiency of HVAC control mechanisms is the improvement of thermal comfort. For this purpose, we study this metric in terms of the Predicted Percentage of Dissatisfied (PPD) people,<sup>5</sup> which portrays the percentage of the buildings' occupants that are dissatisfied with the current thermal conditions. Since we consider summer period, we quantify the efficiency of 17 typical RBC values ranging between 23 °C and 27 °C with a step of 0.25 °C. The results of this analysis are summarized in Fig. 8.

According to this analysis, we can conclude that the introduced decision making mechanism results to higher thermal comfort values compared to the RBC solutions, since it minimizes the overall PPD value during the whole day. Although the RBC solutions that correspond to 23.25 °C and 23.75 °C exhibit slight improvement during noon and afternoon, respectively, the overall performance of our framework is superior in reference to the whole day. Note that the spikes early in the morning (at 6:00 am) occur due to the fact that people enter to a "closed" building; thus, the thermal conditions cannot be considered as optimal for the occupants. Since the experimental setup is identical for all the studied control techniques, identical spikes are presented among the alternative solutions as well. Furthermore, we have to note that these spikes do not affect buildings #2–#4 because to these buildings we apply a warming-up/cooling phase equal to 20 min,<sup>6</sup> as it was discussed in Table 1.

Along with the occupants' thermal comfort, we are equally interested in reducing the total energy consumption and thus the energy expenses as well. For demonstration purposes, Fig. 9 depicts the variation of energy cost regarding the various RBC solutions for the same August day. To be consistent, this analysis does not take into account either the power saving from PV panels, or the energy stored in batteries.

<sup>5</sup> Lower PPD values are preferable since they increase the occupant's satisfaction.

<sup>6</sup> The HVAC systems start to operate 20 min prior to the occupants' entrance.

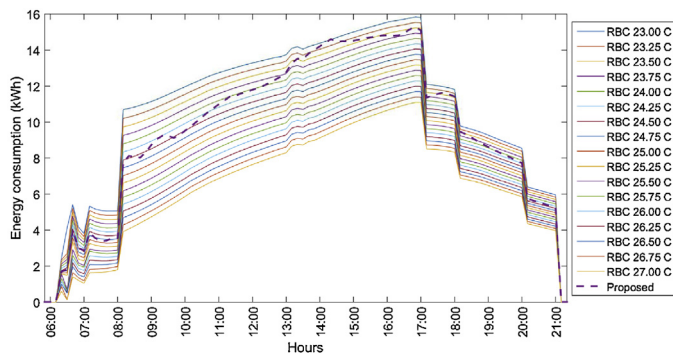


Fig. 9. Variation of energy consumption during a summer day.

The aforementioned analysis pinpoints the fact that higher set-points lead to less energy consumption (regarding the summer months), since the cooling is not that intense. On the other hand, these set-points usually lead to increased PPD values. Hence the decision making mechanism has to trade-off between these two cost metrics by taking into consideration parameters posed by the external weather conditions (such as humidity and solar radiation) in order to achieve the optimum balance. These results highlight the superiority of our introduced framework, as it achieves considerable reduction in energy consumption compared to RBC set-points of comparable thermal comfort.

## 5.2. Comparison versus existing control techniques

To proceed with, we study the efficiency of the introduced framework compared to two well-established control techniques, namely the *Pattern Search* [30] and the *Fmincon* [31]. Both of these techniques are implemented in Matlab's Optimization Toolbox as an open-loop optimization procedure. Weather data regarding a 5 month period (May–September) are employed, while, throughout the analysis discussed in this subsection, only the cooling operation of HVACs is considered. Due to the enormous computational complexity imposed by the aforementioned existing solvers, each month is studied as a separate sub-problem and is addressed individually.

For demonstration purposes, Fig. 10(a) depicts the variation of the PPD (%) for the alternative decision making techniques regarding the last week of August. Same as before, analogous spikes are exhibited at each morning by all the studied control techniques. Also note that we are primarily interested in the duration of these spikes since that is which affects the overall performance according to Eq. (1). Based on our analysis regarding the 5 months experiment, their duration is less than 20 min (on average). This is inline to the EN15251 standard [32] and to the Renewable Energy Road Map [33], in order to ensure a comfortable indoor environment. Both of them suggests that the PPD must be kept approximately below 10–15%. These limits should not be violated except for small intervals during the buildings' operation.

Along to the thermal comfort level, the energy consumption is of paramount importance as well. The results of this analysis are summarized in Fig. 10(b). More thoroughly, this figure plots the variation of energy consumption regarding the same time period (last week of August) for the three alternative control techniques. This analysis identifies daily periods of maximum energy consumption (e.g. noon) in order to meet the desired cooling needs. Note that as before, we are not interested in peak values but for the area under each curve, since it is proportional to the energy cost. To be consistent, neither the power saving from PV panels nor the energy stored in batteries are considered, since these gains are expected to be constant among the alternative control techniques.

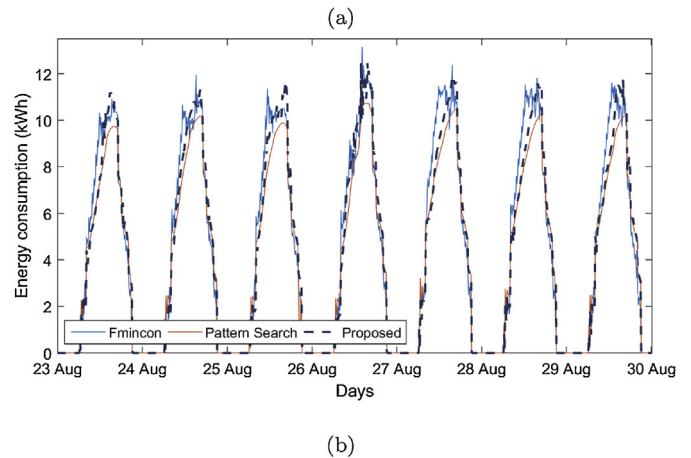
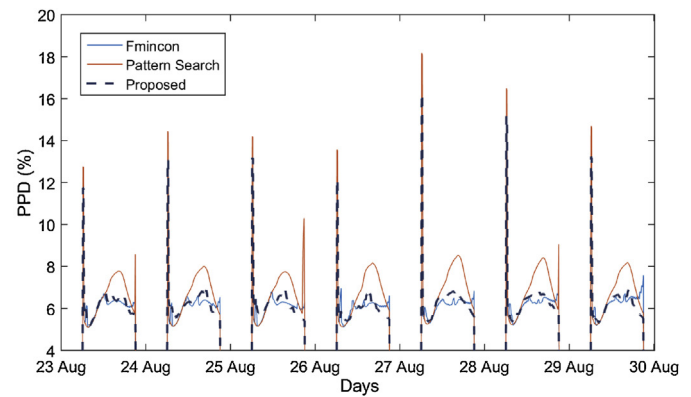


Fig. 10. Variation of (a) thermal comfort and (b) energy consumption regarding the last week of August.

Our analysis so far indicates that the introduced framework exhibits comparable efficiency, in terms of occupants' thermal comfort and energy consumption, to well-established and sophisticated control techniques. In accordance with this outcome, Table 4 presents the percentage enhancement regarding the overall cost (Eq. (1)) achieved by the studied control technique compared to the RBC temperature set-points. According to these results, the proposed framework improves the corresponding configurations retrieved by the RBCs between 18% and 40%, on average. Additionally, the introduced solution enhances the results derived by the Pattern Search solver by 27% on average, while the Fmincon achieves an additional improvement by 13%.

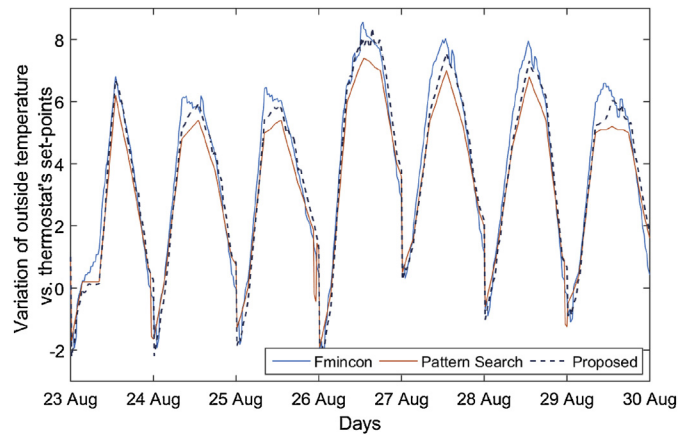
Along with the aforementioned analysis, it is well-worth to evaluate the impact of the different decisions making mechanisms in terms of the selected temperature set-points. To do so, Fig. 11 gives the temperature difference between the thermostat's set-points and the external air temperature. For demonstration purposes, this figure corresponds to the last week of August; however, similar results occur for the entire 5 month experiment. This analysis can be viewed as an extension of the PPD metric, since the chosen set-point highly affects the occupants' thermal comfort. More thoroughly, the temperature set-points computed by the introduced framework vary less than  $0.1^{\circ}\text{C}$  on average compared to Fmincon; thus, it exhibits identical performance to computationally intensive solvers.

Last but not least, it is noteworthy that both Fmincon and Pattern Search solvers exhibit considerable computational complexity. The results of this analysis regarding the month of August is plotted at Fig. 12. Note that the execution both of these solvers is performed for 7000 Matlab iterations, each of which takes around

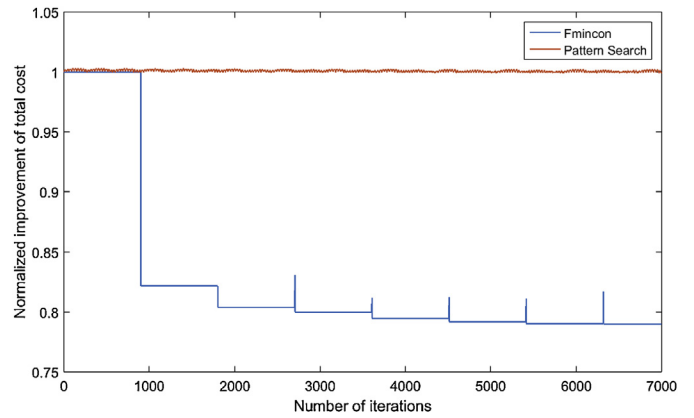


**Table 4**  
Cost improvement for alternative control techniques as compared to RBC temperature set-points.

RBC	May			June			July			August			September		
	Fmincon	Pattern search	Proposed	Fmincon	Pattern search	Proposed	Fmincon	Pattern search	Proposed	Fmincon	Pattern search	Proposed	Fmincon	Pattern search	Proposed
wrt 23.00 °C	43.9%	41.6%	46.6%	69.5%	63.2%	65.9%	50.6%	34.4%	43.9%	50.2%	35.2%	45.9%	73.0%	69.9%	69.3%
wrt 23.25 °C	38.5%	35.9%	41.4%	63.4%	55.8%	59.0%	40.9%	21.6%	32.9%	41.3%	23.6%	36.2%	67.9%	64.3%	63.5%
wrt 23.50 °C	32.8%	29.9%	35.9%	56.0%	46.7%	50.6%	30.1%	7.3%	20.7%	31.5%	10.8%	25.5%	61.5%	57.2%	56.3%
wrt 23.75 °C	27.0%	23.9%	30.4%	47.0%	35.9%	40.6%	19.3%	-7.1%	8.4%	21.8%	-1.8%	15.0%	53.8%	48.6%	47.5%
wrt 24.00 °C	21.4%	18.1%	25.1%	37.0%	23.8%	29.4%	10.5%	-18.7%	-1.5%	13.7%	-12.3%	6.2%	44.4%	38.2%	36.9%
wrt 24.25 °C	16.1%	12.5%	20.0%	27.1%	11.7%	18.2%	6.1%	-24.6%	-6.5%	9.2%	-18.3%	1.2%	33.9%	26.5%	25.0%
wrt 24.50 °C	11.3%	7.6%	15.5%	19.2%	2.3%	9.4%	7.5%	-22.7%	-4.9%	9.4%	-17.9%	1.5%	23.3%	14.6%	12.9%
wrt 24.75 °C	7.4%	3.5%	11.7%	15.9%	1.1%	5.7%	14.4%	-13.6%	2.9%	14.4%	-11.4%	7.0%	14.6%	5.0%	3.0%
wrt 25.00 °C	4.4%	0.4%	8.9%	18.3%	1.1%	8.4%	24.5%	-0.2%	14.3%	22.8%	-0.4%	16.1%	10.3%	0.2%	-1.8%
wrt 25.25 °C	2.5%	-1.6%	7.1%	25.5%	9.9%	16.5%	35.5%	14.5%	26.9%	32.7%	12.4%	26.9%	12.0%	2.1%	0.1%
wrt 25.50 °C	1.7%	-2.4%	6.3%	35.3%	21.7%	27.5%	45.9%	28.3%	38.7%	42.5%	25.2%	37.5%	19.1%	10.0%	8.1%
wrt 25.75 °C	2.0%	-2.2%	6.5%	45.5%	34.0%	38.9%	55.0%	40.3%	48.9%	51.4%	46.7%	47.2%	29.2%	21.3%	19.7%
wrt 26.00 °C	3.1%	-1.0%	7.6%	54.6%	45.1%	49.1%	62.5%	59.1%	57.4%	59.1%	46.7%	55.5%	40.0%	33.2%	31.9%
wrt 26.25 °C	5.0%	0.9%	9.4%	62.4%	54.5%	57.8%	68.6%	58.4%	64.4%	65.5%	55.1%	62.5%	49.7%	44.1%	42.9%
wrt 26.50 °C	7.4%	3.5%	11.7%	68.6%	62.0%	64.8%	73.6%	64.9%	70.0%	70.8%	67.6%	68.2%	57.9%	53.2%	52.3%
wrt 26.75 °C	10.1%	6.4%	14.3%	73.6%	68.1%	70.5%	77.6%	70.2%	74.6%	75.1%	72.1%	72.9%	64.6%	60.7%	59.9%
wrt 27.00 °C	13.1%	9.4%	17.1%	77.6%	73.0%	74.9%	80.8%	74.5%	78.2%	78.6%	72.1%	76.7%	70.0%	66.6%	65.9%
Average	14.6%	11.0%	18.6%	46.9%	35.7%	40.4%	41.4%	22.2%	33.5%	40.6%	22.7%	35.4%	42.7%	36.2%	34.9%



**Fig. 11.** Variation of outside temperature versus the average thermostat's set-points.



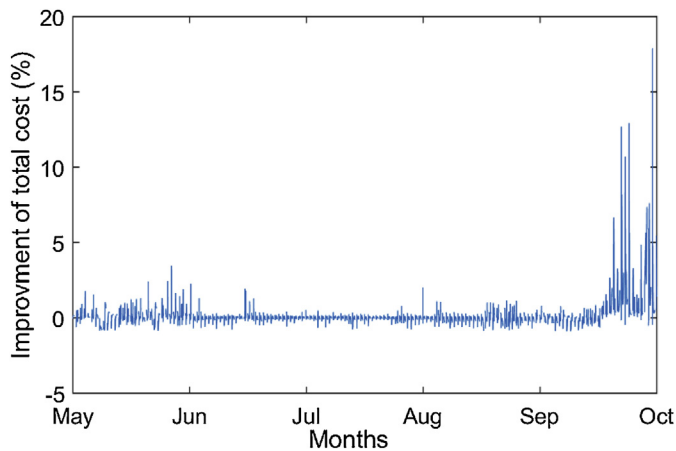
**Fig. 12.** Evolution of cost function (Eq. (1)) for existing solvers.

2–3 min in a workstation PC.<sup>7</sup> Based on this figure, a number of conclusions can be derived. Among others, their efficiency is almost negligible for the first 900 iterations. Furthermore, the efficiency of Pattern Search is limited, as it cannot improve the cost metric for our problem even after 7000 iterations. On the other hand, the Fmincon solver achieves to reduce cost metric up to 23%. Even though the majority of the cost reduction is achieved during the first 900 iterations, this still imposes a much higher computational cost as compared to the introduced decision making framework. Consequently, it is not feasible to implement the existing control techniques as part of an embedded platform, similar to the ones found in smart thermostats. Additional details concerning the hardware implementation of our decision making framework, as well as the complexity of the derived solution, can be found in Section 5.4.

5.3. Evaluation of the dynamic energy management

To continue with, we evaluate the efficiency of the introduced framework in terms of redistributing the energy consumption during a certain period of time in a way that improves considerably the occupant's thermal comfort without affecting the overall energy consumption. This analysis refers to the whole year. Note that the corresponding results regarding existing solvers are not feasible to be provided in this analysis, due to the excessive computational complexity for solving the problem of customizing multiple smart thermostats during a whole year.

<sup>7</sup> Intel Xeon CPU E5-2650v2@2.60 GHz, 8 cores/16 threads, 64 GB DDR3 RAM.



**Fig. 13.** Improvement of total cost (%) as compared to the set-points derived from the ANN.

In our case, Fig. 13 depicts the variation of total cost as derived from the FIS compared to the initial solution by the ANN. For demonstration purposes this figure plots the previously analyzed 5 month period. Meanwhile similar results occur for the rest of the months as well. This analysis indicates that the usage of fuzzy logic achieves the redistribution of energy in a way that considerably improves the total cost (average enhancement by 7%). More thoroughly, our solution achieves to improve the thermal comfort by 19% on average with almost the same energy cost (average increase by 5%). The augmented performance occurs by taking into consideration both constraints posed by weather conditions (like the majority of the existing control techniques do), as well as inherent limitations related to the available funds ( $AF$ ) for purchasing energy and the current energy cost ( $P^E(t)$ ).

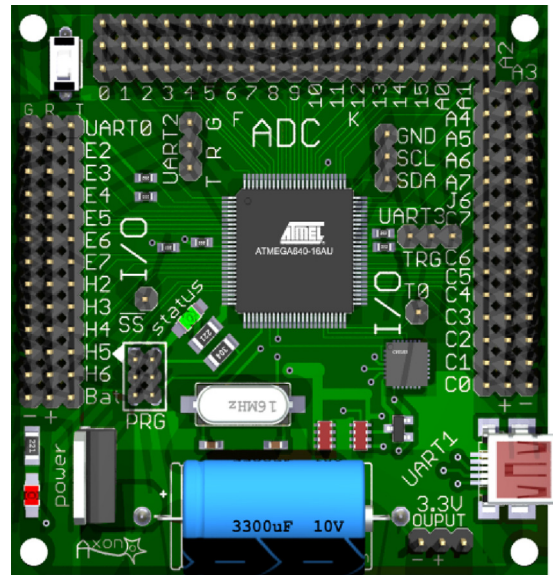
The aforementioned improvement of total cost is more aggressive in September, as indicated in Fig. 13. That is due to the fact that, as we discussed in Table 4, the ANN's efficiency is limited during this month compared to the reference control techniques. However, if we take into account the entire framework, consisted of both the ANN and the FIS, we can infer that it achieves analogous performance to Fmincon regarding September as well, since the FIS compensates for the ANN's shortcoming during this month.

Finally it is essential to emphasize that additional improvement is feasible by employing a more aggressive reasoning mechanism for the FIS, which can be further customized for a particular city. However, this is beyond the scope of this work, since we are primary interested in proposing a generally applicable framework for designing and implementing low-cost decision making mechanisms for smart thermostats.

#### 5.4. Hardware implementation and system integration

The entirety of the aforementioned solvers (Fmincon and Pattern Search) focus on the accuracy of their results. Even though this is a desirable feature in terms of proposing a decision making mechanism, their increased computational complexity makes them non-suitable for being implemented onto low-cost embedded platforms. This section discusses the hardware implementation of the introduced decision making mechanism onto a low-cost ATMEGA640 microcontroller [34]. Fig. 14 gives an overview of the target platform, where both the processing core, as well as the interface to the rest of the integrated circuits (through serial port) can be identified.

In this direction, we developed the proposed decision making mechanism into ANSI C code, which in turn programs the aforementioned controller. The developed solution supports multiple



**Fig. 14.** Printed board of the employed ATMEGA640 microcontroller.

configurations and various levels of control for the thermal zones, while its inherent intelligence paves the way for the elimination of free riders, provides greater load reduction, and offers more equitable control across occupants. Finally, with an eye toward future-proofing, it maximizes the performance and extends the device's lifespan.

After the implementation phase, we proceed to the evaluation phase. More thoroughly, we managed to implement the ANN's and FIS' functionalities with only approximately  $0.77 \times 10^6$  and  $1.2 \times 10^6$  cycles respectively. Note that these results are orders of magnitude lower than the corresponding 7,000 Matlab iterations imposed by existing controllers, as it was discussed in Fig. 12.

By taking into consideration that the employed controller operates at 16 MHz, this results in each of the temperature set-points being computed in less than 0.2 s; this is by far less than the typical 10 min period between consecutive set-point configurations. Additionally, the aforementioned hardware implementation enables straightforward firmware upgrades in order to either customize the aggressiveness of the employed decision making mechanism depending on the occupants' requirements, or support the implementation of additional functionalities that further enhance the flexibility of our solution.

## 6. Conclusion

This paper introduces a novel framework for a flexible and efficient Decision Making Mechanism for smart thermostats. The proposed solution supports the task of temperature regulation in a smart building environment while being an active participant in the energy market by facilitating the usage of renewable resources, batteries and dynamic energy pricing policies. Furthermore, following the current market trend, we established that the proposed framework facilitates its implementation into low-power, low-complexity embedded devices, proving it ideal for deployment as part of a smart thermostat. As such, it is straightforwardly applicable to existing HVAC installations in a smart building environment.

The proposed framework consists of two operation modes, a *typical* mode, that makes use of an Artificial Neural Network (ANN), and a *refinement* mode, that utilizes two Fuzzy Inference systems which try to reach a consensus. Contrary to relevant approaches, our framework derives close to optimal results, without the need of weather forecasts or historical data. The *typical* mode is

responsible for deriving the initial temperature set-point, unaware of the buildings' dynamic behavior, under real time constraints. On the other hand the *refinement* mode emphasizes in the redistribution of the energy cost over time, with the goal of maximizing the occupants' thermal comfort without affecting the overall energy cost. As such, it can be considered as a human-centric implementation, since it configures its aggressiveness according to occupants' requirements, contrary to other approaches. Additionally, it is able to interact with the main grid in order to purchase and sell energy according to the current pricing policy.

Experimental results highlight the superiority of the introduced framework compared to existing approaches along with the added benefit of the significantly smaller computational complexity. Our framework was evaluated in three stages. Firstly, comparisons versus rule based controllers proved that our framework can achieve higher thermal comfort for the occupants with considerable reduction in energy consumption. More thoroughly, the proposed framework improves the corresponding configurations retrieved by the RBCs between 18% and 40%, on average. Secondly, as compared to existing control techniques, the introduced solution enhances the results derived by the Pattern Search solver by 27% on average, while achieving comparable results to Fmincon, without exhibiting the substantial computational complexity that these solvers impose. Specifically, even for the initial 900 Matlab iteration (during which the aforementioned solvers exhibit their maximum improvement), and an average time of 2.5 min for each one, the state of the art solvers require 1.5 days to finish their execution, while our framework requires less than 0.2 s. Thirdly, the evaluation of the dynamic flavor of our framework indicated that the usage of fuzzy logic, and by taking into account the dynamic behavior of the world, it can achieve a considerable improvement of the total cost (average enhancement by 7%, 19% improvement on the thermal comfort level with negligible penalty in the energy consumption).

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## References

- [1] Eurostat, Energy Balance Sheets, Data 2002–2003, Luxembourg, 2005.
- [2] E.U. Commission, European Energy and Transport – Trends to 2030, 2008 (Update 2007) <http://aei.pitt.edu/46140/>.
- [3] European Environment Agency, Annual European Union Greenhouse Gas Inventory 1990–2012 and Inventory Report, 2014 <http://www.eea.europa.eu/publications/european-union-greenhouse-gas-inventory-2014#tab-data-references>.
- [4] C.D. Korkas, S. Baldi, I. Michailidis, E.B. Kosmatopoulos, Intelligent energy and thermal comfort management in grid-connected microgrids with heterogeneous occupancy schedule, *Appl. Energy* 149 (2015) 194–203.
- [5] J. Clarke, S. Conner, G. Fujii, V. Geros, G. Jóhannesson, C. Johnstone, S. Karatasou, J. Kim, M. Santamouris, P. Strachan, The role of simulation in support of internet-based energy services, *Energy Build.* 36 (8) (2004) 837–846.
- [6] W.-M. Lu, J. Doyle,  $H_\infty$  control of nonlinear systems: a convex characterization, *IEEE Trans. Autom. Control* 40 (9) (1995) 1668–1675, <http://dx.doi.org/10.1109/9.412643>.
- [7] T. Bañar, P. Bernard, *Optimal Control and Related Minimax Design Problems*, 1995.
- [8] D.Q. Mayne, J.B. Rawlings, C.V. Rao, P.O. Sokaert, Constrained model predictive control: stability and optimality, *Automatica* 36 (6) (2000) 789–814.
- [9] L. Magni, G. De Nicolao, L. Magnani, R. Scattolini, A stabilizing model-based predictive control algorithm for nonlinear systems, *Automatica* 37 (9) (2001) 1351–1362.
- [10] S. Research, Global Smart Thermostats Market 2015–2019, October 2015 <http://www.sandlerresearch.org/global-smart-thermostats-market-2015-2019.html/>.
- [11] B. Sun, P. Luh, Q. Shan Jia, Z. Jiang, F. Wang, C. Song, Building energy management: integrated control of active and passive heating, cooling, lighting, shading, and ventilation systems, *IEEE Trans. Autom. Sci. Eng.* 10 (3) (2013) 588–602, <http://dx.doi.org/10.1109/TASE.2012.2205567>.
- [12] W. Huang, H. Lam, Using genetic algorithms to optimize controller parameters for HVAC systems, *Energy Build.* 26 (3) (1997) 277–282.
- [13] Y. Yao, Z. Lian, Z. Hou, X. Zhou, Optimal operation of a large cooling system based on an empirical model, *Appl. Therm. Eng.* 24 (16) (2004) 2303–2321.
- [14] K. Fong, V. Hanby, T. Chow, HVAC system optimization for energy management by evolutionary programming, *Energy Build.* 38 (3) (2006) 220–231.
- [15] R. Kumar, R. Aggarwal, J. Sharma, Energy analysis of a building using artificial neural network: a review, *Energy Build.* 65 (2013) 352–358, <http://dx.doi.org/10.1016/j.enbuild.2013.06.007> <http://www.sciencedirect.com/science/article/pii/S0378778813003459>.
- [16] R. Alcalá, J. Casillas, O. Cordon, A. González, F. Herrera, A genetic rule weighting and selection process for fuzzy control of heating, ventilating and air conditioning systems, *Eng. Appl. Artif. Intell.* 18 (3) (2005) 279–296.
- [17] S. Huang, R. Nelson, Rule development and adjustment strategies of a fuzzy logic controller for an hvac system: Part I and II (analysis and experiment), *ASHRAE Trans.* 100 (1) (1994) 841–850, 851–856.
- [18] F. Calvino, M.L. Gennusa, G. Rizzo, G. Scaccianoce, The control of indoor thermal comfort conditions: introducing a fuzzy adaptive controller, *Energy Build.* 36 (2) (2004) 97–102, <http://dx.doi.org/10.1016/j.enbuild.2003.10.004> <http://www.sciencedirect.com/science/article/pii/S0378778803001312>.
- [19] N. Lu, An evaluation of the HVAC load potential for providing load balancing service, *IEEE Trans. Smart Grid* 3 (3) (2012) 1263–1270, <http://dx.doi.org/10.1109/TSG.2012.2183649>.
- [20] R. Velik, P. Nicolay, Grid-price-dependent energy management in microgrids using a modified simulated annealing triple-optimizer, *Appl. Energy* 130 (2014) 384–395.
- [21] U.S. Department of Energy, Energyplus Energy Simulation Software, 2015 <http://apps1.eere.energy.gov/buildings/energyplus/>.
- [22] D.B. Crawley, L.K. Lawrie, F.C. Winkelmann, W. Buhl, Y. Huang, C.O. Pedersen, R.K. Strand, R.J. Liesen, D.E. Fisher, M.J. Witte, J. Glazer, Energyplus: creating a new-generation building energy simulation program, *Energy Build.* 33 (4) (2001) 319–331.
- [23] Weather Data, Weather Data Sources for Energyplus Framework, 2015 [http://apps1.eere.energy.gov/buildings/energyplus/weatherdata\\_sources.cfm/](http://apps1.eere.energy.gov/buildings/energyplus/weatherdata_sources.cfm/).
- [24] Wholesale Electricity and Natural Gas Market Data, November 2015 <http://www.eia.gov/electricity/wholesale/#history>.
- [25] ASHRAE, ANSI/ASHRAE Standard 55-2004: Thermal Environmental Conditions for Human Occupancy, American Society of Heating, Refrigerating and Air-Conditioning Engineers, 2016.
- [26] ASHRAE, Thermal Environmental Conditions for Human Occupancy, ANSI/ASHRAE Standard 55-2013, 2013.
- [27] Z.Z. ZiQi Hao, H.-C. Chao, A cluster-based fuzzy fusion algorithm for event detection in heterogeneous wireless sensor networks, *J. Sens.* (2016), <http://dx.doi.org/10.1155/2015/641235>, Article ID 641235.
- [28] M.T. Hagan, M.B. Menhaj, Training feedforward networks with the Marquardt algorithm, *Trans. Neural Netw.* 5 (6) (1994) 989–993.
- [29] K.-L. Du, M.N.S. Swamy (Eds.), *Neural Networks and Statistical Learning*, Springer, 2014.
- [30] C. Audet, J.E. Dennis Jr., Analysis of generalized pattern searches, *SIAM J. Optim.* 13 (3) (2002) 889–903.
- [31] R.H. Byrd, J.C. Gilbert, J. Nocedal, A trust region method based on interior point techniques for nonlinear programming, *Math. Program.* 89 (1) (2000) 149–185.
- [32] European Committee for Standardization (CEN), EN 15251 Indoor Environmental Input Parameters for Design and Assessment of 686 Energy Performance of Buildings-Addressing Indoor Air Quality, Thermal Environment Lighting and Acoustics, 2007.
- [33] Communication from the Commission to the Council the European Parliament, Renewable Energy Road Map Renewable 688 Energies in the 21st Century: Building a More Sustainable Future, 2007.
- [34] ATMEL, Specifications for ATMEL ATMEGA640 Micro-Controller, 2016.