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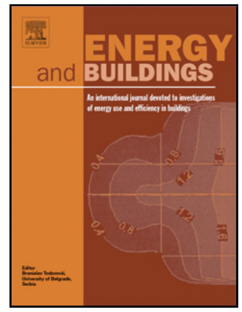

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Authors: Marcel Macarulla, Miquel Casals, Núria Forcada, Marta Gangolells

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Implementation of predictive control in a commercial building energy management system using neural networks

Marcel Macarulla*[a], Miquel Casals[a], Núria Forcada[a], Marta Gangolells[a]

Authors' affiliation

[a] Universitat Politècnica de Catalunya, Department of Project and Construction Engineering, Group of Construction Research and Innovation (GRIC), C/Colom, 11, Ed. TR5, 08222 Terrassa, Barcelona, Spain

Corresponding author

Marcel Macarulla, PhD, Universitat Politècnica de Catalunya, Department of Project and Construction Engineering, Group of Construction Research and Innovation (GRIC), C/Colom, 11, Ed. TR5, 08222 Terrassa, Barcelona, Spain, marcel.macarulla@upc.edu

Highlights

- An adaptive control strategy was developed to manage building boilers
- Data tracked by a BEMS were used to improve the performance of the building
- Savings were found to amount to nearly 20% with the adaptive control

- Adaptive control reduced the boiler operation costs and ensured the building's thermal comfort

Abstract

Most existing commercial building energy management systems (BEMS) are reactive rule-based. This means that an action is produced when an event occurs. In consequence, these systems cannot predict future scenarios and anticipate events to optimize building operation. This paper presents the procedure of implementing a predictive control strategy in a commercial BEMS for boilers in buildings, and describes the results achieved. The proposed control is based on a neural network that turns on the boiler each day at the optimum time, according to the surrounding environment, to achieve thermal comfort levels at the beginning of the working day. The control strategy presented in this paper is compared with the current control strategy implemented in BEMS that is based on scheduled on/off control. The control strategy was tested during one heating season and a set of key performance indicators were used to assess the benefits of the proposed control strategy. The results showed that the implementation of predictive control in a BEMS for building boilers can reduce the energy required to heat the building by around 20% without compromising the user's comfort.

Keywords

Building energy management system; energy savings; boiler management; neural networks

1 Introduction

Most of the literature states that the global contribution from buildings towards energy consumption is around 20–40% in developed countries [1]. In Europe, buildings are responsible for 40% of energy consumption and 36% of CO_2 emissions [2], consuming more energy than the industry and transportation sectors [3]. Buildings consume energy in their entire life cycle, but 80–90% of their lifecycle energy use is consumed during the operational stage [4–7]. As a consequence, recent EU directives have focused on reducing operational building energy consumption [8].

One challenge in the building sector is to optimise heating, ventilation, and air-conditioning (HVAC) systems because they consume half of the operational energy used in a building [9]. Moreover, HVAC systems often work inefficiently [10]. Building energy management systems (BEMS) play an important role in this area [11]. BEMS contribute to continuous building energy management [11], enabling buildings to be more intelligent through real-time automatic monitoring and control [12], and optimizing their energy use [13]. According to Lee and Cheng [14], the implementation of a BEMS to manage HVAC systems leads to savings of around 14%. The savings are directly correlated with the functions used by the BEMS to optimise energy demand.

Generally, commercial BEMS adopt demand-driven control strategies, and usually the demand is not measured and the control strategy is simply schedule-based [15]. In addition, BEMS generate a tremendous amount of data that is rarely fully interpreted and utilized [12]. These data could be used to optimize building maintenance activities and building energy usage [16].

The aim of this research was to demonstrate how predictive control could be implemented in a commercial BEMS for the heating system, and to present the benefits of the proposed approach in comparison with the traditional schedule-based on/off control strategy currently used in commercial BEMS. In particular, this paper addresses how much time is needed to condition a tertiary building to achieve thermal comfort levels at the beginning of the working day.

The paper is structured as follows. Section 2 describes the problem statement and the research goal. Section 3 presents the building in which predictive control was implemented, and describes how the boiler was managed before this implementation. Section 4 describes the methodology used to define the control strategy, and the key performance indicators (KPIs) for assessing the proposed control strategy. Finally, Section 5 presents and discusses the results, and Section 6 details the conclusions and future work.

2 Problem statement and research goal

In the non-residential HVAC domain, central heating systems using water circulation are commonly used. Generally, a boiler heats water through combustion of gas, among other fuels. Then, the heated water is distributed to the emission elements such as radiators or fan-coils using pumps, and the water returns to the boiler [10]. Buildings with radiators tend to need more time to achieve thermal comfort, due to thermal inertia. Such buildings generally require an extra effort to manage discontinuities during operation time.

Many control methods have been developed or proposed in the literature for HVAC systems (see [14] and [17] for a summary). According to Afram and Janabi-Sharifi [17], control methods for HVAC systems are divided into classical control (on/off, P, PI, and PID control), hard control (gain scheduling, nonlinear, robust and optimal control and model predictive control), soft control (fuzzy logic and neural network control), and hybrid control (fusion of hard and soft control techniques). Even so, a classical control approach based on an on/off, P, PI or PID control with a schedule is still used in many HVAC systems [15]. This approach cannot optimize energy use as it does not take into account the uncertainty that affects the surrounding environment due to weather conditions, internal loads caused by occupancy dynamics, or external factors such as energy grid dynamics [15]. As a result, the performance of these systems is low.

The main cause of the extended use of the classical approach is that nowadays most BEMS available on the market are reactive rule-based [18]; this means that when an event occurs an action is produced. In terms of analysis, existing BEMS are only capable of carrying out simple data analysis and visualization functions [12]. Hence, they cannot learn over time [19] or predict future events or scenarios. In addition, the interoperability of the BEMS available on the market is very low, and this makes it difficult to implement external control modules [20]. As a consequence, it is difficult to implement proactive control strategies.

Another relevant aspect is that data recorded by BEMS are usually underused [10]. Data stored in BEMS are rarely interpreted and utilized to obtain knowledge for improving building operational performance [12]. According to Domínguez et al. [10], this is due to the fact that operators do not have the skills to exploit the large amount of data available in BEMS, and only create basic graphs of independent variables. However, it is undeniable that the building automation industry needs to implement tools to analyse the captured information, to help to analyse data and provide actions to optimize the building operational performance [12].

One common energy efficiency measure is adjustment of the temperature set point according to occupancy [21–23]. Conventional HVAC control systems relax the thermal set points when the building is presumed to be unoccupied, for example at night [9]. Temperature setbacks have been well-studied in the literature, with reports of good energy saving results [24,25]. However, the challenge in implementing the setback approach is to ensure thermal comfort during occupied times [24]. Temperature set points should be changed with enough time to start conditioning the building or room to ensure thermal comfort when the occupants arrive. The time required for conditioning a building or room depends on the HVAC system, building characteristics and weather conditions [25]. Usually, the building energy manager's experience is used to determine the time needed to condition the building, and it is scheduled in the BEMS.

This paper addresses the issue about how to implement predictive control in a commercial BEMS. More precisely, it focuses on how to determine the optimal time to turn on the boiler each day to achieve the target temperature at 8.00 am, the time when the building starts operation. To solve this problem, the historic data of two heating seasons were used to develop predictive control. The proposed control system was based on a neural network that determined the optimum time to turn on the boiler each day to achieve comfort levels at the beginning of the day.

3 Building description and operation

The proposed control strategy was implemented in the *Universitat Politècnica de Catalunya's* (UPC) building TR8. This is an academic building constructed in 1992, with 3 floors and 5,333.03 m^2, located in Terrassa (Barcelona, Spain). Table 1 presents the main characteristics of the building.

The building heating system was comprised of a boiler with a nominal power of 360 kW fuelled by natural gas. The hot water produced in the boiler was distributed through

4 pumps to the radiators that were located in the different zones of the building, and then the water returned to the boiler.

The boiler was managed by a BEMS using a scheduled on/off control strategy. The building BEMS enabled the building energy manager to schedule the time when the boiler should be turned on and off each day from his computer. Every two or three days, the building energy manager analysed the internal temperature curve through the BEMS and adjusted the time when the boiler had to be turned on to achieve an average internal temperature of 20 degrees at 8.00 am. Throughout the rest of the day, the system was regulated automatically with proportional regulation to achieve an average internal temperature of 22ºC. One hour before the end of the working day, the boiler was turned off. During the coldest months, usually from mid-November until the first week of March, the building energy manager did not turn off the boiler at all. The boiler worked 24 hours a day, 7 days a week. It was considered that the effort required to change the boiler schedule each day was higher than the energy savings produced. In addition, before the proposed control was implemented, the building energy manager did not have any tools to assess the time needed to condition the building. As a consequence, it was difficult to manage the boiler schedule without compromising the users' thermal comfort. Therefore, the control policy applied before the implementation of predictive control was based on maximizing the users' comfort and avoiding user claims.

The existing BEMS had a set of 22 temperature sensors located in the building. Temperature sensors were placed in representative rooms and corridors covering the entire building area and distributed evenly. The mean of the sensors was used to carry out the proportional regulation. In addition, every quarter of an hour the mean of all temperature sensors was stored in the BEMS. The external temperature was also measured with one temperature sensor and one value every quarter of an hour was stored in the BEMS. Finally, the building BEMS also monitored the performance of the boiler via a temperature sensor in the water circuit located after the boiler, and a gas meter that measured the cumulative gas consumption. Both boiler performance measurements were stored every quarter of an hour.

The BEMS implemented in the building was a commercial BEMS that could take inputs from the system, carry out a set of basic logic functions, and provide an output. In addition, the system enabled the configuration of schedules to turn on and off elements, or change temperature set points. Therefore, the installed BEMS could not execute iterative processes. The challenge of this research was to develop and implement predictive control in this existing BEMS.

4 Methodology

This section describes the methodology used to develop and test the proposed predictive control based on a neural network. First, experimental data from two heating seasons were used to obtain the training patterns. Then, various neural network structures were tested and the best one was used to develop and implement the predictive control strategy in the existing BEMS. Finally, a set of KPIs were used to assess the benefits of the control strategy (Fig. 1).

4.1 Predictive control using a BEMS

The proposed control strategy was designed to predict when the boiler should be turned on every day to achieve 20ºC at 8.00 am without human intervention. The prediction was based on a neural network with: (i) one output, the time required in quarters of an hour for conditioning the building at 20ºC; (ii) one hidden layer, with n neurons; and (iii) 3 inputs, the average internal temperature, the external temperature and the water heating system temperature. This section details how the training patterns were obtained, how the neural network was developed, which control algorithm was proposed, and how it was implemented in the BEMS.

4.1.1 Training patterns

Data stored in the existing BEMS were used to obtain the training patterns for the neural network. The input in the training patterns were the internal temperature (T_i), the external temperature (T_e) and the temperature of the water circuit (T_w). The output of the training patterns was the time in quarters of an hour required to condition the building at 20ºC (t_m).

A total of 145 training patterns were obtained from two heating seasons stored in the BEMS.

4.1.2 Neural network structure

The success of using neural networks to carry out predictions depends on the design of the neural network structure [26]. The choice of input data and the number of neurons used in the hidden layer are critical aspects. However, there is no science for this; it is a matter of trial and error [27].

Two empirical formulas are used in the literature to determine the optimal number of hidden neurons (Eq.1 and Eq.2) [28,29].

[Eq. 1]

$$N_h = 2 \times N_i + 1$$

[Eq. 2]

$$N_h = 1/2 \times (N_i + N_o) + \sqrt{NTP}$$

Where N_h is the number of hidden neurons, N_i is the number of inputs, N_o is the number of outputs, and NTP is the number of training patterns.

Various neural network structures were tested with different numbers of neurons in the hidden layer. Eq. 1 and Eq. 2 were used to determine the minimum and maximum number of neurons in the hidden layer, according to the number of inputs and the number of training patterns. When we used Eq. 1, the minimum number of neurons in the hidden layer was 7, and when we used Eq. 2, the maximum number of neurons in the hidden layer was 14.

The activation function generally used in the literature for neurons in the hidden layer is sigmoid or hyperbolic tangent [30]. For the output layer neurons, the best solution is to use a linear function [31]. In this research, the hyperbolic tangent was used in the hidden layer and a linear function was used for the output layer.

The software used to calculate the weights and assess the performance of the neural network was the Neural Network Toolbox from Matlab R2014b. The training algorithm used in this research was the Levenberg-Marquardt algorithm.

The structure with the best performance was a neural network with 10 neurons in the hidden layer. The root mean square error reported for the best model was 2.38 quarters of an hour, and the correlation between the actual and predicted data was 0.96. These values were considered acceptable and the model was implemented in the BEMS to test the proposed predictive control strategy.

4.1.3 Predictive control implementation in the existing BEMS

The algorithm implemented in the BEMS to carry out predictive control is presented in Fig. 2. When the boiler was turned off and the building internal temperature was lower than 20ºC, the BEMS was assessed every quarter of an hour, which was the time needed to achieve 20ºC through the implemented neural network. The predicted time (t_p) was calculated using the internal temperature (T_i), the external temperature (T_e) and the water heating system temperature (T_w). The prediction was compared with the time until the start of the next working day (t_w). When the predicted time was higher than the time until the start of the next working day, the BEMS turned on the boiler. During the rest of the day, the system was regulated automatically with proportional regulation to achieve thermal comfort with the same setup as before predictive control implementation. One hour before the end of the working day, the boiler was turned off.

The predicted time (t_p) was calculated using the neural network defined in the previous section. The mathematical formulation of the neural network was implemented in the BEMS. It was not possible to implement the learning algorithm, because the BEMS could not do the required calculations. Hence, the implemented neural network was static: the weights of the neural network did not change during the time.

Fig. 3 presents the block diagram of the implemented neural network in the BEMS. Input boxes normalize the values of T_i, T_e and T_w. For example, the formula introduced in Input 1 is:

[Eq. 3]

$$Input\ 1 = \frac{(T_{i_{cur}} - T_{i_{min}}) \times 2}{(T_{i_{max}} - T_{i_{min}})} - 1$$

Where $T_{i_{cur}}$ is the current value of T_i provided by the BEMS, $T_{i_{min}}$ is the minimum value of T_i in the training patterns, and $T_{i_{max}}$ is the maximum value of T_i in the training patterns.

NH_i boxes are the weighted sum of the three inputs and the bias. Each NH_i box has its own weights ($w_{NH_i,j}$) and bias (b_{NH_i}) (Eq. 3). Then, the hyperbolic tangent of each NH_i is calculated (Eq. 4). Subsequently the output is calculated as the weighted sum of the 10 neurons of the hidden layer and the bias (Eq. 5). The weight of each neuron is denoted as Lw_i , and the bias as b_{output}. Finally, the predicted time is calculated using Eq. 6, where $t_{m_{max}}$ is the maximum value of t_m in the training patterns, and $t_{m_{min}}$ is the minimum value of t_m in the training patterns.

[Eq. 3]

$$NH_i = \sum_{j=1}^{3} \left(Input_j \times w_{NH_i,j}\right) + b_{NH_i}$$

[Eq. 4]

$$tanh_i = \frac{e^{NH_i} - e^{-NH_i}}{e^{NH_i} + e^{-NH_i}}$$

[Eq. 5]

$$output = \sum_{i=1}^{10} (tanh_i \times Lw_i) + b_{output}$$

[Eq. 6]

$$t_p = \frac{(output + 1) \times (t_{m_{max}} - t_{m_{min}})}{2} + 1$$

To assess the performance of the proposed control strategy, the neural network was tested during one heating season. In this study, the heating season was considered to be from November to April.

4.2 Assessment of the control algorithms' performance

To assess the benefits of each implementation, a set of 3 key performance indicators (KPIs) were used: energy savings, interior building temperature at the beginning of the working days, and energy manager hours to manage the system. These KPIs were selected because they cover all aspects of the heating system operation: the supply costs due to gas consumption, the users' thermal comfort, and the operational costs due to the maintenance and management of the boiler.

The first KPI, energy savings, was calculated using the International Performance Measurement and Verification Protocol [32]. IPMVP establishes that energy savings can be determined by comparing measured energy use before (at baseline) and after implementation of energy savings measures. The protocol proposes adjusting the baseline to take into account changes due to weather conditions, occupation or building physical changes. Adjustments can be divided into routine adjustments and non-routine adjustments. Routine adjustments are parameters that can be expected to happen during the reporting period and for which a relationship with energy consumption can be identified. Non-routine adjustments are known changes in the facility during the reporting period, such as increments of building surface or increments in building time use [32].

[Eq. 7]

$$E_s = E_{baseline} - E_{reporting} \pm A_{routine} \pm A_{nonroutine}$$

Where $E_{baseline}$ is the building energy consumption during the baseline period, $E_{reporting}$ is the building energy consumption during the implementation, and the adjustments are $A_{routine}$ and $A_{nonroutine}$. The literature agrees that gas energy consumption is linearly correlated with heating degree days (HDD) [33,34]. According to the literature, the routine adjustment is considered a linear function in which the variable is the HDD. The base year gas energy consumption data were analysed through a linear regression performed on monthly energy consumption and HDD (denoted in the following as $HDD_{scenario,\ i}$), in order to obtain the coefficients m and b of the linear equation. The analysed period was one heating season with monthly granularity.

[Eq. 8]

$$A_{routine} = (m \cdot HDD_{scenario,\ i} + b) - E_{base\ year,\ i}$$

HDDs are defined as simple subtractions of the external temperature (T_e) from the base temperature (T_{base}), considering only positive values [35]. The base temperature is the external temperature above which the building does not have thermal demand [36]. To determine the daily gas energy consumption, the daily external average temperature was used. A regression was performed and the independent parameter was set as the base temperature. In order to calculate the HDD for month i, the daily HDD were aggregated.

[Eq. 9]

$$HDD_{scenario,\ i} = \sum_{n=1}^{k_i} \left(T_{base} - T_{e,\ n}\right)\ if\ T_{e,\ n} < T_{base}$$

Where k is the number of days of the month i, T_{base} is the baseline temperature and $T_{e,\ n}$ is the average external daily temperature. T_{base} is determined by a linear regression between daily gas energy consumption and daily mean external average temperature.

Non-routine adjustments were discarded, because no physical changes occurred during the reporting periods.

In order to calculate the monthly energy savings, Eq. 7 and Eq. 8 were combined. The resulting equation used to calculate the savings of each month is presented below:

[Eq. 10]

$$E_{s,\ i} = E_{baseline,\ i} - E_{reporting,\ i} + (m \cdot HDD_{scenario,\ i} + b) - E_{baseline,\ i}$$

Where $E_{baseline,\ i}$ is the building energy consumption during month i from the baseline period, and $E_{reporting,\ i}$ is the building energy consumption during month i from the implementation period. Simplifying Equation 11, we obtain the formula to calculate monthly savings.

[Eq. 11]

$$E_{s,\ i} = (m \cdot HDD_{scenario,\ i} + b) - E_{reporting,\ i}$$

To calculate the energy savings of the entire heating season, all monthly energy savings were aggregated.

[Eq. 12]

$$E_s = \sum_{i=1}^{t} E_{s,\ i}$$

Where E_s are the savings for the entire heating season, and $E_{s,\ i}$ represents the savings for month i.

In order to ensure that the boiler efficiency do not varies before and after the implementation, a Testo 330-2 LL was used to measure the boiler’s efficiency. The boiler efficiency was measured at the beginning of the baseline period and at the beginning of the report period.

The second KPI used was the interior building temperature at the beginning of the working days. A boxplot was used to display the aforementioned temperature, because it enables easy characterization and comparison of distributions. The beginning of the working days was considered 8 am, because this was when users started to arrive in the building.

Finally, to assess the costs of boiler operation and maintenance, the third KPI was the number of hours required by the building energy manager to operate the system. The number of hours per heating season that the building energy manager spent managing the system was recorded.

5 Results and discussion

The control strategy was tested during the period October 2015 to April 2016. In this section, the results of the KPIs used to assess the benefits of the implementation are presented and discussed.

5.1 Energy baseline analysis

The linear analysis of the daily gas energy consumption and the daily external average temperature reported that the base temperature for the building used in this research was 17ºC. This value was used to calculate the daily HDD and the monthly HDD.

The linear analysis of the baseline data revealed a reasonable correlation between the HDD and the gas energy consumption. The resulting values of the linear regression are 41.0 m^3/HDD for parameter m, and 2,349.8 m^3 for parameter b (Eq. 8). The variance showed by the linear model compared to the total variance of the sample was 90%; consequently 90% of the gas energy consumption variance could be explained by the

HDD. As a result, the assumption related with the routine adjustment can be used to calculate the energy savings.

5.2 Assessment of the proposed control strategy

The monitored gas energy consumption during the baseline period was 32,299.40 m^3, the adjusted gas energy consumption baseline was 28,779.82 m^3, and the monitored gas energy consumption during the reporting period was 22,418.19 m^3 (Fig. 4). As a result, the control approach proposed in this research allowed 19.69% gas energy consumption savings (Table 2). Usually, savings achieved by implementing a BEMS are 14.07% on average [14]. Consequently, the approach followed in this research gives better results than other approaches presented in similar studies.

The boiler efficiency at the beginning of the baseline period was 92.2%. In the other hand, the boiler efficiency at the beginning of the reporting period was 90.6%. The boiler efficiency at the beginning of the reporting period was slightly lower than at the beginning of the baseline period. As a consequence, reported savings are slightly underestimated and can be attributable to the proposed approach.

Reported savings are correlated with external temperature (Fig. 5). The proposed predictive control reported highest savings during November, March and April (Fig. 6). The external mean temperature of these months is closer to the building's base temperature than in the other months. In addition, during the aforementioned months the difference between the highest temperature and lowest temperature is slightly greater than in the rest of the months. During the coldest months (December, January and February), savings were lower. Although December and January were colder months than February, savings reported in December and January were higher than in February.

This is because there are usually more holidays in December and January than in February, due to the Christmas break. During the baseline period, the building energy manager did not have any tools to determine the optimal time to turn on the boiler in order to ensure thermal comfort at the beginning of the working day. During official holidays in the coldest months, the boiler was not turned off in order to ensure the users' thermal comfort at the beginning of the next working day. After implementing the predictive control one hour before the end of the working day, the boiler was turned off each day, including the days in the coldest months. The predictive control determined the optimal time to turn on the boiler in order to achieve the expected thermal comfort at the beginning of the next working day.

In this way, the proposed predictive control could reduce the energy consumption and maintain the thermal comfort levels (Fig. 7). The control policy applied during the baseline period was based on maximizing the users' comfort. In contrast, predictive control was based on achieving a compromise between energy savings and users' thermal comfort.

The variability of the average internal temperature at the beginning of the working day was also reduced with the implementation of predictive control (Fig. 7). During the baseline period, the variability in average internal temperature at the beginning of the working day was 4.91ºC. During the testing period, this variability was 2.76ºC. The interquartile range was also reduced, from 1.77ºC in the baseline period to 0.85ºC in the testing period. The top whisker was increased slightly; however the bottom whisker was reduced significantly. The median was also reduced from 20.63ºC to 20.00ºC. Both boxplots were slightly skewed down and the average value was not equal to the median value. During the baseline period, this value was 20.36ºC, and during the testing period it was 19.86ºC. The standard deviation was reduced from 1.18ºC to 0.63ºC, and the coefficient of variation was reduced from 5.80% to 3.17%.

The variability in average internal temperature at the beginning of the working day during the baseline period was due to the boiler being turned on without considering environmental factors. In the other hand, during the testing period the variability in temperature was produced due to the error in the estimation generated by the neural network. The error in the time estimation was greater on Mondays. Mondays did not have the same performance as the rest of the days of the working week because the boiler was turned off during the weekend. As a consequence, it took considerably longer to condition the building on Mondays than on the other days of the working week. The reduced number of these singularities in training patterns led to a reduction in the accuracy of the trained neural network for Mondays. The neural network learns from past experiences and the more data it has, the more accurate the predictions are.

The predictive control also reduced the costs of boiler operation because the system was completely autonomous. The proposed control strategy did not require any action from the building energy manager.

6 Conclusions

This paper presented a predictive control strategy, based on neural networks, which can be implemented in most commercial BEMS. The proposed strategy assesses the time required to condition the building, and compares this value with the time until the start of the working day.

In this study, the boiler was turned off when the building was supposed to be unoccupied; basically at night and during weekends and holidays. Before the start of a working day, the system predicts the time required to condition the building. This time is compared with the time until the start of the working day. When the time required to condition the building is equal or higher than the time until the start of the working day, the boiler is turned on.

The results of the testing period revealed that the proposed control strategy reduced gas energy consumption by 19.69%, without compromising the building users' thermal comfort. Savings increased in the months in which the external temperature was closest to the base temperature. In addition, the proposed system was automatic, and did not require any action by the energy manager to optimize energy consumption. The reported savings were higher than those in similar studies that proposed control strategies based on commercial BEMS.

Further research is needed to reduce the amount of data required to configure the predictive algorithm. The configuration of the proposed control algorithm required two heating seasons to train the neural network. This is a limitation, because the system can only be implemented in buildings with historical data. One solution could be to use building simulation tools to generate the data required to train the neural network.

Although the coefficient of variation of the temperature at the beginning of the working day is low (3.17%) and the average temperature is close to the target value, simulation tools can also be used to generate data in order to improve the accuracy of the predictions. This variability could also be improved by introducing other inputs in the neural network. The neural network topology used in this research was only based on the external temperature, the internal temperature and the heating system temperature. However, in the future, other input related with minimum external temperature or the decrease in internal temperature should be assessed.

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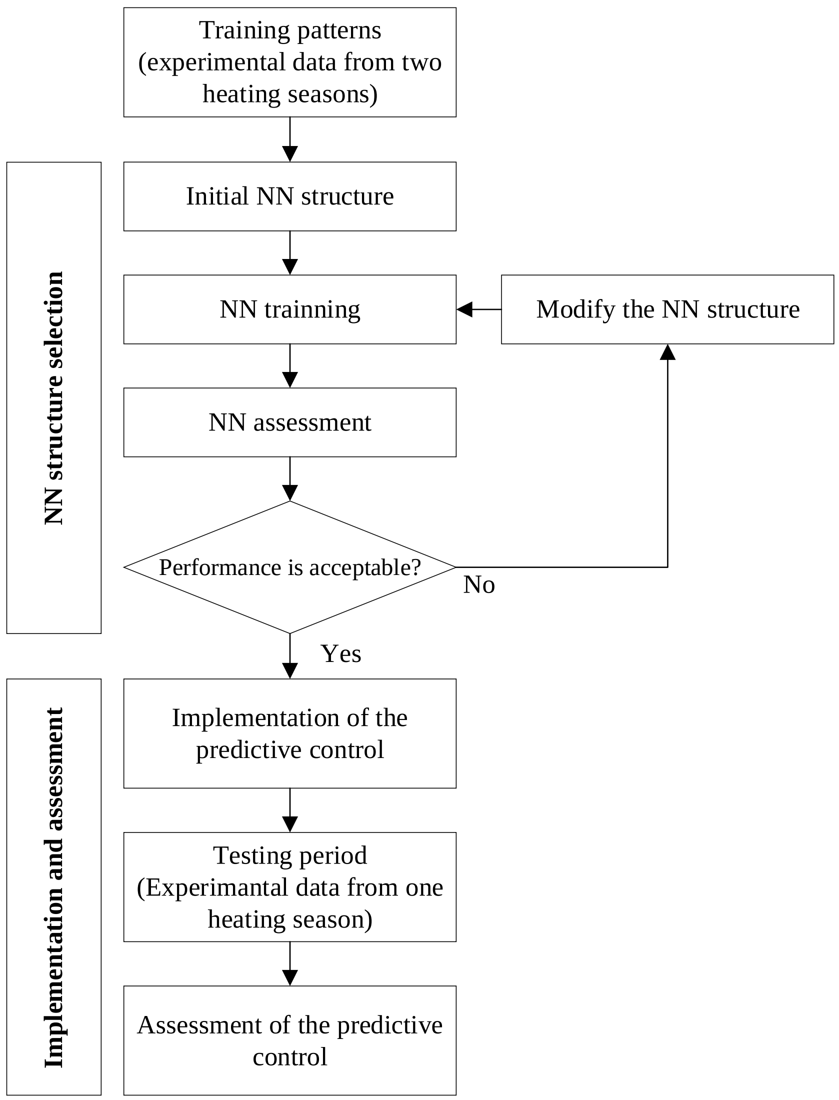

Fig. 1. Research methodology

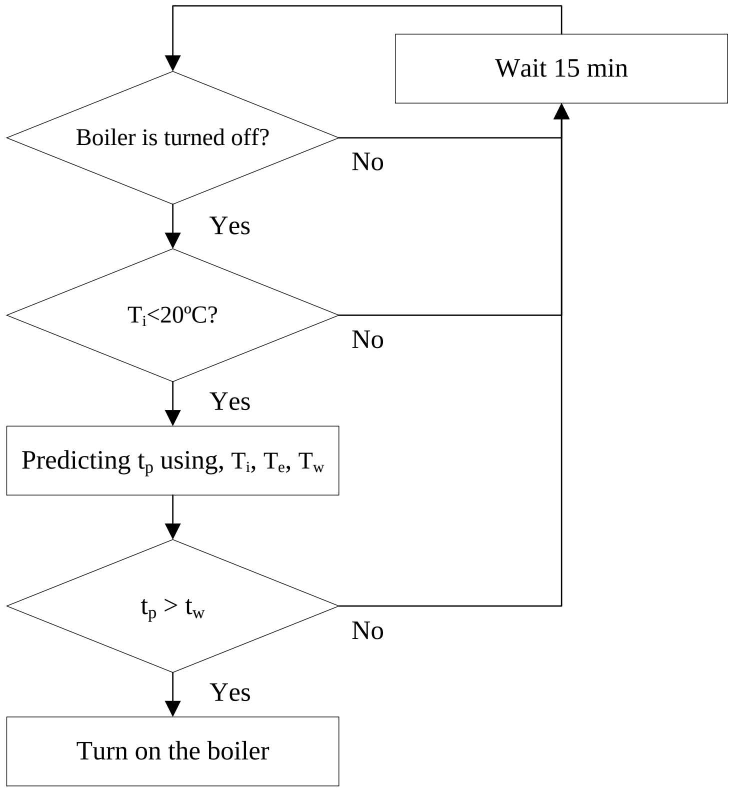

Fig. 2. Proposed control strategy flow chart

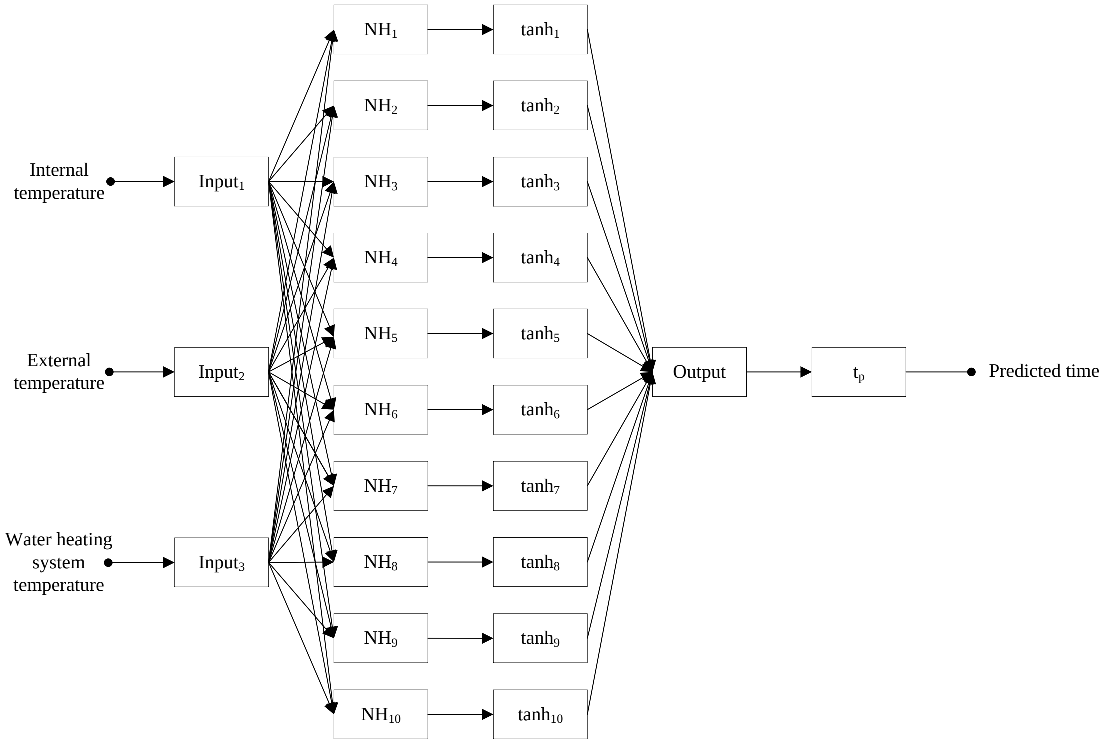

Fig. 3. Block diagram of the implemented neural network in the BEMS

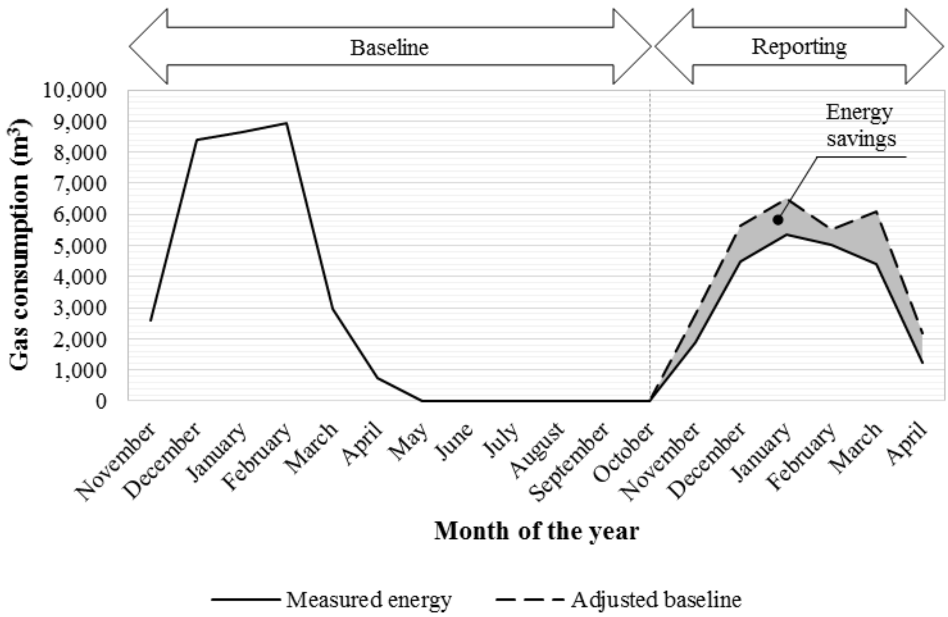

Fig 4. Measured gas energy consumption during the baseline period and the reporting period, and the adjusted gas energy consumption baseline

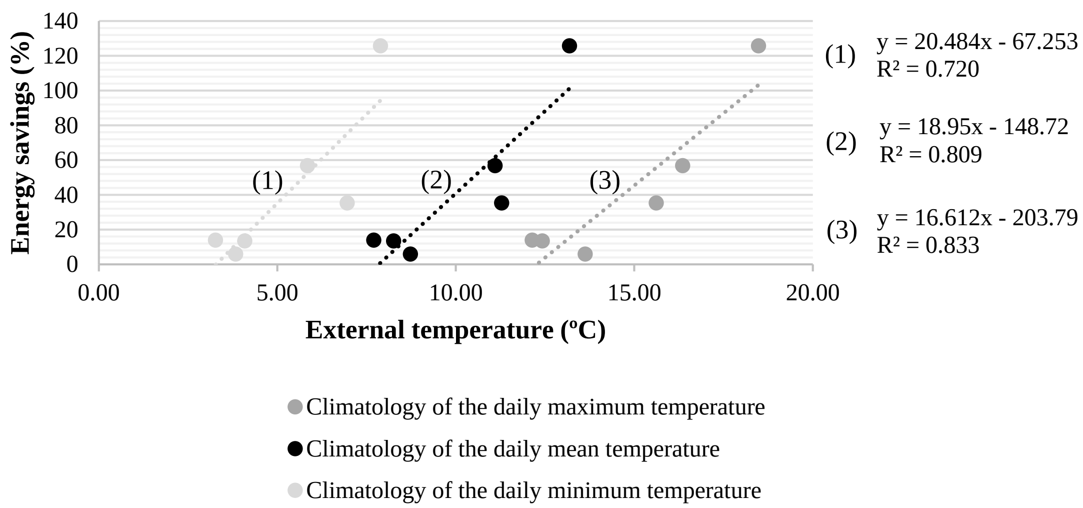

Fig 5. Correlation between energy savings and climatology of the daily maximum, mean and average temperature from 1965 to 2015

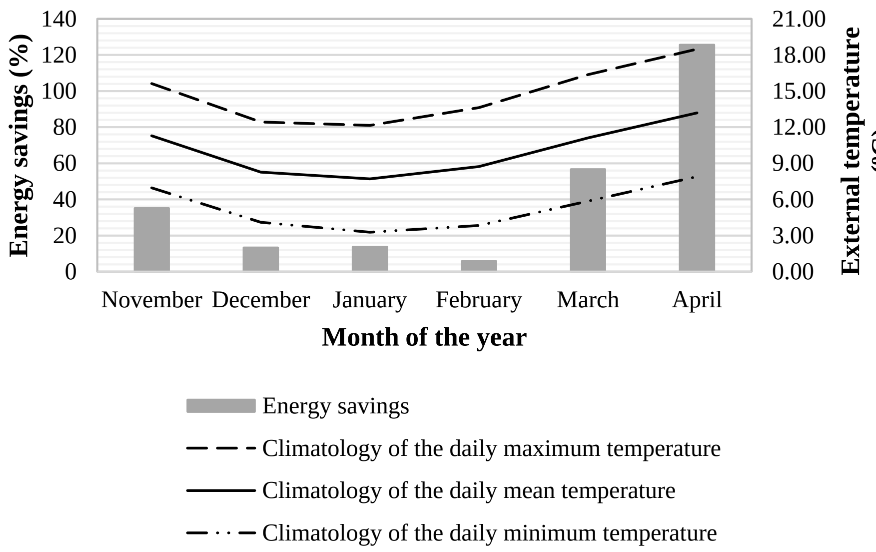

Fig 6. Reported monthly energy savings (primary y-axis), and monthly climatology of the daily maximum, mean and average temperature from 1965 to 2015 (secondary y-axis)

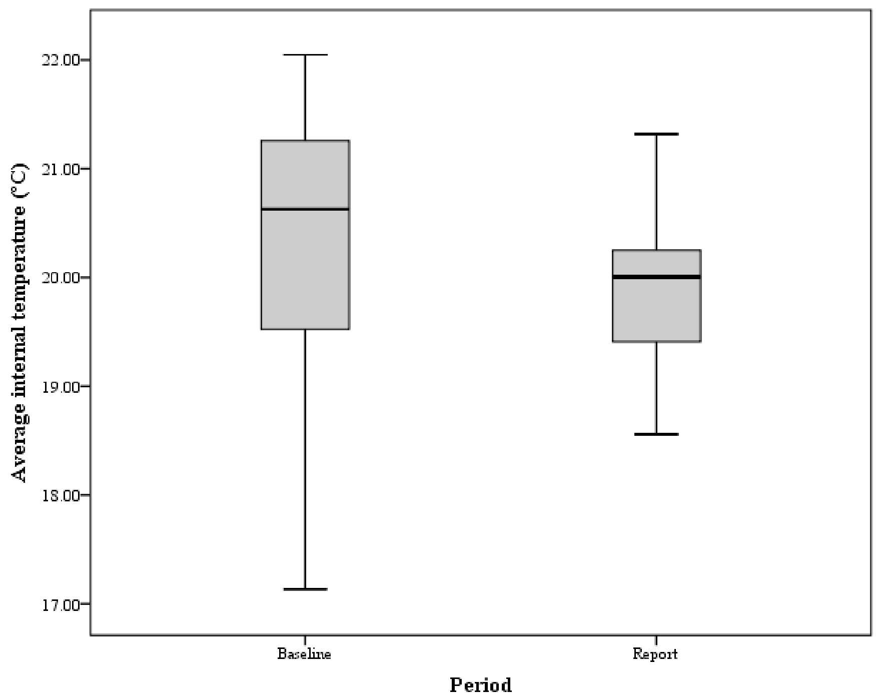

Fig. 7. Average internal temperatures at the beginning of the working day

Table 1. Building characteristics

	Surface (m^2)	Thermal transmittance ($W/m^2 \cdot K$)
Façade	2,987.16	1.20
Roof	2,005.30	0.82
Windows	961.19	5.76

Table 2. Summary of KPIs to assess different implementations

	Baseline	Reporting
Energy savings during the entire heating season (%)	-	19.69
Energy savings in the period February-March-April (%)	-	24.79
Boiler efficiency (%)	92.2	90.6
Average interior building temperature at the beginning of the working days (ºC)	20.36	19.86
Standard deviation (ºC)	1.18	0.63
Coefficient of variation (%)	5.80	3.17
Energy manager hours to manage the system (h)	44	0