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

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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.

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 life-cycle 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.

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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 °C 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 22 °C. 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 h 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,

Table 1
Building characteristics.

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