Energy and Buildings 152 (2017) 409–417

Contents lists available at ScienceDirect

Energy and Buildings

journal homepage: www.elsevier.com/locate/enbuild

An energy-efficient predictive control for HVAC systems applied to tertiary buildings based on regression techniques

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A R T I C L E   I N F O

Article history:
Received 12 April 2017
Received in revised form 4 July 2017
Accepted 17 July 2017
Available online 24 July 2017

Keywords:
Heating ventilation and air conditioning (HVAC)
Building energy management system (BEMS)
Energy efficiency
Optimisation algorithms
Building automation
Thermal comfort
Supply air temperature optimal control

A B S T R A C T

Heating ventilation and air conditioning (HVAC) systems represent an important amount of the total energy use in office buildings, accounting for near 30%. Moreover, in countries affected by extreme climates HVAC systems' contribution to energy demand increases up to 50%. Therefore, the automation of energy efficient strategies that act on the Building Energy Management System (BEMS) in order to improve building energy use becomes increasingly relevant. This paper delves into the devising of a novel HVAC optimization framework, coined as Next24h-Energy, which consists on a two-way communication system, an enhanced database management system and a set of machine learning algorithms based on random forest (RF) regression techniques mainly focused on providing an energy-efficient predictive control of the HVAC system. Therefore, the proposed framework achieves optimal HVAC ON/OFF and mechanical ventilation (MV) schedule operation that minimizes the energy consumption while keeps the building between a predefined indoor temperature margins. Simulation results assess the performance of the proposed Next 24 h-Energy framework at a real office building named Mikeletegi 1 (M1) in Donostia-San Sebastian (Spain) yielding to excellent results and significant energy savings by virtue of its capability of adapting the parameters that control the HVAC schedule in a daily basis without affecting user comfort conditions. Specifically, the energy reduction for the test period is estimated in 48% for the heating and 39% for the cooling consumption.

1. Introduction

As mentioned by the Independent Statistics & Analysis of the U. S. Energy Information Administration in 2015, office buildings represent nearly one-fifth of all delivered energy consumed by commercial buildings, and are therefore an important focus for energy efficiency improvements. In fact, median savings from the existing building commissioning was 15% of the whole building energy use [1]. These energy improvements usually depend on the optimal operation strategy implemented at the building energy management system (BEMS), which is the agent responsible for reducing the energy consumption while ensuring user comfort conditions. Nowadays there is a lack of approaches unifying both developments, i.e. the design of optimal energy efficient strategies and its integration for interacting with BEMS. In this context, authors in [2] state that there is already a gap between sensor deployment infrastructures and facility manager's real actuations.

As widely known, energy demand in office buildings has a large variability depending on the time and the day of the week which severely affects the energy consumption. Consequently, in order to maximize energy savings in an office building's domain, the automation of optimization procedures which dynamically adapt the HVAC operation mode to the indoor and outdoor conditions becomes essential. Otherwise energy improvements highly depend on an important human component, i.e. the facility manager of the building, which should act on the BEMS at specific times for ensuring energy efficiency.

In this context, previous studies [3–10] deal with the dynamic optimization problem for building heating and cooling systems based on three main approaches: (1) physical based models; (2) grey-box models; and (3) black box models. From the first to the latest the knowledge of the structural building characteristics, the computational complexity and the effort to be implemented is decreased while generalization capabilities are gradually increased. The first two approaches involve static conditions based on complex differential equations, heat and mass balance equations and a deep knowledge of the thermal characteristics of the building. This results in a large engineering knowledge, intensive computer simulations and a need of considerable simulation time to

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http://dx.doi.org/10.1016/j.enbuild.2017.07.056
0378-7788/

model the building in order to provide accurate predictions. In this sense, authors in [11] propose optimization techniques based on dynamic programming providing an ON/OFF schedule and temperature set-points for optimizing the cost function and avoiding peak electrical demand. Nevertheless, in this case the authors assume non-realistic conditions, such as a perfect weather forecast, and also a deep knowledge of thermal building characteristics. In order to characterize the thermal building performance, authors consider the heat balance equations whose parameters are determined by means of employing the building heat transfer simulation program `HASP/ACLD/8501`. Authors in [12] use the `TRNSYS` dynamic model for the evaluation of energy saving techniques in HVAC systems, such as heat pumps with heat recovery. In the same line of research, `DOE-2` is another building energy analysis program especially designed for allowing engineers to perform design studies of building energy use under certain weather conditions [13]. [14] in his thesis employs `DOE-2` as a fitness function providing building energy and cost calculation to be hybridized with a Genetic Algorithm as an optimization procedure. The proposed grey-based algorithm optimizes building control parameters such as: indoor temperatures, shade position, artificial light power, and outdoor air ventilation rates for an entire building achieving savings between 10 and 30% in a typical building in Montreal. With the aim at reducing the computational complexity of the hybrid schemes, the authors in [15] propose a Neural Network (NN) approach as a multi-parametric non-linear forecast procedure. In this case `DOE-2` is employed as a tool for generating the training and testing data to be used in a mixed expert system based on a fuzzy-neural assistant prediction, which has shown significant advantages for optimizing building energy use as a dynamic method. Another highly employed solution is to call `EnergyPlus` module as an hourly energy building simulation. `EnergyPlus` is a modular loop based method which estimates thermal zone loads based on heat balance equations [17].

Dealing with the numerous drawbacks of physical based approaches, authors in [18] explain the causes of the cost function's discontinuities present in the above-mentioned building simulation programs and evaluate a set of algorithms for such optimization problems with different smoothness levels. The authors show that due to the computational complexity of these methodologies, stochastic optimization algorithms are employed using a reduced set of simulations which conditioned the probability to be stacked at a local minimum, reducing their accuracy. As mentioned in [19] practical applications demonstrate that there exist large discrepancies in results from different models using distinct Building Energy Modeling programs. Therefore, the authors in this work summarize methodologies, processes and the main assumptions of three widely used simulation tools which could be responsible for those discrepancies. Due to the above-mentioned limitations of both physical and grey box approaches, in the last decade an upsurge of black box models based on machine learning procedures [20–24] has emerged. More specifically, in [23] the authors present a Support Vector Machine black box model to learn the features of the thermal model of a room.

More recent studies propose the integration of these approaches with the existing BEMS using a specialized web based approach [24]. The main advantage of analytical approaches based on machine learning procedures is that they operate as black box models, learning the relationship between inputs (environmental magnitudes) and outputs (control parameters) based only on the study of previously recorded data. Consequently, if it is assumed that the dynamic relationship between the weather and occupancy magnitudes which affect building energy consumption is recorded in the historical data, the use of black box models provides higher generalization capabilities without the necessity to spend a huge amount of time and effort developing physical or grey-box based models. Another advantage of black box models is that they can be adapted to dynamic responses of the building due to possible buildings' structure changes, such as windows replacement or others affecting building energy consumption, just selecting the adequate training data set which is affected by these structural changes.

This paper advances over the state of the art in building energy management optimization by presenting a novel framework, hereafter coined as Next 24 h-Energy, for providing an optimal energy-efficient predictive control of the HVAC system in terms of two main actuators: (1) HVAC ON/OFF and (2) Mechanical Ventilation (MV) schedule operation optimization. The main core of the Next 24 h-Energy framework is based on an internal temperature estimation, based on Random Forest (RF) techniques, with utilizes a minimal set of measured magnitudes trying to provide its maximum generalization capability to other locations or building characteristics. The automation of this optimization procedure integrated with the BEMS is implemented in a real office-building in Mikeletegi 1 (M1) in Donostia-San Sebastian (Spain) demonstrating its energy savings' capabilities. In order to perform the simulations, specific indoor conditions of office buildings in Spain based on the Royal Decree 1826/2009 in [25] are considered. In summary, it defines among other conditions indoor temperatures between 21 and 26 °C (Celsius degrees).

The paper is organized as follows: Section 2 presents the proposed methodology: M1 office building characteristics, the HVAC description and the test deployment architecture and the proposed Next 24 h-Energy optimizer. Section 3 presents the simulation and tests results of the proposed approach and outlines the energy savings results. Finally, Section 4 ends the manuscript by presenting the conclusions extracted from this work and by outlining future research lines.

2. Methodology

2.1. Site M1 office building characteristics

Mikeletegi 1 (M1) is a 8500 m^2 office building located in Donostia-San Sebastian, Spain. The building area is divided in three floors that are vertically split into two identical parts (North and South orientation) by the common areas. Fig. 1 depicts the North side of the second floor area under which the simulation tests have been carried out. It can be observed that the main area is an open plan space with some cellular offices and meeting rooms located in the perimeter areas.

2.2. HVAC system description and test deployment architecture

The main HVAC (heating ventilation and air conditioning) system is a centralized system consisting of an Air Handling Unit (AHU) which provides a constant tempered fresh air to all the spaces (open plan and perimeter areas). The final elements in the open plan area consist of 4 pipe Fan Coil Units (FCU). The AHU preconditions the outdoor air at a temperature set point by the facility manager and the FCUs then further provide heating or cooling to reach the set point temperature. In the open plan area there are three room thermostats that control three areas. The perimeter offices and meeting rooms also receive fresh air from the same AHU.

The heating and cooling required in the AHU and FCU are produced by two reversible air to water heat pumps. A centralised Building Manager System (BMS) controls parameters of the HVAC devices (heat pumps, AHU and fan coils).

Table 1 presents in detail the elements that form the HVAC system at M1 building considering the different sections: generation, distribution and control.