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Predictive control of multizone heating, ventilation and air-conditioning systems in non-residential buildings

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ABSTRACT

In France, buildings account for a large part of the energy consumption and carbon emissions. Both are mainly due to heating, ventilation and air-conditioning (HVAC) systems. Because older, oversized or poorly maintained systems may be using more energy and costing more to operate than necessary, new management approaches are needed. In addition, energy efficiency can be improved in central heating and cooling systems by introducing zoned operation. So, the present work deals with the predictive control of multizone HVAC systems in non-residential buildings. First, a real non-residential building located in Perpignan (south of France) has been modelled using the EnergyPlus software. We used the predicted mean vote (PMV) index as a thermal comfort indicator and developed low-order ANN-based models to be used as controller's internal models. A genetic algorithm allowed the optimization problem to be solved. In order to appraise the proposed management strategy, it has been compared to basic scheduling techniques. Using the proposed strategy, the operation of all the HVAC subsystems is optimized by computing the right time to turn them on and off, in both heating and cooling modes. Energy consumption is minimized and thermal comfort requirements are met. So, the simulation results highlight the pertinence of a predicitive approach for multizone HVAC systems management.

1. Introduction

Within non-residential buildings, almost half of the energy consumption is due to heating, ventilation and air-conditioning (HVAC) systems [1]. In addition, older, oversized or poorly maintained systems may be using more energy and costing more to operate than necessary. As a consequence, new approaches dealing with energy ressources management are needed to make HVAC systems more efficient. First, energy efficiency can be improved in central heating and cooling systems by introducing zoned operation. This allows a more granular application of heat and each HVAC subsystem can be controlled independently. Another key point is thermal comfort. Thermal comfort can be defined as "that condition of mind which expresses satisfaction with the thermal environment" [2]. It is mainly related to indoor conditions and impacted by both the effectiveness of the building envelope and the way the HVAC system is used.

Many research studies focusing on improving the operation of centralized or zoned HVAC systems have been conducted over the last few years. Recently, Haniff et al. provided a detailed review of basic, conventional, and advanced HVAC scheduling techniques [3]. First, the "interruption", "early switch-off" (ESO), "pre-heating (or pre-cooling) in the demand reduction" (DR), and "alternate switch-on/off" (ASOO) basic scheduling techniques are discussed. The "interruption" technique consists in suspending the HVAC operation for several hours during occupancy periods. In opposition, in case of the ESO technique being used, the HVAC system is (usually) stopped 2 h before people leave the building. The DR technique is about pre-heating (or pre-cooling, depending of the season of the year) a building during off-peak periods (i.e. non-occupancy periods). Finally, the ASOO technique is based on alternately switching on and off the HVAC system during office hours [4].

Usually, with a conventional scheduling technique, the HVAC system operates 24 h a day and the "night setback" mode allows energy saving objectives to be achieved. Note that, due to its simplicity, the "baseline" approach is widely used in HVAC management. With such an approach, the setpoint temperature value is chosen to be at the lower boundary of the thermal comfort zone

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Nomenclature

k	time index (–)
PMV_j	predicted mean vote in the room j of the building (–)
L_j	difference between the heat produced and the heat lost in the room j of the building (W m^{-2})
M_j	occupants' metabolic activity in the room j of the building (W m^{-2})
W_j	external work in the room j of the building (W m^{-2})
$H_{j,1}$	heat loss by diffusion through the skin in the room j of the building (W m^{-2})
$H_{j,2}$	heat loss by sweating in the room j of the building (W m^{-2})
$H_{j,3}$	heat loss by latent respiration in the room j of the building (W m^{-2})
$H_{j,4}$	heat loss by dry respiration in the room j of the building (W m^{-2})
$H_{j,5}$	heat loss by radiance in the room j of the building (W m^{-2})
$H_{j,6}$	heat loss by convection in the room j of the building (W m^{-2})
T_j^a	air temperature in the room j of the building (°C)
T_j^r	radiant temperature in the room j of the building (°C)
HR_j	relative humidity in the room j of the building (%)
v_j^a	air speed in the room j of the building (m s^{-1})
ICL_j	clothing thermal insulation in the room j of the building (clo)
T_6	outdoor temperature at 6 a.m. (°C)
T_{out}	outdoor temperature (°C)
P_j	consumption of electrical power in the room j of the building (kW)
O_j	occupancy in the room j of the building (–)
T_j^{sp}	HVAC temperature set-point in the room j of the building (°C)
T_l^{sp}	HVAC temperature set-point in the room l of the building (°C)
T_m^{sp}	HVAC temperature set-point in the room m of the building (°C)
$\tilde{T}_j^{sp}$	value of T_j^{sp} allowing to obtain PMV_j^{sp} in the room j of the building (°C)
PMV_j^{sp}	PMV set-point in the room j of the building (in the present study, $PMV_j^{sp} = 0$) (–)
t_j	right time to turn the HVAC susbsytem in the room j of the building on or off (–)
$\bar{t}$	vector bringing the optimal HVAC switching times together (–)
p	forecast horizon (–)
$PMV_j^{\min}$	thermal comfort threshold (in the present study, $PMV_j^{\min} = -0.5$) (–)
$PMV_j^{\max}$	thermal comfort threshold (in the present study, $PMV_j^{\min} = +0.5$) (–)
C_F	crossover fraction (genetic algorithm) (–)
A_M	amount of mutation (genetic algorithm) (–)
C	sum over all the output neurons of the magnitude of the correlation between V_e and $E_{e,o}$ (–)
$\partial C/\partial w_i$	partial derivative of C with respect to each of the incoming weigths of the candidate unit (–)
V_e	value of the candidate unit for example e (–)
$\overline{V}$	averaged value of V over all the training examples (–)
$E_{e,o}$	residual output error measured at neuron o (–)
$\overline{E_o}$	averaged value of E_o over all the training examples (–)
σ_o	correlation between the value of the candidate unit and neuron o (–)
f_e'	derivative of the candidate's activation function with respect to the sum of its inputs (for example e) (–)
$I_{i,e}$	input received by the candidate unit from unit i (for example e) (–)

during occupancy periods whereas the "night setback" mode is applied during innocupancy [5].

Advanced scheduling techniques can also be considered in HVAC management. So, Lee and Braun used short-term measurement data to determine demand-limiting control setpoint trajectories [6]. The authors developed three different methods, named "semi-analytical" (SA), "exponential setpoint equation-based semi-analytical" (ESA), and "load weighted-averaging" (LWA) methods, respectively. Each method gives an estimate of a building-specific setpoint trajectory that gives a "flat" cooling load profile during a specified demand-limiting period [7]. Another possible technique is the "5-period division" scheduling [8]. Using this technique, the day is divided into five periods, according to occupancy, with specific operation in each period. One can also talk about the "extended pre-cooling with zone temperature reset" technique [9]. Such an approach is based on varying the temperature setpoints and shifting the heating/cooling loads from daytime to night time [10]. The last advanced scheduling technique one can highlight is the "agressive duty cycling" technique [11]. Based on occupancy, the HVAC system is turned on and off many times in a day and, as a result, an efficient real-time detection of people is needed.

One can also highlight efficient approaches based on artificial intelligence tools. In Ref. [12], Gouda et al. proposed an efficient fuzzy controller for HVAC systems by taking into account a wide range of human comfort criteria in the control action formulation. In Ref. [13], Dounis and Caraiscos developed a multi-agent control system in order to manage air quality as well as thermal and illuminance comfort. As another interesting approach, Bermejo et al. designed a thermal comfort adaptive system based on fuzzy logic and on-line learning [14]. In most cases, these approaches require to turn the HVAC system on then off at fixed times. Consequently, this can impact thermal comfort negatively if the system is started too late or energy consumption if triggering happens too soon.

Another interesting option in HVAC management lies in considering predictive control techniques. As it has been highlighted by many other studies, these advanced techniques can take advantage of the intermittent use of non-residential buildings and allows the behaviour of the considered system to be anticipated [15]. In this sense, Paris et al. developed a model predictive controller (MPC) in order to control indoor temperature and minimize energy consumption in multi-energy buildings (buildings that use several sources of energy) [16]. In Ref. [17], Moroşan et al. proposed a distributed predictive approach to control several areas simultaneously, while taking into account thermal transfers. In this approach, thermal comfort is defined on the basis of a reference temperature. The proposed algorithm is useful but on-line optimization is needed and computation time is extensive. Because predictive control is well adapted to the management of energy resources, we recently developed a new approach allowing the HVAC operation in a non-residential building to be optimized by turning the subsystems on and off at the right time [18]. Only one operation mode (in that case, heating) has been considered. We used the

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