A MODEL-PREDICTIVE CONTROLLER FOR AIR HANDLING UNITS

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ABSTRACT

Heating and cooling for thermal comfort are the main consumers of energy in buildings, and there is a growing need to improve the energy efficiency (and thereby reduce CO_2 emissions) of these building services. The regular increase in energy tariffs only exacerbates the problem.

Building owners are seldom willing to invest in a deep retrofit that may lower their energy consumption, but are instead willing to replace their outdated HVAC systems. Indeed, off-the-shelf controllers are often based on (only) the outdoor temperature, and occasionally take into account the indoor temperature. In particular, practically no commercial systems take into account weather forecasts. Consequently, these control systems lead to poor comfort and sub-optimal energy efficiency.

In this paper, a novel model-predictive control (MPC) algorithm for fan coil units (FCU) is presented, which aims at reducing the operational costs while guaranteeing thermal comfort. It is planned to be deployed on a test site in Greece within the second half of 2015.

The simulation results are presented and compared to a standard PI controller. For the MPC based controller, the trade-off between the user comfort and the energy consumption of the will be presented and commented. Simulations have demonstrated energy savings of up to 57% compared with the reference controller. Results from field tests are expected by the end of 2015.

Keywords: thermal regulation, MPC

INTRODUCTION

Thermal comfort regulation, linked to Heating, Ventilating and Air Conditioning (HVAC), is one of the main energetic expenditure in buildings. In order to reduce that consumption, without degrading user comfort, two distinct, yet complementary paths can be taken. First, retrofit can be carried out. Extra insulation can be added to the walls and roof and the windows can be upgraded. Second, the means of controlling the temperature within the building can be changed. In this work, the second option was chosen.

It is shown in [1] that available control systems in buildings rely mostly on conventional techniques such as cooling curves, classical Proportional Integral Derivative (PID) controllers and fuzzy controllers. These are the most widely used controllers in the industry [2]. While PID controllers are an improvement compared to thermostats, they still have several issues, mainly due to the difficulty to choose the gain values [3]. To address this problem, self-tuning adaptive PID controllers based on recursive least-squares [4] and fuzzy control [5] have been developed. Other strategies include adaptive controllers, which have the ability to adapt according to climate conditions and building properties. Adaptive systems can include parameters estimation methods using Recursive Least-Squares (RLS) algorithms [6], genetic algorithms (GA) [7], nonlinear disturbance rejection controllers with thermal load estimation and fuzzy controllers [8]. In order to achieve simultaneous and often contradictory energetic and comfort objectives, model predictive control (MPC) strategies have been developed.

Ruano et al. [9] have used a multi-objective genetic algorithm (MOGA) for designing an off-line radial basis function (RBF) neural network (NN) model. When compared to a simple on-off control strategy the authors claimed a 27% reduction in the use of the air conditioner for a better thermal control. Ferreira et al [10] also used a predictive model implemented by RBF NN identified by a multi-objective genetic algorithm to minimize energy consumption while achieving a desired thermal comfort level.

In the present article, a Model-Predictive Control (MPC) algorithm applied for heating and cooling is presented. While the developed algorithm is meant to be used to control a Fan Coil Unit (FCU), it can easily be adapted for other devices, i.e. more generally an air handling unit (AHU), however for clarity reasons and given the test site specificities, the term FCU will be used throughout the article. The developed MPC controller is benchmarked against a PI controller.

The document is organized in four main sections. First the simulation environment, the model-predictive control (MPC) algorithm and the test case are presented. Second, the simulation results are presented. Third, the results are analysed and discussed. Finally, the works is summarized and an outlook is provided.

METHOD

Simulation environment

In order to develop and validate our MPC algorithm, a simulation environment had to be developed. Naturally, the various elements available on the test site had to be modelled with enough accuracy, so as to allow the porting of the work to the test site. The chosen simulation platform was MATLAB and Simulink. The main blocks are:

- Heater chiller[1]: simulates the heating/cooling of the water which is delivered to the fan coil units;
- Room[1]: simulates the thermal behaviour of the room (including the FCU);
- Controller: a PI and our MPC controller;
- Simulation inputs: weather, temperature set points and energy tariffs.

MPC controller

The MPC controller aims at guaranteeing user comfort while minimizing energy expenditure. Accordingly, the objective function is a weighted sum of the two following terms:

- Temperature error (comfort): its role is to penalize deviations between the indoor temperature and its setpoint
- Power consumption: its role is to penalize the cost of the energy consumption.

The formulation of the objective function is shown below (equation (1)):

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[1] The work was performed in the framework of the European project AMBASSADOR (Seventh Framework Programme Grant Agreement No. 314175) and is meant to be deployed on a test site in Lavrion (Greece) in the second half of 2015. The heater/chiller as well as simulated room model were developed by members of the AMBASSADOR consortium.

$$\underset{P_t,\forall t}{\text{minimize}} \sum_{t=1}^{N}\left[K_E \cdot C_t^2(P_t) + Occ_t \cdot K_C \cdot \left(T_t - \hat{T}_t(P_t, weather)\right)^2\right] \quad (1)$$

With: $C_t\,(P_t) = K_{heat} \cdot \max(P_t,0) + K_{cool} \cdot \min(P_t,0)$ (2)

Where:

- P_t: power applied during the interval t
- K_C: weighting coefficient for the comfort term
- K_E: weighting coefficient for the energetic term ($K_E = 1 - K_c$)
- C_t: cost of using the FCU (€) at interval $\hat{T}_t$
- T_t: temperature set-point
- $\hat{T}_t$: temperature given by the building temperature prediction model
- Occ_t: binary variable used to discard the discomfort computation when there is no occupancy in the room (i.e. when Occ_t is set to zero)
- K_{heat}: the “cost” of heating (€/W)
- K_{cool}: the “cost” of cooling (€/W)
- N: number of time intervals over the prediction horizon

Beside the objective function, two additional functions are required:

- The **building temperature prediction model**: It is based on an ARMAX model and takes as inputs: the FCU power, the outdoor temperature and the solar irradiance. This model is used to predict the evolution of the room temperature over the prediction horizon.
- The **FCU cost model**: It predicts the power needed to process the air. The model is based on the physics of the heater/chiller and essentially computes the cost associated with treating the air.

Simulation conditions and simulation cases

The following boundary conditions were used for all the simulations:

- Weather data: Neuchâtel (Switzerland)
- Temperature set points: 2 scenarios (see Figure 1):
    - scenario 1 (full occupancy: Occ = 1): 20°C during daytime, 22°C during night-time;
    - scenario 2 (partial occupancy: Occ = 0): 20°C during daytime, no occupancy (i.e. occupancy parameter $Occ_t = 0$) during night-time (i.e. free set point).
- Daytime: 9 am to 6 pm, night-time: 6 pm to 9 am).

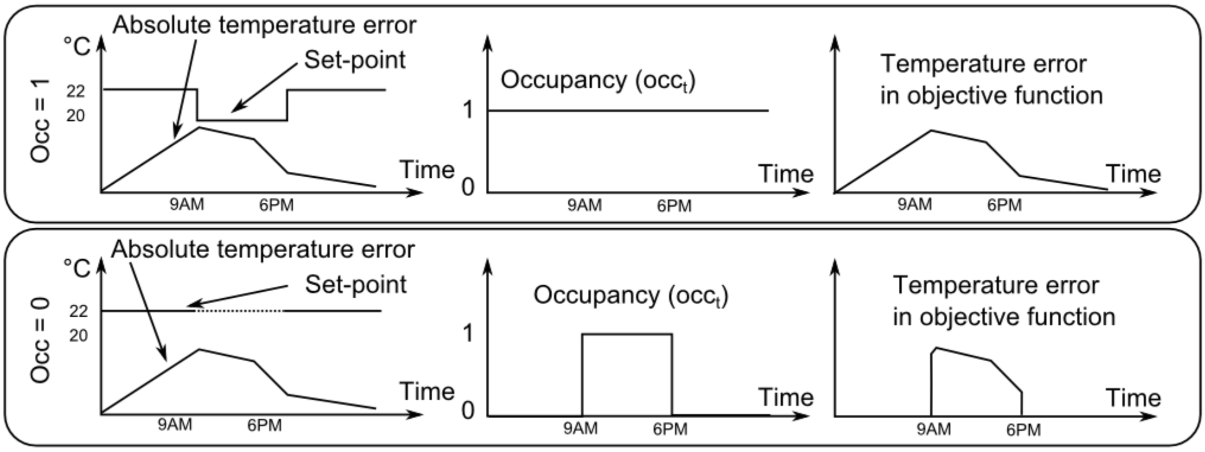

Figure 1: Illustration of the effect of Occ = 1 or 0 in the objective function. In the top line, comfort is to be achieved all the time (even during the night). In the bottom line, the temperature error is not computed during periods without occupancy.

First a series of short simulations (~60 days) were performed in different conditions. The following settings were tested: full (Occ = 1) vs partial occupancy (Occ = 0) scenarios, summer versus winter external conditions and various values of the comfort-energetic trade-off, i.e. parameter K_c taking values between 0 and 1.

Finally, one year simulations were undertaken to assess the algorithm over long durations.

All the simulation cases and associated results are summarized in Table 1. In addition, for a specific simulation with high comfort (i.e. K_C = 1 and Occ = 1) an illustration of the measured and desired room temperature is depicted in Figure 2.

RESULTS

The simulation results are provided in Table 1. Note that the mean temperature error is defined as the average over the simulation of the absolute value between the desired room temperature and the measured room temperature.

Simulation parameters				**Simulation results**	
Duration	**Season**	**K_c**	**Occ**	**Mean T. error [K]**	**Energy [kWh]**
60 days	Summer	1	1	0.112	2.25E+03
60 days	Summer	1	0	0.186	9.96E+02
60 days	Winter	1	1	0.089	5.60E+03
60 days	Winter	1	0	0.351	3.40E+03
1 year	All	1	1	0.093	2.78E+04
1 year	All	1	0	0.216	1.48E+04
60 days	Summer	0.9999	1	0.128	2.13E+03
60 days	Summer	0.9995	1	0.343	1.85E+03
60 days	Summer	0.999	1	0.607	1.57E+03
60 days	Summer	0.9985	1	0.896	1.28E+03
60 days	Winter	0.9999	1	0.110	5.39E+03
60 days	Winter	0.9995	1	0.268	5.32E+03
60 days	Winter	0.999	1	0.521	5.23E+03
60 days	Winter	0.9985	1	0.777	5.14E+03
60 days	Summer	0.999	0	0.953	5.23E+02
60 days	Winter	0.999	0	1.022	3.02E+03
1 year	All	0.999	0	0.871	1.16E+04

			Energy	
Duration	**Season**	**K_c**	**Occ = 0**	**Occ = 1**
60 days	Summer	1	9.96E+02	2.25E+03
60 days	Winter	1	3.40E+03	5.40E+03
1 year	All	1	1.48E+04	2.78E+04
60 days	Summer	0.999	5.23E+02	1.57E+03
60 days	Winter	0.999	3.02E+03	5.23E+03

Table 1: Test cases with associated simulation parameters and simulation results (left). Focus on the effect of Occ on the energy expenditure (right)

DISCUSSION

The effect of the comfort-energy trade-off parameters K_c, K_E, and the effect of taking into account non-occupancy by discarding the comfort term in the objective function when there is partial occupancy (scenario Occ = 0) versus assigning another set point temperature during the same period (Occ = 1), are presented below.

First, the effect of K_c is highlighted in Figure 2. We can notice an almost linear relationship between the mean temperature error and the consumed energy. It can also be observed that our MPC algorithm consumes less than the PI controller (MPC: 2130 kWh, PI: 2200 kWh), for a better comfort level (mean temperature error MPC: 0.12°C, PI: 0.18°C).

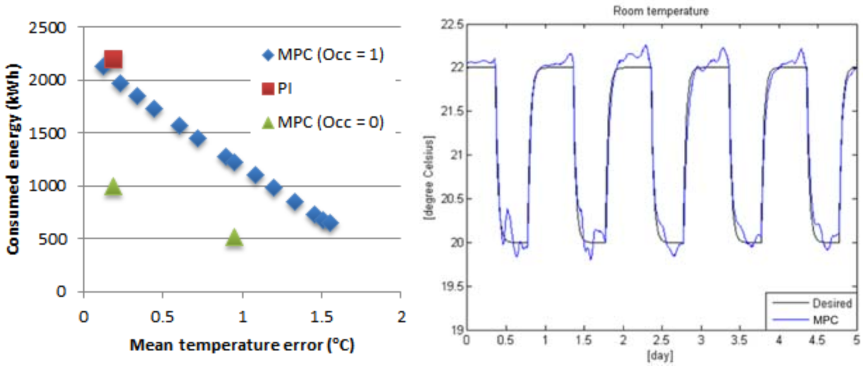

Figure 2: Total energy consumption as a function of the mean temperature error, obtained by changing the K_c parameter (left). Desired and measured room temperature for a high comfort (K_c = 1) simulation (right).

Second, the effect of the occupancy parameter Occ is shown in Table 1 and compared with our reference PI controller in Figure 2. It can be observed that letting the system free when there is partial occupancy (Occ = 0) reduces the energy consumption almost by a factor two for a similar comfort value (during the occupancy periods). It is to be noted that the MPC anticipates the heating and cooling needs before the transition from un-occupied to occupied, which maintains an acceptable level of comfort. The PI controller is unable to perform such preemptive actions.

It can be seen that as expected, the K_c and Occ parameters affect the comfort and energy expenditure. In addition, the MPC algorithm achieves a better comfort for a lower energy expenditure, especially in the partial occupancy scenario (Occ = 0), i.e. when non-occupancy is exploited in the optimization. Finally, a similar behaviour was observed when starting the algorithm at various times of the year or during all-year simulations.

CONCLUSION AND OUTLOOK

This article presented an MPC algorithm developed for FCU control. The optimization is based on an objective function, which includes a comfort and an energetic/cost term. The user has the possibility to adjust the trade-off between these two terms with a single and simple parameter, ranging between 0 (only energy/cost optimization) and 1 (only comfort optimization). In addition, the system can take advantage of unoccupied periods. Simulation results have shown that, by taking into account the energy/cost in the optimization and/or by exploiting the unoccupied periods, the energy consumption could be drastically reduced while maintaining user comfort.

The algorithms will be deployed in the test site in Lavrion (Greece) during the second half of 2015.

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