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Neural Network based HVAC Predictive Control

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Abstract: This paper addresses the problem of controlling Heating Ventilation and Air Conditioning (HVAC) systems with the purpose of maintaining a desired thermal comfort level, whilst minimizing the electrical energy required.

Using a pilot installation, in the University of Algarve, Portugal, a Model Based Predictive Control (MBPC) strategy is used to control the HVAC equipment. The thermal comfort is assessed using the predicted mean vote (PMV) index. The MBPC methodology uses predictive models, implemented by radial basis function neural networks, identified by means of a Multi-Objective Genetic Algorithm (MOGA). Experimental results show that this approach is feasible and robust, and able to obtain energy savings greater than 50%, under normal building occupation.

Keywords: HVAC Predictive Control, Predicted Mean Vote, Neural Networks, Multi-Objective Evolutionary Algorithms, Wireless Sensor Networks

1. INTRODUCTION

According to recent studies, energy consumption of buildings (residential and non-residential) represents approximately 40% of total world energy consumption, mainly attributed to HVAC systems (Moroşan, Bourdais, Dumur, & Buisson, 2010; Pérez-Lombard, Ortiz, & Pout, 2008). It is of fundamental importance to control efficiently the existing HVAC systems, in order to decrease energy usage and increase compliance with the European Directive (2010/31/EU) on the energy performance of buildings (European Parliament, 2010).

MBPC is perhaps the most proposed technique for comfort control (Donaisky, Oliveira, Freire, & Mendes, 2007; Ma, Kelman, Daly, & Borrelli, 2012; Ruano, Crispim, Conceicao, & Lucio, 2006), since it offers an enormous potential for energy savings. Despite of that, there are only a few reported applications of the use of MBPC for existing buildings, under normal occupancy conditions, which is the topic of this paper.

Section 2 describes the experimental setup. The PMV index is used to quantify thermal comfort and is described in Section 3. MBPC uses predictive models. Their design, using MOGA, is described in Section 4. The MBPC formulation is briefly addressed in Section 5, and results are presented in Section 6. Conclusions and directions for future work end this paper.

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2. THE EXPERMENTAL SETUP

The control experiments were conducted in three areas, each on a different floor, of the Faculty of Sciences & Technology of the University of Algarve, in the South of Portugal (please see Fig. 1). Algarve has a temperate climate, with daily average temperatures of 23ºC and 13ºC, in August and December, respectively.

16 rooms of that building are equipped with wireless data acquisition devices, and internal HVAC units which may be independently controlled and monitored. Additionally, a weather station, located in the roof of an additional building in the campus provides several atmospheric measurements. Of importance to this work, the air temperature (T_{ao}) and relative humidity (H_{ao}), as well as the global solar radiation (R_{sg}). All the elements involved are connected to the TCP/IP network, enabling PC stations to monitor the different variables and control any of the rooms. Fig. 2 provides an illustration of the systems integration.

2.1 Wireless Sensor Networks

Each of the three building areas has one Wireless Sensor Network (WSN) with sensors in all rooms to monitor the air temperature (T_{ai}) and humidity (H_{ai}), the globe temperature (T_g), the state of windows and doors (open/closed), and movement using a passive infra-red activity sensor. Fig. 3 illustrates, for rooms A, B and C in fig. 1, the layout of the sensors.

The WSNs have a centralized architecture, where each unit is collecting information once per minute and sending it to a central node with storage and database capabilities. Each node is composed of one Tmote Sky platform connected with the required sensors. This platform is an IEEE 802.15.4 standard compliant device that uses the TinyOs (TinyOs, 1999) operating system, a component based operating system for low power wireless devices. Fig. 4 illustrates one WSN node.

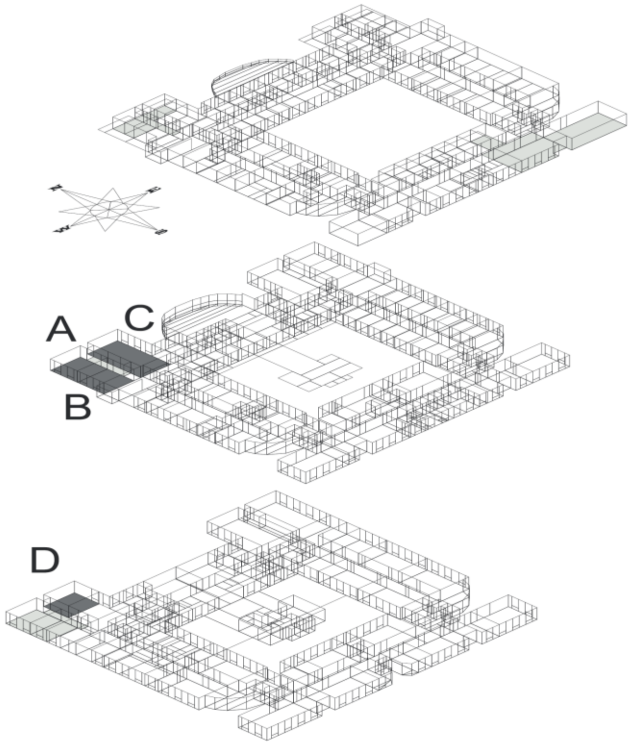

Fig. 1. The FCT building. From top to bottom: ground, 1st and 2nd floors. The monitored rooms in each floor are marked.

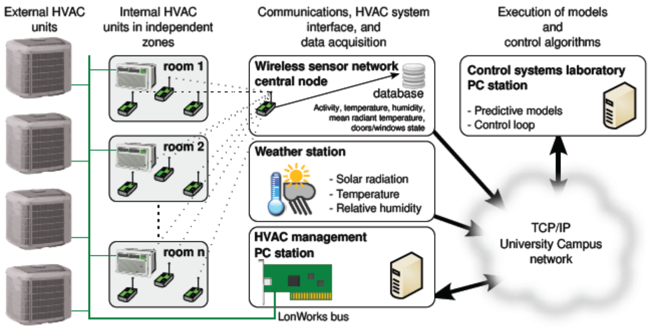

Fig. 2 Overview of the setup used

2.2 HVAC system

The HVAC used in the experiments is composed of 3 independent Mitsubishi Variable Refrigerant Flow (VRF) systems, each one with an outdoor air cooled inverter compressor unit - PUHY-250YMF-C (denoted in the sequel as outdoor unit), located on the building roof, connected to ceiling concealed ducted indoor units - PEFY-P63VMM (denoted as interior units).

In each independent room there is at least one internal unit, with its own wall controller. The system can be centrally managed by a PC management station to which all the units are connected via a LonWorks communication bus. This station is able to monitor and Control many aspects of all the HVAC system, through the Mitsubishi LMAP02 interface (LMAP02, 2001).

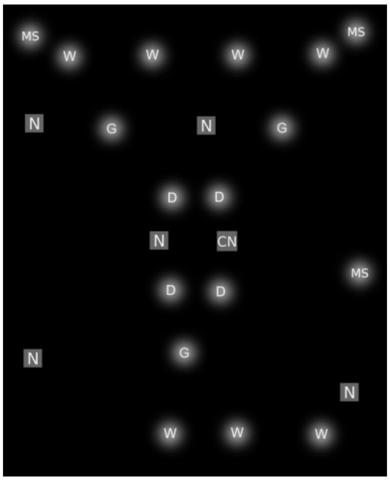

Fig. 3. Layout of Rooms A, B and C. Legend: MS-Movement Sensor; N-Node; CN–Central Node; G –Globe temperature; W–Windows; D–Doors

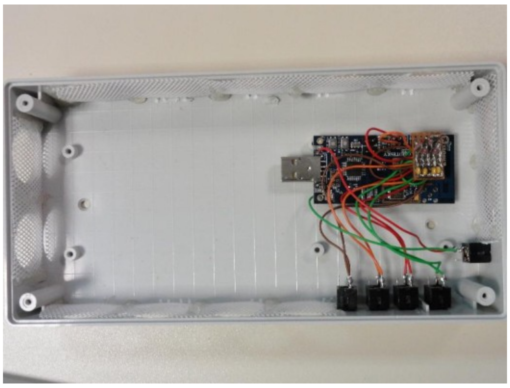

Fig. 4. One WSN node

3. PREDICTED MEAN VOTE

The PMV index predicts the mean response (in a statistical sense) of the thermal sensation of a large group of people exposed to certain thermal conditions for a long time. The value of PMV index is a seven-point thermal sensation, between -3 (cold) and +3 (hot), 0 being neutral (ASHRAE, 2004).

The PMV index is based on human thermal sensation which is strongly related with the energy balance of the body when the human body is considered in a heat balance situation, i.e. the heat produced by metabolism equals the net loss of heat. The classical way in which the PMV index can be estimated was presented in (Fanger, 1972) and is dependent on six variables: metabolic rate (M), clothing insulation (I_{cl}), T_{ai}, H_{ai}, air velocity (V_{ai}), and mean radiant temperature ($\bar{T}_r$). The PMV can be computed as:

$$PMV = \left(0.303e^{-0.036M} + 0.028\right)L \qquad (1)$$

In (1), L is the thermal load in the human body, defined as the difference between the internal heat production and the heat loss which occurs when the person is in a thermal situation, and can be estimated as:

$$L=(M-W)-0.0014M(34-T_{ai})-3.05*10^{-3}(5733-6.99(M-W)-P_{ai})-$$
$$-0.42(M-W-58.15)-1.72*10^{-5}M(5867-P_{ai})-0.0014M(34-T_{ai})- \quad (2)$$
$$-3.96*10^{-8}f_{cl}\left[(T_{cl}+273)^4-(\overline{T}_r+273)^4\right]-f_{cl}h_c(T_{cl}-T_{ai})$$

where M and W are the metabolic rate and external work, both in W/m^2, P_{ai} is the partial water vapour pressure in Pascal, and both T_{ai} and $\overline{T}_r$ are given in degrees Celsius. T_{cl}, the clothing surface temperature, and h_{cl}, the convective heat transfer coefficient (both in ºC), can be estimated as:

$$T_{cl}=35.7-0.028(M-W)-$$
$$-0.1555I_{cl}\left[39.6*10^{-9}\left[(f_{cl}+273)^4-(\overline{T}_r+273)^4\right]+f_{cl}h_c(T_{cl}-T_{ai})\right] \quad (3)$$

$$h_{cl}=\begin{cases} h_c^* & if\ h_c^*>12.1\sqrt{V_{ai}} \\ 12.1\sqrt{V_{ai}} & if\ h_c^*<12.1\sqrt{V_{ai}} \end{cases} \quad (4)$$
$$h_c^*=2.38(T_{cl}-T_{ai})^{1/4}$$

These two equations are solved recursively, until a prescribed degree of accuracy is obtained. Finally, in (2) and (3), f_{cl}, which is the ratio of body surface area covered by clothes to the naked surface area, is defined by:

$$f_{cl}=\begin{cases} 1.00+1.29I_{cl} & if\ I_{cl}\le 0.078 \\ 1.05+0.645I_{cl} & if\ I_{cl}>0.078 \end{cases} \quad (5)$$

In practice, in order to obtain the PMV, reference values of M and I_{cl} are obtained from tables found in many handbooks related to HVAC systems and are also provided in (ASHRAE, 2004). P_{ai} is easily related to H_{ai}, by means of Antoine's equation:

$$P_{ai}=10H_{ai}e^{16.6536-\frac{4030.188}{T_{ai}+235}} \quad (6)$$

Finally, $\overline{T}_r$, that can be defined as the uniform temperature of an imaginary enclosure in which radiant heat transfer from the human body equals the radiant heat transfer in the actual nonuniform enclosure (ASHRAE, 2004), can be estimated using different methods (ASHRAE, 2004):

- From the plane radiant temperature in six opposite directions, weighted according to the projected area factors for a person;
- Or, using a black globe thermometer, which is the method used here. Denoting the globe temperature by t_g, $\overline{T}_r$ may be determined as:

$$\overline{T}_r=\left[(T_g+273)^4+\frac{1.1\times10^8V_{ai}^{0.6}}{\varepsilon D^{0.4}}(T_g-T_{ai})\right]^{1/4}-273, \quad (7)$$

where D and ε are the globe diameter in meters and the globe emissivity coefficient, respectively.

As it can be understood from the above, the computation effort for calculation of the PMV is high, and due to the recursive computations, it is not constant. For these reasons, some researchers have proposed the use of neural models (Atthajariyakul & Leephakpreeda, 2005; Yao & Xu, 2010) or Least-Squares Support Vector Machines (Kumar & Kar, 2009) for its computation. The authors have proposed the use of RBFs, associated with the concept of a Context Vector for each room.

For most HVAC real-time control applications, the environment is controlled in closed spaces where all occupants are assumed to be dressed similarly regarding the type of clothing they wear. Moreover it is likely that within each type of closed space they will be performing similar activities like attending a lecture, sitting writing a research paper, or having breakfast at the cafeteria.

These two assumptions mean that for a given space it is possible to specify the values of the clothing insulation, I_{cl}, and the metabolic rate, M, allowing therefore these variables to be removed from the PMV model input. If it is further assumed that V_{ai} varies little within the space and its value is determined by measurements, V_{ai} may be considered constant and may also be removed from the PMV model input.

By defining a context vector $C=\{I_{cl},M,V_{ai}\}$, and by using (1) to (7), a set of input-output data pairs may be generated in order to train an RBF model to approximate the mapping

$$PMV(T_{ai},H_{ai},\overline{T}_r), \quad (8)$$

which will be used for each room with the context C, as shown in Fig. 5.

This approach was proposed in (Ferreira, Silva, Ruano, Negrier, & Conceicao, 2012), where it was shown that, using a RBF with just 5 neurons, it was possible to obtain an average and maximum absolute error of 0.0025 and 0.011, respectively, over wide ranges of the input and the PMV variables. Moreover, the computation of this model is approximately 55 times faster than the classical PMV computation, for the same accuracy proving, additionally, the advantage of constant computation time. For more details, please see (Ferreira, et al., 2012).

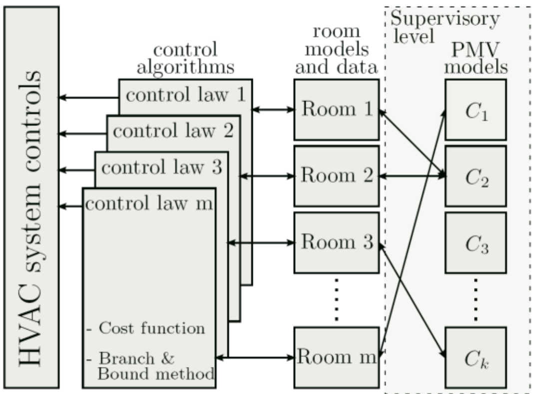

Fig. 5. Using different PMV models in an HVAC control system

4. PREDICTIVE MODELS

Using the neural network static mapping (8), and the context vector, it is possible to predict the evolution of the PMV over a prediction horizon (ph) for each room, provided that the prediction of the PMV inputs are obtained.

This is accomplished using a series of models, as indicated in Fig. 6, for the case of T_{ai}.

The inside air temperature is modelled as a Nonlinear Auto-Regressive model with eXogeneous inputs (NARX), whose inputs are the HVAC reference temperature $-T_r$ (a value of 0 indicating that the unit is off), T_{ai}, T_{ao} and R_{sg}:

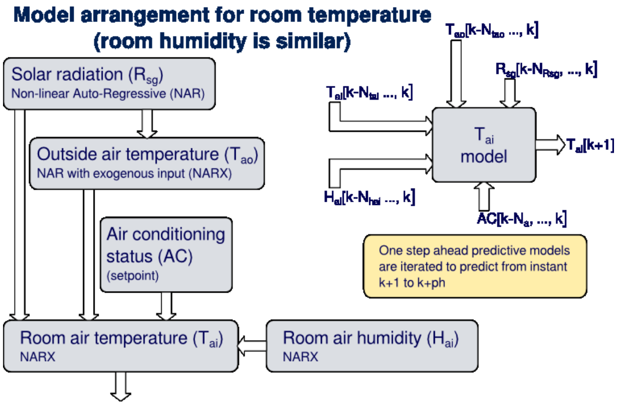

Fig. 6. Model arrangement for room temperature

$$T_{ai} = NARX\left(T_r, H_{ai}, T_{ao}, R_{sg}\right) \tag{9}$$

In the same way, H_{ai} (10), H_{ao} (11) and T_{ao} (12) are modelled as NARX models:

$$H_{ai} = NARX\left(T_r, T_{ai}, T_{ao}, R_{ao}, R_{sg}\right) \tag{10}$$

$$H_{ao} = NARX\left(T_{ao}, R_{sg}\right) \tag{11}$$

$$T_{ao} = NARX\left(R_{sg}\right) \tag{12}$$

Finally, R_{sg} is modelled as a NAR model. These one-step-ahead models are iterated to predict the evolution of the corresponding variable along the prediction horizon, using, as values for the lagged terms, weather measured values (if available) or forecasted values, available from the execution of the corresponding model.

All NARX and NAR models are implemented using RBF neural networks designed with a MOGA framework. Two different models for H_{ai} and T_{ai} were designed, to be used in summer (cooling mode) and in winter (heating mode). In order to design these models, the first step was the preparation of control input signals for the HVAC internal unit. For that, the room was controlled randomly by varying the temperature set-point within the range [18, 19, . . ., 27] or by switching off the unit for varying time intervals. This task was accomplished by means of Pseudo Random Binary Signals (PRBS), as described in (Ferreira & Ruano, 2008a).

The model design employed is exemplified for the inside temperature model, to be used in summer conditions. PRBS signals with 4416 data patterns were generated, corresponding to approximately 15 days of data at 5 min sampling interval. Different times-of-day were covered and distinct days (concerning the outside weather) were used, all during early summer. The next figure shows a sample PRBS sequence of set-points and the resulting T_{ai} and R_{ai}.

This data was divided into three sets: training set - $\mathbf{X}^t$, used to estimate the model parameters, generalization or test set - $\mathbf{X}^g$, used to implement an early-stopping and to assess each model in fresh data, and a validation set - $\mathbf{X}^v$, used to compare different designed models on fresh data. The design cycle used in the MOGA framework is shown in Fig. 8.

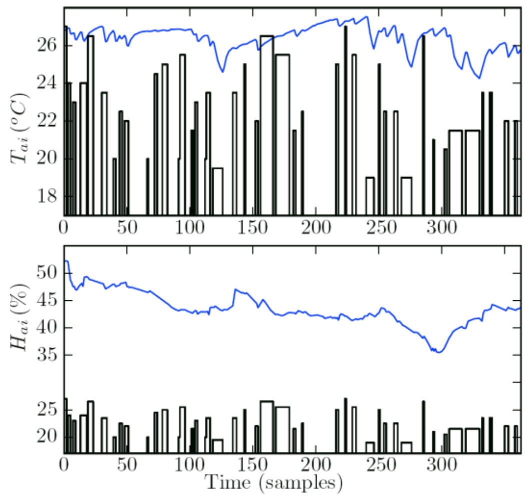

Fig. 7. Sample of PRBS sequence applied to HVAC system and the resulting temperatures and humidities. Summer conditions.

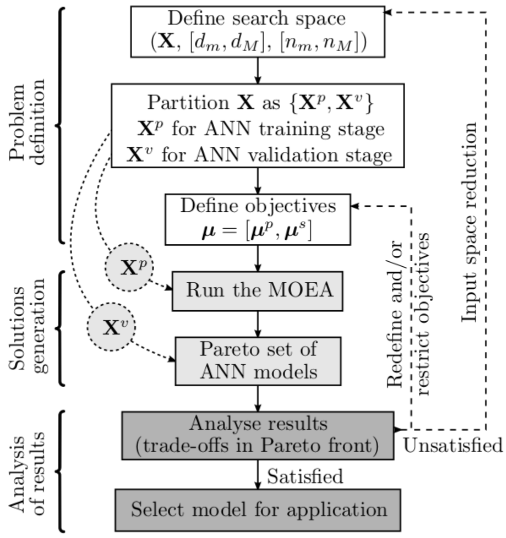

Fig. 8. Model design cycle.

The evolutionary algorithm searches for the best number of neurons and the best set of inputs to be used by the models. The parameters of each model are estimated using an improved version of the Levenberg-Marquardt algorithm.

In this case, 60 possible inputs, corresponding to current and delayed values of $\left\{T_{ai}, AC, H_{ai}, T_{ao}, R_{sg}\right\}$ were considered, and models with inputs between 2 (d_m) and 30 (D_m) were allowed. The number of neurons were allowed to vary between 2 (n_m) and 20 (n_M). The dimension of the search space is therefore $19 \times \sum_{i=2}^{30} \binom{60}{i} \approx 1.2 \times 10^{19}$.

The objectives were formulated according to Table 1. The two first objectives (denoted in Fig. 5 as μ^p) are the Root-Mean-Square-Errors (RMSE) on the training and generalization set, and reflect how good is the mapping obtained by the training. The third objective is directly related to the models application, the performance over the *ph* considered (which is 48 steps - 4 hours).

Table 1: MOGA Objectives

Objective	Setup to	Value
RMSE ($\mathbf{X}^t$)	restriction	0.5ºC
RMSE ($\mathbf{X}^g$)	minimization	-
$\varepsilon\left(\mathbf{X}^v, ph\right)$	minimization	-

Assume that $\mathbf{X}^v$ has p data points and that for each point the model is used to make predictions up to ph steps ahead. An error matrix can be constructed:

$$E\left(\mathbf{X}^v, ph\right)=\begin{bmatrix} e[1,1] & e[1,2] & \cdots & e[1,ph] \\ e[2,1] & e[2,2] & \cdots & e[2,ph] \\ \vdots & \vdots & \ddots & \vdots \\ e[p-ph,1] & e[p-ph,2] & \cdots & e[p-ph,ph] \end{bmatrix} \quad (13)$$

where $e[i,j]$ is the model prediction error taken from instant i of $\mathbf{X}^v$ at step j within ph. Denoting the RMS function operating over the i^{th} column of its argument matrix by $\rho(.,i)$, then the third objective in Table 1 is defined as:

$$\varepsilon\left(\mathbf{X}^v, ph\right)=\sum_{i=1}^{ph}\rho\left(E\left(\mathbf{X}^v, ph\right), i\right) \quad (14)$$

The next figure shows some results of the MOGA execution.

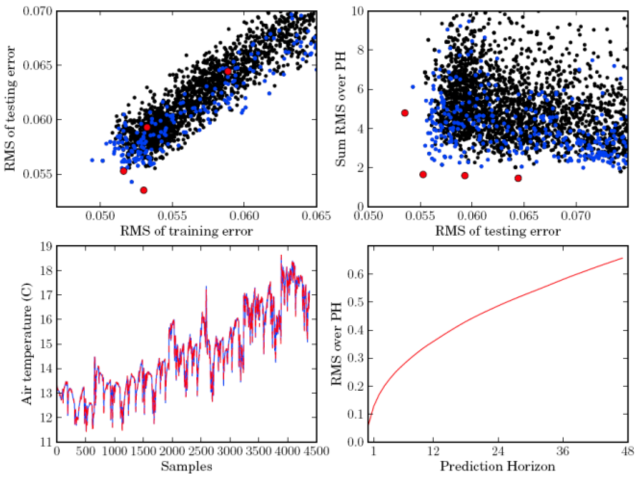

Fig. 9. MOGA results. Summer Temperature model

The two top scatter plot show the performance obtained by the models in the RMSE ($\mathbf{X}^t$) - RMSE ($\mathbf{X}^g$) space (left) and in the RMSE ($\mathbf{X}^g$) - $\varepsilon\left(\mathbf{X}^v, ph\right)$ space (right). The black dots represent dominated solutions, the blue non-dominated solutions, and the red preferable solutions. The right-bottom plot illustrates the evolution of the RMSE of the chosen model over ph, which increases from 0.06ºC to 0.65ºC. The left-bottom plot shows the one-step-ahead model output (in blue), and the measured temperature (in red) over the whole data. As it can be seen, there is nearly a perfect matching.

5. PREDICTIVE CONTROL

An approach to non-linear MBPC consists in discretising the control space into an appropriate finite set of control actions and performing a search for the optimal future control trajectory within the available set of control options. In that case the MBPC problem may be solved by means of discrete optimisation methods. Branch-and-Bound (BB) has been proposed (Sousa, Babuška, & Verbruggen, 1997) and applied in practice to discrete (or discretised) non-linear MBPC problems (Ferreira & Ruano, 2008b; Mendonça, Sousa, & Sá da Costa, 2004). Since by definition the control space is discrete in common HVAC systems, the referred BB methodology is used in this work.

In order to maintain thermal comfort and simultaneously minimise the energy spent, the problem may be formulated as follows. The cost of selecting one control action, T_r, at instant i is defined as

$$J(i)=\begin{cases} 1+\dfrac{\left|T_r-T_{ao}\right|}{\lambda}, & T_r>0 \\ 0, & T_r=0 \end{cases} \quad (15)$$

The λ scaling factor is used only to make that term small when compared to 1. Using the definition (15) the HVAC control problem is simply determining the control sequence $\mathbf{u}(k)$, over a control horizon ch, such that:

$$\min_{\mathbf{u}(k)} J=\left.\left(\sum_{i=k+1}^{k+ph} J(i)\right)\right|_{\mathbf{u}(k)} \quad (16)$$
$$\textit{subject to } \left|\hat{\Theta}(i)\right|<\Theta_T,\ i=k+1,\ldots$$

where $\hat{\Theta}(i)$ is the estimated PMV index at step i, and Θ_T is a threshold value for the PMV index which should guarantee acceptable thermal comfort for the occupants of the space. The ASHRAE standard (ASHRAE, 2004) recommends a value of 0.5 which predicts that less than 10% of the occupants will be dissatisfied.

6. RESULTS

Several experiments were conducted, both in winter and summer conditions. Two are shown here.

Fig. 10 shows the nonlinear MBPC algorithm under continuous operation, during 48 hours, in summer conditions. Room D in Fig. 1 was used, which is a classroom equipped with computers, where students have a number of courses on different computer science topics. The mean air velocity was found to be, on average, around 0.1 ms^{-1}. A value of 0.65 clo was used for the clothing insulation and a value of 1.0 Met was employed for the metabolic rate. This means that the context, for the PMV model used, was C = {0.65, 1.0, 0.1}. Regarding the MBPC system parameters, ch was set to 5 samples (25 min) and ph to 48 samples (4 h).

In the figure, the shaded areas show the room activity monitor signal. In the upper plot the measured (red dash-dot) and one-step-ahead predicted (red dot) relative humidity are shown. The same (in blue) in the middle plot for the inside air temperature, where the additional dash and solid lines show the outside air temperature and the AC set-point. The bottom plot shows the computed and the one-step-ahead estimated PMV, where the upper limit was set to 0.5. As it can be seen, the one-step-ahead predictions are very accurate, the system maintained good thermal conditions, despite the small amount of time of HVAC operation.

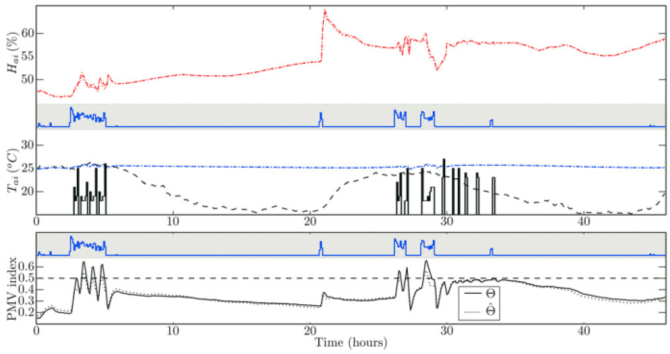

Fig. 10. MBPC HVAC control, in summer conditions

Fig. 11 illustrates the system operation, during 11 hours, in room B of Fig. 1, in winter conditions. The context vector used is $C = \{1.0, 1.0, 0.08\}$ and values similar to the summer case for the MBPC system parameters were employed.

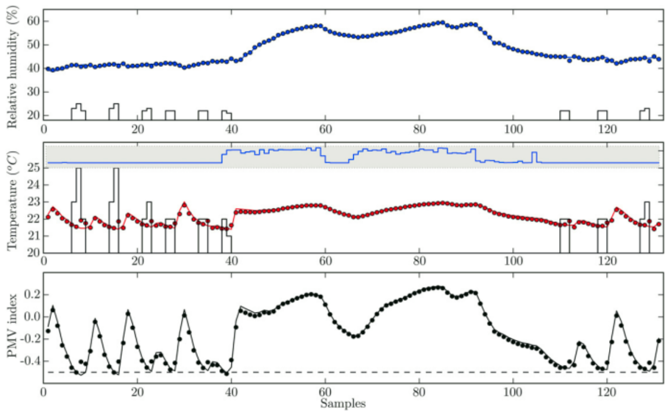

Fig. 11. MBPC HVAC control, in winter conditions

The one-step-ahead predicted values are shown in dots. As it can be seen, again the predictions are very accurate, and the room was kept in thermal comfort, requiring for that only a 15% heating operation during the 11 hours period.

Power transducers were incorporated in three outdoor units, making therefore electric energy values available for these units through the LMAP02 interface. A procedure, suggested by Mitsubishi, was then followed to give a first, crude approximation to the electric energy consumption of each indoor unit (LMAP02, 2001).

With this setup, several experiments were conducted in adjacent rooms (for instance rooms A, B and C in Fig. 1), where one of the rooms were under MBPC control, and the others under normal control, with a temperature set-point required for the season. Energy savings, from 41% to 77%, were obtained.

7. CONCLUSIONS AND FUTURE WORK

A MBPC control methodology using the BB method was formulated and applied to control existing HVAC systems, in buildings under normal operation. Experimental results show that this approach is feasible and robust, and able to obtain energy savings typically greater than 50%, under normal building occupation.

Before this scheme can be applied in commercial use, a few problems need to be solved:

Although the predictions required are very accurate, in some cases the errors obtained should be decreased. Analysing Fig. 10, the errors in the PMV are greater when the room is occupied. The room models were designed with the room empty, and the room thermal load changes significantly with people, and the use of computing equipment. The models performance can be improved if the activity signal is incorporated in the models inputs.

The PMV methodology needs the estimation of $\overline{T}_r$. The approach followed was the use of a globe thermometer, which cannot be used in a commercial application. A simplified version of the plane radiant method should be investigated.

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