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PVM-based intelligent predictive control of HVAC systems

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Abstract: This paper describes the application of a complete MBPC solution for existing HVAC systems, with a focus on the implementation of the objective function employed. Real-time results obtained with this solution, in terms of economical savings and thermal comfort, are compared with standard, temperature regulated control.[1]

Keywords: HVAC Model-Based Predictive Control, Predicted Mean Vote, Neural Networks, Multi-Objective Genetic Algorithm, Weather Station, Wireless Sensor Networks.

1. INTRODUCTION

Model Based Predictive Control (MBPC) is perhaps the most proposed technique for HVAC control (Ruano et al., 2006, Ma et al., 2012, Castilla et al., 2014, Chen et al., 2015, Huang et al., 2015), since it offers an enormous potential for energy savings. Despite the large number of papers in this topic during the last years, there are only a few reported applications of the use of MBPC for existing buildings, under normal occupancy conditions, one of the first them being a previous work by the authors (Ferreira et al., 2012a). To the best of our knowledge, there is not yet a commercial application of MBPC for HVAC control. This paper is a step in this direction. Based on the approach proposed in (Ferreira et al., 2012a), researchers from the University of Algarve, together with the spin-off company EasySensing, Intelligent Systems, and an installation and maintenance company of HVAC systems, Rolear, Ltd, improved the existing MBPC approach (Ferreira et al., 2012a) and installed a complete solution, coined Intelligent MBPC (IMBPC) HVAC, in one building of the University. The current paper discusses the improvements proposed to the existing MBPC approach, focusing on the MBPC objective function, and the results obtained by the IMBPC HVAC system, in terms of energy and economical costs, and thermal comfort.

Section 2 describes the experimental setup. Section 3 introduces the Intelligent MBPC (IMBPC) system, and Section 4 discusses the MBPC objective function. Section 5 addresses the system installation, and Section 6 the results obtained. Conclusions are drawn in Section 7.

2. EXPERIMENTAL SETUP

The experiments were conducted in three lecture rooms, in the second floor of building 7 of the Gambelas campus of the University of Algarve, in the south of Portugal. Rooms 2.13 and 2.12, are adjacent with walls facing west and north (room 2.12). Room 2.11 shares the same corridor with 2.12 and 2.13 and has walls exposed to the north and east. Room 2.11 has a capacity of 71 occupants, and an area of 253.13 m2. The other two rooms have an area of 131.25 m2 and a capacity of 31 occupants.

The HVAC system used in the experiments is composed of one Mitsubishi Variable Refrigerant Flow (VRF) system, with an outdoor air cooled inverter compressor PUHY-250YMF-C unit (denoted as outdoor unit), located on the building roof, connected to ceiling concealed ducted EFY-P63VMM indoor units (denoted as interior units). Rooms 2.12 and 2.13 have one internal unit, denoted UI 2.1.2 and UI 2.1.1, respectively, while room 2.11 has two (UI 2.1.5 and UI 2.1.6). The system can be centrally managed by a Task Vista 4 Building Management System (BMS), executing in a dedicated PC, to which all the units are connected via a LonWorks communication bus.

3. THE IMBPC HVAC SYSYEM

3.1 Hardware

IMBPC needs information on the weather variables. An intelligent, energy autonomous weather station provides atmospheric air temperature (*TA*), air relative humidity (*HR*), and global solar radiation (*SR*) measurements, as well as their forecasts over a user-defined Prediction Horizon (*PH*). All this data is wirelessly transmitted to a receptor, which in turn is connected to a TCP/IP network. Further details on the design and operation of the intelligent weather station can be found in (Mestre et al., 2015).

IBMPC needs also information about the climate of the rooms it will control. For this purpose, it uses small, cheap, self-

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powered wireless sensors that were designed and built specifically for building automation applications, by the authors. Three different types of devices were created (Receptor, Repeater and Transmitter). The following inside variables are measured by these Self-Powered Wireless Sensors (SPWS): air temperature (TA_i) and relative humidity (RH_i), movement (*M*), state of windows/doors, wall temperature and light.

3.2 Software

IMBPC assumes, for the moment, the existence of a BMS, able to measure and control the HVAC equipment. Three major software components exist: an interface to the BMS, a data acquisition module, which is responsible to communicate with the intelligent weather station, the SPWS, and with the BMS interface module, and a control module, which is responsible to execute model predictions, the MBPC algorithm, and the communication of the control actions to the BMS interface.

As the predictive models are Radial Basis Function (RBF) Neural Networks (NN), there is additionally the need to design them. In this work, the design is performed by a Multi-Objective Genetic Algorithm (MOGA). The RBF NNs are used as dynamic models, in NAR (Nonlinear AutoRegressive) or NARX (NAR with eXogenous inputs) configurations. Denoting as *y* the modelled variable, and considering only one exogenous input, *v*, the estimation ($\hat{y}$), at instant *k*, can be given as:

$$\hat{y}[k] = f\begin{pmatrix} y\left[k-d_{o_1}\right], \ldots & d_{o_n}\right], \\ \mathrm{v}\left[k-d_{i_1}\right], \ldots & d_{i_n}\right] \end{pmatrix} = \\ = f\left(\left\{y[k]\right\}, \left\{v[k]\right\}\right) \tag{1}$$

As the objective is to determine the evolution of the forecasts over *PH*, (1) must be iterated over the horizon.

The MOGA based model design framework is an hybrid of an evolutionary algorithm and a derivative-based algorithm. The evolutionary part searches the admissible space of the number of neurons and the number of inputs (lags for the modelled and exogenous variables) for the RBF models. Before being evaluated in MOGA, each model has its parameters determined by a Levenberg-Marquardt algorithm (Levenberg, 1944, Marquardt, 1963) minimizing an error criterion that exploits the linear-nonlinear relationship of the RBF NN model parameters (Ruano et al., 1991, Ferreira et al., 2002). For more details on MOGA, please see, for instance (Ferreira and Ruano, 2011).

The IMPBC HVAC approach assumes the existence of schedules for each room under control. Denoting the occupation period by $t_{oc} = \left[t_{os} \quad t_{oe}\right]$, t_{os} being the start of occupation, and t_{oe} its end, and by t_{op} a time (to be defined) before t_{os}, and by k_{os}, k_{oe} and k_{op} the corresponding sample indices, the approach can be formulated as:

$$\min_{U[k]\in v_{PH}} \left(\sum_{i=k+1}^{k+PH} J\left[i\right] \right) \Bigg|_{U_k}, k \in \left[k_{op} \quad k_{oe}\right] \\ s.t. \left|\Theta[j]\right| < \Theta_T, \quad j \in \left[k_{os} \quad k_{oe}\right] \tag{2}$$

In (2), Θ denotes the Predicted Mean Vote (PMV) index (Fanger, 1972), which will be used to measure thermal comfort, $\Theta_T = 0.5$ is the thermal comfort limit, and U[k] represents a sequence of control actions, at time *k*, out of all the allowable sequences of control actions (v_{PH}) within the prediction horizon *PH*. $J\left[i\right]$ represents an estimate of the economic cost incurred in applying the control action $u\left[i\right]$.

The restriction in (2) needs a model to determine the evolution of Θ. It will be obtained using a RBF static model that approximates the mapping:

$$\Theta = f\left(TA_i, HR_i, \bar{T}_r\right), \tag{3}$$

where $\bar{T}_r$ denotes the mean radiant temperature which will be, in this work, estimated by the temperature of the ceiling of the room. Model (3) will be selected from a data base of existing models, parameterized by a context vector $C = \left\{I_{cl}, M_r, V_{ai}\right\}$, where I_{cl} denotes the clothing insulation, *M*, is the metabolic rate, and V_{ai} is the air velocity in the room. For an explanation of the use of context vectors and RBF NNs to estimate thermal comfort, please see (Ferreira et al., 2012d). The evolution of (3) over *PH* is obtained by the evolution of its arguments. As the objective function (2) needs to be computed, the next section discusses the way to do it.

4. MBPC OBJECTIVE FUNCTION

In (Ferreira et al., 2012a), the energy spent in the k^{th} interval was estimated as:

$$J\left[k\right] = \hat{E}\left[k\right] = \begin{cases} 1 + \dfrac{\left|TR\left[k\right] - \hat{TA}_i\left[k\right]\right|}{\lambda}, & TR\left[k\right] \neq 0 \\ 0, \quad TR\left[k\right] = 0 \end{cases} \tag{4}$$

In (4) TR denotes the air conditioning reference temperature (a value of 0 meaning that it is off, and λ a scaling factor.

Two alternatives were considered to estimate the energy: the use of a dynamic model and of a constant model. Noting that in the pilot installation a split system is used (one external unit is shared between up to four internal units), four models had to be determined: (A) internal unit is operating in the sampling interval;(B) internal units operating in the sampling interval; (c) internal units operating in the sampling interval; (D) internal units operating in the sampling interval.

Using historical data, it has been found that models achieve, on average, better results than the old method. The performance of the dynamic and static models is nearly equivalent. As the estimation procedure of the static model is simpler, and its application in real-rime is less time-consuming, the static model, with constants show in Table 1, will be used.

Table 1. Constants used for energy estimation