2010 American Control Conference
Marriott Waterfront, Baltimore, MD, USA
June 30-July 02, 2010

Distributed model predictive control for building temperature regulation

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Abstract— **This paper presents a predictive control structure for thermal regulation in buildings. The proposed method considers a dynamic cost function trying to exploit the intermittently operating mode of almost all types of buildings. One of the key idea is to use the knowledge about the occupation profile. For that purpose, the predictive control strategy is first presented for a single zone building then extended to a multizone building example. Two opposite control strategies commonly exists. The decentralized control structure, which does not offer good performances especially when the thermal coupling among adjacent rooms is not negligible, and on the other hand, the centralized control for which the computational demand grows exponentially with the size of the system, being very expensive for large scale buildings. Our solution is based on a distributed approach which takes the advantages of the both methods mentioned above. A distributed MPC algorithm with one information exchange per time step is proposed with good control performances and low computational requirements.**

I. INTRODUCTION

The scientific and the political communities have been aware for several years of the global warming problem. By consequence, an European target is the reduction of greenhouse gases by 20% until 2020 while allowing economic and demographic growths. This can be reached only if the energy consumption is optimized. In 2007 the services and households sectors use 40% of the total final European (EU-27) energy. Within the buildings, the heating systems consume more than 50% which means about 23% of total energy consumption. Even if the trends are to construct new energy-efficient buildings, an overall energy consumption reduction cannot be achieved without an optimization in the existent buildings. As renovations and isolations have high costs and are time demanding, in this context, an advanced control law is the optimal solution. The challenges of indoor heating system control are to find a compromise between the user thermal comfort and the energy consumption.

Even if many studies were performed in order to optimize the energy efficiency of heating systems, the controllers that are used today remain basic on/off type or PID. To ensure proper regulation auto-tuning methods of PID parameters have been proposed [1]. The major problem of thermal systems is their slow dynamic, usually with time delays [2]. Therefore, other approaches have been proposed in the literature like fuzzy logic [3], neural networks [4] or genetic algorithms [5].

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During the last two decades a growing interest has been granted to model predictive control (MPC). In MPC, the control input is calculated by solving an optimal control problem (minimization of a cost function) over a given horizon. Only the first element of the open-loop command sequence is applied to the system. At the next instant, a new optimization is performed based on current measurements. The predictive control has been successfully used in many and varied applications [6], [7]. In particular, for heating and cooling systems, different formulations of cost functions and constraints have been analyzed in [8] to minimize the consumption or to guarantee a desired comfort level.

In this paper, a predictive control law is proposed in order to regulate the indoor temperature. The idea is to use the future occupation profile of the rooms and to obtain a certain degree of thermal comfort while the room is occupied. In order to reduce the energy consumption, no particular temperature setpoint is imposed when the rooms are empty (without occupants). In the second part of this work, we intend to generalize our approach to a multi-zone building considering the thermal coupling between the zones.

The paper is organized as follows. Section II introduces the control problem in a single zone example defining the minimization criterion which includes the future occupation as an error weighting factor. In Section III, we generalize the proposed predictive approach to a multi-zone building (comparing the decentralized, centralized and distributed approaches). A tractable distributed MPC (dMPC) algorithm is proposed, which offers high performances with low computation cost. The efficiency of the proposed control strategy is illustrated by a comparison between different control structures performances. Conclusions and future directions are proposed in Section IV.

II. SINGLE ZONE APPROACH

A. Presentation

The control problem of a room heating system is to minimize the energy consumption maintaining a certain thermal comfort for the occupants. Assuming that the comfort in this case is defined by a reference temperature, then why do we need a complicated method as predictive control while a simple PI could be sufficient? The reason comes from the fact that the comfort is defined only while the room is occupied and most of buildings are intermitently occupied. The current room temperature controllers have an inoccupation setpoint which is usually motivated only by transient time constraints and to facilitate the building thermal load calculation. This means that the controller maintains a certain indoor temperature only to avoid long transient

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periods between inoccupation and occupation setpoints. The existence of an inoccupation minimal temperature setpoint is not efficient (from the energy consumption point of view) especially if the building is equipped with an electric heating system. In this case, using a simple reactive control law as PI and due to the slow dynamics of the thermal system, the steady state can be reached after few minutes or several hours depending on heater characteristics, isolation, internal and external perturbations. The anticipative effect of the MPC can be used to overcome this issue. Modifying the minimization criterion of the MPC according to future occupation profile allows us to handle the absence of the setpoint during inoccupation periods without reducing the comfort of the occupation phases. The only assumption made is that the future occupation profile is known in advance at least over a finite prediction horizon window.

B. Defining a dynamic cost function

The anticipative effect of MPC consists in using a model of the process in order to predict its behavior during a finite horizon. A linear discrete time representation of the system for a single room building can be the following ARX form:

$$A(q^{-1})y(k) = B(q^{-1})u(k-1) + \xi(k), \tag{1}$$

where $u(k)$ and $y(k)$ are the input, indicating the heating power, respectively the output (the indoor air temperature) of the system, $\xi(k)$ is the perturbation acting as a zero mean white noise, $A(q^{-1})$ and $B(q^{-1})$ are polynomials in q^{-1} (the one step delay operator).

The controller computes the command sequence minimizing a cost function. This optimization criterion has usually two terms, one that includes the error and the other that contains the control effort. One of the common cost function in predictive control is:

$$\begin{aligned} J = &\sum_{j=N_1}^{N_2} \delta(j)[\hat{y}(k+j|k) - w(k+j)]^2 \\ &+ \lambda \sum_{j=0}^{N_u-1} \Delta u^2(k+j), \end{aligned} \tag{2}$$

where N_1 and N_2 are the minimum and the maximum bounds of the prediction horizon, $\hat{y}(k+j|k)$ is the predicted output, $w(k+j)$ the future reference, δ and λ are the weighting coefficients for the error and for the command respectively, N_u is the control horizon and Δu the command increment. The sequence of predicted outputs (3) are computed as follows:

$$\begin{aligned} \hat{y}(k+j|k) = &F_j(q^{-1})y(k) + H_j(q^{-1})u(k-1) \\ &+ G_j(q^{-1})u(k+j-1) \\ &+ J_j(q^{-1})\xi(k+j), \end{aligned} \tag{3}$$

where the polynomials F_j, H_j, G_j and J_j are obtained by solving (recursively) two Diophantine equations, where the model polynomials, $A(q^{-1})$ and $B(q^{-1})$, are included (see [7] for details). The optimal prediction equation is obtained considering the mean (zero here) as the best prediction for the white noise ξ.

To understand our approach it is better to analyze the output behavior of the MPC related to (2) in Fig. 1.

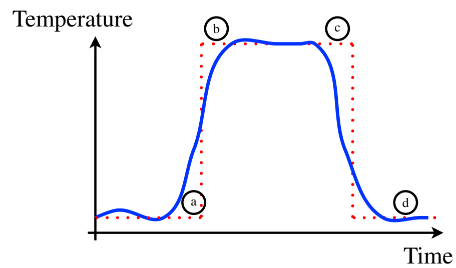

Fig. 1. MPC with the classic cost function

It can be seen that the anticipative effect is present (a) and (c), but the necessity of a temperature setpoint (d) during inoccupation causes a decreasing in the comfort level at the beginning (b) and at the end (c) of the occupation period. In order to remove this drawback another cost function is proposed, as the first main contribution of the paper, that incorporates the future occupation profile as the error weighting term:

$$\begin{aligned} J(k) = &\sum_{j=N_1}^{N_2} \delta^k(j)\, |\hat{y}(k+j|k) - w(k+j)| \\ &+ \lambda \sum_{j=0}^{N_2-N_1} u(k+j), \end{aligned} \tag{4}$$

subject to

$$0 \leq u(k+j) \leq P_{max},\ \forall j = 0..N_2 - N_1, \tag{5}$$

$$u(k+j) = u(k+N_u-1),\ \forall j = N_u..N_2 - N_1, \tag{6}$$

where $\delta^k(j)$ is defined as:

$$\delta^k(j) = \begin{cases} 1,\ if\ k+j \in Occupation \\ 0,\ if\ k+j \in Inoccupation \end{cases}. \tag{7}$$

The vector δ^k represents the future occupation profile and enables to manage the absence of a setpoint during the inoccupation periods when the criterion is minimizing only the consumption. If a person enters the zone and this occupation has not been foreseen then δ^k will be forced to have all the elements equal to 1.

Note that the second term of the cost function (2) was changed in (4) because the objective is to minimize the energy consumption u and not the increment Δu. The quadratic form in (2) was definitely abandoned considering classical control performance indices evaluating energy consumption (8) and thermal comfort (9), which are not in a quadratic form.

Indeed, the consumption index (I_W), in kWh, is the integral of heating power required over the simulation period:

$$I_W = \int_{t_0}^{t_f} u(t)dt. \tag{8}$$

The comfort index (I_C), in ^{o}Ch, acts as a penalty when the room temperature does not meet the comfort objective. As the comfort is defined only within the occupation periods, it can be written as:

$$I_C = \int_{Occupation} |w(t) - y(t)|\, dt. \qquad (9)$$

The input inequality constraint is necessary to guarantee the positivity of the criterion and to define the maximum heat power of the actuators. The role of the equality constraint is to reduce the optimization argument dimensions from $N_2 - N_1 + 1$ to N_u. This decreases the computational demand of the optimization but with a loss of performance. If it is strongly necessary, a minimal temperature constraint can be added to avoid low temperatures during the inoccupation periods as $\hat{y}(k+j|k) \geq T_{min},\ \forall j = N_1..N_2$.

C. First results and discussions

Fig. 2 shows a simulation (using SIMBAD Toolbox) of the proposed control law for a 12m^2 room heated by a 1200W electric convector, under meteorological conditions of 01/01/1998 in Rennes, France. The occupation period is a priori known being between 8:00 and 17:00, during which temperature setpoint equals 20^{o}C.

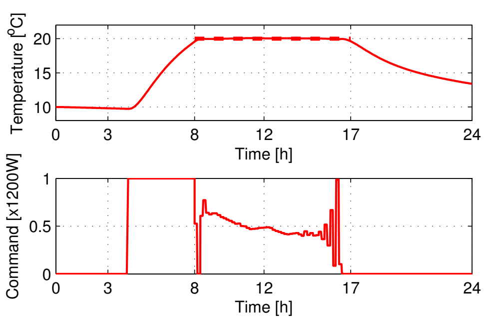

Fig. 2. Temperature and command signals using the proposed MPC

The prediction horizon is chosen to offer enough time for the control system to increase the indoor temperature up to the desired setpoint in the worse situation (low indoor and low external temperatures). In the simulations we used $N_1 = 1$, $N_u = 3$ for single zone and $N_u = 10$ for the multizone case, $N_2 = 30$ and $T_s = 10$min, obtaining a prediction window of 5 hours. As it can be seen in Fig. 2, even if the controller 'sees' the first occupation setpoint at 3:00 the heating starts later, at the optimal time. A similar effect appears at the end of the occupation period when the heater is turned off before the end of the occupation, using in an optimal way the thermal inertia of the building. The command oscillations at the end of the occupation period appears from the moment when an important part of the input blocking horizon $[N_u, N_2 - N_1]$ is in the inoccupation period (and a zero command is favored) and $u(k+j) = 0,\ \forall j = N_u..N_2 - N_1$. Then then unblocked part of the control input sequence tries to compensate this behavior, resulting a more aggressive control input.

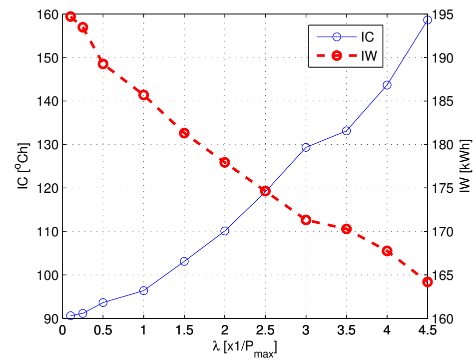

Fig. 3. Comfort and consumption indices achieved for different values of λ

The command weighting factor λ influences the steady state error. A big value of λ means that the energy is very expensive and by consequence the comfort quality will be decreased. Analyzing Fig. 3 we obtain a mean of 2^{o}Ch for 1kWh. However, we can see that the average slope of the two curves are modified for values of λ below $1/P_{max}$ and a small gain in comfort will be reached with a relatively big amount of energy. Even if values between $1/P_{max}$ and $2/P_{max}$ are a good choice, in the simulations presented in this paper, we are using $\lambda = 1/P_{max}$. Note that for $\lambda > 2/P_{max}$, the thermal comfort will be decreased at the beginning and at the end of the occupation periods which will diminish the advantage of using a dynamic cost function.

III. Multizone approach

This section will analyze the generalization of the predictive control law proposed above for multi-zone (large scale) buildings. Even if the controllers working in almost all buildings are zone-independent, the thermal coupling factor can be important (the internal walls isolation is weak). For simplicity purposes, a three-zone building (Fig. 4) equipped with independent convector heaters was used in the simulations and for theory description. However, generalization for several zones can be easily achieved.

As we already mentioned, the experimental results were obtained using SIMBAD Toolbox. The simulated building is a three zones (3x42m^3) with three independent electrical convectors of 1200W maximal power. It has a double glazed window of 2m^2 surface on the larger external wall of each zone. The external wall sandwich consists of 1cm of gypsum, 8cm of extruded polystyrene and 20cm of concrete. The internal wall is 7.2cm thick of gypsum board. The simulator supposes a well mixed indoor air. Concerning the building orientation, the common external wall for zones 1 and 2 faces to the NW.

A. Decentralized MPC

As mentioned above, the most used building thermal control structure is a decentralized one. In this case each room air temperature is regulated by an independent controller. The thermal influences among the subsystems are considered

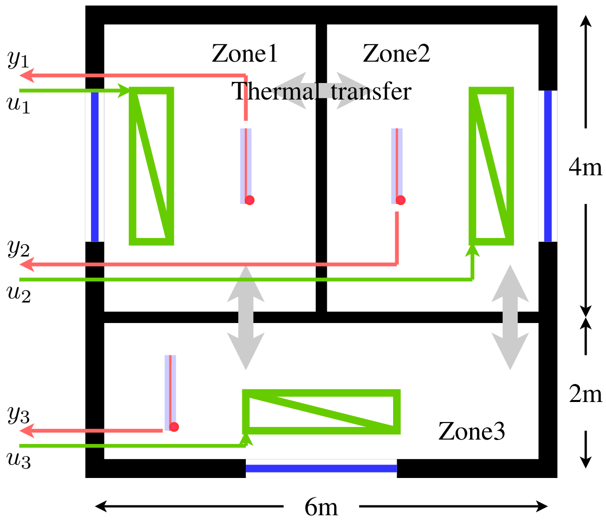

Fig. 4. Three-zone building configuration

as external unknown perturbations. For the indoor heating control system, the positive perturbations have a significant action because the control input is bounded (between 0 and P_{max}) and positive, which means that the controller can only heat up the zone. The decrease of the indoor temperature is caused mainly by losses through walls and infiltrations.

The decentralized MPC approach for the three-zone building is the simplest generalization of the MPC presented in Section II for a multi-zone strategy. This implies that each room temperature is regulated by its own controller independently of all others. Intuitively, as the thermal coupling between the rooms is ignored by the prediction models when these influences are important (and positive) they will not be quickly rejected and certain output overshoots will appear (Fig. 5). The slowness of the MPC controller in the perturbation rejection is due to the relatively large prediction window. We can expect that considering in the control law the entire coupled system will diminish or even eliminate these overshoots and as a result the overall energy consumption will decrease ($I_W \searrow$) and the thermal comfort will be improved ($I_C \searrow$).

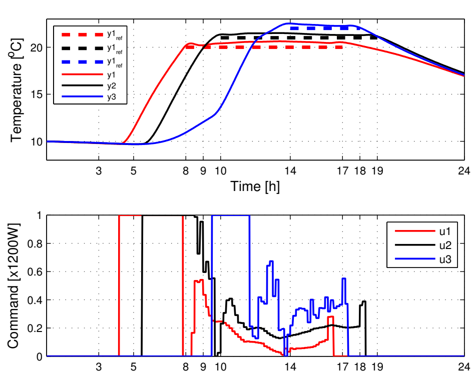

Fig. 5. Decentralized MPC behavior

B. Centralized MPC

In the centralized control structure case, the entire multi-zone system is controlled by one MPC law. The model used for prediction includes the coupling elements.

Knowing that in particular for multi-zone heating systems the coupling element is the output of each subsystem (the measured temperatures [9]) then a model of one zone including this influence with the adjacent rooms can be expressed in a state space formulation as:

$$\begin{cases} \mathbf{x}_i(k+1) = \mathbf{A}_i \mathbf{x}_i(k) + \mathbf{B}_i \begin{bmatrix} u_i(k) \\ \mathbf{y}_{\hbar_i}(k) \end{bmatrix}, \ i = 1..3 \\ \mathbf{y}_i(k) = \mathbf{C}_i \mathbf{x}_i(k) \end{cases} \tag{10}$$

where $\mathbf{y}_{\hbar_i}$ includes the outputs of all adjacent rooms ($\hbar_i$) of i. Using the local models and the building structure, we can derive the global model (14) matrices as:

$$\mathbf{A}_g = \begin{bmatrix} \mathbf{A}_1 & \mathbf{B}_{12}\mathbf{C}_2 & \mathbf{B}_{13}\mathbf{C}_3 \\ \mathbf{B}_{22}\mathbf{C}_1 & \mathbf{A}_2 & \mathbf{B}_{23}\mathbf{C}_3 \\ \mathbf{B}_{32}\mathbf{C}_1 & \mathbf{B}_{33}\mathbf{C}_2 & \mathbf{A}_3 \end{bmatrix}, \tag{11}$$

$$\mathbf{B}_g = \text{block-diag}(\mathbf{B}_{11}, \mathbf{B}_{21}, \mathbf{B}_{31}), \tag{12}$$

$$\mathbf{C}_g = \text{block-diag}(\mathbf{C}_1, \mathbf{C}_2, \mathbf{C}_3), \tag{13}$$

where $\mathbf{B}_{ij}$ represents the column j of $\mathbf{B}_i$.

The global state space representation of the entire (centralized) system can be written as:

$$\begin{cases} \mathbf{x}(k+1) = \mathbf{A}_g \mathbf{x}(k) + \mathbf{B}_g \mathbf{u}(k) \\ \mathbf{y}(k) = \mathbf{C}_g \mathbf{x}(k) \end{cases} \tag{14}$$

where

$$\begin{aligned} \mathbf{x}(k) &= \begin{bmatrix} \mathbf{x}_1^T(k) & \mathbf{x}_2^T(k) & \mathbf{x}_3^T(k) \end{bmatrix}^T, \\ \mathbf{u}(k) &= \begin{bmatrix} \mathbf{u}_1^T(k) & \mathbf{u}_2^T(k) & \mathbf{u}_3^T(k) \end{bmatrix}^T, \\ \mathbf{y}(k) &= \begin{bmatrix} \mathbf{y}_1^T(k) & \mathbf{y}_2^T(k) & \mathbf{y}_3^T(k) \end{bmatrix}^T, \end{aligned} \tag{15}$$

are respectively the state, the control signal and the output of the centralized model.

Considering the positivity and the additivity properties of the cost function used, the global criterion for the 3x3 system can be written as $J(k) = \sum_{i=1}^{3} J_i(k)$ where

$$\begin{aligned} J_i(k) = & \sum_{j=N_1}^{N_2} \delta_i^k(j) \left| \hat{y}_i(k+j|k) - w_i(k+j) \right| \\ & + \lambda_i \sum_{j=0}^{N_2-N_1} u_i(k+j), \end{aligned} \tag{16}$$

subject to

$$0 \le u_i(k+j) \le P_{max_i}, \ \forall j = 0..N_2 - N_1, \tag{17}$$

$$u_i(k+j) = u_i(k + N_u - 1), \ \forall j = N_u..N_2 - N_1. \tag{18}$$

Each output prediction $\hat{y}_i$ will be computed including the modeled coupling factors. In the simulation results (Fig. 6) using the same occupation profiles and external conditions as in the decentralized example (Fig. 5), the zone temperatures presents no overshoots.

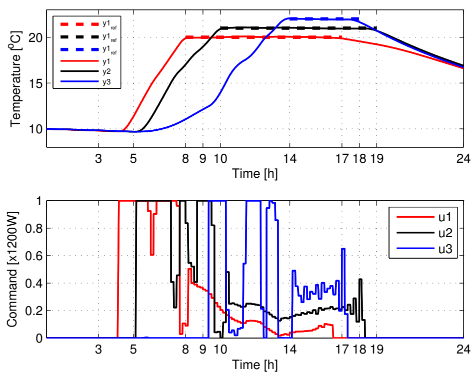

Fig. 6. Centralized MPC behavior

Even if the control performances are good, the computational demand of a centralized MPC grows exponentially with the system size. The implementation of this control law for large scale buildings is time-consuming because of the high necessary computational power of the controller. Moreover, a damage of the central controller will cause the failure of the entire building heating system.

C. Distributed MPC

Because of the computational complexity of the centralized MPC, the application area of this type of control is restricted to only relatively small-scale MIMO systems. A distributed approach (dMPC) seems to be the only solution for large-scale dynamically coupled systems. The dMPC is structured as a decentralized law, with a local controller for each subsystem (Fig. 7). In order to converge to the global optimal solution [10], [11] or to a Nash equilibrium point [12], [13], the local MPCs exchange informations related to their future behavior. A communication network and an algorithm, that allow the collaboration among the local control laws, permit the improvement of global system performance compared to decentralized structure. On the other hand, the computational demand should be significantly reduced compared to the centralized case.

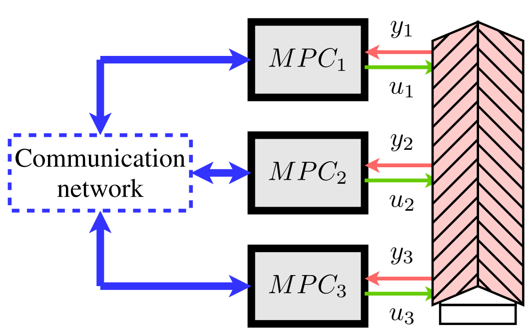

Fig. 7. Distributed MPC configuration

The multi-zone heating system dMPC idea is to use for each local controller the *future output prediction of the neighbor rooms*. Based on the model developed in the previous section, the output prediction equation of subsystem i can be written as:

$$\hat{\mathbf{y}}_i(k) = \mathbf{\Psi}_i \mathbf{x}_i(k) + \mathbf{\Phi}_{i1}\mathbf{u}_i(k) + \sum_{s\in\hbar_i} \mathbf{\Phi}_{is}\mathbf{y}_s(k), \qquad (19)$$

with the following notations:

$$\hat{\mathbf{y}}_i(k) = \begin{bmatrix}\hat{y}_i(k+N_1|k) & \cdots & \hat{y}_i(k+N_2|k)\end{bmatrix}^T,$$
$$\mathbf{u}_i(k) = \begin{bmatrix}u_i(k|k) & \cdots & u_i(k+N_u-1|k)\end{bmatrix}^T,$$
$$\mathbf{\Psi}_i = \begin{bmatrix}\mathbf{C}_i\mathbf{A}_i^{N_1} & \cdots & \mathbf{C}_i\mathbf{A}_i^{N_2}\end{bmatrix}^T,$$
$$\mathbf{\Phi}_{i1} = \begin{bmatrix}\phi_{i1}^{N_1-1} & \cdots & \phi_{i1}^{0} & 0 & \cdots \\ \vdots & \cdots & \vdots & \ddots & \vdots \\ \phi_{i1}^{N_2-1} & \cdots & \cdots & \phi_{i1}^{N_2-N_u+1} & \sum_{k=0}^{N_2-N_u}\phi_{i1}^{k}\end{bmatrix},$$
$$\mathbf{\Phi}_{is} = \begin{bmatrix}\phi_{is}^{N_1-1} & \cdots & \phi_{is}^{0} & 0 & \cdots & 0 \\ \vdots & \cdots & \vdots & \vdots & \ddots & \vdots \\ \phi_{is}^{N_2-1} & \cdots & \phi_{is}^{N_2-N_1} & \phi_{is}^{N_2-N_1-1} & \cdots & \phi_{is}^{0}\end{bmatrix},$$
$$\phi_{ij}^{k} = \mathbf{C}_i\mathbf{A}_i^{k}\mathbf{B}_{ij},$$
$$\mathbf{y}_s(k) = \begin{bmatrix}y_s(k) \\ \hat{y}_s(k+N_1|k-1) \\ \vdots \\ \hat{y}_s(k+N_2-1|k-1)\end{bmatrix}.$$

Replacing (19) in (16) and writing the local cost function in a matrix form we have:

$$J_i(k) = \delta_i^k \left| \mathbf{\Psi}_i\mathbf{x}_i(k) + \mathbf{\Phi}_{i1}\mathbf{u}_i(k) + \sum_{s\in\hbar_i}\mathbf{\Phi}_{is}\mathbf{y}_s(k) - \mathbf{w}_i(k)\right| + \lambda_i \mathbf{e}\mathbf{u}_i(k),$$

where

$$\delta_i^k = \begin{bmatrix}\delta_i^k(1) & \cdots & \delta_i^k(N_2-N_1+1)\end{bmatrix},$$
$$\mathbf{e} = \begin{bmatrix}1 & \cdots & 1 & N_2-N_1+2-N_u\end{bmatrix} \in \mathbb{R}^{N_u}.$$

Algorithm 1 dMPC with one communication step and output coupled model

1: Send $\hat{\mathbf{y}}_i(k-1)$ and $y_i(k)$ to all $j \in \hbar_i$
2: Receive $\hat{\mathbf{y}}_j(k-1)$ and $y_j(k)$ from all $j \in \hbar_i$
3: Replace $\hat{y}_j(k+N_1-1|k-1)$ in $\hat{\mathbf{y}}_j(k-1)$ with $y_j(k)$ for all $j \in \hbar_i$
4: Solve the local optimization problem $min_{\mathbf{u}_i(k)} J_i(k)$ and compute $\hat{\mathbf{y}}_i(k)$
5: Apply the first element of $\mathbf{u}_i(k)$ to the local subsystem
6: $k = k+1$ and go to step 1

Algorithm 1 is close to the idea of [13] with few modifications. Using the output coupled model (10) the information exchanged by the controllers is the predicted output sequence and not the future control input. An innovative aspect is that we included the current measures of neighbors outputs in the first element of the prediction sequence, adding a robustness degree of the command. The convergence and the stability conditions for an unconstrained distributed MPC can be easily formulated using the explicit solution as in [13]. In the constrained case these conditions are an open problem. This paper focuses only on the control performances.

A multiple iteration version of the algorithm 1 has been tested, using a stop condition of the following form:

$$\left|\mathbf{u}_i^{(l+1)}(k) - \mathbf{u}_i^{(l)}(k)\right| \leq \epsilon_i,\ i = 1..3$$

and for $\epsilon_i = 10^{-3}$, $i = 1..3$, the maximum number of iterations was 3. The fast convergence of the algorithm is due to the output coupling of the model. Knowing the slowness of the thermal systems, the coupling element has small variations between two consecutive iterations. Then, the iterative algorithm will converge to a Nash equilibrium. Even if the distributed algorithm does not converge to the global centralized solution, the simulation results show that the control performances of the two methods are close.

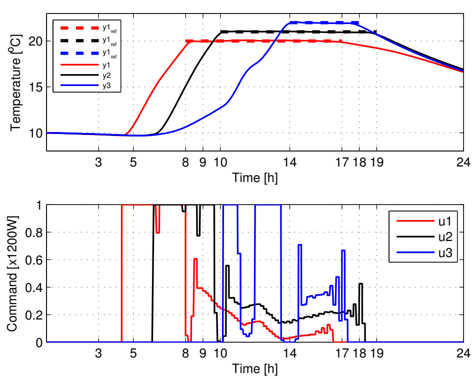

Fig. 8. dMPC behavior using Algorithm 1

From a computational point of view, the proposed distributed MPC (Algorithm 1) has the same complexity as the decentralized approach, considering that the calculation of $\hat{\mathbf{y}}_i(k)$ requires less time than the optimization routine. In the distributed approach, we should also consider the communication efficiency, which can be very important in the overall efficiency of the algorithm.

D. Results analysis

The centralized and the distributed MPC give close performances (Table I), with the mention that dMPC is less computational demanding. For example, using a Dual CPU at 3.00GHz and Matlab routines, we obtained a mean of 0.618s for the centralized optimization time versus 0.19s, the time spent by each distributed controller to minimize its local criterion. In the dMPC case we should add the communication time for one time step which depends on network protocol performances. The performance gap between the dynamic MPC algorithm and a classic control law (on/off, P, PI) with anticipation can be even greater if the occupation periods have a higher frequency.

TABLE I

COMPARISON BETWEEN DIFFERENT CONTROL STRUCTURES

Control law	I_C $[^oCh]$	I_W $[kWh]$
On/off (± 0.1, $T_s = 60s$)	306	312
P (k=0.5)	328	295
PI	306	308
Decentralized MPC	319	288
Centralized MPC	191	279
Distributed MPC	195	273

IV. CONCLUSION

A model predictive control strategy has been proposed for building temperature regulation using electrical convectors. In order to obtain better control performances, the control design is based on the optimization of a dynamic cost function that includes the future occupation profile, which is the first main contribution of the paper. For large-scale buildings, especially when the internal walls have a low thermal isolation, a one-step distributed algorithm was proposed, which gives good results with low computational demand.

Future work will focus on the impact of a more detailed vision of the thermal coupling between zones through open doors. Another research topic is the control problem with multiple heat sources, with different energy costs. A more theoretical theme is a stability study of the dynamic cost function MPC.

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