Receding Horizon Control for Demand-Response Operation of Building Heating Systems

Gianni Bianchini, Marco Casini, Antonio Vicino, Donato Zarrilli

Abstract—In this paper we consider the problem of optimizing the operation of a building heating system under the hypothesis that the building is included as a consumer in a Demand Response program. Demand response requests to the building are assumed to come from an external market or grid operator. The requests assume the form of price/volume signals specifying a volume of energy to be saved during a given time slot and a monetary reward assigned to the participant in case it fulfills the conditions. A receding horizon control approach is adopted for minimization of the energy bill, by exploiting a simplified model of the building. Since the resulting optimization problem is a mixed integer linear programming problem which turns out to be manageable only for buildings with very few zones, a heuristic is devised to make the algorithm applicable to realistic size problems as well. The derived control law is tested on the realistic simulator EnergyPlus to evaluate pros and cons of the proposed algorithm. The performance of the suboptimal control law is evaluated by comparison with the optimal one on a chosen test case.

I. INTRODUCTION

Energy efficiency in buildings operation is one of the key drivers towards the 20-20-20 objective set by the European Union in 2008, consisting in cutting greenhouse gas emissions by 20% (w.r.t. 1990 level), increasing renewable energy usage by 20% and cutting energy consumption by improved energy efficiency by 20%, all within year 2020. Building energy consumption, including both commercial and residential, represents almost 40% of the global energy produced worldwide. About 50% of this huge amount of energy is consumed for heating, ventilation and air conditioning (HVAC). HVAC plants, especially the oldest ones, are operated through simple rule-based strategies, which actuate the system in feedforward at a centralized level, while local thermal control is made through standard thermostatic devices. This out of date state of the art has stimulated research for several years, with the aim of reducing consumption and improving comfort through the design of more appropriate and sophisticated feedback control laws, exploiting real time information from the several components of the buildings. Most of the proposed approaches are based on Model Predictive Control, because of its attractive features, ranging from the possibility of handling constraints on numerous variables involved to optimizing economical objectives in a time-varying context (see e.g., [1], [2], [3], [4], [5] and references therein). A further consideration which calls for specific attention to building thermal control and related energy consumption profiles concerns the increasing interest of the electricity grid operators in the Demand Response (DR) (or Demand Side Management (DSM) or Active Demand (AD)) concept. The concept of DR has been introduced several years ago in the literature on smart energy grids ([6], [7], [8]). Recently, a complete commercial and technical architecture has been developed in the European project ADDRESS ([9], [10], [11]). The key idea is that the end users play an active role in the electricity distribution process, adjusting their consumption patterns according to energy dynamic pricing policies enforced by the various players involved in energy markets. In a scenario characterized by an ever increasing spread of renewables, consumer participation in the DR schemes may greatly help in mitigating the balancing problems arising in the grids due to the intermittent nature of renewables. This participation does not take place on an individual basis, rather through the aggregation of a community of individual consumers, possibly represented by an intermediary subject, the aggregator. The aggregator’s main objective is to value the flexibility of the consumption load profile of individual consumers. An aggregator has a pool of subscribers (end users), and is able to send them price-volume signals in order to affect their consumption pattern. These signals are typically sent once/twice a day and specify a monetary reward (price) if power consumption, during certain hours of the day, is below/above specified thresholds (volume) [11].

In this context, buildings can be considered as excellent candidates for demand flexibility, in the sense that they might find it convenient to schedule certain tasks so that they can obtain the reward, actively contributing to the overall reduction of carbon dioxide production. Actually, buildings are large storage devices, with an inherent capability of shifting HVAC electric loads according to a smart strategy to participate in the DR service. In this context, a building can represent a privileged consumer engaged by an aggregator, who collects a certain amount of energy over specified time intervals, i.e., the energy saved by consumers accepting the aggregator’s offer. This energy can be used for several purposes. For instance, the DSO (Distribution System Operator) may ask an aggregator to enforce energy reduction in a given load area over a given time interval, if an overload is foreseen in that area, in order to counteract possible network unbalancing. Another reason for the aggregator to collect energy is that it could sell on the market options related to reprofiling of the load curve in specific load areas of the distribution system.

In the present paper, an MPC approach is proposed to design a feedback law for the regulation of the thermal comfort in a building equipped with an electrical under-
floor heating system. The novelty introduced here is the inclusion of price/volume signals from an external market player asking the building to participate in a DR service. Participation of buildings in DR programs has been recently addressed in [12], where a pricing policy has been proposed for offering real time regulation services. In our case, the building operator just receives an external price/volume signal and the optimizer analyses whether it is convenient for the building to participate or not in the service. Price/volume signals are usually known to the operator at least 12 hours before the provision of the service. Since the objective is the minimization of the energy bill, participation in a DR program offers an additional opportunity to reduce the operation costs.

We make reference to EnergyPlus [13] as a realistic physical modelling simulator and formulate a receding horizon optimal control problem on the basis of an identified linear model of the building. The devised control law is tested on the physical model simulator and on the linear model for comparison purposes. In this sense, the present contribution is in the spirit of [14], [15], [16], where a different objective is considered. Actually, it turns out that a decoupling approach which decomposes regulation of the different zones in independent problems, provides reliable results in the absence of DR participation. On the contrary, the presence of price/volume signals makes the computational burden of the optimization grow exponentially with the number of zones in the building. For these reasons, a decoupled heuristic relaxation of the problem is devised and the suboptimal results obtained are evaluated with respect to the optimal solution on a three-zone test case. A large scale test case is also worked out.

The paper is organized as follows. In Section II we formulate the problem specifying the objective to be optimized. In Section III, we describe the proposed control algorithm. Section IV reports the experimental results obtained on a small scale and a large scale test case. Finally, conclusions are drawn in Section V.

II. PROBLEM FORMULATION

A. System model

This paper focuses on a building with a centralized heating system (e.g., a government building) composed of \( m \) zones \( Z_1, \ldots, Z_m \) equipped with electrical radiant floor heating systems, i.e., electrical resistance elements placed under the floor. Assume that each zone is equipped with a temperature sensor connected to a centralized controller and that each heater can be independently switched on or off by the control unit. Assume that the system operates at a sampling time \( T_s \) and let \( k \in \mathbb{T} = \{0, 1, \ldots \} \) be the discrete time index. For each zone \( Z_i \), \( i = 1, \ldots, m \), define:

- \( u_i(k) \in \{0, 1\} \): heater status {inactive, active},
- \( q_i \): heater energy consumption [kWh per sampling period],
- \( T_i(k) \): indoor temperature [°C], measured by the sensor,
- \( C_i = [T_i(k), T_i(k)] \): thermal comfort range,

and let

\[
\mathbf{u}(k) = [u_1(k), \ldots, u_m(k)]' \in \{0, 1\}^m
\]

\[
\mathbf{T}(k) = [T_1(k), \ldots, T_m(k)]' \in \mathbb{R}^m.
\]

Other than on the heater status \( \mathbf{u}(k) \), indoor temperature \( \mathbf{T}(k) \) depends on outdoor temperature, solar radiation, indoor lights and appliances, human occupancy, etc., which can be represented by a noise vector \( \mathbf{d}(k) \). Hence, the temperature dynamics can be expressed in regressive form as

\[
\mathbf{T}(k+1) = \mathbf{F}(\phi(k)),
\]

\[
\phi(k) = [\mathbf{T}(k), \ldots, \mathbf{T}(k-k_T)].
\]

\[
\mathbf{u}(k), \ldots, \mathbf{u}(k-k_u), \mathbf{d}(k), \ldots, \mathbf{d}(k-k_d)
\]

where \( k_T, k_u, k_d \) are nonnegative integers and \( \mathbf{F}(\cdot) \) is some (possibly nonlinear and time-varying) function.

Thermal comfort at time \( k \) is guaranteed if \( \mathbf{T}(k) \in C(k) \) where

\[
C(k) = \{ \mathbf{T}(k) : T_i(k) \in C_i \; \forall i = 1, \ldots, m \},
\]

and the overall consumption within the \( k \)-th time step is given by

\[
Q(k) = \sum_{i=1}^{m} q_i u_i(k).
\]

Consider a time horizon \( I(k, K) = [k, k + K] \subseteq \mathbb{T} \). The total consumption in \( I(k, K) \) amounts to

\[
Q(k, K) = \sum_{l=k}^{k+K-1} Q(l).
\]

Assume that \( p(k) \) represents the time series (or a forecast thereof) of electricity price. Energy cost (or expected cost) in the interval \( I(k, K) \) is given by

\[
C(k, K) = \sum_{l=k}^{k+K-1} p(l) Q(l).
\]

B. Demand-Response model

A Demand-Response program \( P \) is a sequence of DR requests \( R_j, j = 1, 2, \ldots, \) where \( R_j \) is the set

\[
R_j = \{ I(h_{j1}, H_{j1}), r_j, R_j \},
\]

being \( I(h_{j1}, H_{j1}) \subseteq \mathbb{T}, I(h_{j1}, H_{j1}) \cap I(h_{j2}, H_{j2}) = \emptyset \; \forall j_1 \neq j_2 \). The request \( R_j \) is said to be fulfilled if and only if

\[
Q(h_{j1}, H_{j1}) \leq r_j,
\]

i.e., the overall energy consumption in \( I(h_{j1}, H_{j1}) \) is no higher than the prescribed threshold \( r_j \), and in this case a monetary reward \( R_j \) is granted to the consumer.

For any time horizon \( I(k, K) \), let \( P(k, K) = \{ R_j : I(h_{j1}, H_{j1}) \subseteq I(k, K) \} \), i.e., the set of DR requests that occur within the time horizon, and \( J(k, K) = \{ j : R_j \in P(k, K) \} \). Moreover, let

\[
\gamma_j = \begin{cases} 1 & \text{if } R_j \text{ is fulfilled} \\ 0 & \text{otherwise.} \end{cases}
\]

The overall cost of operation of the building heating system under the DR program \( P \) in \( I(k, K) \) is therefore given by

\[
C^{DR}(k, K) = C(k, K) - \sum_{j \in J(k, K)} \gamma_j R_j.
\]
C. Optimal heating operation problem

Our goal is to devise a control algorithm for the thermal heating system of each zone in order to minimize the global (building) electricity bill under a DR program $P$, while preserving comfort constraints.

Consider a time horizon $I(k, K)$, and let

$$U(k, K) = \begin{bmatrix} u(k)' \\ \vdots \\ u(k + K - 1)' \end{bmatrix}.$$  

Assuming $d(k)$ (or a forecast thereof) is available, the above problem can be formulated as the following mixed-integer program:

$$U^*(k, K) = \arg \min_{U(k, K)} \quad C^{DR}(k, K)$$

s.t.

$$Q(h_j, H_j) \leq \gamma_j r_j + (1 - \gamma_j) H_j \sum_{i=1}^{m} q_i$$

$$\gamma_j \in \{0, 1\}$$

$$T(l + 1) = F(\phi(l))$$

$$T(l) \in C(l) \quad \forall l \in I(k, K)$$

$$u(l) \in \{0, 1\}^m$$

Note that if the map $F(\cdot)$ is linear, i.e., $T(k+1) = \Theta_\phi(k)$ for some possibly time-varying matrix $\Theta$, then (2) is a mixed-integer linear program (MILP).

III. CONTROL ALGORITHM

It is known that temperature dynamics in a given zone depends on heater status, environmental temperature, solar radiation, internal lights and appliances, occupancy, and temperature of neighboring zones. A complex model which takes into account all the above mentioned aspects is not conceivable in (2) due to unacceptable computational burden. In particular, if the temperature variables $T_i(k)$ and the binary decision variables $u_i(k)$ and $\gamma_i$ are fully coupled via the constraints in (2), then the computational complexity scales exponentially with $m$, thus making the approach totally unfeasible except for very small-scale problems. In order to overcome this limitation, we will derive sub-optimal solutions by suitably decoupling (2) into $m$ smaller problems. To this purpose, the first step is to identify a decoupled regressive building model in which thermal flow between zones is not explicitly considered. Such an assumption is supported by the following arguments:

- if the zones are homogeneous and/or insulation is properly designed, as it happens in office or government buildings, the heat transfer between neighboring zones is really small;
- numerical simulations show good performance of a decoupled identified model of a well-established test case (see Section IV);
- possible discrepancies between the model and the real building can be compensated at each iteration by using sensor information and by using a receding horizon approach.

The need for a receding horizon strategy is further supported by the observation that optimizing "once and for all" over a long time horizon, e.g., one or more days, is quite unreliable. Indeed, satisfying the comfort constraints requires accurate prediction of the indoor temperature of each zone. Such predictions degrade with time due to a number of reasons, like model inaccuracies and lack of reliable weather forecasts. Moreover, long-term energy price forecasts may not be available.

It is worth noticing that if the control signals $u_i(k)$ were continuous rather than binary, then (2) would still be a MILP due to the presence of binary DR decision variables $\gamma_j$. However, the computational complexity would be drastically reduced since the number of DR events in each instance of the problem is typically small.

A. Problem decoupling

Let $T_i(k+1) = \Theta \phi_i(k)$, $i = 1, \ldots, m$ be a decoupled linear model for the system, where $\phi_i(k)$ is the $i$-th row of $\phi(k)$. Along the same line, let $U_i(k, K)$ be the $i$-th column of $U(k, K)$. $Q_i(k) = q_i u_i(k)$, $Q_i(k, K) = \sum_{l = k}^{k+K-1} Q_i(l)$, $C_i(k, K) = \sum_{l = k}^{k+K-1} p_i Q_i(l)$.

Even using this model, it is apparent that the optimization problem (2) cannot be split into $m$ independent MILPs, one for each zone $Z_i$, with overall cost function equal to the sum of $m$ marginal costs. In fact, the decision variables of all zones are coupled through the first constraint in (2), and the DR component in the cost function itself is a coupling term.

At each step $k$, and for each $R_j \in P(k, K)$, let $r = \{r_{j,i} : i = 1, \ldots, m, j \in J(k, K)\}$ and $R = \{R_{j,i} : i = 1, \ldots, m, j \in J(k, K)\}$ be matrices of free real parameters such that $r_{j} = \sum_{i=1}^{m} r_{j,i}$ and $R_{j} = \sum_{i=1}^{m} R_{j,i}$, respectively, and define

$$C_i^{DR}(k, K) = C_i(k, K) - \sum_{j \in J(k, K)} \gamma_{j,i} R_{j,i}.$$  

For each $i = 1, \ldots, m$, let $C_i^{DR}(k, K)$ be the optimal solution of the following MILP:

$$U^*_i(k, K) = \arg \min_{U_i(k, K)} \quad C_i^{DR}(k, K)$$

s.t.

$$Q_i(h_j, H_j) \leq \gamma_{j,i} r_{j,i} + (1 - \gamma_{j,i}) H_j q_i$$

$$\gamma_{j,i} \in \{0, 1\}$$

$$T_i(l + 1) = \Theta \phi_i(l)$$

$$T_i(l) \in C_i(l) \quad \forall l \in I(k, K)$$

$$u_i(l) \in \{0, 1\}$$

which depends on $r$ and $R$. It is not difficult to see that for any choice of the set of parameters $r$ and $R$, the function

$$C^{DR}(k, K) = \sum_{i=1}^{m} C_i^{DR}(k, K)$$

is an upper bound for the optimal cost $C^{DR*}(k, K)$ of (2). Therefore, it makes sense to look for the values of $r$ and $R$.  

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yielding a solution of the \( m \) problems (3) corresponding to the tightest upper bound, i.e., to find

\[
\min_{\tau, \mathbf{r}} C^{\text{DR}}(k, K)
\]

s.t.:

\[
r_j = \sum_{i=1}^{m} r_{j,i}, \quad R_j = \sum_{i=1}^{m} R_{j,i} \quad \forall j \in J(k, K)
\]

This can be achieved by applying a gradient descent algorithm with constraints, involving at each step the solution of \( m \) MILPs of the form (3), or via some heuristic. The latter approach is used in the case studies presented in Section IV.

B. Receding horizon implementation

The optimal control problem (2) (as well as the proposed decoupled version) does not lend itself to a standard MPC implementation, that is, (i) acquire measurements of \( \mathbf{T}(k) \), (ii) optimize the cost over \( I(k, K) \) for fixed \( K \), (iii) apply the optimal control action \( u^*(k) \). Indeed, this basic implementation does not take into account DR requests that partially overlap in time with the moving interval \( I(k, K) \). This issue is easily overcome by performing the further actions after updating the current step \( k \):

(iv) as long as there exists a DR request \( R_j \) such that the current time step \( k \) falls inside the interval \( I(h_j, H_j) \), set \( h_j = k \) and reduce \( H_j \) by one, subtracting the consumption \( Q(k) (Q_i(k)) \) of the current step from \( r_j \) \((r_{j,i})\),

(v) adapt the horizon length \( K = K(k) \) dynamically in a way such that \( I(k, K(k)) \) always fully covers some set \( \mathcal{P}(k, K(k)) \) of DR requests but without making \( K(k) \) less than a base horizon length \( K_{\text{min}} \).

IV. TEST CASES

A. Three-zone case

Let us consider an office building located in Milan (Italy) composed of three zones equipped with radiant floor heating systems. The building characteristics have been taken from an example provided in EnergyPlus. Hereafter, we assume the EnergyPlus model as the true (real) building, and the sampling time is set to \( T_s = 10 \) minutes.

1) Modelling and identification: As stated in Section III, the proposed control technique is based on decoupled linear time invariant models of the building zones.

The ARX family has been chosen to model the thermal behaviour of zones. For a given zone, the input signals are assumed to be heater command, outdoor temperature and internal heat gain (lights, appliances, human occupancy), while output is the indoor air temperature.

The proposed model for the zone \( i \) is as follows:

\[
T_i(k+1) = [a_1 \ a_2] \begin{bmatrix} T_i(k) \\ T_i(k-1) \end{bmatrix} + [b_1 \ b_2 \ b_3] \begin{bmatrix} u_i(k) \\ u_i(k-1) \\ u_i(k-2) \end{bmatrix} + [b_4 \ b_5] \begin{bmatrix} T_o(k+1) \\ T_o(k) \end{bmatrix} + [b_6 \ b_7 \ b_8] \begin{bmatrix} L(k) \\ L(k-1) \\ L(k-2) \end{bmatrix}
\]

where \( T_o(k) \) is the outdoor (environment) temperature and \( L(k) \) denotes the internal heat gain. \( T_o(k+1) \) denotes a forecast of \( T_o(k) \) available at time \( k \).

An identification experiment has been performed to find suitable values for unknown parameters \( a_1, a_2, b_1, \ldots, b_8 \). The estimation stage has been performed on six days, while validation is computed on three different days. The tool used to estimate the parameters of the model from the experiment data is the System Identification Toolbox [17] of Matlab.

Input signals have been chosen as follows:

- the heater command \( u(k) \) is a pseudo-random binary sequence (PRBS),
- outdoor temperature \( T_o(k) \) is the temperature in Milan in January taken from past time series,
- the internal gain \( L(k) \) is a binary signal equal to 1 during the working hours (8:00-18:00) and 0 elsewhere.

In Figure 1, a comparison between the real indoor temperature (computed by EnergyPlus) and the 24-step ahead prediction of model (4) in the validation days for zone 1 is reported. The FIT (according to the standard notation) for all zone is around 80%.

2) Experiment setup: The proposed optimization method has been validated on a three-days experiment. In such days, a DR program consisting in 6 DR requests is assumed as reported in Table I.

<table>
<thead>
<tr>
<th>(K_1)</th>
<th>(K_2)</th>
<th>(K_3)</th>
<th>(K_4)</th>
<th>(K_5)</th>
<th>(K_6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Start (h_i)</td>
<td>65</td>
<td>100</td>
<td>180</td>
<td>250</td>
<td>325</td>
</tr>
<tr>
<td>Duration (H_i)</td>
<td>4</td>
<td>3</td>
<td>5</td>
<td>3</td>
<td>5</td>
</tr>
<tr>
<td>Bound (r_{j,i}) ([\text{kW.h}])</td>
<td>3.6</td>
<td>3.1</td>
<td>4.2</td>
<td>4.1</td>
<td>4.5</td>
</tr>
<tr>
<td>Reward (R_j) ([\text{€}])</td>
<td>0.50</td>
<td>0.40</td>
<td>0.60</td>
<td>0.70</td>
<td>0.15</td>
</tr>
</tbody>
</table>

Heater power ratings for the three zones are set to 12, 8, 8 \([\text{kW}]\). The upper comfort bound is set to 24 \(^\circ\text{C}\) throughout the day, while the lower bound is 22 \(^\circ\text{C}\) from 8:00 to 18:00 and 16 \(^\circ\text{C}\) elsewhere. Energy cost profile has been taken from the Italian Electricity Market.

The heuristic adopted to assign the parameters \(r_{j,i}\) for each zone \(Z_i\) and for each DR request \(R_j \in \mathcal{P}(k, K)\), can be summarized in two stages.

![Graph showing the results](image-url)
Table II summarizes the results obtained by running both

<table>
<thead>
<tr>
<th>Zone</th>
<th>Energy Plus</th>
<th>Simulated</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall Cost [€]</td>
<td>22.97</td>
<td>22.50</td>
<td>21.31</td>
</tr>
<tr>
<td>Fulfilled DR reqs</td>
<td>6</td>
<td>6</td>
<td>5</td>
</tr>
<tr>
<td>DR reward [€]</td>
<td>2.95</td>
<td>2.95</td>
<td>2.80</td>
</tr>
</tbody>
</table>

1) For each zone $Z_i$, evaluate the minimum heater activation time $\tau_{j,i}$ to respect the comfort constraints on $I(h_j, H_j)$. If the total energy needed by all zones, i.e., $e_j = \sum_{i=1}^{m} \tau_{j,i} q_i$ exceeds $r_j$, ignore and skip the request $R_j$. Otherwise, assign $r_{j,i} = \tau_{j,i} q_i \forall i = 1, \ldots, m$.

2) Split the energy excess $r_j - e_j$ among all zones according to weights proportional to the corresponding heater power ratings, i.e.,

$$r_{j,i} \leftarrow r_{j,i} + (r_j - e_j) q_i / \sum_{i=1}^{m} q_i.$$  

The parameters $R_{j,i}$ are simply assigned by splitting $R_j$ according to weights proportional to the power ratings, i.e.,

$$R_{j,i} = R_j q_i \sum_{i=1}^{m} q_i.$$  

The strategy is repeated at each step of the receding horizon optimization algorithm.

Measured indoor temperature and heater command computed by the proposed method applied to the EnergyPlus physical model are depicted in Fig. 2 for zone 1. The overall cost for the three zones is 22.97 €. In Fig. 3, the internal temperature of zone 1 computed on the identified model is reported for both the proposed heuristic and the optimal algorithm.

Table II summarizes the results obtained by running both the proposed heuristic and the optimal algorithm on both the real system (EnergyPlus) and the identified model.

**B. Large-scale case**

Let us consider a building composed of 100 zones. It is assumed that 30 zones are modelled as zone 1 in the previous test case, 35 as zone 2, and 35 as zone 3. Since an EnergyPlus model of the building is not available, simulations have been performed by using the model identified in Subsection IV-A. All building zones are set at different initial conditions. The DR program is assumed as in Table I with consumptions and rewards scaled by a factor of 30.

When dealing with DR requests, a slightly modified version of the heuristic strategy reported in Subsection IV-A is used. Define a macrozone $M_i$ as a set of homogeneous zones. In our case, the building is divided into 3 macrozones, composed of 30, 35 and 35 zones, respectively. The partition of the DR rewards $R_j$ and consumption bounds $r_j$ among macrozones is made according to the procedure reported in Subsection IV-A. Within each macrozone, DR rewards are equally distributed among zones, while the consumption bounds are assigned favouring the zones that currently are at a lower temperature. We remark that despite the above simplifying assumptions, from the computational viewpoint this is indeed a full 100-zone case since all zones are set to different initial conditions.

The overall energy cost for the three-day simulation is 679.39 €. All the six DR requests have been fulfilled, for a total reward of 88.50 €. Building consumption during the DR program is reported in Table III. The average computational time per step for all zones is about 9 seconds on a 3.4 GHz Intel i7 PC, confirming the applicability of the proposed algorithm for large-scale buildings.

Table III summarizes the results obtained by running both the proposed heuristic and the optimal algorithm on both the real system (EnergyPlus) and the identified model.

**C. Discussion**

By comparing the overall cost obtained by the optimal and the suboptimal control laws, both implemented on the simplified model, we observe that while the cost provided
by the heuristic suboptimal control is 1.5% higher than that of the optimal control, the time taken for computation of the suboptimal control law is approximately 2 orders of magnitude smaller than that needed for the optimal solution. Actually, as expected, the computational burden of the optimal algorithm which grows exponentially with the number of zones, leads to untractable problems even when few zones, e.g., 5 or 6, are involved. Obviously, the computational burden scales linearly for the heuristic suboptimal algorithm, allowing for an efficient solution of large-scale problems with hundreds of zones. In addition, it is worthwhile to notice from Figure 3, that the behaviour of the controlled variable is very similar for the two alternative control laws, with few discrepancies specifically concentrated in the time intervals where demand response signals are active.

A second observation concerns the quality of the adopted simplified model. Several identification trials performed on data generated in different conditions by an Energy Plus model, invariably show that the decoupled model performs very satisfactorily on validation data. This fact is confirmed quite neatly by the cost achieved by the control law designed on the simplified model and applied on the EnergyPlus simulator. The data reported in Table II show that the degradation of performance is approximately 7%, both for the optimal and the suboptimal control laws.

A final comment concerns the relationship between the true optimization problem and the relaxed one. While it is clear that the cost produced by the latter is an upper bound of the true minimal cost, it is not well understood yet if there exists a combination of the heuristics parameters (r and R), such that the solution of the suboptimal problem achieves the optimal solution. Our conjecture is that the answer to this question is positive, but a formal proof is still to come. What is important to notice is that if this statement will be proved, this would open the door to a systematic way of improving the approximating optimization problem towards the exact one. This fact, which appears of marginal importance for the three zone setup, could become very important when dealing with large-scale realistic applications, where conservatism of the heuristic could be conceivably more severe than in few zone building applications.

V. CONCLUSION

In this paper the problem of optimizing the operation of a building heating system under the hypothesis of participation in Demand Response program has been addressed. A receding horizon control approach has been proposed for minimization of the energy bill, in which the opportunity provided by the DR price/volume signals is exploited for reducing the cost of the heating operation of the building. The control law has been tested both on the simplified identified model used for the design and on the realistic building simulator provided by EnergyPlus. Ongoing work is directed towards optimal control of a more complex model of the building considered as a microgrid, including the entire HVAC plant, different renewable generation sources, electric and thermal storage devices, electric appliances and other kinds of electric loads.

REFERENCES


