Receding-horizon Supervisory Control of Green Buildings

Truong X. Nghiem, George J. Pappas
Department of Electrical and Systems Engineering
University of Pennsylvania
{nghiem, pappasg}@seas.upenn.edu

***Abstract*— Buildings account for about 40% of total energy use in the United States, according to the U.S. Department of Energy. Consequently, there has been a growing interest in green buildings, i.e., energy-efficient buildings, particularly control strategies for their HVAC systems. In this paper, we present a receding-horizon supervisory control strategy for optimizing total electric cost, which is the sum of an energy usage cost and an infinity-norm-like demand charge. The controller utilizes an optimizer to minimize an objective function whose evaluation involves simulation of the building energy system. This paper also presents a Matlab toolbox we developed for co-simulation and simulation-based optimization with the building energy simulation software EnergyPlus. The toolbox was applied to a benchmark example showing the potential of the proposed controller.**

I. Introduction

A heating, ventilation, and air conditioning (HVAC) system provides heating, ventilation and/or cooling within a building to control its indoor climate. According to the U.S. Department of Energy, buildings account for about 40% of all energy use in the United States ([1]). For this reason, green buildings (i.e., energy-efficient buildings) have been of strong interest not only in the buildings and HVAC community but also in the control community. From the control perspective, a building energy system is a highly complex and stochastic system that needs to be controlled and optimized efficiently. There are many factors affecting the performance of such a system that need to be accounted for, e.g., occupancy schedule and weather condition. Consequently, advanced supervisory control is necessary to fully address problems in designing low-energy buildings.

Model Predictive Control (MPC) is a control strategy that uses a model of the plant to predict its future behavior so as to optimize an objective function in a receding-horizon manner ([2]). Interest in MPC for buildings and HVAC control is growing quickly despite its heavy computational requirement and the need for a good building model ([3], [4], [5], [6], [7]). In this paper, we developed a receding-horizon optimal supervisory control strategy for the HVAC system of a building in order to minimize the total electric cost. While the aforementioned papers only considered as the objective function either energy cost (the charge for the amount of energy used) or demand charge (the charge for the maximum demand during peak demand periods), we sought to minimize the sum of these costs. This total cost is the actual amount billed to the customer by the utility company. The optimization problem becomes more difficult to solve because its objective function now consists of a sum and an infinity-norm-like value which spans the entire billing period instead of the much shorter prediction horizon of the controller. To resolve this difficulty, we re-formulated the optimization problem with a trade-off parameter between the two cost components, as to be discussed in section III. In [8], the author approached the same problem by assuming a fixed upper bound on the peak demand and minimizing only the energy cost. This approach is certainly less flexible than ours because of the hard constraint on demands, which could lead to significant increase in energy cost or even infeasibility of the optimization. To the extent of our knowledge, our paper is the first attempt to directly minimize the total cost.

In order to solve the optimization problem within the supervisory controller, we employed *simulation-based optimization* method, which has been investigated in the literature for design and control of building energy systems ([9], [10], [11], [6], [5]). Similar to [6], EnergyPlus was used to carry out the building energy simulation. However, instead of using a third-party optimization program, e.g., GenOpt as in [6], we used the so-called *co-simulation* technique ([12]), in which Matlab directly executes the EnergyPlus model and exchanges data with it on-the-fly. This allows us to utilize the standard Global Optimization Toolbox ([13]) in Matlab for optimization. As a result, a Matlab toolbox was developed to facilitate simulation-based optimization and control for buildings and HVAC systems.

The optimal supervisory control problem of HVAC systems is introduced and formulated in the next section. Section III develops our receding-horizon supervisory control strategy. Section IV presents an implementation of the proposed control strategy in a Matlab toolbox. The effectiveness of this control strategy is demonstrated by simulation results for a benchmark small office building in section V. The final section concludes the contributions of this paper and describes possible future research directions.

II. Optimal Supervisory Control Problem

An optimal supervisory controller for an HVAC system determines the optimal control modes and set-points that minimizes energy cost, or total energy input, of the system while maintaining a comfortable and healthy environment

This work is supported by the Greater Philadelphia Innovation Cluster (GPIC) for Energy Efficient Buildings sponsored by the U.S. Department of Energy. The views and conclusions contained in this paper are those of the authors and should not be interpreted as representing the official views of the U.S. Department of Energy.

in the building ([14], [15]). The problem of designing such a controller is significantly complex due to a large number of factors such as HVAC system type (electric-driven system, gas-driven system, with or without energy storage, etc.), equipment characteristics, utility rate structure, weather condition, load profile, occupancy schedule, etc.

In this paper, we consider the optimal supervisory control problem for an electric-driven HVAC system with the objective function being the total electric cost of the HVAC system. In a demand-based tariff for commercial energy customers, the electric cost for a billing period (often a month) consists of three parts:

- **Basic charge**: the fixed meter charge;
- **Energy charge**: the charge for the amount of energy used by the customer during the billing period;
- **Demand charge**: the charge for the maximum electric demand of the customer during the peak demand hours of the billing period.

Electric power demand and energy are measured over fixed time intervals Δ_T (often 15 minutes or one-half hour). The total cost can then be written as follows ([14]):

$$\text{cost} = C_b + \textstyle\sum_{k=0}^{N-1} C_{u,k} P_k \Delta_T + \max_{k \in \mathcal{P}} \{C_{d,k} P_k\} \quad (1)$$

In (1), N is the number of time intervals in a billing period and C_b is the fixed basic charge. For each time interval k, $0 \leq k \leq N-1$, P_k is the average electric demand of the HVAC system (kW), $C_{u,k}$ is the cost per unit of energy used ($/kWh), $C_{d,k}$ is the cost per unit of demand ($/kW), and $\mathcal{P} \subseteq \{0,\ldots,N-1\}$ is the set of peak demand intervals (or critical intervals) over which the demand charge is imposed. On the right hand side of (1), the second term is the energy charge and the last term is the demand charge. Here, $C_{d,k}$ is usually much higher than $C_{u,k}$, for example by approximately 240 times in Pennsylvania, USA ([16]).

The objective of the supervisory controller is to determine temperature set-points such that the total electric cost of the HVAC system is minimized.

A. Problem Formulation

Let $t_k \geq 0$ be the instant at the beginning of time interval k, $k = 0,\ldots,N-1$. We introduce the following variables

- $x_k \in \mathbb{R}^n$, $n \in \mathbb{N}$, is the state of the HVAC system at time t_k (e.g., x_k includes zone temperatures at t_k);
- $u_k \in \mathbb{R}^m$, $m \in \mathbb{N}$, are the zone temperature set-points during time interval k;
- $w_k \in \mathbb{R}^p$, $p \in \mathbb{N}$, is the disturbance to the HVAC system at time t_k (e.g., outside air temperature, solar radiation, internal heat generated by humans and machines). In most cases, predictions of w_k are available, for instance through weather forecast services and operation schedules. Thus, the actual disturbance can be written as $w_k = \bar{w}_k + \epsilon_k$ where $\bar{w}_k$ is the prediction of w_k and ϵ_k is the prediction error at t_k.

The HVAC system is a dynamical system. To formulate a mathematical representation of the optimal supervisory control problem, we assume that the *exact* dynamics of the HVAC system were known. Of course, such an assumption cannot be satisfied in practice; however, it will be addressed in the next section. For now, let us suppose that the exact dynamics is available and is given by function $f : \mathbb{R}^n \times \mathbb{R}^m \times \mathbb{R}^p \to \mathbb{R}^n$ such that $x_{k+1} = f(x_k, u_k, w_k)$ for $k = 0,\ldots,N-1$. Let $g : \mathbb{R}^n \times \mathbb{R}^m \times \mathbb{R}^p \to \mathbb{R}_+$ be a function that computes the average electric demand of the HVAC system during an interval, i.e., $P_k = g(x_k, u_k, w_k)$. The optimal supervisory control problem can be formulated as the following optimization:

$$\begin{aligned} \underset{u_0,\ldots,u_{N-1}}{\text{minimize}} \quad & J = \sum_{k=0}^{N-1} C_{u,k} P_k \Delta_T + \max_{k \in \mathcal{P}} \{C_{d,k} P_k\} \qquad (2) \\ \text{subject to} \quad & x_{k+1} = f(x_k, u_k, w_k),\ k = 0,\ldots,N-1 \\ & P_k = g(x_k, u_k, w_k),\ k = 0,\ldots,N-1 \\ & x_k \in X_k, u_k \in U_k,\ k = 0,\ldots,N-1 \end{aligned}$$

in which:

- X_k is the state constraint, e.g., the range of zone temperatures to maintain thermal comfort;
- U_k is the set of permissible set-point values; and
- constant C_b is dropped in the objective function J.

An optimal solution of (2) represents a trade-off between the energy charge and the demand charge components of the total cost. In order to reduce demand charge, i.e., to reduce peak demand during critical periods, a *load-shifting strategy* is often employed in which the cooling (heating) temperature set-point is lowered (raised) during a certain period before the peak demand hours so as to move part of the cooling (heating) load to non-critical hours. Load-shifting certainly increases energy usage, consequently energy charge, and may thus increase the total cost. Finding a balance between the two cost components, so that to minimize their sum, is the objective of the optimal supervisory controller.

B. System Model

As mentioned above, one issue in formulating and solving the optimization (2) is the impractical assumption that an exact model of the HVAC system is available. Furthermore, even if an exact model were available, it would be too complex to be used directly. One could obtain an approximate abstraction of the dynamics of the HVAC system by means of system identification and model calibration ([17], [18], [14]). A parametric mathematical model, in the form of ordinary differential equations, of the system is derived using the first-principles and its parameters are determined from the system specifications and experiments ([17]). Usually the dynamics f is approximated by a linear system of the form

$$x_{k+1} = A x_k + B_u u_k + B_w w_k$$

and function g is linear, as assumed in [7]. In this case, (2) can be solved using mathematical programming, for example using convex programming ([19]) if (2) is convex.

Using *black-box models* for f is another approach that has been investigated in the literature. Typically, learning algorithms are used to train a model of the HVAC system that empirically maps inputs to outputs ([14]). The method employed in this paper is to use a specialized simulator (e.g., EnergyPlus) to simulate the HVAC and building system, given concrete inputs and weather conditions, and compute the objective value J. An advantage of this *simulation-based approach* is the rigorousness of the model built inside the simulator, which allows for higher accuracy of the computation of J. However, because black-box models are not differentiable, a derivative-free optimization algorithm (e.g., a direct search algorithm or an evolutionary algorithm) needs to be used to solve (2), which usually results in considerable computational inefficiency. Therefore, a trade-off between model accuracy and optimization efficiency often needs to be made. More details will be discussed in section IV.

III. RECEDING-HORIZON CONTROL

Another obstacle in solving optimization problem (2) is its large size. With 15-minute time intervals ($\Delta_T = 15$-minutes) and one-month billing period, the number of variables could be of the order of thousands. Combined with a simulation-based optimization algorithm, it becomes very inefficient to solve (2) directly. Furthermore, acceptable predictions $\bar{w}_k$ of disturbance w_k are often available only for a short horizon of time, typically a day or two. Thus, solving (2) requires an approximation method that can resolve these two problems.

Recently, *Model Predictive Control* (MPC) has been widely studied in the building and HVAC control literature ([3], [4], [5], [6], [7]). The fundamental idea is to solve a large optimal control problem in a *receding-horizon* manner: at any step, the optimization problem is solved only for a short time horizon from the current state, then the first control action in the solution is applied, and the procedure is repeated at the next step.

The same idea can be applied to the problem in this paper. In particular, at any step t, optimization problem (2) is solved for only a horizon T, $0 < T \ll N$, and the set-point values at the first step of the solution are applied. Using this method, both aforementioned issues, namely the large size of (2) and the limited availability of disturbance predictions, are resolved. *However, the objective function of* (2) *consists of both a sum of cost values over time steps and an infinity-norm-like cost function, i.e., the demand charge. This poses a problem in rewriting* (2) *in the receding-horizon form because the demand charge is evaluated over the entire billing period while the receding horizon is only a small, moving part of it.* We propose the following receding-horizon formulation of (2) to overcome this difficulty.

A. Receding-horizon formulation

Let t be the current time step, $0 \leq t \leq N-1$, and D_t be the peak demand charge the system has reached prior to time t, i.e., $D_t = \max_{k \in \mathcal{P} \cap \{0,\ldots,t-1\}} \{C_{d,k} P_k\}$ for $t > 0$ and $D_0 = 0$. Clearly, D_t is non-decreasing with t and at the end of the billing period, the final demand charge is equal to D_N. During the horizon of length T starting at time t, the peak demand charge should be kept below D_t if possible, however should also be allowed to exceed D_t if that helps reducing the total cost. Therefore, we need a soft constraint that tries to limit the demand charge below D_t and if this is not satisfied, i.e., the demand charge exceeds D_t, punishes the cost function for the excess amount. In the rest of this paper, we assume that $C_{u,k} = C_u$ and $C_{d,k} = C_d$ are constant, which is often the case in practice. The above idea is implemented as the following receding-horizon formulation of (2):

$$\begin{aligned} \underset{u_t,\ldots,u_{t+T-1},y}{\text{minimize}} \quad & J(x_t) = C_u \sum_{k=t}^{t+T-1} P_k \Delta_T + p_t y \qquad (3) \\ \text{subject to} \quad & x_{k+1} = f(x_k, u_k, \bar{w}_k), k = t, \ldots, t+T-1 \\ & P_k = g(x_k, u_k, \bar{w}_k),\ k = t, \ldots, t+T-1 \\ & x_k \in X_k, u_k \in U_k,\ k = t, \ldots, t+T \\ & C_d P_k \leq y,\ k \in \mathcal{P} \cap \{t, \ldots, t+T-1\} \\ & D_t \leq y \end{aligned}$$

in which $p_t > 0$ is a penalty parameter and y is the prediction of D_{t+T}. Actual disturbances w_k, which are unknown at time t, are replaced by their predictions $\bar{w}_k$ in (3). If $y = D_t$ in the optimal solution of (3), the demand charge until time step $t+T$ is kept at D_t; otherwise, if $y > D_t$, the demand charge exceeds D_t and a penalty equal to $p_t(y - D_t)$ is added to the cost. Note that, to be precise, $J(x_t)$ should have been $C_u \sum_{k=t}^{t+T-1} P_k \Delta_T + p_t(y - D_t)$, however the constant was eliminated. After (3) is solved and u_t is applied, D_t will be updated as:

$$D_{t+1} = \begin{cases} \max\{D_t, C_d P_t\} & \text{if } t \in \mathcal{P} \\ D_t & \text{otherwise} \end{cases} \qquad (4)$$

Remark: In [3], [4], [5], [6], [7] that studied MPC for building and HVAC systems, the objective function is either the energy cost or the demand charge. In this paper, we seek to minimize the total cost, which is the sum of these costs. This requires us to re-formulate the optimization problem as (3) and (4) because the objective function now consists of a sum and an infinity-norm-like value.

In optimization problem (3), parameter p_t determines the trade-off between energy charge and demand charge, i.e., between limiting peak demand and letting it increase. Assuming that there exists an algorithm to solve (3), our goal will be to design a strategy to compute p_t so as to reduce the final total cost (1). Let $\mathcal{RH}(p)$ denote the instance of (3) with parameter $p_t = p$. In Fig. 1, which illustrates the proposed receding-horizon controller, the top-left box is the optimization algorithm that solves (3) with parameter p_t and the bottom box is the algorithm that computes p_t.

The rest of section III will present a general scheme for computing p_t, followed by two particular strategies.

B. General scheme for computing p_t

Given a value of p_t, we need to decide how good it is compared to other possible values. Hence, one key point in computing p_t is to define a way to measure the quality of each decision p_t. In other words, we need a function

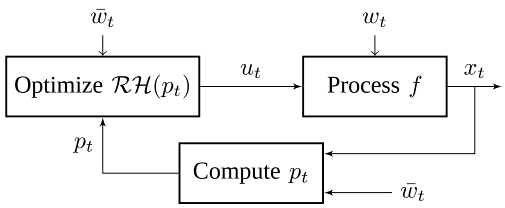

Fig. 1. Control structure: the top-left box is the optimizer to solve (3) with parameter p_t, the bottom box is the algorithm to compute p_t.

$Q(p_t|x_t, D_t, \bar{w}_t, \ldots, \bar{w}_{t+T-1})$ that returns a real value representing the quality of p_t given state x_t, D_t, and predictions $\bar{w}_t, \ldots, \bar{w}_{t+T-1}$. We assume that the smaller this value is, the better p_t is.

Once a quality function Q is selected, we choose at each step t the value $p_t = \arg\min_p Q(p|x_t, D_t, \bar{w}_t, \ldots, \bar{w}_{t+T-1})$. If p_t cannot be solved analytically, it needs to be approximated. In particular, learning algorithms can be used to derive a strategy for computing p_t based on historical data of weather and building activities. In the following sections, two quality functions are presented and their corresponding p_t computation strategies are derived. These strategies are simple and do not exploit information on the current state as well as disturbance predictions.

C. Cost increment function Q^{inc}

At each time step t, a decision of p_t will result in a control sequence $u_t^\star, \ldots, u_{t+T-1}^\star$ (the optimal solution of (3)), which may increase the total cost. This cost increment can be used as a quality measure of p_t. Specifically, the quality measure is defined as

$$Q^{\text{inc}}(\cdot) = C_u \sum_{k=t}^{t+T-1} P_k^\star \Delta_T + (y^\star - D_t)$$

subject to $y^\star$ and all $P_k^\star$ being in the optimal solution of $\mathcal{RH}(p_t)$. It is straightforward to see that $\arg\min_p Q^{\text{inc}}(p|x_t, D_t, \bar{w}_t, \ldots, \bar{w}_{t+T-1}) = 1$. Therefore, using Q^{inc} as the quality measure yields a stationary strategy $p_t = 1, \forall t \geq 0$.

D. Predicted final total cost function Q^{total}

Since predictions $\bar{w}_k$ are only available for a short horizon of time (often a day or two), it is difficult to predict the future behavior of the system. However, at time step t, if we assume that future disturbances $w_{t+1}, \ldots, w_N$ are similar to past disturbances $w_0, \ldots, w_t$, then we can approximate the final cost by scaling up the current cost. Indeed, let C_t be the accumulated energy charge from time 0 until t, i.e., $C_0 = 0$ and $C_t = C_u \sum_{k=0}^{t-1} P_k \Delta_T$ for $t > 0$. A decision p_t at time t will result in a sequence of controls $u_t^\star, \ldots, u_{t+T-1}^\star$ and an energy charge

$$C_{t+T} = C_t + C_u \sum_{k=t}^{t+T-1} P_k^\star \Delta_T.$$

The final cost can be predicted by scaling up C_{t+T} and can be used as a measure of quality of p_t. Specifically, we define

$$Q^{\text{total}}(\cdot) = \left(C_t + C_u \sum_{k=t}^{t+T-1} P_k^\star \Delta_T\right) \frac{N}{t+T} + y^\star$$

subject to $y^\star$ and all $P_k^\star$ being in the optimal solution of $\mathcal{RH}(p_t)$. Since C_t and $\frac{N}{t+T}$ are positive constants, minimizing Q^{total} is equivalent to minimizing $C_u \sum_{k=t}^{t+T-1} P_k^\star \Delta_T + \frac{t+T}{N} y^\star$, which implies that $\arg\min_p Q^{\text{total}}(p|x_t, D_t, \bar{w}_t, \ldots, \bar{w}_{t+T-1}) = \frac{t+T}{N}$. Therefore, using Q^{total} as the quality measure yields a linear strategy $p_t = \frac{t+T}{N}$ for $t \geq 0$.

IV. IMPLEMENTATION

In this section, an implementation of the simulation-based optimization of receding-horizon problem (3) is discussed. Simulation-based optimization of buildings and HVAC systems have been investigated for design ([9], [10], [11]) and control ([5], [6]). Such an optimization algorithm consists of two main components: a simulator to compute the objective function and a (usually derivative-free) optimization algorithm.

A. Co-simulation with Matlab and EnergyPlus

Standard building energy simulation software such as EnergyPlus, TRNSYS, and ESP-r are popularly used in the buildings and HVAC community. For an existing or a newly designed building, a model in one of these software is often available (and in many cases, it is the only model available). For this reason, we used a standard simulation software, in particular EnergyPlus, for the online model in the simulation-based optimization. There are several disadvantages of this approach which make it not ideal for practical purposes, including slow run-time and inability to access the underlying equations. Nevertheless, it is an appealing approach, at least in the near term, due to its inexpensive cost (mostly free) and the wide availability of benchmark models.

Simulation-based optimization for the purpose of control using standard building energy simulation software usually requires the so-called *co-simulation* technique ([12], [20]). Co-simulation is essentially a simulation setup where at least two simulators solve coupled equations together and exchange data in the process. More details can be found in the above references. We developed a Matlab toolbox [21] to facilitate co-simulation and simulation-based optimization with EnergyPlus from Matlab and to implement our receding-horizon supervisory control algorithm (section III).

B. Simulation-based optimization

In our implementation, the standard Matlab Global Optimization Toolbox ([13]) is used for black-box optimization. This toolbox is suitable for solving optimization problems where the objective function is complex, includes simulations, or does not possess derivatives. It provides multiple solvers, including pattern search and genetic algorithm, which do not need any details about the objective function other than a black-box computer routine to evaluate it.

For the optimization (3), the pattern search algorithm computes a sequence of solutions (points) that approach an optimal solution. At each step, it searches a set of points on a mesh around the current point, which was computed at the previous step. If a point that improves the objective function

J is found, the new point becomes the current point at the next step of the algorithm. The mesh is constructed around the current point by a scalar multiple of a set of vectors, which are either predefined and fixed or generated randomly. This set of vectors is called a pattern. More details can be found in [13] and the references therein.

Given x_t and a sequence of set-points $\{u_t, u_{t+1}, \ldots, u_{t+T-1}\}$, the evaluation of the objective function J is carried out by the following steps:

1) Call the simulator to simulate the HVAC system with x_t and the set-point sequence, then obtain power values P_k for each time intervals;
2) Compute $y = \max\left\{D_t, \max_{k\in\mathcal{P}\cap\{t,\ldots,t+T-1\}}\{C_d P_k\}\right\}$;
3) Compute $J = C_u \sum_{k=t}^{t+T-1} P_k \Delta_T + p_t y$.

Because the objective function needs to be evaluated for a large number of times in each optimization, the computational performance is often slow. For practical purposes, the number of iterations of the solver, or the computation time it uses, needs to be limited to an acceptable value.

C. Improving computational performance

As mentioned before, a disadvantage of the simulation-based optimization method is its slow performance. This is largely due to the inefficiency of the simulation software. For example, in our experiments, we observed that in each co-simulation session with EnergyPlus, the actual computation took less than 20% of the time while the rest was spent by EnergyPlus on warm-up periods (i.e., loading and parsing model files, and initialization of the simulation), despite that the model did not change between simulations. However, unless the simulation program supports re-initialization of model states, this inefficiency cannot be avoided.

Several techniques, some of which were implemented in our experiments, could help improve the efficiency of the optimization. Good starting points for the solver can be obtained from heuristic rules, from the solution at the previous time step, or are computed offline. Heuristics can also be used to restrict the search space to regions that are likely to contain good solutions. Finally, better simulation tools, such as those that allow access to their internal equations, or provide their gradients, could significantly improve the efficiency.

V. Simulation Results

In this section, we present simulation results of our receding-horizon supervisory control algorithm for the HVAC system of a benchmark building. Its model was obtained by modifying the EnergyPlus model of a small office building in the U.S. Department of Energy's Commercial Reference Buildings ([22]). It is a single-story, five-zone rectangular building of $511\,\mathrm{m}^2$ total floor area. The heating type is gas furnace and the cooling type is unitary DX. More information on this building can be found in [22].

For our purpose, we only considered the cooling system, which uses electricity, and its supervisory controller. The weather profile is of Baltimore, Maryland, USA in July, the month with the highest average temperature. Temperature set-points for the five zones are the same and are constrained to remain between $22°C$ and $26°C$. Working hours are 8am to 5pm, Monday through Friday. The HVAC system is turned on at 6am and off at 6pm. During July, the heating system is always off. The electric tariff is summarized in Table I.

TABLE I
Electric rate structure for the benchmark example

Billing period	Monthly
Peak demand hours	Monday – Friday: 12pm – 6pm Saturday, Sunday, Holiday: none
Electric rate	8.64¢/kWh
Demand rate	13.04$/kW
Demand interval	15 minutes

The EnergyPlus model of the building was used both for simulation-based optimization in the supervisory controller and for simulation of the "actual" building. For simplicity, we assumed that $w_k = \bar{w}_k$, i.e., the weather forecasts were exact. Note that in this experiment, only the electric cost of the HVAC system was considered, i.e., the lighting system and other electric equipments were excluded from the computation. The simulation period is entire July (31 days).

We simulated four different control strategies for computing temperature set-points, with 15-minute time-steps, of the cooling system. All controllers set the cooling set-point to $30°C$ during off hours (before 6am and after 6pm).

- In the base-line controller $\mathcal{C}_1$, the set-point remains constant at $24°C$ between 6am and 6pm. It is the default controller implemented in the original benchmark model and is used for comparison.
- In the linear-rise controller $\mathcal{C}_2$, the cooling set-point is $25.8°C$ from 6am to 10am, $24°C$ from 10am to 12pm, then increases linearly from $24°C$ to $25.8°C$ between 12pm and 6pm. This is a simple set-point strategy for demand-limiting ([23]).
- In the receding-horizon controller with stationary strategy $\mathcal{C}_3$, the cooling set-point remains constant at $25.8°C$ between 6am and 9am and is computed by the proposed supervisory control algorithm from 9am to 6pm, with constant $p_t = 1$ (section III-C). The control horizon T is one day, hence there are 36 variables u_k.
- The receding-horizon controller with linear strategy $\mathcal{C}_4$ is similar to $\mathcal{C}_3$ except that parameter p_t is computed as $p_t = \frac{t+T}{N}$ (section III-D).

For controllers $\mathcal{C}_3$ and $\mathcal{C}_4$, simulation-based optimization was limited to 4 hours for each day and was carried out on a Pentium 4 2.4-GHz computer with 1 Gb RAM, running Linux and Matlab version 7.9.0.

The simulation results are given in Table II. Obviously, both $\mathcal{C}_3$ and $\mathcal{C}_4$ achieved lower energy usage and peak demand than $\mathcal{C}_1$ and $\mathcal{C}_2$ due to the optimization. Controller $\mathcal{C}_3$ reduced the total HVAC electric cost by 25.47% compared to the base-line $\mathcal{C}_1$ and 6.77% compared to $\mathcal{C}_2$. Controller $\mathcal{C}_4$ reduced the total HVAC electric cost by 26.26% compared to $\mathcal{C}_1$ and 7.76% compared to $\mathcal{C}_2$. That $\mathcal{C}_3$ and $\mathcal{C}_4$ outperformed $\mathcal{C}_2$ by small margins might be attributable to the inefficiency of the simulation-based optimizer. Observe that, because

TABLE II

SIMULATION RESULTS FOR THE BENCHMARK EXAMPLE

Controller	Elec. Usage (kWh)	Peak Demand (kW)	Total Elec. Cost (USD)
$\mathcal{C}_1$ (base-line)	2035.144	8.718	289.52
$\mathcal{C}_2$ (linear-rise)	1387.333	8.557	231.45
$\mathcal{C}_3$ (stationary)	1309.046	7.875	215.79
$\mathcal{C}_4$ (linear)	1265.826	7.984	213.48

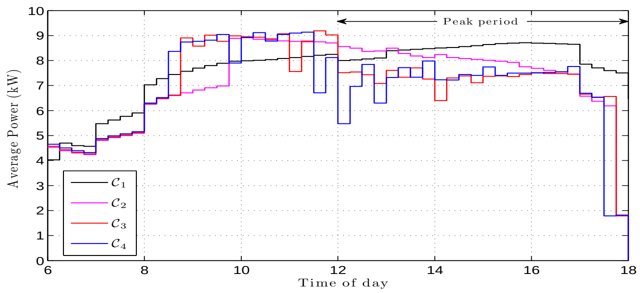

Fig. 2. Power demands for controllers $\mathcal{C}_1$, $\mathcal{C}_2$, $\mathcal{C}_3$, and $\mathcal{C}_4$ on July 9$^{\text{th}}$.

parameter p_t of $\mathcal{C}_3$ is (much) larger than that of $\mathcal{C}_4$, $\mathcal{C}_3$ tends to limit the peak demand rather than reducing energy usage, while $\mathcal{C}_4$ gives priority to the latter. For July 9$^{\text{th}}$, the average electric powers of the HVAC system and the temperature set-points between 6am and 6pm corresponding to controllers $\mathcal{C}_1$, $\mathcal{C}_2$, $\mathcal{C}_3$ and $\mathcal{C}_4$ are plotted in Figures 2 and 3. The peak demand period is from 12pm to 6pm.

VI. CONCLUSIONS AND FUTURE DIRECTIONS

In this paper, we proposed a receding-horizon supervisory control strategy for minimizing total electric cost. The main contribution of this paper is a technique to resolve the difficulty in solving the optimization problem, caused by the demand charge component of the total cost. Simulation results for a benchmark building model showed that the proposed control strategy could reduce the total electric cost compared to both the base-line controller and a rule-based controller. A Matlab toolbox for co-simulation and simulation-based optimization with EnergyPlus was developed and used in the experiment.

Several improvements can be made to the results in this paper. With respect to the receding-horizon control algorithm, current strategies for computing trade-off parameter p_t are fairly simple and do not exploit available information such as the current state and disturbance predictions. More sophisticated strategies, for example by applying regression or reinforcement learning algorithms, could have promising potential to improve the optimization and will be investigated in our future research. Also, migrating from the current simulation-based optimization to a model-based approach, by means of system identification of the temperature dynamics from measured data, will benefit the optimization performance.

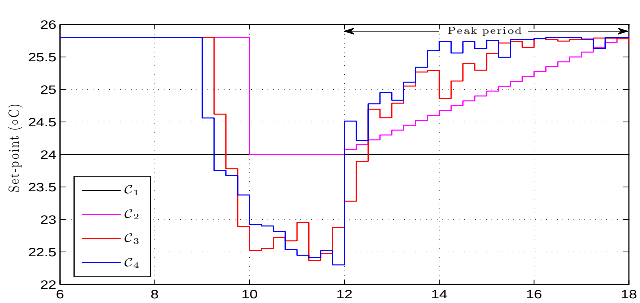

Fig. 3. Setpoints by controllers $\mathcal{C}_1$, $\mathcal{C}_2$, $\mathcal{C}_3$, and $\mathcal{C}_4$ on July 9$^{\text{th}}$.

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