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Demand reduction in building energy systems based on economic model predictive control

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ABSTRACT

This paper proposes and demonstrates the effectiveness of an economic model predictive control (MPC) technique in reducing energy and demand costs for building heating, ventilating, and air conditioning (HVAC) systems. A simulated multi-zone commercial building equipped with of variable air volume (VAV) cooling system is built in Energyplus. With the introduced Building Controls Virtual Test Bed (BCVTB) as middleware, real-time data exchange between Energyplus and a Matlab controller is realized by sending and receiving sockets. System identification is performed to obtain zone temperature and power models, which are used in the MPC framework. The economic objective function in MPC accounts for the daily electricity costs, which include time-of-use (TOU) energy charge and demand charge. In each time step, a min–max optimization is formulated and converted into a linear programming problem and solved. In a weekly simulation, a pre-cooling effect during off-peak period and a cooling discharge from the building thermal mass during on-peak period can be observed. Cost savings by MPC are estimated by comparing with the baseline and other open-loop control strategies. The effect of several experimental factors in the MPC configuration is investigated and the best scenario is selected for future practical tests.

1. Introduction

It is well known that the commercial and residential building sectors consume nearly 40% of total U.S. primary energy and electricity takes up approximately three quarters of this energy (Kelso, 2009). Besides accumulated energy use, buildings, especially commercial buildings, tend to have high demand in electricity simultaneously, which causes significant peak demand exertion on the grid. Both electricity suppliers and customers are concerned with the peak demand due to financial and capacity challenges. For one thing, numerous new power plants are built every year merely to feed the rapidly increasing peak electrical demand, which reduces efficiency at off-peak hours and leads to higher energy costs. Moreover, uncontrolled high peak demand also makes it difficult to integrate renewable and distributed energy resources. Therefore, it is of great interest to develop advanced technologies to flatten the peak demand relative to base load.

Recently, demand response (DR) has become a promising concept in the electricity market. DR is an approach to stimulate end users to change electric usage from their regular consumption patterns, in response to the time-varying price of electricity (Albadi and El-Saadany, 2007; Rahimi and Ipakchi, 2010). Thermal storage in building thermal mass has been recognized as an important passive asset to shift demand for decades, and there has been a number of simulation and experimental studies on reducing the peak demand by adjusting temperature setpoints of HVAC systems (Braun, 1990; Rabl and Norford, 1991; Henze, 2005).

Advanced control techniques for DR and building energy efficiency constantly emerge, facilitating the level of DR from manual to semi-automated and fully-automated (Kiliccote et al., 2006). Some methods, for example artificial intelligence-based (Krarti, 2003) and reinforcement learning (Liu and Henze, 2007) are model-free but usually need large amounts of data from specific buildings, meaning that even though they have been proven successful for a particular building, their performance cannot be guaranteed for another. Therefore, modeling still plays an important role in building energy control. With more and more modeling approaches proposed and the assistance of various modeling packages, accurate modeling for large scale buildings is not a barrier any longer (Hong and Jiang, 1997; Crawley et al., 2001; Yu et al., 2010).

Development of model-based control is desirable because simulation can be carried out during the building design phase and tested even before a building is built. Significant peak demand reduction

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has been shown by previous studies of model-based demand response control that took into account an electricity market where a time-varying rate is applied. Pre-cooling (or pre-heating) is the basic action to shift peak demand away from on-peak periods (Xu and Haves, 2006). In the demand limiting strategy, the zone temperature trajectories are obtained by solving an optimization problem under a pre-determined target demand during on-peak hours (Lee and Braun, 2008a,b,c). However, these methods are not able to deal with the impact of disturbances like building internal loads and weather conditions. While many studies focused on reducing the energy consumption and peak demand, there has been less work on reducing the energy and demand costs of building energy systems (Henze et al., 2008).

The objective of the work reported in this paper is to propose a closed-loop control system based on an economic model predictive control technique to reduce energy costs in commercial buildings considering real-time uncertainties and constraints. MPC has been proven as a successful approach by numerous industrial applications (Qin and Badgwell, 2003). It is essentially an optimization-based strategy in which an explicit model is employed to predict the behavior of the controlled plants over a receding horizon (Rao and Rawlings, 2000). In each time step, an open-loop optimal control problem is formulated and solved, and only the control action of the current time step will be implemented on the plant. This routine is iterated at subsequent intervals with new measurements and updated plant information. In this work, the objective function directly represents the energy and demand costs, which is an economic objective to be optimized. The building dynamics and the time scale of pricing and disturbances intertwine which lends itself to an economic objective with dynamic models as constraints. Comfort specifications are also incorporated as constraints. After all, it is the money saved on the utility that gives the owners of commercial buildings the incentive to take actions on importing new technologies and attaining building retrofits. Unlike previous studies in this area that used simplified models of buildings and their HVAC systems (Xu et al., 2004; Ma et al., 2009), this work relies on system identification to establish a direct input-output relationship from temperature setpoints to actual indoor zone temperature and power.

The reminder of the paper is organized as follows. The closed-loop simulation environment is described in Section 2. Section 3 shows the model identification procedure in the Matlab system identification toolbox. The economic model predictive control algorithm is developed in Section 4. Section 5 describes the virtual building modeling in EnergyPlus and simulation results, shows energy and cost savings brought by MPC comparing with the pre-programmed control strategies and analyzes the effect of some control parameters to the MPC performance. The final section concludes the paper.

2. System framework

The framework of the building energy simulation system is illustrated in Fig. 1. The steps followed to set up the system are described below:

(a) Create a virtual model of a commercial building with moderate thermal mass using EnergyPlus version 4.0;
(b) Design an input sequence and excite the EnergyPlus model to generate corresponding output signals;
(c) Identify mathematical models for temperature and power consumption in the Matlab System Identification Toolbox with the input and output data (Ljung, 2010);
(d) Employ the identified models and develop MPC algorithm that gives control actions of temperature setpoints for the building HVAC system;
(e) Apply the MPC controller to the original EnergyPlus model;
(f) Obtain and report the actual zone temperature, power and demand profiles.

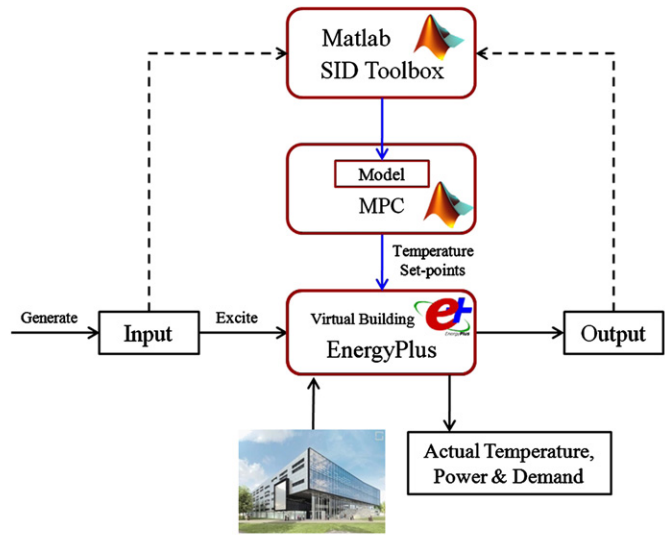

Fig. 1. Framework of the building energy simulation system.

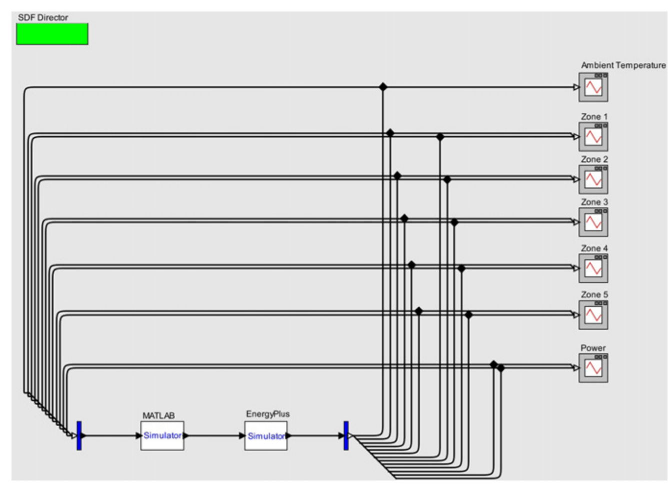

Fig. 2. System diagram that enables EnergyPlus and Matlab exchange data in real-time on BCVTB.

EnergyPlus is one of the most comprehensive simulation tools developed for building energy analysis. However, one limitation of EnergyPlus is the lack of a friendly graphical user interface. It carries out simulation by reading input data files (idf-files), which contain all of the pre-defined information regarding the building to be simulated including the simulation period, building dimension, layout and material, HVAC schedules and so on. This means that once a simulation is started, it cannot be paused to wait for data updates. As a result, it can only run in batch mode given pre-determined HVAC schedules and closed-loop controllers cannot be implemented external to the simulation.

In order to solve this problem, the Building Controls Virtual Test Bed (BCVTB) is employed as a middleware. BCVTB (Wetter and Haves, 2008) is an open-source software developed in Ptolemy II environment (Brooks et al., 2007). It allows users to couple different programs and conduct synchronized simulation. Matlab and EnergyPlus both play the role of clients connected to BCVTB as shown in Fig. 2. As soon as the simulation starts, there is a socket connection established from the middleware to each client. In each time step, which is 15 min in simulation time, both clients save and load data to and from the socket. The socket moves back and forth between the two programs directed by the middleware and data exchange is realized inside the middleware. This co-simulation process keeps running until a termination signal is received.

3. System identification

The building thermal and energy behavior can be simulated by EnergyPlus very well, but control-relevant input–output dynamic models are still required to implement model-based controllers. System identification is therefore performed on the EnergyPlus simulation to obtain dynamic models that can be used as prediction models in MPC.

Autoregressive exogenous (ARX) models are used here where their inputs are zone temperature setpoints of the cooling system and outputs are actual zone temperature and power measurements. The task of model identification is challenging due to nonlinearity, intermittent HVAC operations and disturbances (Salsbury, 2005). An experiment is designed to identify the models while the cooling system is being operated over normal conditions.

A pseudorandom binary sequence (PRBS) is generated as the excitation input. The binary levels of the PRBS are the lower and upper bounds of the thermal comfort region, which in this work are set as 21 and 25 °C. The selection of thermal comfort region is modified from Lee and Braun (2008a), by changing the upper and lower bounds to integers after converting it from Fahrenheit to Celsius. For the considered single-floor, five-zone building, each zone is excited separately in order to reduce the interactive effects among the HVAC control actions of different zones. In other words, when one zone is excited with the PRBS, the cooling of the other four zones is maintained in action as much as possible. This is done by altering the zone setpoint of the excited zone with lowered setpoint values during PRBS tests. The cooling setpoints are set as Eq. (1). The EnergyPlus model is fully excited over an 1 month period and the input–output data of occupied hours is used for system identification, which is shown in Fig. 3.

$$T_{sp,i}(k) = \begin{cases} 21, & \text{excited zone, PRBS} = 0 \\ 25, & \text{excited zone, PRBS} = 1 \\ 25, & \text{non-excited zones} \end{cases} \quad (1)$$

The model order is determined by the Matlab System Identification Toolbox. The power prediction model is fourth-order multi-input single-output (MISO), which is described by

$$A_P(q)P(k) = B_P(q)u(k) + e(k) \quad (2)$$

where q is a shifting factor, $P(k)$ is the power at the time k and $e(k)$ is a white noise sequence. $u(k)$ is the model input that has the form

$$u(k) = [T_{sp}^T(k) | T_a(k)]^T \quad (3)$$

where $T_{sp}(k)$ is the vector of zone temperature setpoints

$$T_{sp}(k) = \begin{bmatrix} T_{sp,1}(k) \\ T_{sp,2}(k) \\ T_{sp,3}(k) \\ T_{sp,4}(k) \\ T_{sp,5}(k) \end{bmatrix} \quad (4)$$

and $T_a(k)$ is the ambient temperature obtained from the typical meteorological weather data file (TMY2). It plays the role of a measured disturbance input and the history weather data will be replaced by a weather forecast or weather estimator module when this work is expanded to a field test on real building plants.

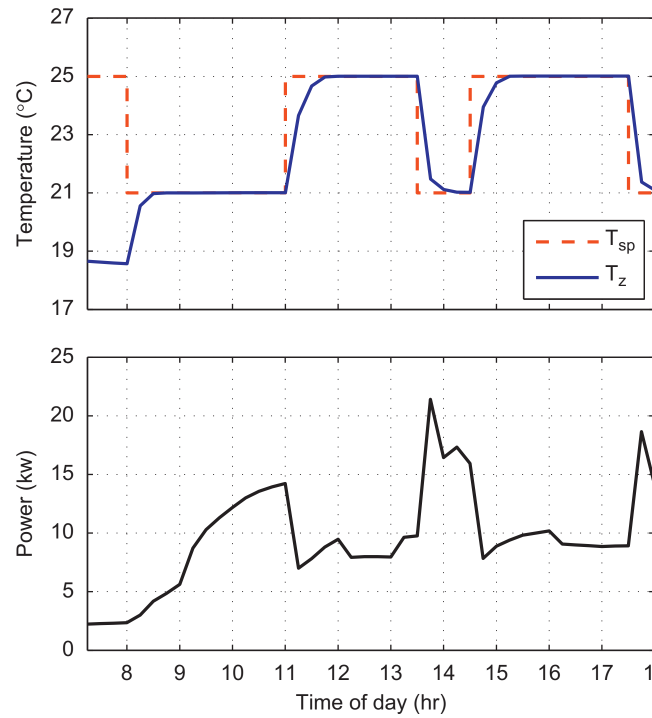

Fig. 3. Input–output data of an excited zone for model identification.

The $A_P(q)$ and $B_P(q)$ are model parameter matrices defined as

$$A_P(q) = 1 - a_1 q^{-1} - a_2 q^{-2} - a_3 q^{-3} - a_4 q^{-4} \quad (5)$$

$$B_P(q) = \begin{bmatrix} B_{P,1}(q) \\ B_{P,2}(q) \\ B_{P,3}(q) \\ B_{P,4}(q) \\ B_{P,5}(q) \\ B_{P,a}(q) \end{bmatrix}^T \quad (6)$$

Similarly, the zone temperature prediction model is identified as a second-order multi-input multi-output (MIMO) as shown in Eq. (7). $T_z(k)$ is comprised of five-zone temperatures:

$$A_T(q)T_z(k) = B_T(q)u(k) + e(k) \quad (7)$$

$$T_z(k) = \begin{bmatrix} T_{z,1}(k) \\ T_{z,2}(k) \\ T_{z,3}(k) \\ T_{z,4}(k) \\ T_{z,5}(k) \end{bmatrix} \quad (8)$$

The model parameters are listed in the Appendix A. Note that it is difficult to use the above linear models to accurately model the complex virtual building model in Energyplus. There is therefore inevitable model mismatch and further investigation needs to be carried out to understand its impact to the control performance.

4. Economic model predictive control

Instead of using a quadratic criterion as in the classical MPC (Rao and Rawlings, 2000), an economic objective function is designed as follows:

$$\min J = C_e + C_d \quad (9)$$

where J denotes the total daily electricity expense which is a combination of energy and demand costs defined by Eqs. (10) and (11) respectively:

$$C_e = \sum_{t=1}^{N} [Ec(t) \cdot \Delta t \cdot P(t)] \tag{10}$$

$$C_d = Dc \cdot \max_{t_d \le t \le N} \{P(t)\} \tag{11}$$

where t_d is the time when demand charges begin and $Ec(t)$ accounts for the time-of-use electricity rate and Dc is the demand charge rate. A rate plan offered by Southern California Edison (SCE) is used here (SCE, 2008), in which each day is divided into on-peak, mid-peak and off-peak. It is particularly designed for medium-sized commercial and industrial customers and its detailed information can be seen in Appendix B. $\Delta t = 0.25$ h is the time interval and N is the total number of time step per day:

$$N = \frac{24}{\Delta t} \tag{12}$$

Eq. (9) is a min–max optimization problem. We can convert the maximum term into a linear term so that it can be solved by linear programming routine.

Suppose at the current time k, the energy costs $C_e(k)$ can be decomposed into two terms:

$$C_e(k) = C_{e,h}(k) + C_{e,f}(k) \tag{13}$$

where $C_{e,h}(k)$ is the energy cost before k, which has been calculated and stored in the history data, and $C_{e,f}(k)$ denotes the predicted energy cost in the future horizon:

$$C_{e,h}(k) = \sum_{t=1}^{k} [Ec(t) \cdot \Delta t \cdot P(t)] \tag{14}$$

$$C_{e,f}(k) = \sum_{t=k+1}^{N} [Ec(t) \cdot \Delta t \cdot P(t)] \tag{15}$$

Introduce a new variable z to represent the peak demand of the day:

$$z = \max_{t_d \le t \le N} \{P(t)\} \tag{16}$$

and define $y(k)$ as

$$y(k) = [P(k+1) \ \cdots \ P(k+N_p)]^T \tag{17}$$

where $N_p = N - k$ is the width of prediction horizon. Extended from the current time to the end of the day, the prediction horizon shrinks over time, which differs from the traditional MPC where the prediction horizon is usually a receding window with fixed width. The shrinking horizon is chosen to minimize the energy cost on the daily basis. By simplifying the objective to the form in Eq. (18), the costs can be optimized on a daily basis:

$$\min \tilde{J}(k) = C_{e,f}(k) + C_d = [Dc \ \ Ec_f^T(k)] \begin{bmatrix} z \\ y(k) \end{bmatrix} \tag{18}$$

The ability to handle constraints is one of the most important advantages of MPC. The inequality constraints in Eqs. (19) and (20) need to be handled first, to guarantee the feasibility of Eq. (16). Eqs. (19) and (20) are necessary because the definition of z in Eq. (16) is not automatically incorporated into the optimization problem:

$$z \ge \max_{t_d \le t \le k} \{P(t)\} \tag{19}$$

$$\begin{bmatrix} -1 & 1 & & & \\ -1 & & 1 & & \\ \vdots & & & \ddots & \\ -1 & & & & 1 \end{bmatrix} \begin{bmatrix} z \\ y(k) \end{bmatrix} \le \mathbf{0} \tag{20}$$

By setting $x(k)$ and $U(k)$ to be augmented vectors of zone temperature and temperature setpoints over the control horizon N_c respectively as

$$x(k) = [T_z^T(k+1) \ \cdots \ T_z^T(k+N_c)]^T \tag{21}$$

$$U(k) = [T_{sp}^T(k) \ \cdots \ T_{sp}^T(k+N_c-1)]^T \tag{22}$$

where N_c is selected to be equal with N_p for simplicity, additional inequality constraints can also be directly imposed to regulate the zone temperature and setpoints within a range with respect to time:

$$T_{sp,min}(k) \le U(k) \le T_{sp,max}(k) \tag{23}$$

$$T_{z,min}(k) \le x(k) \le T_{z,max}(k) \tag{24}$$

There are also two more sets of equality constraints brought by the identified models. From Eqs. (2) and (7), the equality constraints can be written as

$$[A_y \ \ -B_y] \begin{bmatrix} y(k) \\ U(k) \end{bmatrix} = \mathbf{0} \tag{25}$$

$$[A_x \ \ -B_x] \begin{bmatrix} x(k) \\ U(k) \end{bmatrix} = \mathbf{0} \tag{26}$$

where A_y, B_y, A_x and B_x are matrices derived from the model parameters A_P, B_P, A_T and B_T.

Rewrite Eq. (18) with the new terms $x(k)$ and $U(k)$ added, the objective function finally becomes the following linear form:

$$\min_{\Psi} \tilde{J}(k) = [Dc \ \ Ec_f^T(k) \ \ \mathbf{0} \ \ \mathbf{0}] \begin{bmatrix} z \\ y(k) \\ x(k) \\ U(k) \end{bmatrix} \tag{27}$$

where $\Psi = [z \ y(k) \ x(k) \ U(k)]^T$ is the decision vector.

With the inequality constraints described by Eqs. (19), (20), (23) and (24), and the equality constraints as Eqs. (25) and (26), the optimization problem has been formulated as a linear program, which can be solved by the Matlab built-in function *Linprog*. We constantly monitored the status variable *flag*, which indicates whether a feasible solution is obtained. We found that Matlab can always get a feasible solution in each time step. However, the feasibility is not theoretically guaranteed, which is subject to one of our ongoing theoretical studies.

In each time step, only the current temperature setpoints $T_{sp}(k)$ (the first component of $U(k)$) in the optimal solution will be sent to the EnergyPlus model. This optimization procedure will be repeated and a new problem will be formulated in subsequent time steps when new measurement data are available.

Note that the definition of z as Eq. (16) requires that at least one of the inequalities in Eqs. (19) and (20) holds with equality, which can be shown by the following Theorem 1.

Theorem 1. *If* $\overline{\Psi} = [\overline{z} \ \overline{y} \ \overline{x} \ \overline{U}]^T$ *is an optimal solution of Eq. (27),* $\exists \ i \in [1,N]$ *s.t.* $z = P(i)$.

Proof. Suppose the opposition, i.e. $\overline{z} > P(i)$ for $\forall \ i \in [1,N]$, then $\exists \ \sigma > 0$ s.t. $\overline{\overline{z}} = \overline{z} - \sigma \ge P(i)$ for $\forall \ i \in [1,N]$. By simply replacing $\overline{z}$ with $\overline{\overline{z}}$ in the $\overline{\Psi}$, another feasible solution $\overline{\overline{\Psi}} = [\overline{\overline{z}} \ \overline{y} \ \overline{x} \ \overline{U}]^T$ is obtained. Then we have

$$\tilde{J}_{\overline{\overline{\Psi}}} - \tilde{J}_{\overline{\Psi}} = -\sigma \cdot Dc < 0 \tag{28}$$

which contradicts the proposition that $\overline{\Psi}$ is an optimal solution. The theorem is proved. □

5. Simulation studies

5.1. Virtual building modeling in EnergyPlus

A single story commercial building located in Chicago, Illinois, with a simple layout is modeled in EnergyPlus. The building is divided into five conditioned zones which include one interior and four exterior as shown in Fig. 4. A set of VAV boxes with controllable actuators and temperature sensors is installed in each zone. Other major features of the modeled building are listed in Table 1.

The impact of building cooling loads such as occupants, lighting and electrical equipment is included in the EnergyPlus model. Fig. 5 shows the internal load schedules in normal weekdays where the factors represent the ratios between actual and full loads. About 60% of the occupants are assumed to go outside the building during lunch breaks. The schedule of lighting is consistent with the occupancy schedule. The higher load of equipment in afternoon indicates that more equipment needs to be turned on in this period, and this is one of the reasons why this period is usually counted as on-peak. Note that different schedules of internal loads are used for weekends.

Energyplus is also capable of simulating the external loads. A weather file that contains historical measurements of ambient temperature, relative humidity and various types of solar radiation is incorporated.

5.2. Constraint scenario selection

In the MPC simulations, the zone temperature can be regulated by real-time constraints $[T_{z,min},T_{z,max}]$. In this work 1 day is divided into five periods as described in Fig. 6, which is similar to the approach described in (Henze et al., 2008). However, the time

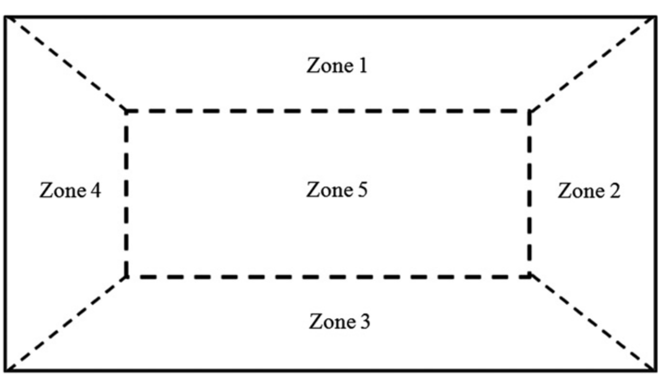

Fig. 4. Five-zone division floor plan.

Table 1
Major building features modeled in EnergyPlus.

Floor area	5000 ft^2
Orientation	30° east of north
Window to wall ratio	0.29
Internal loads	
Occupant	1 occupant/100 ft^2
Lighting	16.18 W/ft^2
Equipment	10.79 W/ft^2
Occupied hours	7:00–18:00
Cooling system	VAV direct expansion (DX)
Heating system	N/A
Natural ventilation	N/A

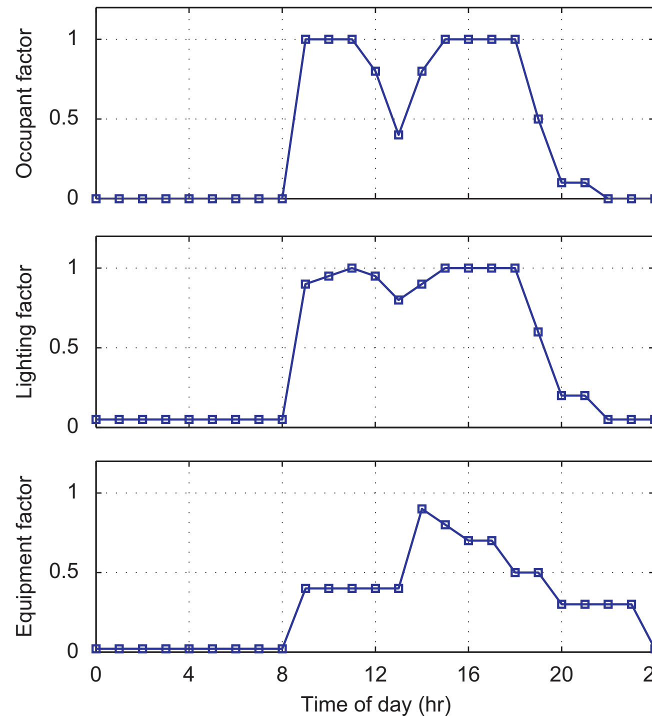

Fig. 5. Weekday schedule of the building internal loads: occupant (top), lighting (middle) and equipment (bottom).

periods are determined so that zone temperature level in each period can be maintained with in an appropriate range, rather than at a constant temperature setpoint as in Henze's work.

(1) Period 1 (t_1-t_2): The building can be pre-cooled at as low as 18 °C from the early morning until the occupied period starts. Cooling is expected to be stored in the building thermal mass and released later when necessary.
(2) Period 2 (t_2-t_3): During the off-peak and mid-peak occupied hours, zone temperature is maintained in lower half of the thermal comfort range 21 °C–23 °C with the hope that the stored cooling can be saved for utilizing in on-peak period.
(3) Period 3 (t_3-t_4): Zone temperature is free as long as within the comfort range. The stored cooling in building envelope can be either supplied or released.
(4) Period 4 (t_4-t_5): Maintain zone temperature in 23 °C–25 °C with the contribution of stored cooling.
(5) Period 5 (t_5-t_1 of the next day): Shut down the cooling system to avoid needless energy consumption.

Since t_2 and t_5 are fixed to the beginning and end of the occupied hours, there are three parameters (t_1, t_3 and t_4) that can be adjusted to reach a good scenario in regard to the setting of upper and lower bounds of temperature constraints. Step response tests of the EnergyPlus model previously done in Ma et al. (2011) suggested that it takes 4 h to fully pre-cool the considered building. Manipulating t_3 and t_4 can be interpreted from Fig. 6 as cutting off the areas of A and B from the thermal comfort region. Note that changing t_4 should not affect the control results a lot because the MPC controller tends to adjust the zone temperature trajectories to approach the upper bound of comfort region during the on-peak period so that cooling stored in the building thermal mass can be released to reduce the demand cost.

Weekly simulations were performed to investigate impact of t_1 and t_3 in the MPC configuration, which are shown as in Figs. 7 and 8. The weather temperature features of that week in July are

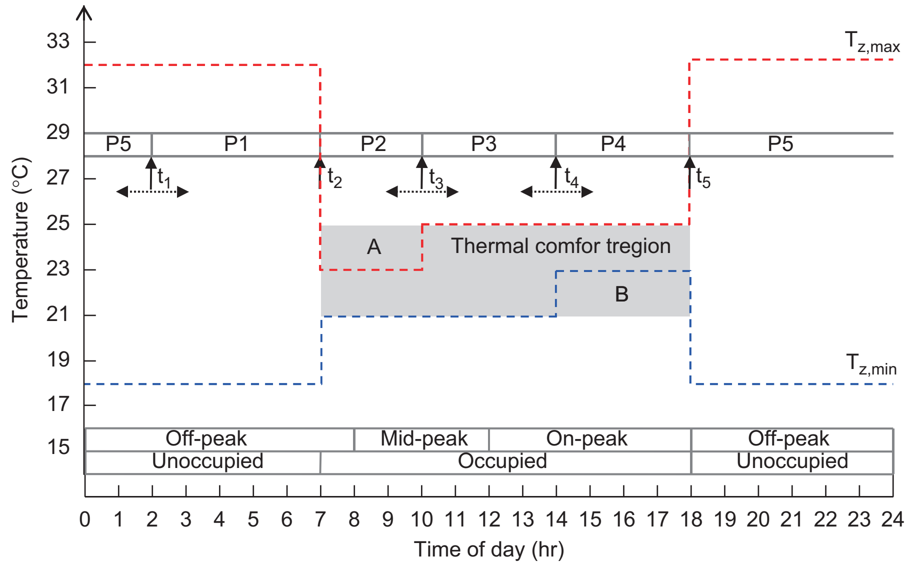

Fig. 6. Period division in MPC simulations.

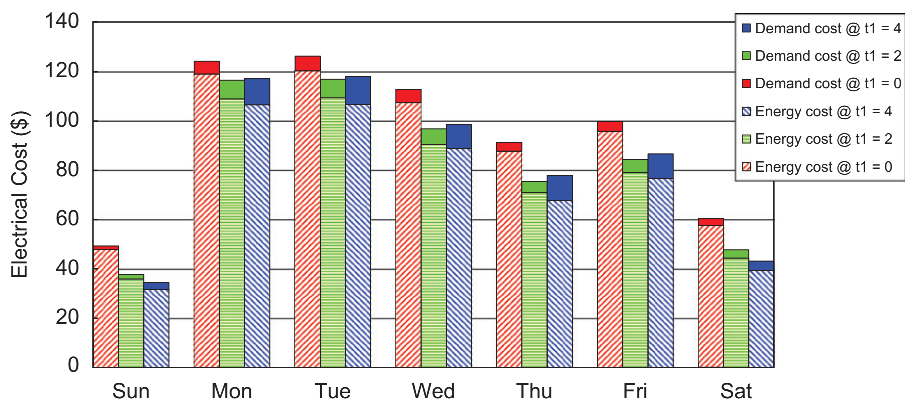

Fig. 7. Weekly electrical costs vs. varying t_1, ($t_3 = t_4 = 12$).

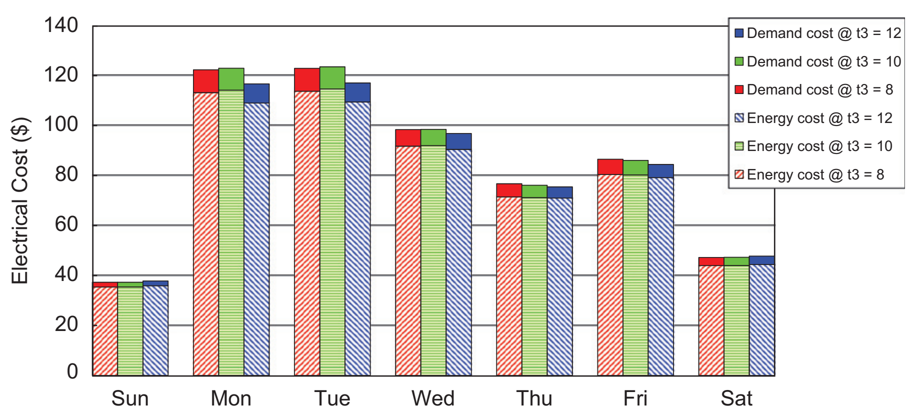

Fig. 8. Weekly electrical costs vs. varying t_3, ($t_1 = 2$, $t_4 = 12$).

listed in Table 2. A trade-off can be observed from Fig. 7 that starting pre-cooling earlier can lead to lower demand cost but higher energy cost, and a balanced point of t_1 is found around 2 a.m. Fig. 8 indicates that setting t_3 as late as possible in the non-peak period can reduce both energy and demand costs.

Consequently, the best scenario is selected to be $t_1 = 2$, $t_3 = 12$ and $t_4 = 12$, and this selection is not affected by the weather conditions. The selection is made only based on the observation of

Table 2
Ambient temperature of the simulation week (°C).

July	Sun. 1	Mon. 2	Tue. 3	Wed. 4	Thu. 5	Fri. 6	Sat. 7
Ave.	24.0	26.8	28.9	22.4	19.8	21.7	25.6
Hi.	31.7	31.1	34.4	26.1	25.0	27.8	32.2
Lo.	14.7	19.4	23.3	17.2	13.3	11.7	16.7

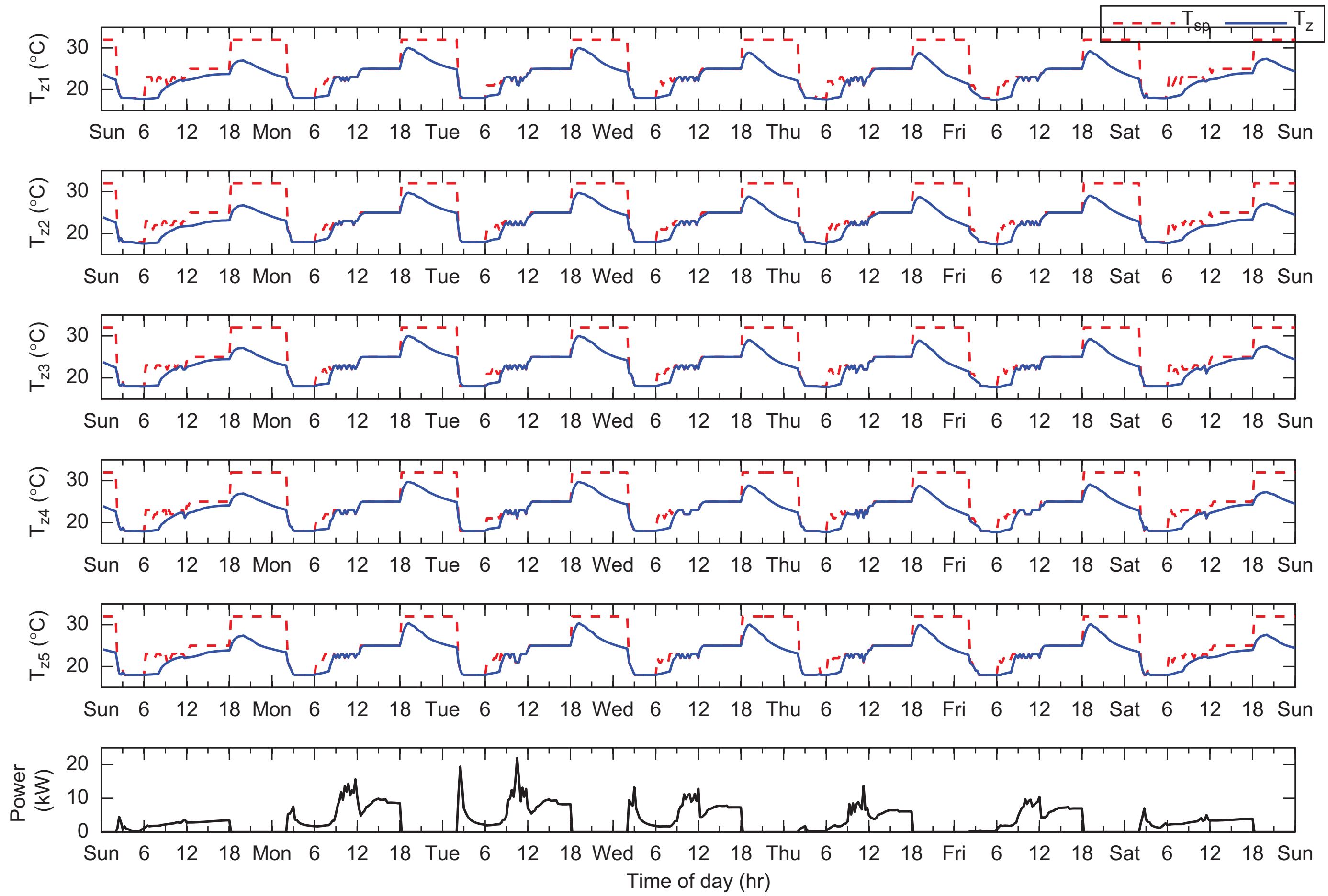

Fig. 9. Zone temperature and power profiles in the weekly simulation.

the 7 day testing results so probably it may not be optimal for other situations. The ambient temperature in that simulation week varies a lot as indicated in Table 2, showing that the selection is not sensitive to the weather condition. When dealing with other buildings, however, we should certainly repeat the routine to find different configurations.

Corresponding simulation results of zone temperature and power profiles are shown as Fig. 9. It can be observed that the peak loads have been shifted away from the on-peak period and the on-peak power profile has been flattened. The impact of ambient temperature to energy consumption can also be seen clearly. For example, the power spike at about 3 a.m. on Tuesday was caused by the relatively warm night that made the building thermal mass more difficult to be pre-cooled. Less power was consumed over weekend than weekdays due to the different schedules of internal loads (occupants).

5.3. Cost savings brought by MPC

The performance of MPC in saving electrical costs is compared with the baseline and other pre-programmed control strategies. The baseline night-setup strategy (BL) is applied in many buildings, in which the temperature setpoints are simply set to the lower bound of comfort region during entire occupied hours and cooling is shut down for all unoccupied hours. Therefore, the building thermal mass always plays the role of resistance rather than assistance. Simple alternative methods include linear-up (LU) and step-up (SU) (Lee and Braun, 2008b), in which setpoints are set to the lower bound of comfort region until on-peak hour begins, and then raised with a linear and step pattern respectively.

Table 3
Weekly savings compared to the baseline.

Strategy	Energy saving (%)	Cost saving (%)
Linear-up	15.29	17.42
Step-up	21.49	24.35
MPC	25.31	28.52

Savings in energy and costs are shown in Table 3. It can be seen that MPC brings more savings than the pre-programmed control strategies.

6. Conclusions

In this paper, a building energy demand reduction has been developed via model predictive control to demonstrate the effectiveness in saving energy and demand costs. The Building Controls Virtual Test Bed software was employed as middleware to link Energyplus and Matlab and the real-time data exchange between the two programs enabled implementation of closed-loop controllers. In the proposed model predictive control algorithm, the min–max optimization problem with an economic objective, a shrinking prediction horizon and several constraints was transformed into a linear program and solved at each time step. The proposed method aims at minimizing the costs on the

Table B.1
TOU-GS-3 energy charge rate.

	Energy charge ($ / kWh)	
Summer season Jun. 1–Oct. 1	On-peak 12:00–18:00 weekdays except holidays	0.31176
	Mid-peak 8:00–12:00, 18:00–23:00 weekdays except holidays	0.14200
	Off-peak 23:00–08:00, weekdays and all day on weekends and holidays	0.06866
Winter season Oct. 1–Jun. 1	Mid-peak 8:00–21:00 weekdays except holidays	0.10468
	Off-peak 21:00–8:00, weekdays and all day on weekends and holidays	0.07151

daily basis (within each calendar day), which is why the shrinking horizon is chosen. This shrinking horizon also allows us to eventually implement this method to dynamic pricing cases, in which the electricity rate is released by utility at the beginning of the day based on a load forecast.

It was shown by simulation that under the time-of-use electrical pricing structure, MPC brings substantial cost savings by automatically triggering pre-cooling effect and shifting the peak demand away from on-peak hours. Moveover, the simulation conducted in this work also provided knowledge on the configuration of MPC parameters for the particular building modeled in EnergyPlus, which can make the potential practical field tests more efficient.

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Appendix A. Identified model parameters

The parameters of the ARX models obtained by system identification are listed as follows:

(a) Power prediction model $\{A_P, B_P\}$

$$A_P = [1\ \ -0.6725\ \ 0.0289\ \ -0.0243\ \ 0.0222] \tag{A.1}$$

$$B_P = \begin{bmatrix} -1458 & 1482 & -267.9 & 13.24 \\ -1045 & 974.6 & -181.4 & 9.968 \\ -1557 & 1612 & -274.7 & 29.49 \\ -890.8 & 740.5 & -115.1 & -54.21 \\ -1773 & 2068 & -628.0 & 158.1 \\ 1243 & -1512 & 1280 & -803.3 \end{bmatrix}^T \tag{A.2}$$

(b) Temperature prediction model $\{A_T, B_T\}$

The multivariate ARX model can be written as

$$A_{T0}T_z(k)+A_{T1}T_z(k-1)+A_{T2}T_z(k-2)$$
$$= B_{T1}u_(k-1)+B_{T2}u_(k-2)+e(k) \tag{A.3}$$

where

$$A_{T0} = \mathbf{I}_{\times 5} \tag{A.4}$$

$$A_{T1} = \begin{bmatrix} -0.8821 & -0.0380 & -0.1011 & -0.1070 & -0.0428 \\ -0.0037 & -0.8922 & 0.0171 & -0.0035 & 0.0039 \\ -0.0353 & -0.0425 & -0.8032 & -0.0203 & 0.0082 \\ -0.0531 & 0.0230 & -0.1082 & -0.9793 & -0.0525 \\ -0.0651 & -0.0059 & 0.0094 & -0.1103 & -0.9116 \end{bmatrix} \tag{A.5}$$

$$A_{T2} = \begin{bmatrix} 0.1536 & 0.0195 & 0.0339 & 0.0652 & 0.0393 \\ 0.0015 & 0.0825 & -0.0029 & 0.0040 & -0.0018 \\ 0.0161 & 0.0148 & 0.1098 & 0.0248 & 0.0041 \\ 0.0134 & 0.0062 & 0.0257 & 0.1350 & 0.0143 \\ 0.0436 & 0.0113 & 0.0043 & 0.0693 & 0.1505 \end{bmatrix} \tag{A.6}$$

$$B_{T1} = \begin{bmatrix} 0.7684 & -0.0322 & -0.0129 & -0.0364 & 0.0232 & 0.0884 \\ -0.0020 & 0.8049 & -0.0014 & -0.0050 & 0.0001 & 0.0030 \\ -0.0150 & -0.0378 & 0.7815 & -0.0600 & -0.0085 & 0.0147 \\ 0.0118 & -0.0108 & 0.0011 & 0.7061 & 0.0224 & 0.0734 \\ 0.0041 & -0.0151 & -0.0015 & 0.0027 & 0.7618 & 0.0782 \end{bmatrix} \tag{A.7}$$

$$B_{T2} = \begin{bmatrix} -0.4901 & 0.0098 & -0.0562 & -0.0132 & -0.0270 & -0.0765 \\ -0.0003 & -0.6061 & 0.0153 & 0.0049 & 0.0023 & -0.0035 \\ -0.0054 & 0.0045 & -0.4681 & 0.0508 & 0.0200 & -0.0092 \\ -0.0492 & 0.0434 & -0.0834 & -0.5451 & -0.0595 & -0.0739 \\ -0.0298 & 0.0158 & 0.0127 & -0.0493 & -0.5116 & -0.0714 \end{bmatrix} \tag{A.8}$$

Appendix B. Electricity price structure from SCE

The rate plan of TOU-GS-3 (Time of use-General service-3) from SCE (SCE, 2008) is used in the simulation conducted in this paper. Medium-sized commercial and industrial customers such as 24-h service stations, restaurants, motels and so on may benefit from choosing this plan. End users can save electric bill if they are able to use a majority of energy during, or shift a significant amount of energy use to, the mid- and/or off-peak hours. The electricity price is comprised of energy charge, demand charge and customer charge. The energy charge is depicted in Table B.1. The demand charge is $9.83 per monthly maximum kW. Since customer charge is fixed, it is not included in the optimization scheme in this work.

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