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EnergyPlus model-based predictive control within design–build–operate energy information modelling infrastructure

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This study proposes a design–build–operate energy information modelling (DBO-EIM) infrastructure to allow users to deploy the design-stage building energy model for model predictive control (MPC) system in the building operation. A newly constructed office building is studied as a test bed. An EnergyPlus model-based predictive control (EPMPC) system is designed and simulated in the Matlab/Simulink environment within the DBO-EIM infrastructure. EPMPC aims at minimizing heating, ventilation, and air conditioning energy consumption while maintaining occupant thermal comfort. Compared to the baseline rule-based control system, EPMPC demonstrates a 28.9% energy reduction in one-week simulation in the heating season and 2.7% energy reduction in one-week simulation in the cooling season. The comfort constraint is met during more than 90% of the simulated hours. The study demonstrates one significant contribution of the DBO-EIM infrastructure that a design-stage EnergyPlus model can be integrated in an MPC system and the preliminary simulation results are satisfactory.

Keywords: energy modelling; model predictive control; comfort; EnergyPlus; Matlab/Simulink; life cycle

1. Introduction

Green buildings aim to save land, energy, water, and material, as well as create a healthy and comfortable environment for their occupants throughout the building life cycle. The concept has been well acknowledged in the USA and around the world. The annual market growth rate of a widely used green building rating system – Leadership in Energy and Environmental Design (LEED), is over 100% from 2000 to 2011 in the USA (Zhao and Lam 2012).

Reducing operating energy cost is one of the primary goals for the design of green buildings. In LEED 2009 for New Construction and Major Renovation (LEED 2009 NC) rating system, the energy and atmosphere section has the highest possible credit points (35 out of 110) among seven different sections. The whole-building energy modelling is being increasingly used in the building industry, mainly due to the requirements of LEED, EnergyStar, BREEAM (Lam et al. 2013), and other green building rating systems. Theoretically, at the design stage, the building energy modelling should be used as a method to generate and evaluate alternative design options to reach a better design solution. However, in current practice, building energy modelling rarely plays a role during the early design stage. Typically, building energy models are created after the design has been decided to demonstrate compliance for codes and standards (Vaughn 2011). As a result, the cost of creating energy models is treated as an "added cost" rather than as part of the design fees (LEEDuser 2013). So the potential contribution of building energy modelling is not fully recognized in the design phase.

Furthermore, the design case energy model can remain useful in other phases of the building life cycle. For example, in order to get three points for LEED measurement and verification, energy models are calibrated during the one-year post-construction occupancy period, but in most cases, energy models are discarded after this LEED certification is awarded.

The design-stage energy model can also be useful to assist building controls during the building operation phase. Over the past two to three decades, numerous studies have focused on model-based (or simulation-based) building control theories and applications. In 1980s, simplified heating, ventilation, and air conditioning (HVAC) and building models have been used for "evaluating and optimizing building control strategies" (Kelly 1988). According to Kelly, two different types of simulation-based control systems were studied. The first type, known as "static simulation-based control", simulation was performed during the control system design period to generate a set of "scenarios" for the control system to select in operation. The second type known as "real-time model-based control" used "real-time building system models, expert systems, or

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a combination of both" to assist control decisions in real time. Mahdavi systematically introduced the idea of model (simulation)-based control of building system operation. The two methods – "generate-and-test" and "bi-direction inference" – were proposed and tested for lighting controls in an actual office building case (Mahdavi 2001). Other studies also demonstrated the feasibility of model-based controls in lighting, shading, and HVAC control areas (Clarke et al. 2002; Jayada 2003; Mertz 2003; Mo 2003; Mahdavi and Pröglhöf 2008).

One particular topic in the model-based control field is model predictive control (MPC) (Garcia, Prett, and Morari 1989). Two types of building and system modelling methods are often used – "forward (classical) approach" and "data-driven (inverse) approach". The forward approach is "to predict the output variables of a specified model with known structure and known parameters when subject to specified input variables". The data-driven approach is "to determine a mathematical description of the system and to estimate system with known input and output variables" (ASHRAE 2009).

The early studies focused on controlling the HVAC system at the component level using forward modelling approach. Wang and Jin (2000) developed an adaptive MPC controller for variable air volume (VAV) system using the simplified first principle-based single-zone building and VAV system component models (Wang and Jin 2000). Several other studies have developed MPC systems to control various building systems to minimize energy consumption (or cost) and maintain indoor set point using forward modelling approach (Henze, Dodier, and Krarti 1997; Yuan and Ronald 2006; Dong 2010; Gyalistras 2010; Castilla et al. 2011; Yu, Loftness, and Yu 2013).

Some MPC studies used data-driven modelling approach to create models for control and optimization, such as Kolokotsa et al. (2009), Paris et al. (2010), Freire, Oliveira, and Mendes (2008), and Privara et al. (2011). The experimental and/or simulation input and output data were collected to identify model parameters.

The studies mentioned above suggest that both forward and data-driven modelling methods are effective for MPC studies in the building field. However, from the practical point of view, a few difficulties of directly using forward and data-driven models in practice can be further discussed. (1) The forward modelling approach is suitable for single-zone and simple geometric buildings, but can be difficult to be applied to the buildings with multiple zones and irregular geometric shapes. (2) The data-driven modelling approach often requires sensor data at the system component level and/or in the indoor/outdoor environment, which may not be available for some building projects. Besides, in some cases, full system dynamics may not be easily obtained from the available input data.

Various building energy modelling tools may provide an alternative solution for the MPC research in the building field. For instance, EnergyPlus is a well-developed, validated, and constantly updated whole-building energy simulation program (Crawley et al. 2001). EnergyPlus is built based on forward modelling approach, but some newly developed system modules are created using data-driven modelling approaches. Therefore, EnergyPlus can be treated as a front-end platform that helps users to access the various system modules in the back end. However, using EnergyPlus in MPC studies is not straightforward.

First, time synchronization between EnergyPlus and other control system development tools needs to be addressed. EnergyPlus has its internal run-time mechanism, while control system design and performance simulation programs, such as Matlab, have their own simulation time management methods. The synchronization may not be direct. Recently, the development of Building Control Virtual Test Bed (BCVTB) (Wetter 2011a) provided a solution to solve the problem. Time synchronization and co-simulation can be achieved by using BCVTB together with EnergyPlus Energy Management Systems for external co-simulation (DOE 2013).

Second, data interoperability can be an issue. EnergyPlus simulation uses external weather file with sequential static time stamps as one of the model inputs. It may cause problems for optimization, which need numerous repeated runs for each of the optimization iteration. A new method to process the model input data (e.g. occupancy, lighting, and equipment schedules) is needed to solve this data interoperability problem.

Third, the "black-box" model optimization for MPC can be challenging to implement. One solution is to use simulation tools to develop the building model, and to use the simplified forward or data-driven system model for control optimization. Braun developed an optimal controller to optimize energy cost and peak electrical demand for building thermal storage. TRNSYS zone model is used for simulation and a forward model is developed for system optimization (Braun 1990; TRNSYS 2012). Yahiaoui et al. proposed an MPC controller using ESP-r model as the plant model. The simplified system model and control laws were implemented in Matlab/Simulink (Yahiaoui et al. 2006; ESP-r 2000). Bernal et al. introduced a control system that can link EnergyPlus model with Matlab/Simulink via MLE+ as the plant model (Bernal et al. 2012). A forward system model was optimized in Matlab/Simulink environment and the control performance was simulated in the EnergyPlus model. TRNSYS and GenOpt (Wetter 2011b) were used for plant modelling and optimization, respectively, to solve the "black-box" optimization problem in the studies of Coffey et al. (2010) and Kummert, Leduc, and Moreau (2011).

Two studies have addressed all the three difficulties above. May-Ostendorp et al. developed an MPC control system that was built in Matlab and connected to EnergyPlus by writing and reading text files. The control rules were generated by optimizing the window opening schedules to save energy (May-Ostendorp et al. 2011). On the basis of the offline optimization framework above, Corbin et al. developed a real-time optimization framework for the MPC system by linking EnergyPlus, Matlab, and Building Automation System (BAS). The test cases reported that the MPC system resulted in "54% energy savings with often improved occupant comfort" (Corbin, Henze, and May-Ostendorp 2012).

The literature review given above indicates a clear value added for the building energy modelling at the building operation stage. In order to use the design-stage energy model in the model-based predictive control in the operation stage, a "design–build–operate energy information modelling" (DBO-EIM) infrastructure is proposed. This DBO-EIM framework suggests that a detailed whole-building energy model (1) should be created during the design phase to assist design decision-making and to be used for code and standard compliances; (2) should be updated during the construction and calibrated during the commissioning and operation phases to become the as-built and well-tuned energy model; and (3) should be continuously used during the operation phase to be integrated with BAS to reduce energy consumption and improve occupant comfort by the model-based predictive control.

This study demonstrates one key part of the DBO-EIM infrastructure – to use the design-stage building energy model for MPC systems in the building operation. An EnergyPlus model-based predictive control (EPMPC) system is developed for an office building within the DBO-EIM infrastructure. The EnergyPlus model is directly co-simulated and optimized in Matlab/Simulink via MLE+. The preliminary simulation results and limitations are discussed. Conclusions and future work are presented.

2. DBO-EIM infrastructure

The DBO-EIM infrastructure is shown in Figure 1. During the design stage, the baseline building energy model should be built according to the preliminary design and ASHRAE (American Society of Heating, Refrigerating and Air Conditioning Engineers) 90.1-2007 and/or other building energy standards. Then the multidisciplinary design team should work together to propose alternative sustainable strategies, including design strategies for building envelope, HVAC, and daylight/lighting systems. These alternative design strategies should be modelled using the same assumptions on lighting schedules, equipment schedules, occupancy schedules, zone parameters, and other model inputs as the baseline building energy model. The energy performance of these alternative design models can then be compared and optimized to uncover a better choice for the final proposed design case. In the end of the design stage, the proposed design case model can be created based on the final design decision.

During the construction stage, the building energy model should be updated based on the as-built drawings incorporating any changes, in order to accurately reflect the actual completed building.

During the commissioning and the early operation stages, HVAC, lighting, and other building systems are tuned and tested. Accordingly, the system parameters in the building energy model should be calibrated. The environmental aspects and other model inputs, such as occupancy, equipment, and lighting schedules of the building energy model should be calibrated by using spot and long-term environmental and energy data measurements. In addition, the real-time weather information collected from an on-site weather station should be applied into the as-built building energy model to further calibrate the model.

To demonstrate the design-stage modelling method of the DBO-EIM infrastructure, a two-storey 2262 m^2 office building – Center for Sustainable Landscapes (CSL) at Pittsburgh, PA, USA – was modelled. Detailed whole-building energy simulation models were developed by using DesignBuilder (2012) and EnergyPlus programs. Baseline energy models were built based on ASHRAE 90.1-2007 energy standard. Several design alternatives and the proposed design case energy models were created by employing various sustainable design strategies for comparison. The design phase energy modelling results indicate that compared to the ASHRAE 90.1-2007 baseline energy model, the annual energy consumption of the design case model was reduced by 39.8%. The annual energy use intensity of the proposed design case model was 52.2 kWh/m^2 based on total floor area. The detailed modelling methods and results during the design stage are available in Zhao et al. (2012).

The building system of the proposed design case is already reasonably efficient with normal operation schedules compared to the ASHRAE baseline requirements. Therefore, it is worthwhile to explore more advanced control strategies for the system to further reduce the HVAC operation energy consumption.

This paper focuses on the model-based control system design and performance simulation at the operation stage using the design-stage EnergyPlus model. The construction of the CSL building was completed in December 2011 and the building was officially occupied in spring 2012. The building is currently at its commissioning stage for LEED certification and Living Building Challenge (ILFI 2013). The research team was able to access the building operation data since August 2013 and the model calibration study is currently being done.

3. Control system design and simulation

3.1. Building and system modelling

The CSL building is equipped with a central air handler unit (AHU) with ground source heat pump as its cooling and heating source. The underfloor air distribution system is used for the open office, conference rooms, and

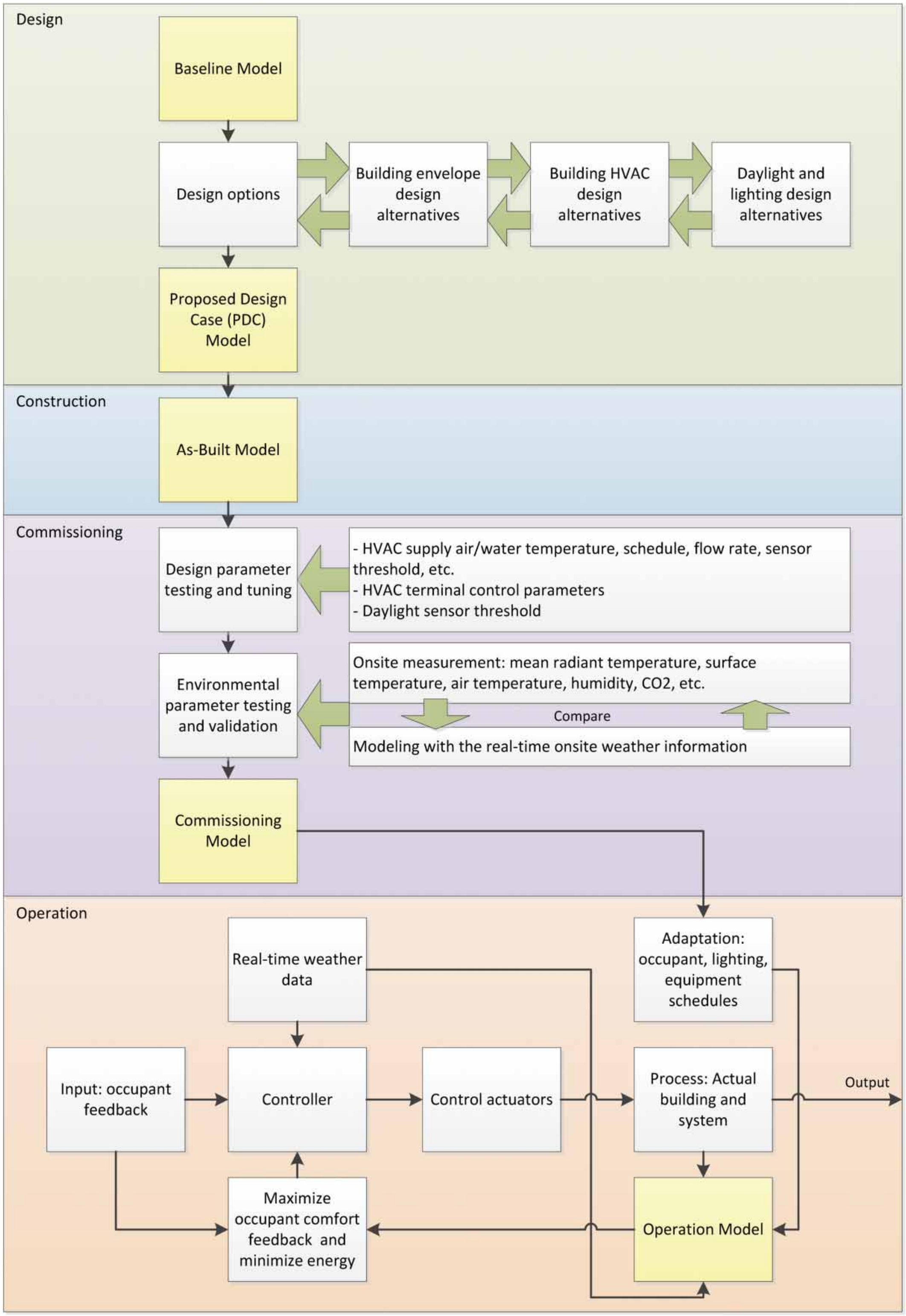

Figure 1. DBO-EIM infrastructure.

other consistently occupied spaces. The ceiling-based air distribution/exhaust system is used for several service spaces, such as restrooms, mechanical rooms, and storage rooms.

The proposed design case EnergyPlus model is created using DesignBuilder and EnergyPlus programs. Figure 2(a) and 2(b) illustrates the whole building and the first floor model views in DesignBuilder. There are 30 occupied

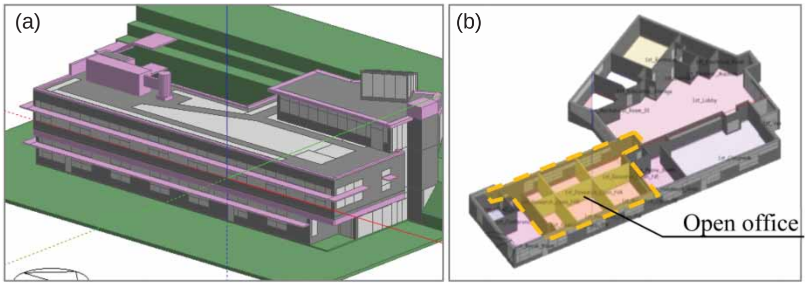

Figure 2. Model views in the DesignBuilder program. (a) Whole building view and (b) first floor zoning view.

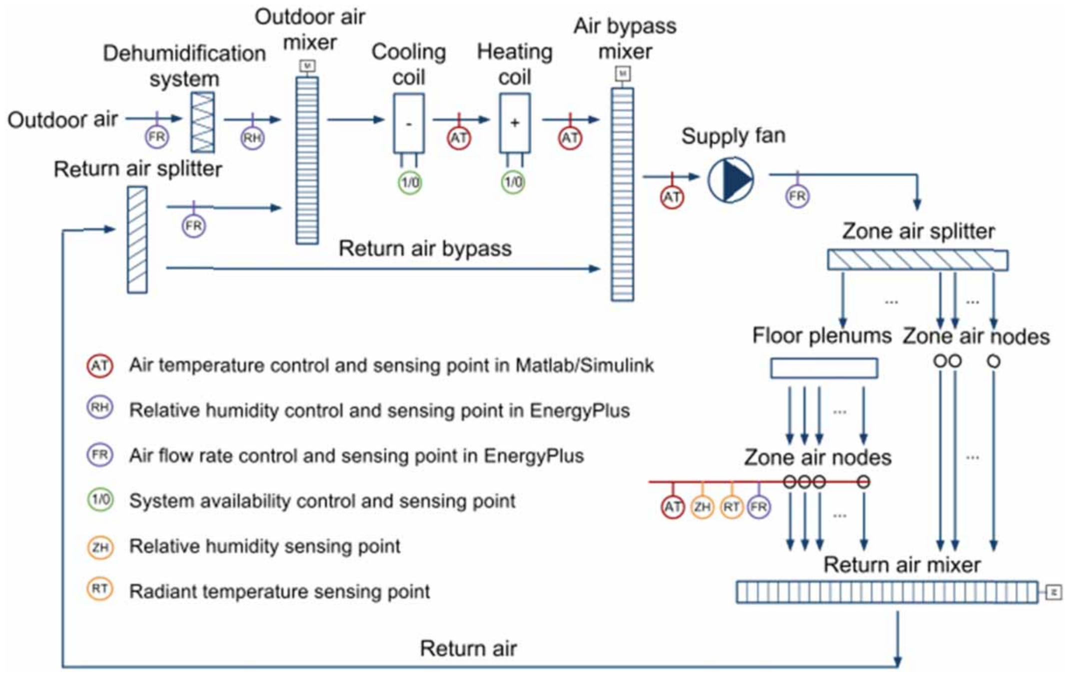

Figure 3. HVAC diagram and control/sensing points.

thermal zones in the building. Six of them on the first floor are the more consistently occupied open office spaces.

Figure 3 shows the HVAC diagram of the EnergyPlus model, as well as the control and sensing points in the air loop system. Four types of control and sensing points are shown in the diagram. "AT" represents the air temperature control points with the control logic implemented in Matlab. "RH" represents the relative humidity set point control of the desiccant dehumidification system in EnergyPlus, which is $< 50\%$ for occupied hours. "FR" represents the air flow rate of the outdoor air, the return air (and its bypass), and the supply air, which are controlled in EnergyPlus based on the temperature set points "AT". "1/0" represents the binary control signal for the availability of the cooling and heating coils. "RH" and "RT" represent the relative humidity and radiant temperature measurements, respectively, in each different open office zone, as shown in Figure 2(b). All the points shown in the diagram are simulated in EnergyPlus using the "System Node Output" function (Pang et al. 2011).

3.2. *Baseline control implementation*

The goal of the baseline control is to set up a co-simulation framework using Matlab/Simulink and EnergyPlus to perform multi-zone rule-based control and obtain its energy and thermal comfort performance. Predicted mean vote (PMV) is used as the thermal comfort control criterion for the six open office zones in Figure 2(b). Previous studies have shown that using PMV as a control objective may better represent occupant comfort than merely using air temperature. Three out of six variables in the PMV calculation matrix are pre-defined in Table 1, which are metabolic rate (met), air speed, and clothing insulation (clo). The air temperature, mean radiant temperature, and relative humidity

Table 1. Assumptions for the baseline and EPMPC controls.

	Baseline	EPMPC
Weather and schedules	TMY3 – Pittsburgh International Airport, design case occupancy, lighting, and equipment schedules	.csv files with the same information as the baseline's
Weekdays setpoint 7:00–20:00	PMV control: [−0.5, 0.5]	
	Temperature control: [22, 24]°C for other conventional controlled zones	
Weekends and weekdays setpoint 20:00–7:00	PMV control: [−2, 2],	
	Temperature control: [18, 28]°C for other conventional controlled zones	
Comfort assumptions	Met = 1.0, air speed = 0.137 m/s	
	Cooling season clo = 0.7, heating season clo = 1.0	

values are calculated in EnergyPlus at each simulation iteration. Other thermal zones are controlled by the conventional temperature dual-set point method in EnergyPlus. Table 1 lists the set point, comfort, weather, and schedule assumptions.

MLE+ (version 1) together with BCVTB is used as the co-simulation platform for Matlab/Simulink and EnergyPlus. "MLE+ is a Matlab toolbox for co-simulation with the whole-building energy simulator EnergyPlus". It "provides a set of Matlab functions and classes, as well as a Simulink library, for performing co-simulation with EnergyPlus" (Nghiem 2012). MLE+ enables users to directly develop algorithms and use functions in Matlab/Simulink. Although MLE+ adopts the same data exchange mechanism as BCVTB, the users do not need to do the data transfer through Ptolemy (Buck et al. 1994) interface that is used in BCVTB. Figure 4 shows the baseline control implementation schema. Two-loop cascade control is implemented in the co-simulation environment. At the central level, the AHU set point is controlled by rule-based control law using both outdoor air temperature and average zone PMV feedback. At the zone level, air flow rate is controlled by the adjusting the floor-based diffuser's damper position in EnergyPlus according to the temperature set point calculated in Matlab/Simulink. Each zone can have different temperature set points based on its PMV value, which is calculated at each simulation iteration.

3.3. *EPMPC problem description*

The objective of EPMPC is to maintain the same comfort criteria as the baseline control but to minimize the HVAC power consumption by optimizing the AHU supply air temperature. The objective function can be described as

$$\mathrm{J(x,t) = min(Q_c(x,t) + Q_h(x,t) + Q_f(x,t) + Q_p(x,t))} \tag{1}$$

subject to

$$|\mathrm{PMV}| = \begin{cases} \le 0.5, & \mathrm{f_{occ}(t)} \neq 0 \\ \le 2, & \text{otherwise} \end{cases} \tag{2}$$

$$\mathrm{T_c(x,t)} \in (14, 18) \tag{3}$$

$$\mathrm{T_H(x,t)} \in (24, 32) \tag{4}$$

$$\mathrm{A_H{}^*A_c = 0} \tag{5}$$

$$\mathrm{T_s(x,t)} \in \begin{cases} (14, 20), & \mathrm{A_c = 1} \\ (24, 32), & \mathrm{A_c = 0} \end{cases} \tag{6}$$

where t is the time (s); x the optimized supply air temperature set point (°C); $J(\mathrm{x}, \mathrm{t})$ the total HVAC system power at time t (kW); $Q_c(x,t)$ the cooling system power at time t (kW); $Q_h(x,t)$ the heating system power at time t (kW); $Q_f(x,t)$ the supply air fan power at time t (kW); $Q_p(x,t)$ the water pumps power at time t (kW); $f_{occ}(t)$ the occupancy status at time t (0, 1); $T_c(x,t)$ the cooling coil air outlet temperature set point at time t (°C); $T_H(x,t)$ the heating coil air outlet temperature set point at time t (°C); A_H the availability of heating coil (0, 1); A_c the availability of cooling coil (0, 1); and $T_s(x,t)$ the supply air temperature at time t (°C).

The exhaustive search algorithm (or Brute-force algorithm) is chosen to solve the problem. First, it is a "test-and-generate" algorithm, which works for the "black-box" simulation-based optimization (Kolda, Lewis, and Torczon 2003). Second, the algorithm is suitable for the problem that has "reasonable" computation time and discrete variables (Sinha 2008). EPMPC optimization problem has multiple constraints which results in a small search space. For example, in the cooling mode, the search space for the cooling coil is from 14°C to 18°C. And for practical reasons, 0.5°C difference is a reasonable discrete interval, resulting in nine iterations per planning horizon. The total optimization time for each planning horizon is about five minutes, which is feasible for real-time simulation for one-hour execution horizon. Although the planning horizon is one hour, the total optimization simulation period is 24 hours in accordance with the EnergyPlus run time.

Equations (3)–(6) indicate that the optimization problem has binary parameters, which needs to be separated into two modes: cooling mode and heating mode. The optimization is conducted in these two modes separately using the outdoor temperature as the threshold in accordance with the real

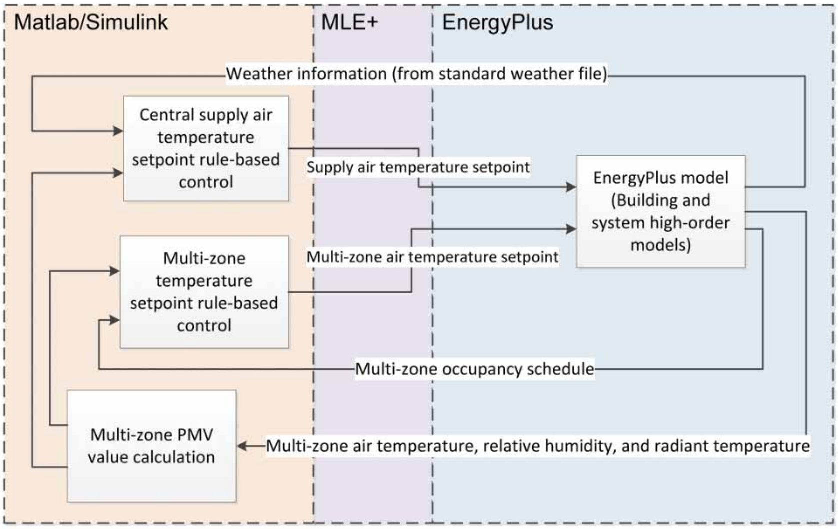

Figure 4. Baseline control implementation schema.

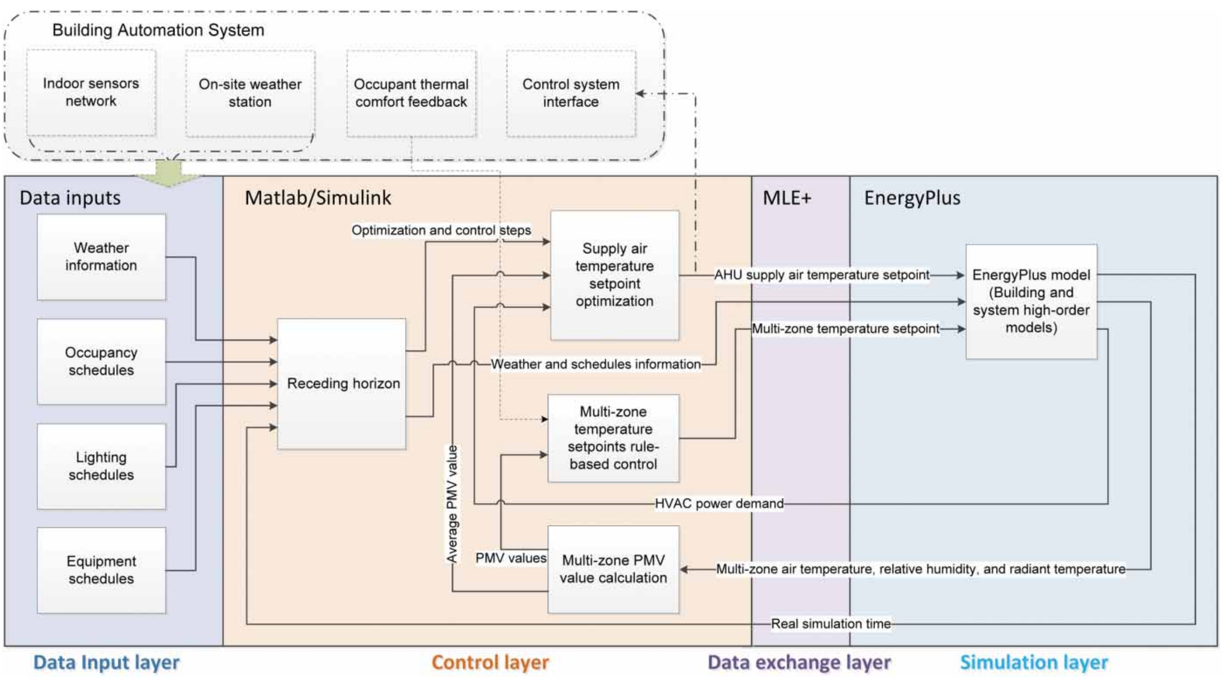

Figure 5. EPMPC implementation schema.

system operation:

$$\begin{cases} J = \min(f_{\text{power}}(x,t)), & \text{if Eq.(2) is satisfied} \\ J = \min(|f_{\text{PMV}}(x,t)|), & \text{otherwise} \end{cases} \quad (7)$$

The constraints are handled by Equation (7) to guarantee that the thermal comfort performance is prioritized when the constraints are not met. If the comfort constraint defined in Equation (2) is met, the algorithm will minimize the power consumption; otherwise, the algorithm will ignore the power consumption, but find the value that is the closest to the boundary defined in Equation (2) from the past iteration results. This penalty function is evaluated at each iteration. The constraint choice between the PMV boundary and power boundary can switch during the same planning horizon.

3.4. *EPMPC implementation*

Figure 5 shows the EPMPC implementation schema. Compared to the baseline rule-based control implementation schema, EPMPC introduces a "BAS integration module" and a "Data input layer". The BAS integration module, as indicated with dash-and-dot lines, has not been implemented in this study. As future work, it is discussed in Section 5. In "Data input layer", weather, occupancy,

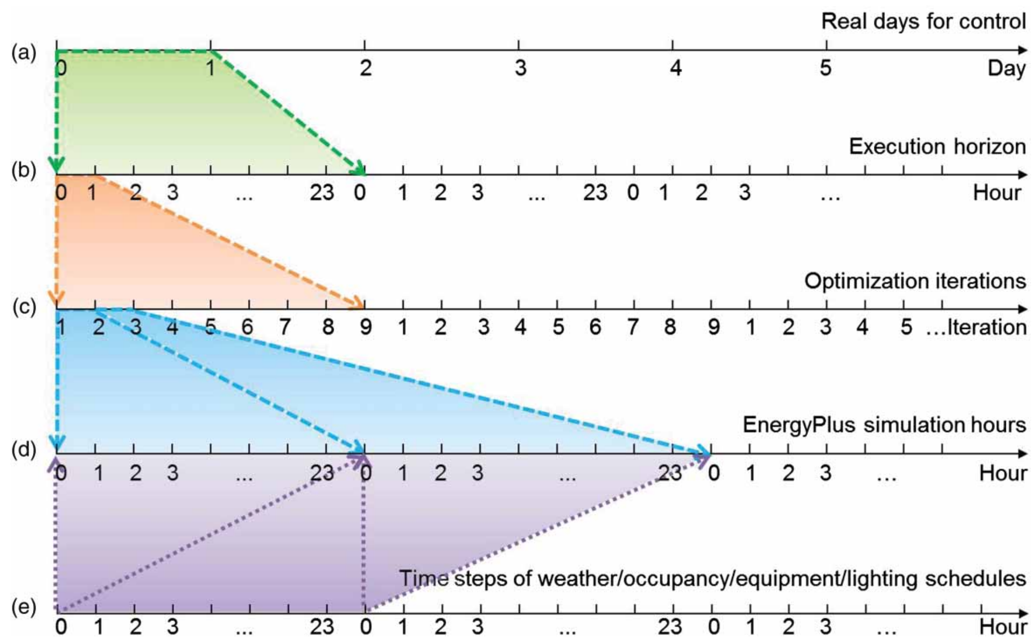

Figure 6. EPMPC receding horizon mechanism.

lighting, and equipment information is contained in independent text files (CSV, comma separated values). It is essential and beneficial to override the EnergyPlus internal weather and schedule data by using the "Data input layer" and the "Receding horizon" module in the "Control layer". "External Interface – Actuator" function in the EnergyPlus model is used for the data override (Pang et al. 2011). The "Data input layer" is implemented to solve the critical data interoperability issue in the following two aspects.

First, EPMPC needs to perform optimization in EnergyPlus, which will use the same day weather and schedule information multiple times for one execution horizon. Some of the rules in EnergyPlus require that at least 24 hours simulation should be performed for each of the optimization iteration. For instance, EnergyPlus only permits solar radiation data input from 5 am to 8 pm in accordance with sun position and building site location. The rule requires each of the optimization iteration to be at least 24 hours no matter how long the actual planning horizon is. In this study, the planning horizon and execution horizon are both one hour. Figure 6 illustrates the concept of "Receding horizon" for EPMPC. Axis (a) represents real days for the control system. The one-hour execution horizon of the control system is represented in Axis (b). Axis (c) represents the optimization iterations. For each one-hour execution horizon, nine optimization iterations are required, as indicated by the orange arrows in Figure 6. Axis (d) represents the real simulation time steps in EnergyPlus. For each optimization iteration, 24 hours of simulation time steps in EnergyPlus is needed as explained above. Axis (e) represents the time steps of the various EnergyPlus input files, including weather file, occupancy schedule, equipment schedule, and lighting schedule. For each of the optimization iteration of the same execution horizon, the same day model input data should be used nine times, as indicated by the purple arrows pointing to Axis (d).

Second, using separate data inputs to override the weather and schedule information can facilitate the potential real-time control in the real building operation. The data files in "CSV" or other machine readable format can be easily updated with the real-time information by linking with indoor sensors network and on-site weather station via BAS, as shown in Figure 6. The "Data input layer" in fact provides an interface for potential real operation data input.

Figure 5 explains the optimization and control process of EPMPC. "Weather and schedules information" and "control and optimization steps" are the two pieces of output information from the "Receding horizon" module. The latter is one input of the "Supply air temperature set point optimization" module. "Optimized supply air temperature set point" is determined at each execution horizon based on the "Average PMV value" and "HVAC power demand" information from EnergyPlus. This set point then goes to EnergyPlus as the input to perform next hour optimization and simulation.

"Multi-zone temperature set point rule-based control" and "Multi-zone PMV value calculation" modules are the same as the ones in the baseline control. The dash-and-dot lines linking BAS and "Multi-zone temperature set point rule-based control" module will be used to collect the real-time occupant thermal comfort feedback. This information is then used to calculate PMV in each zone. It is a significant part of the future work.

"Data exchange layer" is used for data communication and time synchronization functions; technical details can be found in Nghiem (2012). In "Simulation layer", the inputs of the EnergyPlus model are "AHU supply air temperature set point", "Weather and schedules information", and "Multi-zone temperature set point". The outputs are "HVAC power demand", "Multi-zone air temperature, relative humidity, and radiant temperature", and "Real simulation time", which are used for time synchronization between Matlab/Simulink and EnergyPlus.

4. Results

4.1. Heating season results

The baseline control and EPMPC are simulated for one typical design week in the heating season (8–14 January) using TMY3 weather information in Pittsburgh, Pennsylvania, USA (Pittsburgh Intl AP 725200). The same initial warm-up condition is set to be 8 January for both the baseline model and EPMPC. Figure 7 shows the supply air temperature, outdoor air temperature, and supply air mass flow rate of the baseline and EPMPC. EPMPC can maintain an average lower supply air temperature and supply air mass flow rate than the baseline in the heating mode before 9 am 12 January. From 9 am 12 January to 12 am 14 January, the system changes from heating mode to cooling mode, mainly due to the rise of the outdoor temperature. EPMPC generally has a higher supply air temperature during this period for the energy saving purpose. It is common that in the heating season, due to the heat gain from occupants, equipment, and other internal loads, the office building's cooling load may exceed its heating load when the outdoor temperature rises. Another observation is that EPMPC can reduce PMV spikes found in the baseline rule-based control. In the baseline model, the dual-set point PMV control only makes changes once the PMV has violated the set point boundaries, and this delayed response may result in overshoots and undershoots. EPMPC is able to look ahead the future possible situations and make an optimal decision for the control set point at each execution horizon to reduce the total instances of overshoots and undershoots.

Figure 8 illustrates the HVAC power comparison between the baseline control and EPMPC. Due to a lower heating supply air temperature as shown from 8 to 12 January in Figure 7, a higher cooling supply air temperature as shown from 12 to 14 January in Figure 7, and lower fan speed, the energy consumption reduction is found to be 28.9% during the one-week heating season simulation period, as shown in Table 1.

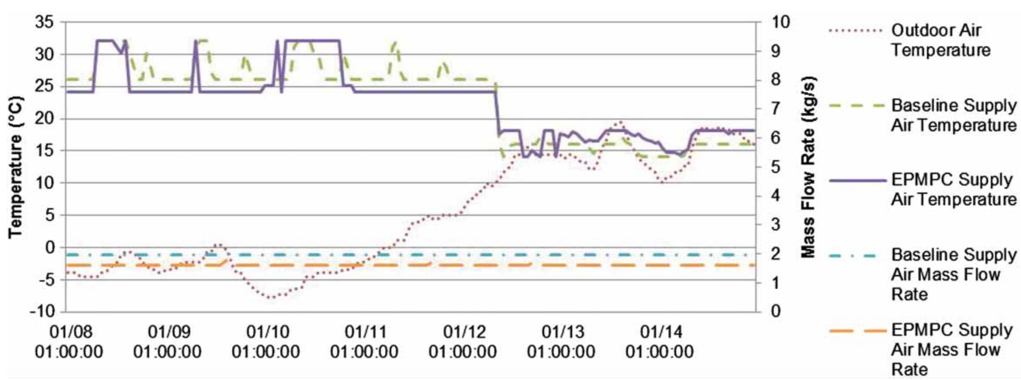

Figure 7. Outdoor temperature and control variables of the baseline and EPMPC in the heating season.

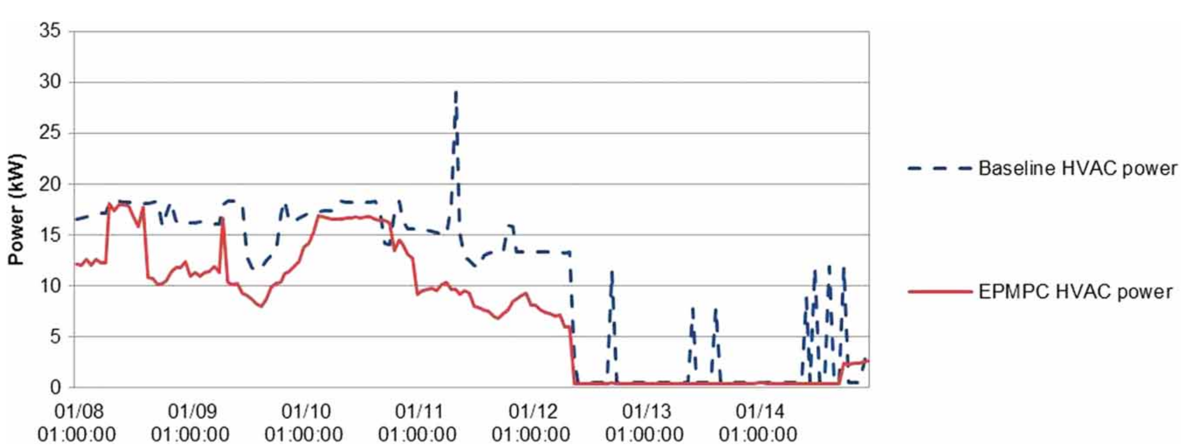

Figure 8. Energy performance of the baseline and EPMPC in the heating season.

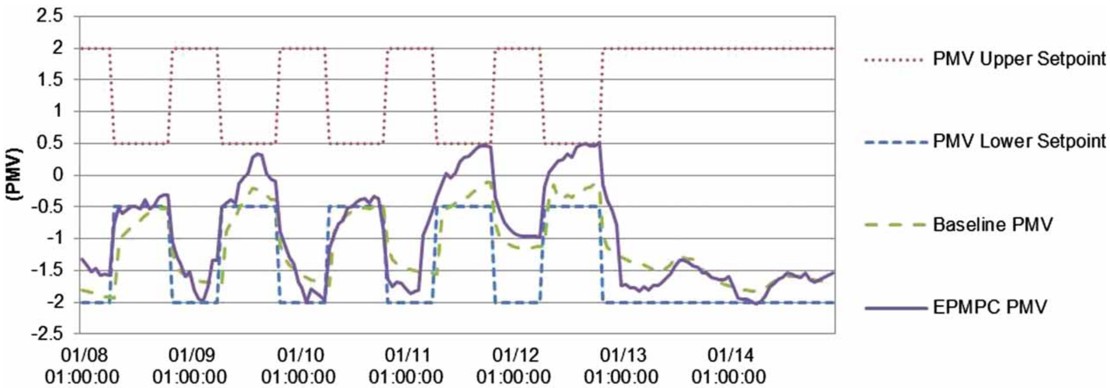

Figure 9. Thermal comfort performance of the baseline and EPMPC in the heating season.

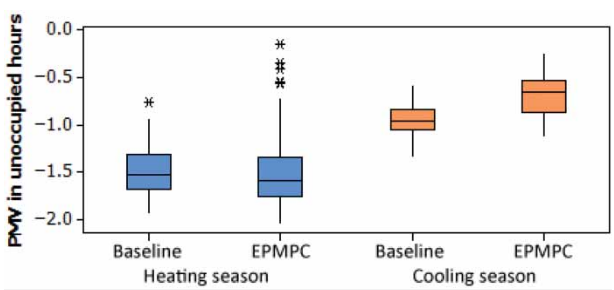

Figure 10. PMV distribution in unoccupied hours.

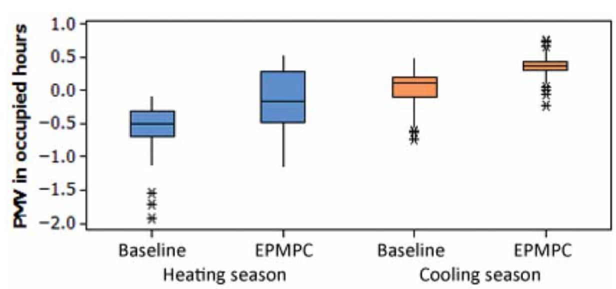

Figure 11. PMV distribution in occupied hours.

Figure 9 shows the average zone PMV comparison between the two systems. In the first three days in the heating mode, the PMV value is closer to the lower constraint boundary, and in the last two days in the cooling mode, the PMV value is closer to the upper constraint boundary. EPMPC pushes the PMV value to the boundaries to minimize energy.

In Figure 10, the heating season median PMV in the unoccupied hours is −1.60 (with a lower quartile of −1.76 and an upper quartile of −1.35) for EPMPC, and −1.54 (with a lower quartile of −1.68 and an upper quartile of −1.32) for the baseline, respectively. EPMPC makes majority of the PMV values in the unoccupied hours to be lower than the baseline but still within the constraint boundary. However, in the morning of 10 January, there are instances that PMV is out of the constraint boundary. One reason could be that only 6 out of 30 thermal zones of the whole building are controlled by EPMPC using the PMV criterion. Other zones are controlled by conventional temperature dual set point in EnergyPlus. With only one central AHU supplying for all the thermal zones, the impact of the AHU supply air temperature and flow rate change may not be sensitive enough. In other words, the thermal conditions of the other 24 zones may influence the 6 PMV-controlled zones. It is a limitation of the study. However, from the practical standpoint, it is reasonable and economical to only consider controlling the six highly occupied open office zones with more advanced control strategies without considering other rarely occupied service zones, such as restrooms and mechanical rooms. The other possible reason is that the planning horizon of EPMPC is one hour, which may not be ideal if considering the building thermal mass effect. The optimizer is only able to see what will happen in the next hour, but cannot take into consideration of a longer period. It is a limitation of the study.

In Figure 11, the heating season median PMV in occupied hours is −0.15 (with a lower quartile of −0.48 and an upper quartile of 0.29) for EPMPC, and −0.54 (with a lower quartile of −0.69 and an upper quartile of −0.32) for the baseline, respectively. The PMV of EPMPC has fewer low value outliers, which implies EPMPC has better ability to maintain the PMV constraints in the heating season occupied hours.

4.2. *Cooling season results*

The baseline control and EPMPC are simulated for one typical design week in the cooling season (8–14 July) using the TMY3 weather information in Pittsburgh, Pennsylvania, USA (Pittsburgh Intl AP 725200). The same initial warm-up condition is set to be 8 July for both the baseline and EPMPC. The supply air temperature, outdoor air temperature, and supply air mass flow rate of the baseline and EPMPC are shown in Figure 12. Unlike the baseline, EPMPC varies the supply air temperature set point more often. During the highly occupied afternoon hours, the supply air temperature is clearly lower than that in the baseline control, which indicates more cooling energy consumption.

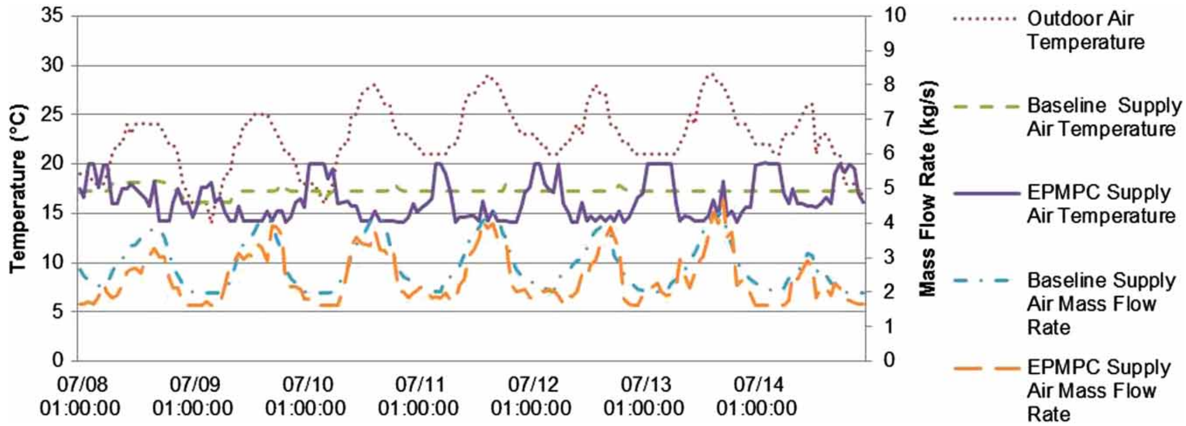

Figure 12. Outdoor temperature and control variables of the baseline and EPMPC in the cooling season.

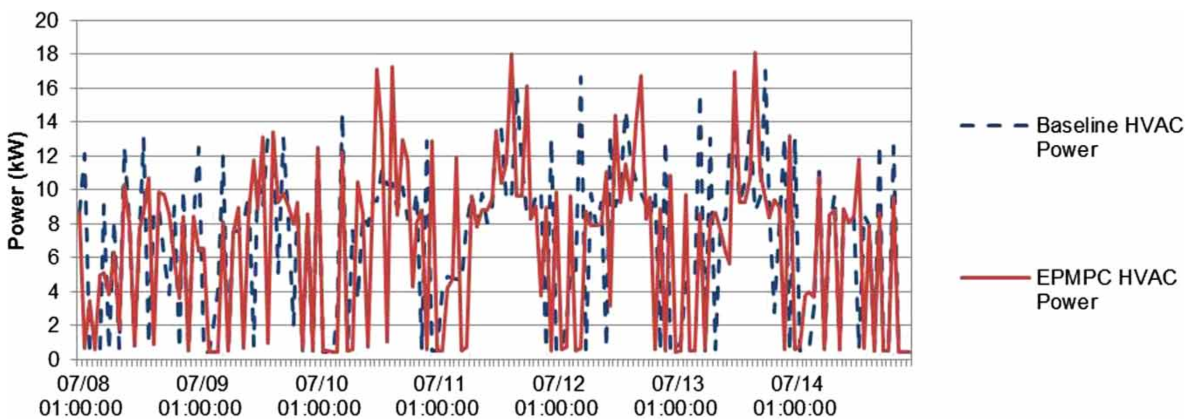

Figure 13. One-week plot of energy performance of the baseline and EPMPC in the cooling season.

However, in less or non-occupied hours, the supply air temperature tends to increase up to 20°C, which indicates less cooling energy consumption. In general, the supply air flow rate of EPMPC is lower than that of the baseline, which implies that the supply fan power consumption decreases over the simulation period.

Figures 13 and 14 show the hourly power consumption profiles for one week and one day, respectively. Although it is difficult to see a general pattern of energy savings from the figures, the cumulative energy savings during one cooling week is 2.7% as shown in Table 2.

The PMV value of the two systems is shown in Figure 15. Similar to the heating season results, the PMV value is pushed towards the upper boundary during both the occupied and unoccupied hours. On 10–12 July, there are a few times around noon when the PMV value exceeds the

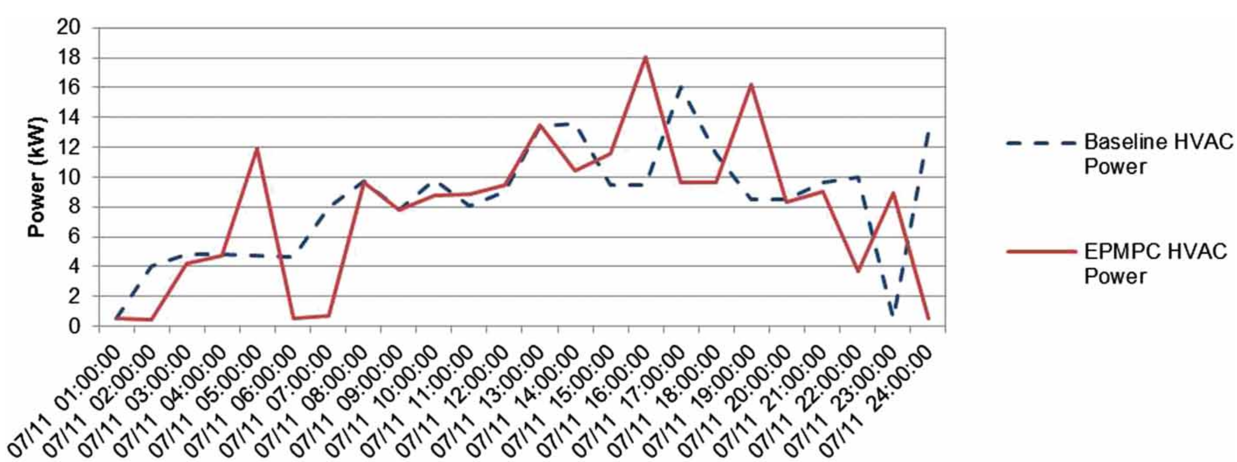

Figure 14. One-day plot of energy performance of the baseline and EPMPC in the cooling season.

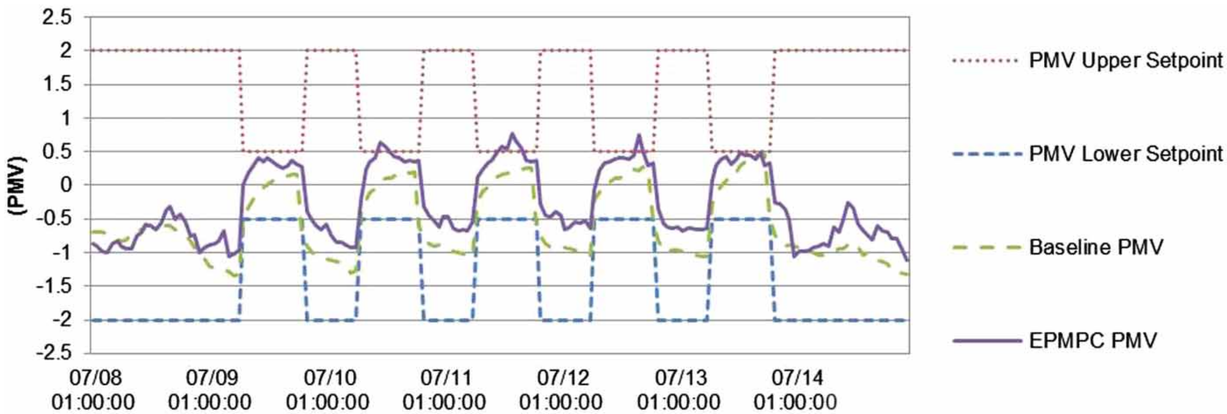

Figure 15. Thermal comfort performance of the baseline and EPMPC in the cooling season.

Table 2. One-week HVAC energy consumption comparison.

	Baseline energy (kWh)	EPMPC energy (kWh)	Energy savings (%)
One-week heating season simulation	1784.8	1268.7	28.9
One-week cooling season simulation	1154.8	1123.8	2.7
Total	2949.6	2391.5	18.9

upper constraint boundary. The reasons for this violation should be the same as discussed in Section 4.1.

Figures 10 and 11 provide a clearer picture on the PMV distribution. In the unoccupied hours, EPMPC median PMV is −0.66 (with a lower quartile of −0.87 and an upper quartile of −0.54); the baseline median PMV is −0.97 (with a lower quartile of −1.05 and an upper quartile of −0.84). Similarly, in the occupied hours, EPMPC median PMV is 0.37 (with a lower quartile of 0.30 and an upper quartile of 0.44); the baseline median PMV is 0.11 (with a lower quartile of −0.10 and an upper quartile of 0.20). EPMPC has higher average PMV within the constraint boundary for energy saving purpose compared to the baseline rule-based control.

5. Discussion

The results suggest that EPMPC can reduce the HVAC energy consumption and maintain the occupant thermal comfort within the PMV range of (−0.5, +0.5) during more than 90% of the simulated hours compared to the baseline rule-based control. However, a few limitations and necessary future work should be discussed.

First, as mentioned in Section 2, the design-stage EnergyPlus model is used in the control system design and simulation. The model input data, including weather, occupancy, lighting, and equipment schedules, as well as model parameters need to be calibrated. The indoor/outdoor environmental and system operation data are being collected via the BAS since August 2013. The occupancy data collection system has also been installed in the CSL building. A pilot study of modelling occupant behaviour using office appliance electricity consumption and Fitbit pedometer (2013) has been completed in an office space (Zhao et al. 2013). A similar experiment has been set up for the office workers in the CSL building. Future study will focus on calibrating the CSL building and system model using various types of data with some model calibration methods (Prívara et al. 2012).

Second, six more consistently occupied open office zones out of 30 thermal zones of the whole building are controlled by EPMPC. In addition to the comfort implications as mentioned in Section 4.1, the energy impact of EPMPC may not be as large as if it was applied to the whole building.

Third, the planning horizon of the MPC is set to be one hour mainly due to the limitation of the computation time. This control algorithm setting may overlook the long-term building thermal mass effect, as discussed in Section 4.1. Control algorithm with longer planning horizon and more advanced optimization algorithms that can reduce computation time can be explored in future work.

Fourth, as shown in Figure 5, “BAS integration module” should be developed and EPMPC can be linked to the actual building system. The real-time occupant thermal comfort “votes” can feed back to EPMPC to re-determine the optimization constraints in real time and the optimized execution inputs can feed into the AHU for real control testing.

6. Conclusions

The proposed DBO-EIM infrastructure is a building energy modelling method for the entire building design, construction, commissioning, and operation stages that aims to reduce energy consumption and improve occupant thermal comfort by using the MPC system in the building operation.

This study demonstrates one significant contribution of the DBO-EIM infrastructure that a design-stage energy model can be used for the MPC simulation study in an office building. A detailed design case building and system model is built using the DesignBuilder and EnergyPlus programs. The model is then used in EPMPC for the HVAC control simulation in Matlab/Simulink. TMY3 weather data are used for one-week simulation for heating and cooling seasons, respectively. Compared to the baseline rule-based control performance, EPMPC demonstrates a 28.9% energy reduction in the heating season and 2.7% energy reduction in the cooling season. The comfort constraint is met during more than 90% of the simulated hours. The average PMV value is as good as the baseline performance if not better.

EPMPC following the DBO-EIM infrastructure provides an alternative method for researchers to directly use the EnergyPlus model in MPC studies in the building field. Especially for the building that is too complicated to create a forward model directly, and for the building that has limited data points to create a data-driven model, EPMPC can be useful for MPC performance simulation.

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