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Building Energy Management: Integrated Control of Active and Passive Heating, Cooling, Lighting, Shading, and Ventilation Systems

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***Abstract*—Buildings account for nearly 40% of global energy consumption. About 40% and 15% of that are consumed, respectively, by HVAC and lighting. These energy uses can be reduced by integrated control of active and passive sources of heating, cooling, lighting, shading and ventilation. However, rigorous studies of such control strategies are lacking since computationally tractable models are not available. In this paper, a novel formulation capturing key interactions of the above building functions is established to minimize the total daily energy cost. To obtain effective integrated strategies in a timely manner, a methodology that combines stochastic dynamic programming (DP) and the rollout technique is developed within the price-based coordination framework. For easy implementation, DP-derived heuristic rules are developed to coordinate shading blinds and natural ventilation, with simplified optimization strategies for HVAC and lighting systems. Numerical simulation results show that these strategies are scalable, and can effectively reduce energy costs and improve human comfort.**

***Note to Practitioners*—Reducing demand on HVAC and lighting systems by effectively using free natural resources is a good way to conserve energy. This paper presents an integrated control of HVACs, lights, shading blinds, and natural ventilation to minimize the total daily energy cost. A novel model is established to capture the key interactions among the above devices. To overcome computational difficulties and obtain effective strategies in a timely manner, a price-based coordination methodology is developed to manage couplings among rooms that share an HVAC system with a limited capacity. Interactions of these devices is then resolved within each room by using stochastic dynamic programming. These strategies are further refined to obtain heuristic rules for shading blinds and natural ventilation, and simplified optimization strategies for HVACs and lights. The methods are scalable and shown to result in significant energy cost savings as compared with selected traditional control strategies.**

***Index Terms*—HVAC, integrated control, lighting, natural ventilation, rollout, shading, surrogate optimization.**

I. Introduction

BUILDINGS account for nearly 40% of global energy consumption [1]. About 40% and 15% of that are consumed, respectively, by HVAC and lighting systems. In view of the increasing energy cost, government mandates for energy efficiency [2], and the rising human comfort requirements, controlling shading blinds and natural ventilation to make effective use of natural resources can reduce energy consumption and is therefore of great interest [3], [4]. In addition, improving the HVAC control can also result in significant cost savings [5].

HVACs, lights, shading blinds, and natural ventilation interact with each other in energy consumption via thermal phenomena and in satisfying human comfort requirements for temperature, humidity, fresh air quantified by CO_2 concentration, and illuminance in each room. As shown in Fig. 1, indoor temperature is affected by all the above-mentioned devices; both indoor humidity and CO_2 concentration are affected by HVAC and natural ventilation; and illuminance by lights and shading blinds. In summer, for example, if blinds are open to use the daylight, energy consumption of lights is reduced. However, energy consumed by HVAC will increase due to the increased solar heat brought by inlet sunlight [3]. Therefore, the control of blinds must consider not only the energy consumption of lights but also that of HVAC. Integrated control of these devices is important to manage such interactions. In addition, individual rooms share an HVAC system, and are coupled in competing for its limited capacity. Integrated control of these devices is therefore also important for preventing the cooling demand from exceeding HVAC capacity and essential for human comfort [5].

In most of buildings, active and passive sources of heating, cooling, lighting, shading, and ventilation, however, are not coordinated. Analytical studies on their optimal integrated control have not been found in the literature. Possible reasons might

Manuscript received May 08, 2012; accepted May 30, 2012. This paper was recommended for publication by Associate Editor J. Li and Editor K. Goldberg upon evaluation of the reviewers' comments. This work was supported in part by the Tsinghua-UTC Research Institute for Integrated Building Energy, Safety and Control Systems, and the United Technologies Research Center. The work of Q.-S. Jia was supported in part by the National Natural Science Foundation of China under Grant 60704008, Grant 60736027, Grant 61174072, and Grant 90924001, in part by the Specialized Research Fund for the Doctoral Program of Higher Education (No. 20070003110), in part by the Tsinghua National Laboratory for Information Science and Technology (TNLIST) Cross-Discipline Foundation, and in part by the National 111 International Collaboration Project (No. B06002).

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Digital Object Identifier 10.1109/TASE.2012.2205567

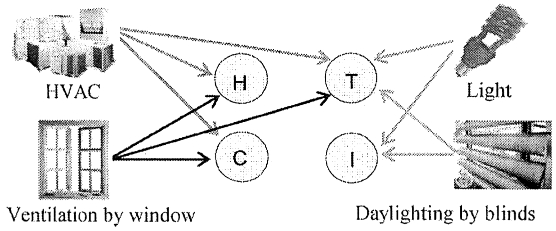

Fig. 1. Couplings of different devices on human comfort. T: temperature, H: humidity; L: illuminance; C: CO_2 concentration.

be that: 1) it is difficult to establish models which have a good balance between accuracy and simplicity for optimization; 2) models are difficult to calibrate [6]; and 3) the interactions between devices and the coupling among rooms make it time consuming to search for the optimal or effective control strategy. While there are many advanced model calibration methods [7], this paper focuses on managing issues 1 and 3.

In Section III, a new problem formulation is developed, in which HVAC, lights, shading blinds and natural ventilation are controlled jointly while satisfying system dynamics, equipment capacities, and human comfort under uncertain weather conditions and numbers of occupants. Simplified gray-box models of buildings are first established based on mass and energy conservation to capture key interactions among the above devices. For each discretized time interval, e.g., 10 min, these devices are controlled to minimize the expected total energy cost of the following 24 h. To keep a good balance between model accuracy and simplicity for optimization, two time scales are used, a large one for making decisions and a small one for system dynamics. Also, suitable variables are selected as decision variables to avoid physical device details and enable easy implementation of close-loop control. The problem is not separable because rooms share an HVAC with nonlinearities.

In Section IV, to manage the coupling of rooms competing for the limited HVAC capacity, Lagrangian relaxation (LR) a price-based decomposition and coordination approach is used. To overcome the computational difficulty due to the inseparability of HVAC, the surrogate optimization framework is used. The key idea is that all decision variables associated with one particular room are collected to form a subproblem. By keeping the decision variables not belonging to this room at their latest available values, a method combining Stochastic Dynamic Programming (SDP) and the rollout technique is developed to resolve the interactions of devices in the subproblem. To obtain effective feasible strategies, two heuristics are developed based on the strategies obtained by SDP and the rollout. For practical implementation in large buildings, the strategies are further refined to obtain DP-derived heuristic rules for shading blinds and natural ventilation, and a simplified optimization problem for HVAC and lights.

In Section V, to evaluate the performance of the problem formulation and the solution methodology, the strategies obtained are applied in detailed building models which are implemented in the building simulation software DeST [8]. The numerical results of three examples are presented to demonstrate that the strategies can effectively reduce energy costs and improve human comfort compared with traditional individual control strategies. Besides, the methodology developed saves significant computation time compared with several other methods and are scalable for large buildings. The results also show that the DP-derived rules, which consider key interactions among devices, are more effective than individual rules now used in buildings.

II. Literature Review

Although no rigorous studies on integrated control of HVAC, lights, shading blinds, and natural ventilation have been found in the literature, there are studies on the integrated control of some of the above devices [3], [4], [9]. However, these studies focused on rule-based control but not the optimal control. For example, shading blinds were controlled considering energy consumption of both HVACs and lights in [4] by using a rule based on outside radiation and indoor temperature. As for optimal control of HVAC alone, there are many studies on model-based optimal control, and some of them also have the same three difficulties presented in Section I.

A typical approach to optimal control of HVAC is first to establish and calibrate models. The models are used to predict future building behavior and energy costs of devices according to selected control strategies for devices and predicted weather and numbers of occupants, etc. Optimization methods are then used to obtain the optimal control strategy [6]. The following is a review on models and optimal control methods based on the models.

There are three types of models: detailed physical models [6], [10], black-box models such as neural network models [5], [11], and gray-box models [12]. Physical models are usually too complicated for optimization because there are too many parameters to be calibrated and it is time consuming to predict building behavior and energy costs based on physical models. However, they can be used as simulation models to evaluate strategies obtained by optimization methods [6], [10], [12].

Compared with physical models, black-box models are much more simplified because they use only measured inputs and outputs to represent key characteristics of buildings and devices. Artificial neural networks are in common use to establish models of buildings and devices [5], [13]. For example, in [5], a neural network model was trained based on measured data to calculate energy consumption of HVACs. Since energy consumption of HVACs was affected by many key factors such as set points for indoor temperature and humidity, thermal load, weather, day of week and time of day, a lot of data was needed for calibration and the data should cover large ranges of the key factors. That made the calibration of the neural network model too complicated.

Compared with black-box models, gray-box models use physical knowledge about buildings in combination with measured data. Since parameters in gray-box models have physical meanings, calibration of gray-box models tends to be easier. For example, a gray-box model of a building was used in [12] for the optimal control of a multi-zone variable air volume (VAV) air-conditioning system. This model was established based on mass and energy conservations, and was calibrated using online measurements. For each time interval of 60 s, decisions were made to optimize the energy cost of the following 300 s. To minimize daily energy costs, looking forward 300 s, however, usually is not enough because it does not facilitate: 1) the use of precooling to take advantage of lower electricity prices at night; 2) natural ventilation during nights for precooling; and 3) the use of precooling to reduce peak cooling demand so that it will not exceed the HVAC capacity.

Based on the above-mentioned models of buildings and devices, numerous methods are developed to obtain optimal or effective strategies for the control of devices.

Model predictive control (MPC) is popular for building control [14]. It uses building models to predict building behavior and energy costs in according to different control strategies of devices. An optimization problem is solved to obtain the optimal control strategy. Energy costs can be saved by efficient use of building thermal mass [15], building thermal storage [16], a variable energy price [17], etc. In addition, energy peak can also be reduced by MPC [18].

Another method in common use for building control is fuzzy logic controllers [19]–[21]. A large number of studies have demonstrated that fuzzy logic controllers can save significant energy costs and maintain human comfort. For example, in [19], five fuzzy logic controllers were developed to control shading, lighting, cooling, heating, and air changing. A coordinator composed of fuzzy rules and fuzzy negotiation machines was developed to eliminate inconsistencies between these five fuzzy logic controllers. Simulation results showed that the fuzzy control system successfully managed energy conservation and maintained human comfort.

As presented in Section I, a major difficulty related to model-based control is that interactions between devices and couplings among rooms make it time consuming to search for the optimal control strategy. To overcome this computational difficulty, two types of methods are usually used—intelligent optimization algorithms such as genetic algorithm (GA) [10], [12], and decomposition and coordination methodologies, such as Lagrangian relaxation (LR) [5]. In [12], set points for indoor temperatures in all rooms and the flow rate of fresh air shared by all rooms were controlled using a GA. Since multiple rooms were coupled in sharing the same multi-zone VAV air-conditioning system, the computational time would increase exponentially when the number of rooms increases. In [5], multiple HVAC systems were controlled to minimize energy costs. The problem had coupling constraints that were separable. It was solved using LR, which is effective in solving problems with separable coupling constraints. However, in an HVAC system with nonlinearities in couplings among rooms, the problem will not be separable. As a result, the LR method in [5] cannot be directly used. To deal with such inseparability, a method is developed based on LR for the optimal integrated control problem after the description of problem formulation in Section III.

III. Problem Formulation

A novel problem formulation for daily building energy cost optimization is presented in this section. The human comfort requirements are for indoor temperature, humidity, CO_2 concentration and illuminance. Devices, controlled to satisfy these requirements, include fans and water valves in fresh air unit (FAU) and fan coil units (FCUs) (FAU and FCUs are major components of the HVAC studied in this paper), fresh air valves in rooms, lights, blinds, and windows for natural ventilation. Indoor temperature is affected by all the devices and indoor humidity by all the devices except lights and blinds. Indoor CO_2 concentration is affected by the FAU fan, the fresh air valve in each room and natural ventilation. Illuminance is affected by lights and blinds. Simplified models of these devices and also buildings are developed for optimization purpose. Device models and their decision variables are presented in Subsection A. Dynamics of buildings capturing key interactions among devices, and human comfort requirements are presented in Subsection B. Dynamics of devices are ignored because their time constants are too small compared with those of buildings. Uncertainties in weather and numbers of occupants have large effects on energy consumption, and are presented in Subsection C. The objective function for the integrated control is then presented in Subsection D.

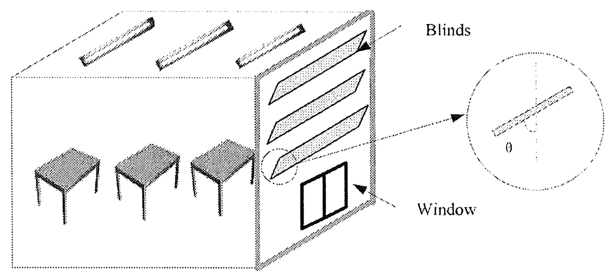

Fig. 2. A schematic of blinds, lights, and a window for natural ventilation.

A. Device Models and Decision Variables

Assume that a building consists of I individual rooms, with room index i ranging from 1 to I. The time horizon of the problem is the following 24 hours from the current time on. It is divided into K discrete time intervals of equal duration Δt (e.g., 10 minutes), with time index k ranging from 1 to K. Each room has a glass curtain wall facing outside, blinds for sun shading, and a window for natural ventilation as shown in the schematic of a room in Fig. 2. Each room is also equipped with a fan coil unit (FCU) and all rooms share an FAU. All the devices are explained in details next.

Models of Blinds, Lights, and Natural Ventilation: The blinds are installed on the upper half of the glass wall. The transmittance of the blinds varies with different weather, time of a day, day of a year, and blind angle. It is measured by experiment in [22]. To avoid glare, a lower bound is set for the blind angle to prevent direct sunlight from coming into the room. The gap between daylight illuminance and the illuminance required by human comfort is filled by dimming lights with controllable power Plight [23]. The window is located in the lower half of the glass wall and has no overlap with the window, as shown in Fig. 2. Natural ventilation flow rate is calculated based on outside wind speed and direction, and pressure due to temperature difference between indoor and outdoor air [24].

Model of the HVAC System: An HVAC system is used to maintain comfortable indoor temperature and humidity, and provide fresh air. The HVAC system studied here is widely used and depicted in Fig. 3. For summer days, indoor air is first supplied to the FCU by a fan, cooled and dehumidified by

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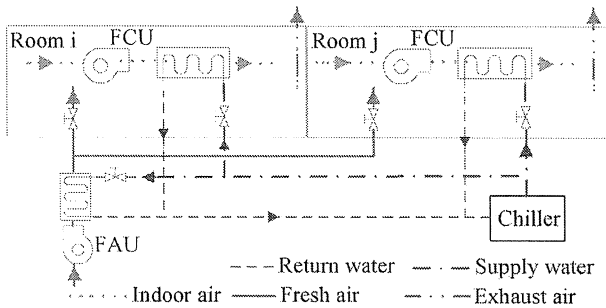

Fig. 3. An HVAC system.

chilled water, and then supplied to the room to decrease indoor air temperature and humidity. The chilled water is produced by a chiller and its flow rate is controlled by the FCU water valve. Fresh air required by occupants is provided by an FAU shared by all rooms. Since supplying outside hot and humid fresh air directly into rooms would make occupants uncomfortable, fresh air should be cooled and dehumidified in the FAU before supplied into rooms. This paper focuses on the control of terminal devices in rooms, and therefore other devices in the HVAC system, such as cooling towers and pumps, are not plotted in Fig. 3. For winter days, the chiller produces hot water rather than chilled water, and the FCUs and FAU work in the same way. The problem formulation and methodology developed in the rest part of this paper are based on summer days for simplicity, but they can also be applied for winter days.

In the FAU, outlet fresh air temperature T_{FAU} is affected by air flow rate, water flow rate, inlet fresh air temperature and humidity, and inlet water temperature. It is calculated using an FAU model in [25]. Fresh air temperatures supplied from the FAU to all rooms at time k are assumed to be the same for simplicity and equal to FAU outlet air temperature T_{FAU}^k. Since fresh air in the FAU is dehumidified by condensation, outlet air humidity H_{FAU}^k equals the lower of outside air humidity H_o^k and the saturation humidity $H_{T_{\mathrm{FAU}}^k}$ of FAU outlet air temperature as

$$H_{\mathrm{FAU}}^k = \min\left(H_o^k, H_{T_{\mathrm{FAU}}^k}\right). \tag{1}$$

The FAU fan supplies fresh air to all rooms. Fresh air flow rate to room i at time k, $G_{fa,i}^k$, is controlled by a valve in the room. The FAU air flow rate should equal the summation of fresh air flow rates to all rooms as $\sum_{i=1}^{I} G_{fa,i}^k$. The power of the FAU fan, $P_{\mathrm{fan,FAU}}^k$, is nonlinear to the FAU air flow rate as [25]

$$P_{\mathrm{fan,FAU}}^k = P_{\mathrm{fan,FAU,Rated}}^k \left[\sum_{i=1}^{I} G_{fa,i}^k / G_{a,\mathrm{FAU,Rated}}^k\right]^3 \tag{2}$$

where $P_{\mathrm{fan,FAU,Rated}}$ and $G_{a,\mathrm{FAU,Rated}}$ are the rated FAU fan power and the rated FAU air flow rate, respectively.

The FAU cooling power C_{FAU}^k equals the difference between inlet air enthalpy $\mathrm{EN}_{\mathrm{FAU,inlet}}^k$ and outlet air enthalpy $\mathrm{EN}_{\mathrm{FAU,outlet}}^k$. The enthalpy indicates the energy contained in the air and the water vapor in the air. It equals the air flow rate times the energy contained in per unit air and the water vapor. The C_{FAU}^k is therefore given as [25]

$$\begin{aligned} C_{\mathrm{FAU}}^k &= \mathrm{EN}_{\mathrm{FAU,inlet}}^k - \mathrm{EN}_{\mathrm{FAU,outlet}}^k \\ &= \sum_{i=1}^{I} G_{fa,i}^k \left[C_p T_o^k + H_o^k \left(2500 + 1.84 T_o^k\right)\right] \\ &\quad - \sum_{i=1}^{I} G_{fa,i}^k \left[C_p T_{\mathrm{FAU}}^k + H_{\mathrm{FAU}}^k (2500 + 1.84 T_{\mathrm{FAU}}^k)\right] \end{aligned} \tag{3}$$

where C_p is the air specific heat and T_o^k outside temperature. The model for an FCU is very similar to that of FAU, and the difference is that the inlet air for an FCU is indoor air while for the FAU it is outside air.

The chiller, used to produce chilled water, is shared by the FAU and FCUs. Since the chiller has a limited capacity, the cooling power of the HVAC system has an upper bound C_{HVAC}. As a result, the summation of cooling power of the FAU and FCUs should be less than or equal to the capacity limit, C_{HVAC}, and rooms are coupled in satisfying the HVAC capacity constraints as

$$C_{\mathrm{FAU}}^k + \sum_{i=1}^{I} C_{\mathrm{FCU},i}^k \le C_{\mathrm{HVAC}}, \quad k = 1, \ldots, K. \tag{4}$$

Decision Variables: For the integrated control of devices, fans and water valves in FAU and FCUs are not suitable to be controlled directly because, taking the water valve as an example, if the water valve opening of one FCU is changed, the water flow rates of all FCUs and FAU are affected through the water network. As a result, if the fans and water valves are directly controlled, there is no way to use a decomposition and coordination method to deal with the curse of dimensionality as the number of rooms increases, which is presented later in Section III-D.

Set points for indoor temperature and humidity are usually selected as decision variables for an HVAC as in [5] to make it easy to calculate cooling demand for the HVAC. However, FCU air flow rate $G_{a,\mathrm{FCU}}$ and FCU outlet air temperature T_{FCU} need to be calculated to check if these set points for indoor temperature and humidity can be satisfied and to obtain energy cost of the FCU fan. The calculation is complicated because indoor air temperature is a function of the product of $G_{a,FCU}$ and T_{FCU}. In addition, if a look-up table is established to obtain $G_{a,\mathrm{FCU}}$ and T_{FCU}, then another set point for indoor CO_2 concentration is needed to control the fresh air flow rate, and the FAU water valve can be controlled directly.

In our problem formulation, fresh air flow rate G_{fa}, FAU outlet air temperature T_{FAU}, FCU air flow rate $G_{a,\mathrm{FCU}}$, and FCU outlet air temperature T_{FCU} are selected as decision variables. Both cooling demand for the HVAC and energy cost of fans can be easily calculated. In addition, in practical close-loop implementation it is easy to control fans and valves by PID controllers to satisfy set points for these air flow rates and outlet air temperatures, respectively. As for lights, blinds and windows, it is easy to control power of lights, angles of blinds, and

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open/close of windows directly. From the above, decision variable for room i at time k is

$$\left[T_{\text{FAU}}^k, v_1^k, v_2^k, \ldots, v_I^k\right]^T \tag{5}$$

with

$$v_i^k = \left[T_{\text{FCU},i}^k, G_{fa,i}^k, G_{a,\text{FCU},i}^k, P_{\text{light},i}^k, \theta_i^k, W_i^k\right]^T, \quad i = 1, \ldots, I, \tag{6}$$

where FAU and FCU outlet air temperatures T_{FAU}^k and $T_{\text{FCU},i}^k$ are discretized into three values, representing low, middle, and high temperatures. Flow rates $G_{fa,i}^k$ and $G_{a,\text{FCU},i}^k$ can be zero, half or full of their rated flow rates. The blind angle θ_i^k, from 0° to 80°, is discretized into nine steps (each is 10°) for simplicity. The opening of the window W_i^k has two values, zero for close and one for open.

B. State Variables and System Dynamics

Indoor air temperature, wall temperature, indoor humidity, and indoor CO_2 concentration are chosen as elements of the state variable because indoor air can store energy, water vapor and CO_2 and walls can store energy.

Assumptions: The calculation of building dynamics would be very complicated and time-consuming if nonuniform distributions of temperature, humidity and CO_2 concentration and slight changes of indoor air mass are considered. To simply the calculation for our optimization purpose, the following four assumptions are made.

Assumption 1: It is assumed that air in a room has a uniform temperature T_a, humidity H, and carbon dioxide concentration CO_2 for simplicity [10]. Taking indoor temperature as an example, the assumption is reasonable because it is accurate enough to use the uniform indoor temperature as the average indoor temperature for the calculation of: 1) heat transferred between indoor air and walls and 2) temperature of the mixture of indoor air, air from FAU and FCU, and natural ventilated air.

Assumption 2: Interior walls (i.e., walls with no surface facing outside) in a room have a uniform temperature T_w for simplicity [10]. The assumption is reasonable because temperatures of interior walls are mainly affected by indoor air temperatures. Since heat transferred between indoor air and an interior wall is linear to their temperature difference, it is accurate enough to use the average temperature of interior walls and the average indoor temperature to calculate heat transferred between them. As for heat transferred between indoor and outdoor air through the exterior glass curtain wall, as presented later in (8), it is calculated based on temperature difference between indoor and outdoor air and the heat transfer coefficient of the glass wall. Since indoor temperatures are very close in different rooms, the heat transferred between two adjacent rooms through an interior wall is ignored.

Assumption 3: Since room air pressure is almost constant, the air mass in a room is assumed to remain constant to ignore slight changes in indoor air mass for simplicity. This assumption is in common use in building simulation [10].

Assumption 4: It is assumed that the full state information of indoor air temperature T_a, humidity H, carbon dioxide concentration CO_2, and wall temperature T_w is available. In practice, T_a, H, and CO_2 can be measured by sensors. Although T_w can also be measured by sensors, such sensors are not available in most buildings and installing a sensor for each wall is expensive and not practical [26]. An alternative way is to utilize a Kalman filter to estimate T_w in each room based on system dynamics of T_a and T_w (presented later in (8) and (9)) using measured indoor air temperatures, outdoor air temperatures, outside solar radiation, numbers of occupants (e.g., measured by an RFID reader installed beside doors), etc.

State Variable for a Room: Based on the above assumptions, the state variable for room i at time k is

$$x_i^k = \left[T_{ai}^k, T_{wi}^k, H_i^k, \mathrm{CO_2}_i^k\right]^T. \tag{7}$$

Four sets of system dynamic equations for the state variable are obtained based on mass and energy conservations as follows.

Dynamics of Indoor Air Temperature: The indoor temperature at time $k+1$ is affected by: 1) heat generated by occupants, lights, and other equipment; 2) heat transferred from interior walls; 3) heat transferred between indoor and outdoor air through the glass curtain wall facing outside; 4) heat provided by the FAU, the FCU, and natural ventilation; and 5) heat contained in the remaining indoor air, i.e., the indoor air except for that from the FAU, the FCU, and natural ventilation. The energy conservation applied to indoor air in room i lead to the following:

$$\begin{aligned} m_{ai}T_{ai}^{k+1} &= \Delta t \left[O_i^k Q_g + Q_{\text{light},i}^k + Q_{e,i}^k + h_{gs}A_{gs,i}\left(T_o^k - T_{a,i}^k\right)\right. \\ &\quad \left. + h_{w,in}A_{w,i}\left(T_{w,i}^k - T_{a,i}^k\right)\right]/C_p \\ &\quad + \Delta t \left(G_{fa,i}^k T_{\text{FAU}}^k + G_{a,\text{FCU},i}^k T_{\text{FCU},i}^k + G_{nv,i}^k T_o^k\right) \\ &\quad + T_{ai}^k\left[m_{ai} - \Delta t\left(G_{fa,i}^k + G_{a,\text{FCU},i}^k + G_{nv,i}^k\right)\right] \end{aligned} \tag{8}$$

where m_{ai} is the mass of air in room i, O_i number of occupants, Q_g heat generation rate per person, $Q_{\text{light},i}$ and $Q_{e,i}$ heat generated by lights and other equipment, respectively, $h_{w,in}$ heat convection coefficient between interior walls and indoor air, h_{gs} heat transfer coefficient between outdoor and indoor air through the glass curtain wall facing outside, $A_{w,i}$ area of interior walls, A_{gs} area of the glass curtain wall, and $G_{nv,i}$ natural ventilation flow rate. The last line in (8) is the energy contained in the remaining indoor air.

Dynamics of Wall Temperature: The interior wall temperature is affected by heat convection between the wall and indoor air and solar heat gains $S_w(\theta)$, which is resulted from radiation incident through the blinds and then on the wall surfaces and is a function of blind angle θ. The energy conservation applied to the interior walls of room i leads to the following:

$$C_w \frac{m_{w,i}}{2}\left(T_{w,i}^{k+1} - T_{w,i}^k\right) = \Delta t\left[h_w A_{w,i}\left(T_{a,i}^k - T_{w,i}^k\right) + S_w(\theta_i)\right], \tag{9}$$

where C_w is the wall capacitance, $m_{w,i}$ the wall mass, and h_w the convection coefficient between interior wall and indoor air.

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The wall mass is divided by two because an interior wall is shared by two adjacent rooms. Since the heat transferred between indoor and outdoor air through the exterior glass curtain wall is calculated based on the temperature difference between indoor and outdoor air as in (8), there is no need for the dynamic of gall curtain wall temperature.

Dynamics of Indoor Air Humidity: The indoor humidity is affected by humidity: 1) generated by occupants; 2) provided by the FAU, the FCU, and natural ventilation; and 3) contained in the remaining indoor air. The mass conservation for the humidity in room i is thus given by

$$m_{ai}H_i^{k+1} = \Delta t O_i^k H_g + \Delta t \left(G_{fa,i}^k H_{\mathrm{FAU}}^k + G_{a,\mathrm{FCU},i}^k H_{\mathrm{FCU},i}^k + G_{nv,i}^k H_o^k\right) + H_i^k \left[m_{ai} - \Delta t \left(G_{fa,i}^k + G_{a,\mathrm{FCU},i}^k + G_{nv,i}^k\right)\right] \quad (10)$$

where H_g is the humidity generation rate per person, and H_o^k the outside air humidity.

Dynamics of Indoor Co₂ Concentration: The mass conservation applied to CO_2 concentration is similar to that applied to humidity, except that the CO_2 concentrations is not affected by the FCU since no fresh air is supplied to the FCU. The CO_2 mass conservation in room i is thus given by

$$m_{ai}CO2_i^{k+1} = \Delta t O_i^k CO2_g + \Delta t \left(G_{fa,i}^k + G_{nv,i}^k\right) CO2_o^k + CO2_i^k \left[m_{ai} - \Delta t \left(G_{fa,i}^k + G_{nv,i}^k\right)\right] \quad (11)$$

where CO_{2g} is carbon dioxide generation rate per person and CO_{2o} outside air carbon dioxide concentration.

With the above system dynamics (8)–(11), the interaction of devices within each room are well captured. For example, the blind angle θ first affects solar heat gains on the wall surface, S_w. The solar heat gains S_w affect the wall temperature T_w in (9) and T_w then affects the indoor temperature T_a in (8). In addition, the blind angle θ also affects the daylight illuminance and thus the required power of lights, P_{light}. The heat generated by the lights, Q_{light}, then affects the indoor temperature T_a in (8). Finally, energy costs of HVAC and lights are both affected by the blind angle θ.

Discretization of State Variables: The discretization step size for indoor temperature is 1° and that for indoor humidity is 5% of relative humidity. The discretization step size for CO_2 concentration is 100 ppm and that for wall temperature is 0.1 degree. Sometimes, the wall temperature changes slightly in one time interval Δt (e.g., 10 min), and the change is much smaller than the discretization step size. Nevertheless, these small changes cannot be neglected, because the accumulation of them may have a significant lasting effect on the energy cost via heat convection between walls and indoor air. Although the step size for wall temperature can be reduced to overcome this difficulty, the increase in computation requirements could be prohibitive. Our solution is to accumulate the small changes, and to update the wall temperature only when the accumulated change is larger than the discretization step size.

Two Time Scales: To keep a balance between accuracy and simplicity for optimization, two time scales are used. A larger time scale, e.g., the time interval Δt is set to ten minutes, is used for determining decision variables. During each time interval, decision variables and state variables are kept constant. From time k to time $k+1$, however, the indoor and wall temperatures are affected by each other. Keeping either one of them constant in a large time interval to calculate the other may result in large inaccuracy. In addition, mixing the total air volume naturally ventilated during one time interval Δt with indoor air immediately would cause large inaccuracy. Therefore, another finer time interval, e.g., one minute, is used for (8)–(11) to have a better calculation of indoor air temperature, wall temperature, indoor air humidity and CO_2 concentration.

Human Comfort: The human comfort requirements during occupied periods are given as [5]

$$T_a \in [22°\mathrm{C}, 26°\mathrm{C}], \quad H \in [40\%, 60\%], \quad CO2 \leq 900\,ppm, L \geq 400\,lx. \quad (12)$$

During unoccupied periods, there are no requirements for humidity, CO_2 concentration or illuminance. The required indoor temperature range can be lager as

$$T_a \in [20°\mathrm{C}, 28°\mathrm{C}] \quad (13)$$

Compared with occupied periods, the lower bound of T_a during unoccupied periods is lower to allow for precooling especially when outside temperature is much lower than indoor temperature at night or when the electricity price is much lower at night than that in the daytime. The upper bound of T_a during unoccupied periods is higher and is beneficial to save energy.

C. Uncertainties in Future Outside Temperatures and Numbers of Occupants

Uncertainties in outside temperatures and numbers of occupants have an impact on both energy cost and peak cooling demand, which should be no more than the HVAC capacity as in (4). For example, if a room will be occupied by a large number of occupants with a high probability around noon time, the integrated control needs to precool the room so that human comfort requirements and HVAC capacity constraints will be satisfied.

Since outside temperatures predicted by weather stations might be inaccurate, normally distributed noises are added to outside temperatures predicted. Means and variances of the noises are calculated using errors between real temperatures and predicted ones in the past several (e.g., 24) hours.

Numbers of occupants in room i are described by a single-state Markov chain with one-step transition matrix [5]

$$P\left\{O_i^k = b | O_i^{k-1} = a\right\} = \pi_{abi}, \quad i = 1, \ldots, I; a, b \leq p_i \quad (14)$$

where p_i is the maximum number of occupants in room i, and a and b are possible numbers of occupants at time $k-1$ and time k, respectively. Numbers of occupants are updated using the larger time scale with the time interval Δt, which is also used for the updating of decision variables.

D. The Objective Function

Since the control action at the current time affects immediate as well as future energy cost, the objective is to find the current time's optimal control to minimize the expected total costs of

HVAC and lights in a moving time window of the following 24 h.

In the HVAC, energy is consumed by fans in the FAU and FCUs, chillers, pumps, and cooling towers. This paper focuses on the control of FAU and FCUs and the energy consumption of the fans in the FAU and FCUs are calculated using their models (2). Energy consumption of the rest of the above-mentioned devices is calculated using a coefficient of performance (COP) for simplicity. The COP is defined as the ratio of cooling power of the FAU and FCUs to the electric power of chillers, pumps, and cooling towers. It is dimensionless and is obtained based on measured data in several office buildings. The energy consumption of lights is calculated based on the power of lights, P_{light}. After obtaining hourly energy consumption of the HVAC and lights, a time-of-day electricity rate commonly used in Beijing, with the price at time k as c^k, is used to calculate the energy cost. The price is lower at night than that in the day, which allows precooling rooms at night to save daily energy cost. The problem formulation can also be applied for the flat rate and be extended to the dynamic rate with predictive future electricity prices.

At the current time, i.e., time 1, the energy cost optimization problem is given by

$$\begin{aligned}\min J, &\text{ with } J\\ &\equiv E\left\{\Delta t \sum_{k=1}^{K} c^k \left[\sum_{i=1}^{I}\left(C^k_{\text{FCU},i}/\text{COP} + P^k_{\text{fan,FCU},i}\right.\right.\right.\\ &\quad \left.\left.\left. + P^k_{\text{lights},i}\right) + C^k_{\text{FAU}}/\text{COP} + P^k_{\text{fan,FAU}}\right]\right\} \qquad (15)\end{aligned}$$

subject to HVAC capacity constraints (4), system dynamics (8)–(11), and human comfort requirements (12)–(13). In the above, Δt is the time interval, K the number of time intervals in the time window of 24 h, and the expectation is over the uncertain outside temperatures and numbers of occupants. To obtain current time's optimal decision and then apply it to control the devices, the computation time of solving the optimization problem should be less than one time interval Δt, e.g., 10 min. After the devices are controlled, the time window will move ahead one time interval Δt and the same optimization problem as in (15) will be formulated for the next 10 min.

The optimization problem has a two-level structure. The low level is to control FCUs, lights, shading blinds, and natural ventilation in individual rooms. The high level is to control the FAU that is shared by all rooms and to satisfy the HVAC capacity constraints on the FAU and all FCUs. In addition, this problem is similar to the unit commitment problem in power systems and is believed to be NP-hard [5]. In order to obtain a near-optimal solution, a possible method is to use a decomposition and coordination approach. It divides the entire problem into subproblems each related to one room and also forms a high-level problem to coordinate all rooms. This kind of methods requires the original problem to be separable. The problem is, however, not separable because: 1) the FAU is shared by all rooms and its decision variable, FAU outlet air temperature T_{FAU}, cannot be determined by individual rooms and 2) the FAU fan power $P_{\text{fan,FAU}}$ is nonlinear to the sum of fresh air flow rates to all rooms as in (2) and, therefore, the FAU fan energy cost allocated to a room cannot be calculated only based on the fresh air flow rate to this room alone. The problem therefore cannot be solved by directly using a decomposition and coordination approach. Our solution methodology is presented in the next section.

IV. Solution Methodology

In order to overcome the inseparability difficulty and then form subproblems, new decision variables are introduced and the surrogate optimization framework is used in Section IV- A. In the surrogate optimization framework, stochastic dynamic programming (SDP) is used in Section IV-B to solve subproblems. The high-level dual problem, which manages the couplings among rooms, is solved in Section IV-C. Two heuristics are developed to obtain feasible strategies in Section IV-D. To reduce the computational time, a rollout scheme is used in Section IV-E. For easy implementation of the solution methodology in large buildings, the feasible strategies are further refined to obtain DP-derived control rules for shading blinds and natural ventilation, and a simplified optimization problem for HVACs and lights in Section IV-F.

A. *Overcoming the Inseparability Difficulty*

To solve the optimization problem with the coupling HVAC capacity constraints (4), Lagrangian relaxation (LR) is used to obtain a near-optimal solution. LR is a decomposition and coordination approach. It is applicable for separable problems. As presented at the end of last section, the problem formulated, however, is not separable because: 1) the outlet air temperature of the shared FAU, T_{FAU}, cannot be determined by individual rooms and 2) the energy cost of the shared FAU fan cannot be calculated by individual rooms since the FAU fan power $P_{\text{fan,FAU}}$ is nonlinear to the sum of fresh air flow rates to all rooms as in (2).

To overcome the inseparability difficulty caused by the FAU outlet air temperature T^k_{FAU}, new decision variables, $T^k_{\text{FAU},i}$, $i = 1, \ldots, I$, are introduced, representing fresh air temperatures supplied by the FAU to I individual rooms at time k. Since these fresh air temperatures at time k should be the same (all are equal to the FAU outlet air temperature T^k_{FAU}), new constraints are introduced as

$$T^k_{\text{FAU},i} = T^k_{\text{FAU},i+1}, \quad i = 1, \ldots, I; k = 1, \ldots, K \qquad (16)$$

where $T^k_{\text{FAU},I+1}$ is defined as $T^k_{\text{FAU},1}$.

The decision variables are therefore changed from (5) to

$$u^k = [u^k_1, u^k_2, \ldots, u^k_I]^T \qquad (17)$$

with

$$u^k_i = \left[G^k_{fa,i}, T^k_{\text{FAU},i}, G^k_{a,\text{FCU},i}, T^k_{\text{FCU},i}, P^k_{\text{light},i}, \theta^k_i, W^k_i\right], \quad i = 1, \ldots, I \qquad (18)$$

where $T^k_{\text{FAU},i}$ is discretized into three values, representing low, middle, and high temperatures as T^k_{FAU} is.

The HVAC capacity constraints (4) and the FAU fresh air temperature constraints (16) just introduced are relaxed using Lagrangian multipliers $\{\lambda^k, k = 1, \ldots, K\}$ and

$\{\mu_i^k, k = 1, \ldots, K; i = 1, \ldots, I\}$, respectively. The relaxed problem is to minimize the Lagrangian L as

$$\begin{aligned}\min L, \text{with } L \\ \equiv E\Bigg\{&\Delta t \sum_{k=1}^{K} c^k \left[\sum_{i=1}^{I} \left(C_{\mathrm{FCU},i}^k/\mathrm{COP} \right.\right. \\ &+ P_{\mathrm{fan,FCU},i}^k + P_{\mathrm{lights},i}^k\big) + C_{\mathrm{FAU}}^k/\mathrm{COP} + P_{\mathrm{fan,FAU}}^k\big]\Bigg\} \\ &+ \sum_{k=1}^{K} \lambda^k E\left(C_{\mathrm{FAU}}^k + \sum_{i=1}^{I} C_{\mathrm{FCU},i}^k - C_{\mathrm{HVAC}}\right) \\ &+ \sum_{k=1}^{K}\sum_{i=1}^{I} \mu_i^k \left(T_{\mathrm{FAU},i}^k - T_{\mathrm{FAU},i+1}^k\right)\end{aligned} \quad (19)$$

subject to system dynamics (8)–(11) and human comfort requirements (12)–(13).

The relaxed problem (19) is still inseparable because of the nonlinearity of FAU fan power $P_{\mathrm{fan,FAU}}$, and the LR approach therefore cannot be directly used. To overcome this inseparability, the surrogate optimization framework [27] is used. The key idea is to collect all terms related to a particular room i from the Lagrangian to form a subproblem as below

$$\begin{aligned}\min_{u_i^k, k=1,\ldots K} L_i, \text{with } L_i \\ \equiv E\Bigg\{&\sum_{k=1}^{K} \big[\left(c^k \Delta t/\mathrm{COP} + \lambda^k\right) \\ &\times \left(C_{\mathrm{FAU}}^k + C_{\mathrm{FCU},i}^k\right) \\ &+ c^k \Delta t \left(P_{\mathrm{fan,FAU},i}^k + P_{\mathrm{fan,FCU},i}^k + P_{\mathrm{lights},i}^k\right) \\ &+ \left(\mu_i^k - \mu_{i-1}^k\right) T_{\mathrm{FAU},i}\big]\Bigg\}.\end{aligned} \quad (20)$$

subject to system dynamics (8)–(11) and human comfort requirements (12) and (13). Decision variables belong to other rooms are kept at their latest available values. There are totally I subproblems (each related to one room) formed in this way and will be solved in the next subsection. Coordination of the I subproblems will be achieved through iteratively updating the multipliers in a high-level dual problem in Section IV-C and using the updated multipliers to resolve subproblems.

B. Solving a Subproblem

The subproblem formulated in the last subsection is a multistage stochastic optimization problem. It is solved by using backward stochastic dynamic programming (SDP) considering all possible discretized outside temperatures, numbers of occupants and values of decision variables. The optimal cost-to-go at stage k for state variable x_i^k is

$$L_i^{k*}\left(x_i^k\right) = \min_{u_i^k} E\left\{S_i^k\left(x_i^k, u_i^k\right) + L_i^{k+1*}\left(x_i^{k+1}\right)\right\} \quad (21)$$

where x_i^k and u_i^k are used to calculate x_i^{k+1} based on system dynamics (8)–(11), and S_i^k is the current stage cost given by

$$\begin{aligned}S_i^k\left(x_i^k, u_i^k\right) = &\left(c^k \Delta t/\mathrm{COP} + \lambda^k\right)\left(C_{\mathrm{FAU}}^k + C_{\mathrm{FCU},i}^k\right) \\ &+ c^k \Delta t \left(P_{\mathrm{fan,FAU}}^k + P_{\mathrm{fan,FCU},i}^k + P_{\mathrm{lights},i}^k\right) \\ &+ \left(\mu_i^k - \mu_{i-1}^k\right) T_{\mathrm{FAU},i}^k.\end{aligned} \quad (22)$$

After SDP moves from stage K backward and ends at stage 1, the total optimal cost related to room i, L_i^*, equals the optimal cost-to-go $L_i^{1*}(x_i^1)$ at stage 1 for the given initial state x_i^1.

The computational complexity for solving a subproblem is determined by the complexity of SDP. Since for each stage in SDP, all possible values of the state variable and the decision variable are traversed to calculate the system dynamics (8)–(11) and the energy cost, the complexity is $O(K \cdot S \cdot D)$, where K is the number of stages, S the size of the state space, and D the number of all possible values of decision variable [28].

C. Solving the Dual Problem

Since all rooms are coupled by the HVAC capacity constraints (4) and the FAU fresh air temperature constraints (16), these constraints might not be satisfied if subproblems are solved individually. Therefore, subproblems need to be coordinated at a high level. Since the Lagrangian multipliers in the relaxed problem (19) are the prices for the dissatisfaction of these constraints, subproblem solutions are coordinated through the iterative updating of the multipliers to maximize the high-level dual function

$$\max_{\lambda,\mu} q, \text{with } q \equiv \sum_{i=1}^{I} L_i^{1*}\left(x_i^1\right) - \sum_{k=1}^{N} \lambda^k C_{\mathrm{HVAC}}. \quad (23)$$

The standard way to solve the dual problem is to use the subgradient method. It solves all the subproblems optimally to obtain the subgradient direction for updating multipliers. To have a fast convergence of the multipliers, the surrogate subgradient (SSG) method [27] rather than the subgradient method is used in our method to update the multipliers. The key idea of the SSG method is that a proper search direction for multipliers can be obtained without optimally solving all subproblems. Rather, optimization for one subproblem is enough to obtain a proper SSG direction if the optimal decision variable for room i at the nth iteration, $u_{i,n}$, can reduce the Lagrangian, i.e., satisfy the following surrogate optimization condition (see [27, eq. (26)]):

$$\begin{aligned}L(&\lambda_n, \mu_n, u_{i,n}, u_{j:j\neq i,n-1}) \\ &< L(\lambda_n, \mu_n, u_{i,n-1}, u_{j:j\neq i,n-1}).\end{aligned} \quad (24)$$

If the condition is satisfied, the SSG components with respect to λ_n^k and $\mu_{i,n}^k$ at iteration n are, respectively, given by

$$g^k\left(\lambda_n^k\right) = E\left(C_{\mathrm{FAU}}^k + \sum_{i=1}^{I} C_{\mathrm{FCU},i}^k\right) - C_{\mathrm{HVAC}} \quad (25)$$

and

$$g^k\left(\mu_{i,n}^k\right) = T_{\mathrm{FAU},i}^k - T_{\mathrm{FAU},i+1}^k. \quad (26)$$

The multipliers are then updated in the SSG direction as

$$\lambda_{n+1}^k = \max\left[0, \lambda_n^k + \alpha_n g^k\left(\lambda_n^k\right)\right] \quad (27)$$

and

$$\mu_{i,n+1}^k = \mu_{i,n}^k + \alpha_n g^k\left(\mu_{i,n}^k\right) \quad (28)$$

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where α_n is the step size at iteration n and given by

$$\alpha_n = \frac{\beta_n \left[L^U - \sum_{i=1}^{I} L_i^{1*}\left(x_i^1\right)\right]}{g\left(\lambda_n\right)^T g\left(\lambda_n\right) + g\left(\mu_n\right)^T g\left(\mu_n\right)} \tag{29}$$

where L^U is an estimated upper bound of the optimal value L, and $0 < \beta_n < 1$.

If the surrogate optimization condition is not satisfied, the subproblem related to the next room will be solved. This surrogate optimization framework allows more frequent multiplier updating and less computation time while overcoming the inseparability difficulties as compared to the standard subgradient method.

After solving the dual problem, the algorithm moves to solve subproblems with the updated multipliers unless the stopping criterion is satisfied, i.e., $\|u_n - u_{n-1}\| < \varepsilon$ (ε is a given small positive number) or $1 - q/J < 1\%$ or the computation time is higher than one time interval Δt, e.g., 10 min. After the entire optimization problem is solved, the current time's decision u^1 is implemented, and the time window then moves one time interval Δt ahead. The next time slot becomes the current time and the same optimization problem as (15) is formulated. The multipliers of the previous problem are used to initialize the new problem just formulated. In this way, the SSG method requires less iteration.

D. Obtaining Feasible Solutions

Subproblem solutions, when put together, are generally infeasible, i.e., HVAC capacity constraints and FAU fresh air temperature constraints may not be satisfied. Two heuristics have been developed based on subproblem solutions.

1) The first heuristic checks from stage 1 and moves forward to stage K. If the cooling power of the FAU and FCUs at stage k exceeds the HVAC capacity, the method backtracks from stage $k-1$ until a room is found with its FCU fan not at the full speed or its water valve not fully opened. That room is then precooled by increasing fan speed or valve opening.
2) If the FAU fresh air temperature constraints at stage k is not satisfied, i.e., the FAU fresh air temperatures required by all rooms are not the same, then all the FAU outlet fresh air temperature is set to the minimum of the required temperatures. This is because by decreasing fresh air temperature in a room, more cooling demand of that room will be satisfied by the FAU and less by the FCU. As a result, the FCU fan speed can be reduced and the energy cost of the FCU fan is saved.

E. Using the Rollout to Reduce Computation Time

The computation time of solving the overall optimization problem should be less than one time interval Δt so that the decision of the current time, u^1, can be obtained and then applied to control devices. Since stochastic dynamic programming (SDP) is the most time-consuming part in the algorithm, reducing the computation time of SDP is important for saving the whole computation time for large problems.

As presented in (21), the optimal cost-to-go at stage k for room i, L_i^{k*}, equals the current stage cost at stage k, S_i^k, plus the optimal cost-to-go at stage $k+1$, L_i^{k+1*}. Since the control of devices far into the future has little impact on S_i^k or L_i^{k+1*} and only u^1 will actually be implemented, there is no need to obtain the exact optimal cost-to-go for all the stages. Rather, approximate calculation of the optimal cost-to-go is generally good enough to obtain the optimal or a good u^1. Therefore, the rollout technique [29] is used to reduce computation time of SDP. The idea is to approximately calculate the optimal costs-to-go at stage N (smaller than K) by using simple rules to control the devices from stage $N+1$ to stage K. A rule currently used in some buildings is selected: 1) control blinds based on the schedule, e.g., closing the blinds only from 10:00 am to 2:59 pm; 2) control natural ventilation based on the enthalpy difference between indoor and outdoor air; and 3) control the FAU and FCUs using the greedy algorithm, which does not consider the impact of current time' control on future energy cost but minimizes only the current stage's energy cost.

In the rollout from stage $N+1$ to stage K, rooms are controlled individually and there are no multipliers used as the prices for the dissatisfaction of the HVAC capacity constraints (4). Therefore, the decision u^1 obtained might cause the peak demand exceeding the HVAC capacity in the future. The peak demand can be reduced by using precooling. However, precooling can only be derived in SDP. Therefore, to reduce the peak demand without much increasing computation time, our idea is to: 1) predict the peak time when the peak demand happens and the precooling time when the precooling is needed and 2) adaptively adjust the number of SDP stages N so that if precooling is needed, the time period of SDP is larger enough to cover the peak time. Otherwise, N is reduced to a small value, e.g., $K/6$, to save computational time. Since the peak time and the precooling time are usually around noon, they are predicted by using SDP without the rollout to solve the entire optimization problem (15) at the first time interval of each day.

F. DP-Derived Rules for Blinds and Natural Ventilation

The optimization is time consuming and the cost of computing devices is a major concern in practice. Therefore for easy implementation of the above-developed method, hereinafter referred to as LR-DP method, in large buildings, our idea is first to develop rules for controlling blinds and natural ventilation. The rules should consider the interaction between HVACs, lights, shading blinds, and natural ventilation and, therefore, be established based on the LR-DP strategy obtained by the LR-DP method. These rules are referred to as DP-derived rules in the rest of this paper. Then, a simplified optimization problem for the HVAC system and lights, with much fewer decision variables than the original problem (15), is formulated and solved by a similar LR-DP method.

To establish the DP-derived rule for blinds, the idea is to find key factors affecting the control of blinds and their relationship with blind angles. The key factors are found by: 1) calculating the correlation coefficients of the blind angles and other variables such as hour of day and outside radiation based on the data points from the LR-DP strategies and 2) then selecting the variables whose correlation coefficients are higher than a given threshold. Their relationship with blind angles

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is described by using a classifier. The inputs of the classifier are the factors found, and the output is the discretized blind angles. After training by using data points from the LR-DP strategies, the classifier can be used as a rule to control blinds. As for natural ventilation, the DP-derived rule is established in the similar way. The DP-derived rules for blinds and natural ventilation can also be used to improve rules currently used in many buildings.

V. Numerical Testing Results and Discussion

The LR-DP method was implemented in Matlab on a Core i7 2.67 GHz PC with 4 GB memory. The LR-DP strategies are obtained for three examples by solving optimization problems. They are then applied in detailed building models, which are implemented in the building simulation software DeST [8]. In the first example, a simple system with two rooms in a building is tested to show that integrated control strategy outperforms several other strategies in improving human comfort by shifting demand. In addition, the LR-DP method with the rollout technique saves significant computation time compared with several other methods. The second example with a three-floor building shows that energy costs are reduced in two typical days by integrated control and that the LR-DP strategies are robust to prediction errors in outside temperatures and numbers of occupants. In the third example, the solution methodology is implemented for a six-floor building with 144 rooms. The result shows that the LR-DP method has a good scalability, and the DP-derived rules save significant energy cost and computational time.

In the examples, results under four strategies are compared and analyzed, including: two existing individual control strategies: strategy A and strategy B, the greedy strategy, and the LR-DP strategy obtained by the LR-DP method. Strategy A always opens blinds at 80° (i.e., fully opened) and uses no natural ventilation. It controls the FAU and FCUs using a greedy algorithm, which optimizes the HVAC energy cost only at each current stage. Strategy B is the same as that used in the rollout scheme in Section IV-E. It controls: 1) blinds based on the schedule, i.e., closing blinds only from 10:00 am to 2:59 pm; 2) natural ventilation based on the enthalpy difference between indoor and outdoor air; and 3) the FAU and FCUs in the same way as in Strategy A. The greedy strategy controls all the devices to minimize total energy costs of HVAC and lights only at each current stage.

Example 1: Two Rooms in a Building: Two rooms in a building in Beijing are selected to demonstrate how the LR-DP algorithm shifts the cooling demand to satisfy chiller capacity limits and improve human comfort. Both rooms are seven meters long, six meters wide, and four meters high. Each room has a window facing south. Rooms are occupied from 7:00 am to 10:00 pm, which is common in office buildings in universities. The coefficient of performance (COP) used to calculate energy consumption of chillers, pumps and cooling towers in (15) is set to 2.71, the average value measured in nine office buildings in Beijing [30]. The time-of-day energy price of Beijing is used. It is 0.81 RMB/KWh from 7 am to 10 pm and 0.35 RMB/KWh during other hours [31]. The larger time interval Δt is set to 10 min and the finer one for calculating state variables is 1 min.

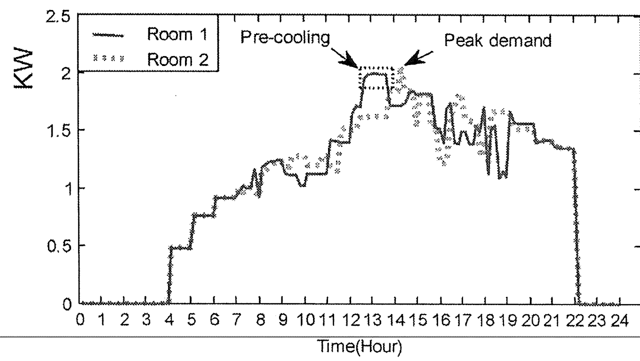

Fig. 4. Cooling power of the FAU and FCUs in two rooms.

The day August 2nd, which has the largest cooling and dehumidifying demand of a typical meteorological year, is considered. If devices are controlled by Strategy A, or Strategy B or the greedy strategy, the peak demand in that day will exceed the HVAC capacity, and temperature and humidity requirements in some of the rooms will not be satisfied. Shifting the demand is therefore important.

Coordination of Two Rooms to Improve Comfort and Save Cost: To coordinate the two rooms and control the devices jointly, the energy optimization problem (15) is solved every 10 min by using the LR-DP method. The cooling power supplied by the FAU and two FCUs into the two rooms is presented in Fig. 4. It shows that the peak demand happens between 2 pm and 3 pm. In order to prevent the peak demand from exceeding the HVAC capacity limit, one of the rooms is precooled from around 1:00 pm, one hour before the peak demand happens. As a result, part of the peak demand is shifted.

In addition, two FCUs do not work at high —ower levels at the same time from 1 pm to 3 pm, and the total cooling power does not exceed the HVAC capacity limit.

In Fig. 4, it can also be seen that the LR-DP strategy pre-cools rooms from 4:00 am to 6:59 am when the rooms are unoccupied. This precooling, with the low energy price, reduces temperatures of walls which have a large heat capacity. The heat transferred from walls to indoor air is therefore reduced after 7:00 am, and the total HVAC energy cost is reduced as well.

Efficiency of the LR-DP Method in Saving Computational Time: To evaluate the efficiency of the LR-DP method with the rollout in saving computational time, two other methods are used to solve the optimization problem (15) for comparison. The first one uses DP but without LR or the rollout, i.e., controls the two rooms together rather than in a decomposition and coordination way. The second one uses LR and DP but without the rollout. The energy costs and the computation time are shown in Table I. It shows that LR-DP method with the rollout saves much computation time and only causes a little increase in energy cost compared with the other two methods.

Example 2: A Three-Floor Building With 15 Rooms: A three-floor building with 15 rooms in Beijing is selected and three cases are studied based on the building. The first two cases demonstrate how energy cost is saved by the integrated control in two typical days, with the first case focusing on the control of blinds and the second on the control of natural ventilation.

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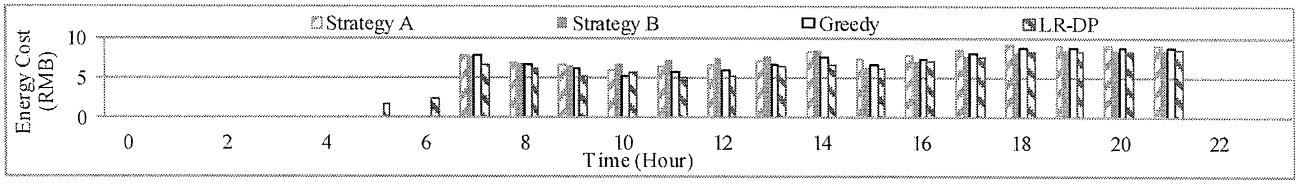

Fig. 5. Hourly energy costs in a hot and humid summer day.

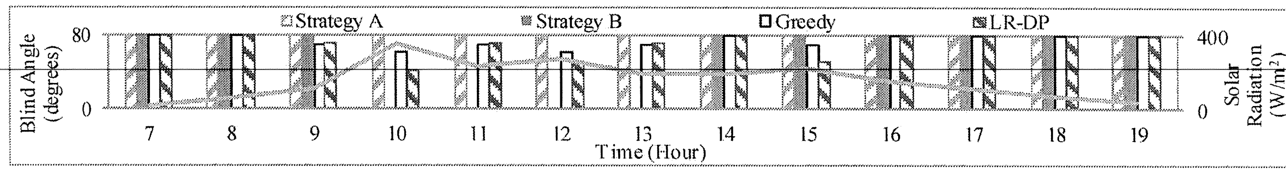

Fig. 6. Blind angles and solar radiation in a hot and humid summer day.

TABLE I
COMPARISON OF THREE METHODS

	Dual cost (RMB)	Feasible cost (RMB)	Duality gap	Computation time
DP	-	37.7	-	314.2 sec.
LR-DP (without rollout)	37.4	38.3	0.8 %	13.2 sec.
LR-DP (with rollout)	37.2	38.5	1.3 %	1.8 sec.

TABLE II
ENERGY COST IN RMB OF THE FOUR STRATEGIES FOR THE TWO CASES

	Str. A	Str. B	Greedy	LR-DP
Case 1	228.2	224.6	218.6	207.1
Case 2	178.8	170.4	176.9	159.0

In the third case, the sensitivity testing is carried out to demonstrate that our LR-DP strategies are robust to prediction errors in future outside temperatures and numbers of occupants.

Case 1: A Hot and Humid Summer Day: A hot and humid summer day in August is considered. The outside temperature is more than 27°C even at night. Solar radiation incident on windows is high around noon time.

The total energy costs of this day under the four strategies are presented in the second line in Table II. The LR-DP strategy, which controls the HVAC and blinds jointly, saves 9.3%, 7.7%, and 5.3% of the costs of Strategy A, Strategy B, and the greedy strategy, respectively.

The hourly energy costs of the four strategies are shown in Fig. 5. It can be seen that energy is consumed by the HVAC from 5:00 am to 6:59 am in the LR-DP strategy to precool rooms with the low energy price. This precooling reduces wall temperatures and energy costs after 7 am in the same way as in Example 1.

In Fig. 6, the blind angles (averaged in each hour) in one of the rooms facing south and solar radiation on the exterior surface of the glass curtain wall are presented. The solar radiation is high around noon time so that the control of blinds is of importance to minimize the total energy cost of the HVAC and lights. When solar radiation reaches its highest from 10:00 am to 10:59 am (normally it reaches its highest from 10 am to 2 pm and in the day we selected for this example there might be some clouds blocking the sunlight after 11 am), the blind angle of the LR-DP strategy is lower than those of Strategy A and the greedy strategy. The lower the blind angle is, the less solar radiation is gained by walls and the lower the wall temperature is. Therefore, the wall temperature in the LR-DP strategy is lower than those of the other two strategies. Consequently, in the LR-DP strategy, less heat is transferred from walls to indoor air in the rest hours of the day, and less energy is consumed by the HVAC. Although in the LR-DP strategy, extra energy is consumed by lights from 10:00 am to 10:59 am, the energy saved by the HVAC is more than that increased by lights. Therefore, integrated control in the LR-DP strategy keeps a good balance between the energy costs of the HVAC and lights, and can save more energy cost than individual control in Strategy A and the greedy strategy.

The average computational time of using LR-DP method to resolve the optimization problem is about 12.2 seconds, much less than the time interval, 10 min.

Case 2: A Summer Day With a Large Temperature Difference between Day and Night: Consider a summer day in July with a large temperature difference between day and night. When the outside temperature is low at night, natural ventilation can be used to precool rooms to reduce the high daytime cooling demand for the HVAC. The integrated control of the HVAC and natural ventilation is shown in this case.

For unoccupied hours before 7:00 am, there is no comfort requirement for humidity. If outside temperature is lower than indoor temperature, natural ventilation is good for precooling rooms. Therefore, the LR-DP strategy uses natural ventilation from 0:00 pm to 6:59 am, as shown in Fig. 7. Wall temperatures under LR-DP strategy is thus lower than those under other three strategies after 7:00, and 6.5%–11.1% (derived from the third line of Table II) of energy cost is saved by the LR-DP strategy compared with other three strategies.

For occupied hours after 7:00 am, a common rule is that natural ventilation is used only if outside air enthalpy is lower than indoor air enthalpy. This rule is used in Strategy B and works well for most of the time since the enthalpy indicates the energy contained in the air and the water vapor. However, an exception to the rule is found by the LR-DP strategy which controls the HVAC and natural ventilation jointly. From 7:00 am to 7:59 am,

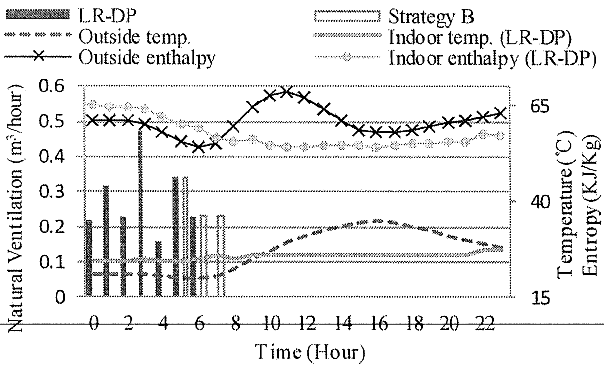

Fig. 7. Natural ventilation and relationships between outdoor temperatures and indoor temperature set points.

although the outside air enthalpy is lower than the indoor air enthalpy, the LR-DP strategy does not use natural ventilation. The reason is presented as follows. As presented in (2), enthalpy is a function of both air temperature and air humidity. From 7:00 am to 7:59 am, the enthalpy of the outside air is lower because of its lower temperature. The outside humidity, however, is higher than that of indoor air. The extra humidity coming from natural ventilation plus what is generated by occupants would exceed the FAU and FCUs' dehumidifying capacity. The integrated control of the HVAC and the natural ventilation therefore does not use the natural ventilation, although it can save energy cost. In this way, the human comfort is improved in the LR-DP strategy.

Since indoor temperatures under the LR-DP strategy in Fig. 7 can also be viewed as temperature set points that are satisfied by the integrated control of devices, relationships between indoor temperature set points and outside temperatures can be seen from Fig. 7. When the outdoor temperature is low at night, the indoor temperature set points are lower than those in the day and are near its lower bond of the comfort range to take advantage of natural ventilation as much as possible to precool the room.

Case 3: Sensitivity Testing: As presented in Section III-C, the values of uncertain outside temperatures and numbers of occupants in the next 24 h are predicted and then used to obtain the LR-DP strategy. Their prediction errors may affect the energy-saving performance of the LR-DP strategy. To evaluate the robustness of the strategy, sensitivity testing is performed and presented below.

The hot and humid summer day in Case 1 is considered. For simplicity but not losing generality, it is assumed that: 1) prediction errors of outside temperatures in the next 24 h by a weather station are equal to a constant ΔT_o and 2) prediction errors of numbers of occupants in the next 24 h are equal to a constant ΔO when rooms are occupied from 7:00 am to 10:00 pm. As for the outside temperature and number of occupants in the current time, it is assumed that they are measured accurately. Under different combinations of values of ΔT_o and ΔO, for each 10 min, the LR-DP strategies are obtained by using the LR-DP method to solve energy cost optimization problems and then the current time's decisions are used to control the devices. Hourly energy costs are presented in Table III (energy costs before 5 am and after 11 pm are all zero).

TABLE III
ENERGY COSTS IN RMB FOR SENSITIVITY TESTING

	ΔT_o=0 ΔO=0	ΔT_o=1 ΔO=0	ΔT_o=-1 ΔO=0	ΔT_o=0 ΔO=1	ΔT_o=0 ΔO=-1
Hour 6	1.52	1.77	1.42	1.92	1.10
Hour 7	2.27	2.47	2.18	2.51	1.81
Hour 8	6.58	6.43	6.69	6.34	7.13
Hour 9	5.98	5.90	6.08	5.86	6.43
Hour 10	5.14	5.12	5.17	5.11	5.42
Hour 11	5.63	5.61	5.65	5.60	5.83
Hour 12	4.78	4.78	4.79	4.77	4.90
Hour 13	5.19	5.19	5.20	5.38	5.26
Hour 14	6.29	6.29	6.29	6.30	6.30
Hour 15	6.54	6.54	6.54	6.44	6.54
Hour 16	5.96	5.96	5.96	5.96	5.96
Hour 17	7.01	7.01	7.01	7.01	7.01
Hour 18	7.53	7.53	7.53	7.53	7.53
Hour 19	8.21	8.21	8.21	8.21	8.21
Hour 20	8.27	8.27	8.27	8.27	8.27
Hour 21	8.29	8.29	8.29	8.29	8.29
Hour 22	8.36	8.36	8.36	8.36	8.36
Total	103.56	103.74	103.65	103.87	104.36

From the table, it can been seen that the inaccurate predictions of outside temperatures and numbers of occupants mainly affect the energy costs for precooling and consequently the energy costs in the first several office hours. That is because the prediction information is mainly used to precool rooms and shift cooling demand over time through building thermal mass [15]. Compared with energy costs under accurate predictions in the first column, the increase in energy costs caused by the inaccurate predictions is less than 1%. This slight increase in energy costs can be ignored compared with the 5.3%–9.3% energy cost savings by our LR-DP strategies in the Case 1. Therefore, our LR-DP strategy is robust to the prediction accuracy of future outside air temperatures and numbers of occupants.

Example 3: A Six-Floor Building With 144 Rooms: To demonstrate the scalability of the formulation and the LR-DP method, a six-floor building with each floor having 24 rooms is used for testing. In this example, the DP-derived rules for blinds and natural ventilation are also obtained and their performance in saving energy costs and computational time is examined.

The LR-DP method is implemented for every ten minutes in all 30 days in June. Based on the LR-DP strategies for the 144 rooms, DP-derived rules for blinds and natural ventilation are obtained by finding key factors that affect the control of blinds and natural ventilation and training the classifiers based on the key factors. These classifiers are then used to control blinds and natural ventilation in July. For the HVAC and lights, a simplified optimization problem is formulated and solved by a similar LR-DP method.

Energy Savings: The DP-derived rules, together with the LR-DP strategies for the HVAC and lights, are much more effective in reducing the total energy cost than rules now used in buildings—about 9.1% and 7.9% of the costs are saved compared with Strategy A, and Strategy B, respectively. So much energy cost is saved mainly because of the following three reasons.

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

1) The rule for blinds is derived from LR-DP strategies which control HVAC and lights jointly and therefore keeps a good balance between energy costs of HVAC and lights.
2) The rule obtained for natural ventilation is based on time of day, number of occupants, CO_2 concentration, indoor temperature and humidity, and outside temperature and humidity. It controls natural ventilation not only to provide fresh air, but also to cool and dehumidify indoor air. The rule coordinates well with the control of HVAC.
3) The simplified optimization problem for HVAC and lights can still use FCUs to precool rooms with low-price electricity and coordinate the FAU and all FCUs.

Scalability of the Method: For this 144-room problem, the computational time to obtain the LR-DP strategy is about 89.1 s, while it is 1.8 s for a two-room problem in Example 1 and 12.2 s for a 15-room problem in Case 1 of Example 2. The computational time is nearly linear to the number of rooms. Since 89.1 s are much less than the time interval, 10 min, the LR-DP strategy can be obtained online and then implemented to control devices in practice. As presented in Section IV-C, after a problem is solved and decisions are applied, the move window moves to the next 10 min and formulate a new problem. The multipliers of the previous problem are used to initialize the new problem. If the multipliers are not initialized in this way but are initialized to a given value, e.g., one, the average computational time is 364 s. Therefore, using multipliers of the previous problem for initialization saves about three quarters of the computational time.

The average computational time of solving the simplified optimization problem is 8.5 s. Compared with the 89.1 s for the original optimization problem, the DP-derived rules save about 90% of the computation time. That is because the dimensionality of the decision space is reduced by using the DP-derived rules for blinds and natural ventilation, and the computational time for the SDP decreases approximately exponentially as this dimensionality decreases. Compared with the LR-DP strategy, only about 1% of the energy cost is increased by the DP-derived rules. Therefore, the DP-derived rules are efficient in saving energy cost and computation time, and are scalable for large buildings.

Impact of the Assumptions on Model Accuracy: LR-DP strategies are obtained by using the model we developed with four assumptions as presented in Section III-B. The strategies are then tested in a simulation model developed in the building simulation software DeST. Therefore, in the absence of actual implementation, the impact of our assumptions on model accuracy can only be examined by comparing the indoor temperature, humidity, etc., under the two models. Since Assumption 4 (the full state information assumption) has nothing to do with model accuracy and the DeST model also has Assumption 1 and Assumption 3 as our model does, we can only use the above-mentioned comparison to evaluate the impact of Assumption 2 concerning about temperatures of interior walls. The results show that the mean of the difference between the wall temperatures under the two models is 0.05° and the standard deviation is 0.04°; and the mean and standard deviation of the difference between the indoor temperatures under the two models are 0.07° and 0.06°, respectively. Therefore, Assumption 2 has little impact on the model accuracy and is reasonable.

VI. Conclusion

Traditionally, heating, cooling, lighting, shading, and ventilation are controlled separately, particularly in situations involving passive and active systems that have distinct time scales and introduce nonlinearity in the coupled system behavior. To minimize daily energy cost of HVAC and lights and maintain occupant comfort, a novel formulation for controlling and coordinating the above-mentioned functions and associated devices is developed to obtain a near-optimal strategy. The formulated daily cost optimization problem is solved by combining Lagrangian relaxation, stochastic dynamic programming, and rollout technique within the surrogate optimization framework. Numerical simulation results show that the near-optimal integrated control strategy and the further derived rules for blinds and natural ventilation obtained work efficiently in saving energy costs and ensuring occupant comfort.

The problem formulation and methodology are developed based on specific devices that are nonlinear and coupled with each other. For terminal devices that are common in HVACs but not studied in this paper, such as humidifiers and VAV boxes, our problem formulation can be extended by modifying constraints, system dynamics, and the objective accordingly. For example if a humidifier is added to a room, we need to modify the system dynamics according to how the humidifier affects indoor temperature, indoor humidity, etc., and include its energy cost in the objective. Our methodology can also be extended because major difficulties that might be caused by these new devices, such as inseparability difficulties due to the sharing of devices by multiple rooms and nonlinearities in devices, have already been overcome in the methodology.

Appendix
Appendix: List of Symbols

$A_{w,i}$	Area of walls in room i.
C_{FAU}	FAU cooling power.
C_{HVAC}	Upper bound of cooling power of an HVAC.
C_p	Air specific heat.
C_w	Heat capacitance of walls.
$CO_{2a,i}$	Indoor air carbon dioxide concentration in room i.
CO_{2g}	Carbon dioxide generation rate per person.
COP	Ratio of cooling power of FAU and FCUs to electric power of chillers, pumps, and cooling towers.
c	Electricity price.
$G_{a,\text{FCU},i}$	FCU air flow rate in room .i
$G_{fa,i}$	Fresh air flow rate from FAU to room i.

$G_{nv,i}$ Natural ventilation flow rate in room i.
H_{FAU} Outlet air humidity from FAU.
$H_{a,i}$ Indoor air humidity in room i.
H_g Humidity generation rate per person.
H_o Outside air humidity.
$h_{w,in}$ Wall convection coefficient with indoor air.
I Number of rooms.
i Room index.
K Number of time intervals in 24 hours.
k Time index.
L Lagrangian function.
L_i^* Total optimal cost related to room i.
L_i^{k*} Optimal cost-to-go at stage k for room i.
m_{ai} Mass of the air in room i.
$m_{w,i}$ Mass of walls in room i.
n Iteration index.
O_i Number of occupants in room i.
$P_{fan,\text{FAU}}$ Power of FAU fan.
$P_{\text{light},i}$ Power of lights in room i.
$Q_{e,i}$ Heat generated by equipment in room i.
Q_g Heat generation rate per person.
$Q_{\text{light},i}$ Heat generated by lights in room i.
$S_{w,in}$ Solar heat gains on the interior wall surface.
S_i^k Current stage cost at stage k for room i.
$T_{a,i}$ Indoor air temperature in room i.
T_{FAU} FAU outlet air temperature.
$T_{\text{FAU},i}$ Fresh air temperatures supplied by FAU to room i.
$T_{\text{FCU},i}$ FCU outlet air temperature in room i.
T_o Outside temperature.
$T_{w,i}$ Wall temperature in room i.
u Decision variable.
W_i Opening of window in room i.
x State variable.
α_n Step size at iteration n.
Δt Time interval.
θ_i Blind angle in room i.
λ^k Lagrangian multipliers for relaxing HVAC capacity constraints.
μ^k Lagrangian multipliers for relaxing FAU fresh air temperature constraints.

Acknowledgment

The authors would like to thank Dr. S. Narayanan, Dr. R. Brahme, and Dr. A. Raghunathan at the United Technologies Research Center for their guidance on the research and constructive comments on the manuscript.

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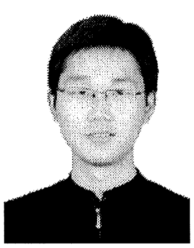

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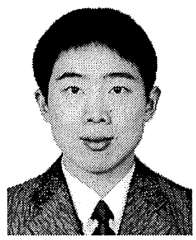

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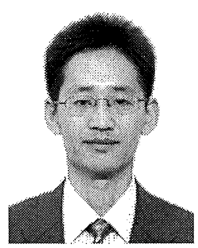

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