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DYNAMIC OPTIMIZATION OF INTEGRATED OPERATION STRATEGIES FOR THE BUILDING VAV SYSTEM AND NIGHT VENTILATION USING THE SIMULTANEOUS COLLOCATION METHOD: A CASE STUDY

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ABSTRACT

This paper presents a systematic approach to address the dynamic optimization of integrated operation strategies for the building VAV system and night ventilation. The objective is to minimize the energy consumption of the cooling coil and fans in a typical summer day. In the optimization scheme, the physical model is developed per differential algebraic equations (DAEs). The simultaneous collocation method is introduced to translate the dynamic optimization problem into a nonlinear program (NLP), which is then implemented in the GAMS platform, using IPOPT as the solver. The case study results indicate that the optimized operation strategies lead to a 45.87% energy saving, and the total energy consumption drops by 6-10% if the value of the required predicted percentage dissatisfied (PPD) is increased by 1%.

INTRODUCTION

The response properties of building materials and plants are at the heart of the management of building energy systems (Levermore, 2000). Because of the thermal storage effect and moisture buffering effect of building materials, excitations from surrounding environment and building equipment may take hours to cause changes in the building energy system. This brings several challenges to the operation design of building heating, ventilation and air conditioning systems (HVAC), the purpose of which is to provide good thermal comfort and acceptable air quality in the indoor environment. First, the lag and decay between various excitations and responses caused by building materials need to be quantified to facilitate the HVAC operation design. Second, the variations of the affecting parameters, such as the outdoor air temperature and relative humidity, over the whole process should be taken into account. In addition, investigating the synergistic influence of the variations of numerous affecting parameters is essential. This is even more challenging when the number of affecting parameters is large and the variations of them are diverse.

To further complicate the problem, both temperature and humidity play critical roles in creating acceptable thermal environment (Fanger, 1970, Hamdi et al., 1999), hence both heat and moisture transfers in the building system need to be concurrently considered in the design of HVAC operations. Maintaining an appropriate indoor humidity level for thermal comfort, either by mechanical methods or chemical methods, will add more burdens to the HVAC systems and consequently cause more energy consumptions. According to previous research on the impact of air humidity in building energy systems in different climatic areas, the energy consumption in the temperature–humidity control (THC) mode is typically 10-45% higher than that in the temperature control (TC) mode (Enshen, 2005, Mazzei et al., 2005).

A variety of energy saving techniques have been developed in the past two decades to improve the performance of building energy systems. Among these techniques, night ventilation (NV) has been proven effective and energy efficient to transfer heat from buildings to natural heat sinks. It makes use of the building thermal mass, both internal and external, to store heat during a warm period and release it later during the day. This not only leads to significant potential to reduce building cooling loads and HVAC energy consumptions, but also offers good indoor air quality and thermal comfort as an indirect positive product (Artmann et al., 2008).

NV has been extensively investigated in the past. Yang and Zhou built the heat transfer model coupling thermal mass and natural ventilation, and estimated the impact of external and internal thermal mass on the cooling load reduction (Yang and Li, 2008, Zhou et al., 2008); Blondeau listed and categorized the key parameters related to the efficiency of night ventilation (Blondeau et al., 1997); Geros et al. investigated the influence of the urban environment on the efficiency of night ventilation (Geros et al., 2005). The feasibility of NV in different climate regions has also been investigated.(Artmann et al., 2007).

In the above studies, however, most of the researchers used the outdoor air temperature as the only index to evaluate the climatic potential for NV without considering the influence of outdoor humidity, and the humidity transfer process was not included in the ventilation model. In these studies, fixed operating strategies were usually pre-defined to study NV's performance from the building physics perspective, and the strategies may have potentials for further improvements. Moreover, it is commonly necessary for NV to cooperate with other active cooling systems, such as VAV systems. As a result, the design of integrated operation strategies, which need to account for the performance of all the involved systems, is even more complex.

Optimization-based decision-making methods can be a power tool in dealing with such complex problems. For example, Zavala et al. established an on-line optimization framework to exploit disturbances of weather conditions for the operation design of a simplified building energy system, and found that more proactive and cost-effective operations can be obtained (Zavala et al., 2009). Sheikhi et al. proposed an optimization model to find the optimal size and operation for combined cooling, heat and power systems, in order to reduce power loss and enhance service reliability of the system (Sheikhi et al., 2012).

This paper aims to analyse and optimize the integrated operation of night ventilation and active building cooling using VAV systems as the case. The study is carried out in two successive steps. First, the building and system physical model is developed based on first principles. Next, a dynamic optimization formulation is introduced to determine the optimal operation strategy. In the optimization algorithm, the simultaneous collocation method is employed to translate the dynamic optimization problem to continuous NLPs, which are further solved by IPOPT that adopts the classic interior point algorithm. This method has been successfully applied to many real-world optimization problems in various research areas such as Chemical Engineering and Economics.

PHYSICAL MODEL DEVELOPMENT

To conduct the optimization task, a physical model describing the performance of building and system needs to be first developed. In this section, a first-principle based lumped single-zone building model including both external and internal thermal mass is built to describe the dynamic process of heat and moisture transfer in the building system, and a moist air thermodynamic property and process model is applied to describe the operation behaviour of the cooling system.

Building model configuration

The configurations of the building model in this study are mostly adapted from Yang's research (Yang and Li, 2008). The size of the zone is 8 m × 6 m × 3 m. The mass of external thermal mass is 1425.6 kg and that of internal thermal mass is 1306.8 kg. The convective heat transfer coefficient is 15 W/(m^2 ℃) at the exterior surface of external thermal mass and 2.5 W/(m^2 ℃) at the interior surface of external thermal mass and the surface of internal thermal mass. The convective mass transfer coefficients of these surfaces are obtained via the Lewis equation in which the Lewis number is assumed to be one (Kloppers and Kröger, 2005). The thermal resistance of external thermal mass is 0.15 m^2 ℃/W. The heat capacity of external and internal thermal mass is 900 J/(kg ℃).

The operation time horizon of interest is set to 24 h. It is assumed that both the outdoor air temperature and relative humidity are sinusoidal harmonic functions with an angular frequency of $\pi/12$ h^{-1}. For the temperature, the average is 28 ℃, the amplitude is 7 ℃ and the phase shift is π. For the relative humidity, the average is 75%, the amplitude is 15% and the phase shift is 0. The office hours are 8:00-18:00h, during which the indoor thermal comfort and air quality have to be well maintained by the VAV system and ventilation.

Heat transfer and storage

To describe the heat transfer in the external thermal mass, a standard three resistances and two capacitances (3R2C) model is introduced, which has been proven successful in transient building load studies (Zheng et al., 2010, Braun, 2002). More specifically, external thermal mass is considered as two separate parts and the heat balance equations for both are developed independently.

Taking the inside part of external thermal mass for example, the heat balance equation is:

$$M_{mei} c_{mei} \frac{dT_{mei}}{dt} + h_{ei} A_{me} (T_{mei} - T_i) + \frac{A_{me}(T_{mei} - T_{meo})}{R_{me}} = 0 \quad (1)$$

On the l.h.s. of Eq. (1), the first term is the energy stored in the inside part of external thermal mass, the second term is the energy transferred between external thermal mass and indoor environment, and the third term is the energy transferred between the outside part and inside part of external thermal mass.

Likewise, the heat balance equations for the outside part of external thermal mass, the indoor air and the internal thermal mass can be derived individually.

Moisture transfer and buffering

In the detailed moisture transfer and buffering model, building materials are treated as capillary porous media and its hygrothermal properties are considered (Wu et al., 2008). The dynamic interactions between building envelope components and mechanical systems (Tariku et al., 2011) and the coupling between the heat and moisture transfer are also addressed (Abahri et al., 2011). To maintain the accuracy of the detailed model, the accurate material properties are usually determined experimentally (Li et al., 2012). All of these lead to the complexity of the detailed moisture transfer and buffering model.

In order to balance the model scale and complexity of the optimization problem, a simplified moisture transfer and buffering model is used in this study, in which the building materials are assumed to be solid and homogeneous and the coupling between heat and humidity transfer is ignored. With these assumptions, the moisture balance equations for the indoor air and moisture buffering material can be obtained in a similar way as the development of the heat balance equations, according to the analogy between moisture migration and heat transfer.

Based on the building model described above, the sensible and latent building loads can be calculated for the further estimation of the energy consumption in the system.

Moist air processes in the operation of VAV

In this study, the energy consumption of the system consists of two parts: one is from the operation of the coil for cooling and dehumidification, and the other is from the operation of the fans for ventilation.

A VAV system is an all-air space conditioning system and is capable of supplying variable air volume. During cooling seasons, the outdoor air (OA) is first mixed with an appropriate amount of return air (RA), and then cooled and dehumidified by the cooling coil. After that, the low-temperature and low-humidity air is supplied into the building space. The temperature and moisture content of the supplied air should be properly manipulated to stay sufficiently low to absorb the total cooling load of the space.

The operation of the VAV system can be divided into several moist air processes, that is, the air mixing process that is assumed adiabatic, the cooling and dehumidification process at the cooling coil, and the heating and humidification process in the building space. In these processes, the analysis of the thermodynamic properties of moist air is essential for the calculation of the energy consumption. For this purpose, the moist air property formulae given by ASHRAE (2005) are used.

Constraints for the optimization

Ensuring the thermal comfort of building occupants during office hours is the primary purpose of building HVAC systems. Therefore, the indoor thermal comfort requirement is considered as a critical constraint for optimization. Although a large number of thermal comfort indices have been developed in many previous research studies, the most widely used is the one developed by Fanger in which predicted mean vote (PMV) and predicted percentage dissatisfied (PPD) are defined (Fanger, 1970). Detailed PMV calculation equations can be found in the ISO-7730 standard (ISO, 2005). In this study, the operation strategy is set to ensure the PPD does not exceed the limit of 10%, which corresponds to the PMV range of ±0.5.

Additionally, sufficient outdoor air needs to be supplied to assure the good indoor air quality. In the optimization formulation, the sum of ventilation and OA airflow rates is specified to be at least 72 m^3/h during office hours. In addition, indoor air temperature should be higher than the dew point temperature in order to prevent moisture condensation, and the supply air temperature should be greater than 16 ℃ to reduce local discomfort. The calculation of the dew point temperature of indoor air can be carried out in the moist air thermodynamic property model stated earlier.

OPTIMIZATION FORMULATION AND SOLUTION STRATEGY

This section sets out the optimization problem based on the aforementioned first-principle based physical model. A dynamic optimization formulation is first presented, which consists of ordinary differential and algebraic equations that satisfy the twice-differentiable condition. Given this, the simultaneous collocation method is used in the solution algorithm, translating the dynamic optimization formulation into an NLP that is solved by IPOPT.

Dynamic optimization formulation

As noted earlier, the system performance is optimized to maintain the indoor comfort indices, while reducing the energy consumption of the cooling coil and fans. The objective function representing the energy load and can be written as:

$$\min \Phi = \int_{t_0}^{t_f} \left(Q_{coil} + Q_{fan}\right) dt \tag{2}$$

where, Φ is the objective function; Q_{coil} and Q_{fan} are the energy consumption rate in the coil and fans, respectively. These quantities can be determined from the intrinsic properties in the physical model. Meanwhile, additional inequality constraints are introduced to represent the requirements on the indoor air confort and quality, as well as equipment capacity limits.

For the optimization task, one needs to determine the corresponding optimal operating profiles of the associated system inputs (also termed as control variables), including the night ventilation amount, VAV outdoor air and return air amounts, supply air temperature and humidity ratio. After proper reformulations, the dynamic optimization problem can be stated in a general form:

$$\begin{gathered} \min \Phi\left(z(t_f)\right) \\ s.t.\ \dot{z}(t) = f\left(z(t), y(t), u(t)\right), z(t_0) = z_0 \\ g\left(z(t), y(t), u(t)\right) = 0 \\ h\left(z(t), y(t), u(t)\right) \leq 0 \end{gathered} \tag{3}$$

where, z and y are the differential and algebraic state variables, respectively; u represents the vector of the control variables. The first-principle based physical model is represented by the DAEs in f and g, while the constraints are noted in h.

Solution approaches for dynamic optimization

Analytical solution of the dynamic optimization problem shown in Eq. (3) requires solving corresponding Hamilton–Jacobi–Bellman equations, which remains quite difficult and they cannot handle inequality constraints. In a different vein, numerical solution techniques have been significantly advanced over the past few decades. These methods can be generally separated into two types, known as the sequential (Feehery and Barton, 1998) and simultaneous approaches (Biegler, 2010). In the sequential approach, optimization is carried out only in the input space and the DAEs are integrated using standard integration algorithms. This approach requires repeated numerical integration of the DAE model that demands significant computational power and the algorithm slows down dramatically with the increase of the time horizon length and degrees of freedom in control. Moreover, the approach converges only along feasible paths that may fail for a system with unstable modes. On the other hand, the simultaneous approaches include the multiple shooting (Bock and Plitt, 1984) and simultaneous collocation method (Biegler and Kameswaran, 2006). In multiple shooting, the time horizon of interest is divided into several segments, and the sequential approach is applied to each time slot. This method unleashes the potential of handling unstable systems while increasing the sizes of resultant problems. The collocation method is motivated by avoiding explicit integration for state profiles that is required by the aforementioned approaches. With this method, a DAE system is fully discretized (for both states and controls). In particular, the time domain is first divided into a proper number of finite elements, and then in each element several collocation points are placed. The choice of collocation points has an influence on the accuracy of the approximation. In this study, Radau collocation points are used for their high accuracy and stability properties. More detailed discussions about Radau collocation points can be found in (Biegler, 2010). A comprehensive review on the simulataneous collocation method is given in (Biegler, 2007). After the discretization, the states and controls are approximated via orthogonal polynomial representations at collocation points. More specifically, for the differential states, a Runge-Kutta basis representation is introduced:

$$z(t) = z_{i-1} + h_i \sum_{j=1}^{K} \Omega_j(\tau)\, \dot{z}_{\,i,j} \tag{4}$$

Here, i is the index of finite elements and j corresponds to collocation points; t is the time from t_i to $t_i + h_i$; $\tau = \frac{t-t_i}{h_i}$ is the normalized time from 0 to 1; z_{i-1} is the value of the variable at the beginning of i; h_i is the element length; $\dot{z}_{\,i,j}$ is the first-order derivative value in element i at point j; and Ω_j is a polynomial of order K, defined as:

$$\Omega_j = \int_0^{\tau} l_j(\tau')d\tau' \tag{5}$$

where, l_j is a Lagrange interpolation polynomial shown as follows:

$$l_j(\tau) = \prod_{j'=0,\neq j}^{K} \frac{\tau - \tau_{j'}}{\tau_j - \tau_{j'}} \tag{6}$$

To this end, the differential variables have been discretized. In addition, to ensure the continuity condition across element boundaries, the following equation is introduced:

$$z_i = z_{i-1} + h_i \sum_{j=1}^{K} \Omega_j(1)\, \dot{z}_{\,i,j} \tag{7}$$

Similarly, for the algebraic states, the profiles can be represented with Lagrange polynomials:

$$y(t) = \sum_{j=1}^{K} l'_j(\tau\,)\, y_{i,j} \tag{8}$$

The weight l'_j is similarly defined as in Eq. (8) with degree K. It is worth to note that discontinuity is allowed for the algebraic states at element boundaries. Furthermore, piece-wise constant profiles are assumed for the process controls, i.e., a control variable possesses a constant value within a finite element.

By applying this collocation scheme, the dynamic optimization problem stated in Eq. (3) is transformed into a standard NLP, featuring favourable sparsity that can be efficiently exploited by NLP methods. To date, there exist several NLP algorithms that can be applied to solve the problem (Schlegel et al., 2005). Among these, the interior point method is able to efficiently handle large-scale problems with large numbers of degrees of freedom. Thus IPOPT is selected as the NLP solver. IPOPT is a Newton type nonlinear optimization solver, which applies to equation-oriented models such that exact derivatives are available to guide and accelerate the optimization search. It applies the barrier method to handle inequality constraints coupled with the filter method for global convergence. The Karush-Kuhn-Tucker conditions for optimality is satisfied at the solution after Newton iterations. The software package is open source and can be accessed through https://projects.coin-or.org/Ipopt. For more details on the description of the algorithm, refer to (Wachter and Biegler, 2006).

OPTIMIZATION IMPLEMENTATION

In this section, the solution algorithm described in the previous section is applied to solve the optimization problem for the integrated operation of VAV and NV. The optimization model is implemented and solved in the General Algebraic Modeling System (GAMS) platform, which is a state-of-the-art tool in mathematical modeling and optimization. GAMS provides both declarative and procedural syntax for the user to describe optimization problems, and offers convenient access to alternative solvers.

In the collocation scheme, 24 finite elements are used in an hourly basis, and 3 Radau points are defined in each element. The 5 control variables are assumed to be piece-wise constant over the finite elements, and therefore the degree of freedom for the optimization problem equals 120 (i.e., the product of the total number of finite elements and controls). For the state variables, a comparative study is conducted to verify the accuracy of the collocation algorithm. For all the test cases, the calculated state profiles agree well with the results obtained in Matlab simulations using the conventional integrator ODE45.

After collocation, the translated NLP problem has 2290 variables, 2170 equality constraints and 459 inequality constraints. For all the simulations reported in this paper, IPOPT is able to solve the problems to optimality with computation times in the magnitude of seconds.

STUDY RESULTS AND DISCUSSIONS

Energy saving analysis

A conventional local control strategy is implemented as the baseline to compare with the optimized operation strategies derived above. In the local control strategy, the temperature setpoint during office hours is set to 25 ℃ ± 1 ℃, while the setpoint at off-office hours (setback temperature) is set to 29 ℃ ±1 ℃. The VAV system operates corresponding to the difference between the indoor air temperature and the setpoint. The supply air temperature and relative humidity are kept as constants, viz. 16 ℃ and 60%, respectively. The ratio between the outdoor air and return air is 1:4 and no night ventilation is provided.

The comparative energy consumptions (including the overall system and components) in the optimized operation strategy and conventional local control strategy are shown in Figure 1.

In the local control scheme, the total consumption is 5.607 kWh compared to 3.035 kWh in the optimized scheme. An energy saving of 45.87% is achieved by implementing the optimized operation strategy. There are also trade-offs between unit energy consumptions. The optimized energy consumption by the cooling coil is reduced by 55.35%, while the consumption by the fans increased by 53.80% due to the night ventilation operation.

Note that idealized weather variable behaviours are assumed in the case study, so the achievable energy savings may decrease when the designed operation strategies are implemented in the real world conditions due to the presence of uncertainties and disruptions.

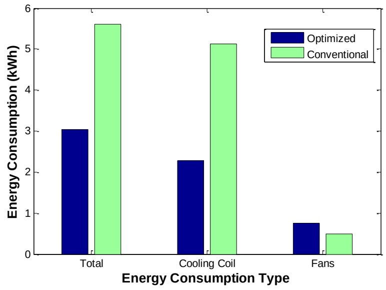

Figure 1 Energy consumptions of the optimized and conventional operations

Optimal operation strategy analysis

As noted earlier, the parameters to be optimized include the night ventilation amount, VAV outdoor air and return air amounts, supply air temperature and humidity ratio.

In general, night ventilation is effected when the outdoor air temperature level is sufficiently low. To obtain the optimal ventilation rates, however, the following three parameters need to be studied: (1) outdoor humidity level - high humidity may increase the energy consumption for dehumidification and consequently offset energy savings in cooling; (2) timing for ventilation - the effect of night ventilation during office hours may considerably decay if the ventilation occurs too early before the office hours commence; (3) ventilation rates - need to be carefully manipulated to balance the energy consumptions in the cooling coil and fans.

The dynamic profiles of the optimal ventilation rates and VAV airflow rates are shown in Figure 2. In this figure, the maximum ventilation rate is observed at 4:00-6:00h, during which the lowest outdoor air temperature occurs (see Figure 3). Before and after the peak (2:00-3:00h and 7:00-8:00h), ventilation is also provided but at lower rates. Such profiles agree with the theoretical analysis. Figure 2 also shows that the VAV system starts to operate at 10:00h, and then the supply air amount gradually rises because of the increase of the outdoor air temperature and humidity ratio, as well as the building loads.

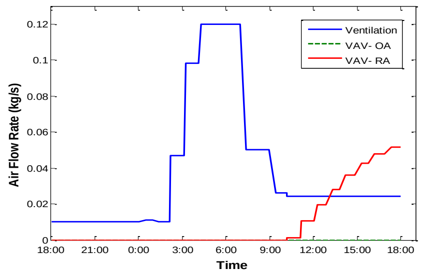

Figure 2 Dynamic profiles of air flow rates in the optimized operation strategy

To maintain the indoor air quality during office hours, the minimum value of the sum of outdoor air and ventilation rates is set to 0.024 kg/s in the optimization. This constraint is satisfied by providing

0.024 kg/s ventilation during office hours and no outdoor air is provided through the VAV system.

During the VAV operation period, the supply air temperature is set to 16 ℃ which is the required minimum value; and the supply air humidity ratio is set to 9 g/kg which is the value of the upper bound. All of these optimized controls eventually generate an indoor environment with acceptable thermal comfort and minimized energy consumption.

Indoor air temperature and humidity profiles

The daily temperature profiles are depicted in Figure 3 as shown below.

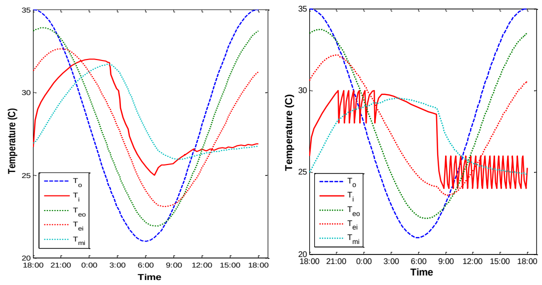

Figure 3 Comparison of daily temperature profiles (l) optimized operation (r) conventional operation

It can be observed in both charts that, there are lags and decays of the temperature profiles of external thermal mass, indoor air and internal thermal mass, when compared with the outdoor air temperature. In the optimized operation strategy, the indoor air temperature begins to drop at around 2:00h when the night ventilation starts. The decrease of the indoor air temperature lowers the temperature of the internal thermal mass, which serves as the cooling storage material in the process. When the office hours begin at 8:00h, the internal thermal mass temperature declines to 25.4 ℃, which is 3.5 ℃ lower than that in the conventional operation strategy. The cooling effect provided by the cooled internal thermal mass during office hours is one main contribution to the energy saving of the optimized operation strategy.

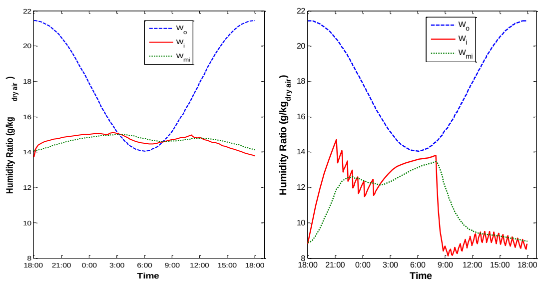

Figure 4 Comparison of daily humidity ratio profiles (l) optimized operation (r) conventional operation

Comparison of daily humidity ratio profiles is drawn in Figure 4. In the left chart corresponding to the optimized operation, the indoor air humidity ratio is quite stable compared with that in the conventional operation shown in the right chart. The reason is that there is only a small amount of ventilation due to infiltration during 18:00-2:00h, when the difference between indoor and outdoor humidity ratio is large; then when large ventilation supply occurs between 3:00-9:00h, the outdoor humidity ratio is at its minimum so that little moisture transfer between indoor and outdoor air is induced. Note that due to the moisture buffering effect of the building material, the humidity ratio of the indoor air is even higher than the outdoor air between 3:30-7:30h.

In the conventional operation strategy, the VAV system operates according to the indoor air temperature only and the indoor humidity level is not considered as a criterion in the operation design. Although the indoor humidity level can be implicitly controlled by the system, it may not stay within the proper range for acceptable thermal comfort. In the optimized operation strategy, however, the humidity ratio of the supply air is well manipulated by taking both the indoor thermal comfort and energy consumption into consideration. This leads to the energy saving from the optimized strategy.

Relative humidity of the indoor air can be calculated from the air temperature and humidity ratio, using the moist air thermodynamic property model.

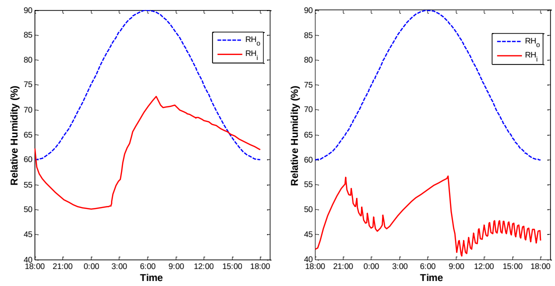

Figure 5 Comparison of daily relative humidity profiles (l) optimized operation (r) conventional operation

Comparison of daily relative humidity profiles is shown in Figure 5. Due to the significant difference in air temperature and humidity ratio, the daily relative humidity profiles in the two strategies also differ remarkably. In the optimized operation strategy, the relative humidity lies in a range between 50% and 75%, while in the conventional case it stays between 40% and 55%.

PPD distribution in the optimized operation

To compare the qualities of the indoor thermal environment provided by both operation strategies, the distribution of daily PPD values during office hours are demonstrated in Figure 6.

It can be seen from the figure that, in the conventional operation strategy, the values of PPD gather around 5-6%, while in the optimized operation strategy they gather around 9-10% which is the upper limit of PPD.

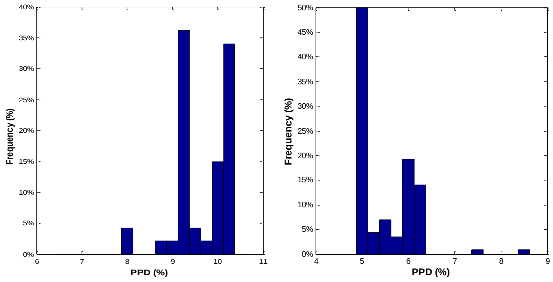

Figure 6 Comparison of daily PPD distributions during office hours (l) optimized operation (r) conventional operation

Influence of PPD limit on optimization potential

From the analysis in the above section, it follows that in the optimized operation design, the PPD of the indoor air is distributed near the upper bound, i.e., the constraint of PPD defined in the optimization limits further reduction of the energy consumption. To elucidate the influence of the PPD constraints on the energy saving, different settings of the value of PPD upper limit during office hours are applied and the computed objective function values are compared in Figure 7.

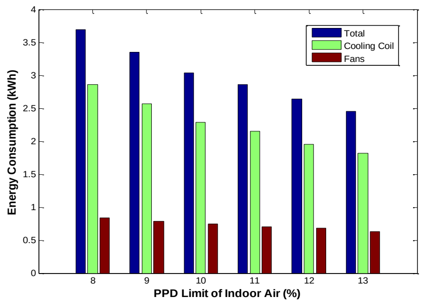

Figure 7 Influence of PPD limit on energy saving potential

As can be seen in Figure 7, the energy consumption decreases as the PPD upper limit increases. This can be explained from the optimization theory perspective. More specifically, a larger PPD upper bound indicates a larger feasible region for the optimization. Thus, the optimizer is able to explore more potential configurations of the system, and consequently captures a better objective. It can be seen in the figure that the total energy consumption drops by 6-10% if the value of the PPD limit is increased by one unit.

CONCLUSION

In this paper, a systematic optimization method is applied to the integrated operation design for the VAV system and night ventilation. A first-principle based single-zone building model including both external and internal thermal mass is built to describe the heat and moisture transfer in the building system, and a moist air thermodynamic property and process model is introduced to describe the operation of the VAV system. The dynamic optimization problem is formulated to address the energy consumption minimization problem, given desired indoor thermal comfort and air quality requirements. In the optimization problem, the participating DAE system is translated into nonlinear algebraic equations by using the simultaneous collocation method. The resulting NLP problem is modelled in GAMS and further solved by IPOPT. The generated optimal operation strategy shows remarkable energy savings compared to the traditional local control strategy according to the simulation results. The synergetic operation of NV and VAV has complementary advantages in manipulating the building system through the associated controls. In addition, the saving potential with respect to the PPD limit is studied. In the future work, more detailed moisture transfer and buffering models will be implemented, and the presence of uncertainties and disruptions in the process will be investigated.

NOMENCLATURE

A_m, surface area of thermal mass (m^2);

c_m, heat capacity of thermal mass (J/kg ℃);

h, convective heat transfer coefficient (W/m^2 ℃);

h_m, convective mass transfer coefficient (kg /m^2 s);

M_m, mass of thermal mass (kg);

Q_{coil}, energy consumption rate of the coil (kW);

Q_{fan}, energy consumption rate of the fans (kW);

R_m, thermal resistance of thermal mass (m^2 ℃/W);

RH, relative humidity (%);

T, temperature (℃);

W, humidity ratio (kg/kg_a).

Subscripts

i, indoor air

me, external thermal mass;

meo, outside part of external thermal mass;

mei, inside part of external thermal mass;

mi, internal thermal mass;

o, outdoor air.

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