Model Predictive Control Strategy of Air Conditioning System Based on Dynamic Passenger Flow: An Airport Terminal Building Case Study

Kai Ma¹, Dan Wang¹-², Wei Wang²-⁴, Shihao Zhu¹, Yuying Sun¹
¹ Beijing Key Laboratory of Green Built Environment and Energy Efficient Technology, Beijing University of Technology, Beijing 100124, China
² Faculty of Information Technology, Beijing University of Technology, Beijing 100124, China
³ Information and Safety Engineering, Beijing Institute of Petrochemical Technology, Beijing 102617, China
* Corresponding author: wangdan9264@bjut.edu.cn, mrwangwei@bjut.edu.cn

ABSTRACT
Airport terminals have rapidly indoor occupancy flow variations and complex backgrounds. Due to the large lag of air-conditioning systems, such systems have difficulty regulating to changes in indoor loads, resulting in untimely control actions, poor thermal comfort and energy waste. To address this challenge, this paper takes the baggage claim hall as case study, and proposes a model predictive control strategy based on dynamic passenger flow. First, the model predictive control strategy of air conditioning system is proposed, and the dynamic passenger flow is introduced into the predictive control to realize the rapid response of the system to passenger flow, improve indoor comfort level and reduce the energy consumption caused by the conditional PI control methods. Moreover, the simulation experiment involving air conditioning system of baggage claim hall in the airport terminal is carried out and the results are analyzed in typical days and the cooling seasons. The simulation results show that the model predictive control strategy based on dynamic passenger flow proposed in this paper could better maintain indoor temperature stability and faster system response, and save 13% and 10% energy in typical days and cooling seasons respectively.

HIGHLIGHTS
- Dynamic passenger flow and integral control feedback were introduced the optimal control.
- Model predictive control (MPC) strategy based on the dynamic passenger flow was developed.
- The proposed MPC strategy can rapid response to changes of the passenger flow and deeply reduce system energy consumption.

INTRODUCTION
Energy saving and emission reduction in public buildings is one of the important fields to achieve the grand strategic goals of carbon peak and carbon neutralization (Daietal.,2022; Tsinghua University Energy Conservation Center 2022). Among the different types of public buildings, airport terminals consume a lot of energy each year(Yildizetal.,2022). Over 50% of the energy in airport terminals is consumed by the HVAC system, and according to relevant studies, the major factor affecting the HVAC system’s energy consumption is related to passengers(Guetal.,2021). Therefore, adjusting and controlling the air conditioning system according to the dynamic passenger flow, while meeting the functional requirements of the terminal and creating a comfortable indoor environment, reducing the operating energy consumption of the air conditioning system, is of great significance for the energy conservation work of public buildings.

The existing researches show that the control of air conditioning system based on occupancy has been realized with a good energy-saving effect (Baroahetal.,2015; Xueetal.,2020). Zheng et.al (2014), introduced occupancy into the control strategy of the HVAC system and set the on/off of air-conditioning system based on the personalized occupancy. The control strategy could save up to 9% of energy. Zou et.al (2017) and Feng et al. (2017) use video image to detect occupancy information for energy-saving control of air conditioning system. Furthermore, there are also studies on the use of wireless signals, such as WiFi, Bluetooth, etc., to detect occupancy, and then optimize the control of air conditioning system (Samarehetal.,2022; Krishnaetal.,2019). In summary, the occupancy-based control strategy has high energy saving potential and development advantages.

However, few airport terminals use occupancy-based control strategy for air conditioning system, and the temperature feedback control is adopted in the most terminals. In the airport terminal, due to the influence of the large space’s thermal inertia(Shenetal.,2013), uncertainty of indoor load caused by dynamic passenger flow, indoor thermal mass diffusion and the sensitivity of sensors, the air conditioning system has large lag and is difficult for to quickly response to the dynamic changes in regional passenger flow. As a result, the energy supply of the system misses the actual indoor load demand in time series, resulting in poor thermal comfort and energy waste (Hsiehetal.,2014; Homodelt.,2013). Therefore, it is urgent to construct a novel control method to address the problem of system lag for airport terminal. In recent years, aiming at the issue of large lag in air conditioning system, model predictive control has become a key method to solve the lag problem of air conditioning system (Wnagetal.,2022;...
Aframetal., (2014). Huang (2011) designs a temperature bi-linear predictive controller and a gain 
nonlinear predictive controller, constituting a cascade 
control system of room temperature, which effectively 
improves the robustness of room temperature control. Li 
et al. (2021) proposed an Elman neural network 
multi-step predictive model and indoor temperature 
predictive control method for the variable air volume air 
conditioning system with time-delay predictive control. 
This method is beneficial to improve the control stability 
of indoor temperature control loop. Zhao et al. (2022) 
established a radiation system model predictive control 
regulation model based on system delay time, effectively 
solving the load mismatch and energy waste problems 
caused by delay time, and the overall energy 
consumption of the system is estimated for reducing by 
8.51% in comparison with the PID. Therefore, the 
model predictive control method could effectively solve the lag 
problem of the air conditioning system and reduces system 
energy consumption. At the same time, it also 
provides a feasible reference for addressing the problem 
that the adjustment of the large space air conditioning 
system in the airport terminal building lags behind 
regional passenger flow changes.

The air conditioning system of baggage claim hall, 
a typical area of an airport terminal in Beijing, is taken as 
the research object, this paper proposes a model 
predictive control strategy based on dynamic passenger 
flow for air conditioning system. Based on model 
predictive control theory, a model predictive control 
strategy introducing dynamic passenger flow changes for 
air conditioning systems has been developed with air 
supply volume and air supply air condition temperature as 
opimization parameters, and indoor comfort and 
minimum system energy consumption as objective functions, 
which improving indoor comfort level caused by 
large lag under traditional control method and 
reducing the energy consumption of system. At the end of 
this paper, with the example of baggage claim hall in 
airport terminal, the feasibility and effectiveness of the 
model predictive control method of air conditioning 
system based on the dynamic passenger flow are 
analyzed through simulation.

METHODOLOGY

Indoor temperature prediction model
In order to better understand the effect of indoor 
temperature control and meet the subsequent model 
predictive control of the system, it is necessary to 
establish a room temperature prediction model. ARX 
model is employed to predict indoor temperature.

ARX model can use the values of the previous step or 
higher in a sequence to predict the value of the next step. 
In this paper, historical room temperature, indoor load 
and cooling delivery, are introduced to predict the room 
temperature at the next moment (Sharma et al., 2022). The 

ARX prediction model of room temperature is shown in 
Equation (1).

\[ T_N(\tau) = \sum_{i=1}^{n} a_i T_N(\tau - i) + \sum_{i=1}^{n} b_i q_i(\tau - i) \]

\[ + \sum_{i=1}^{n} c_i q_i^L(\tau - i) + h \]

where \( T_N(\tau) \) is room temperature at time \( \tau \), minute. \( Q_i \) is 
cooling capacity, kW. \( a, b, h, \) are the parameters to be 
estimated. \( p, q \) and \( r \) are model orders. \( Q_i \) represents the 
disturbance term in the zone, kW, mainly depending on 
the dynamic passenger flow. Typically, this disturbance 
term consists of a heat gain component contributed by 
occupant activity (denote it as \( Q_{t, occ} \)), and other heat gain 
components which are contributed by non-occupant 
activities (denote it as \( Q_{t, non-occ} \)). Mathematically,

\[ Q_{t} = Q_{t, occ} + Q_{t, non-occ} \]

In this paper, \( Q_{t, occ} = q_{ps} f_p p(t) A + q_{pl} f_p p(t) A, \) where \( q_{ps} \) 
and \( q_{pl} \) are the sensible and latent heat gain per person 
respectively, kW. \( f_p \) is cluster factor. \( p(t) \) is 
instantaneous personnel density, P/m²; its calculation 
method refers to the study (Gu et al., 2022). \( A \) is the area 
of the zone, m². \( Q_{t, non-occ} = q_{pl} p(t) A + (q_{pl} \eta) f_{ps} A, \) where \( q_l \) 
and \( q_{pl} \) are approximate per area heat gain from lights and 
equipment respectively, kW/m². \( p(t) \) is instantaneous 
utilization rate of lights. \( q_l \) is simultaneous utilization 
rates of equipment. \( f_{ps} \) is motor installation and load factor. \( \eta \) is motor efficiency.

MPC strategy
The aim of MPC is to minimize energy use while 
ensuring the thermal comfort. The air temperature was 
controlled by the MPC by adjusting air supply volume 
and temperature. The complete model predictive control 
strategy, consists of three components: (1) the prediction 
model, (2) rolling optimization and (3) feedback 
compensation.

Model prediction and rolling optimization
In component (1), dynamic passenger flow, is introduced 
into the prediction model to realize the rapid response of 
the system to passenger flow. Besides the room 
temperature prediction model, the other mathematical 
models, such as cooling capacity model, energy 
consumption model for the fan and the chiller energy 
consumption model need to be established.

The cooling capacity model can be expressed in terms of 
supply air volume, room temperature and supply air 
temperature (Sharma et al., 2022), as shown in Equation 
(3).

\[ Q_i = d_1 T_i + d_2 G_i + d_3 T_i + f_1 T_i G_i + f_2 T_i f_1 T_i G_i + g \]

Where \( G_i \) is air supply volume, kg/s. \( T_i \) is air supply 
temperature, °C. \( d_1, d_2, d_3, f_1, f_2, f_3 \) and \( g \) are unknown 
coefficients of the model.

Fan is an important equipment for conveying energy in 
the variable air volume air conditioning system, and its
energy consumption (Ma et al., 2021) can be simplified into a function of air volume, and the energy consumption model of the fan is shown in Equation (4) - (5).

\[
E_{v-fan} = u_1 G_1^2 + u_2 G_1^2 + u_3
\]
\[
E_{p-fan} = u_4 G_p^2 + u_5 G_p^2 + u_6
\]

where \( G_v \) is air supply volume, kg/s. \( G_p \) is air exhaust volume, kg/s. \( u_1, u_2, u_3, u_4, u_5, u_6 \) are parameters to be estimated.

Furthermore, chiller unit is also one of the energy-consuming equipment for air conditioning system. The energy consumption of chiller unit is related to evaporating temperature, conditioning temperature and system cooling capacity according to ASHRAE Association (Comstock et al., 1999). The evaporating temperature and conditioning temperature are related to the temperature of chilled water supply and cooling water return. Therefore, the energy consumption of chiller unit can be expressed in Equation (6).

\[
E_{chiller} = k_1 Q_{chiller} + k_2 Q_{chiller}^2 + k_3 (T_{in} - T_{in}) + k_4 (T_{in} - T_{in})^2 + k_5 Q_{chiller} (T_{in} - T_{in}) + k_6
\]

where \( Q_{chiller} \) is cooling capacity of the chiller unit, kW. \( T_{in} \) is cooling water return temperature, °C. \( T_{in} \) is chilled water supply temperature, °C. \( k_1, k_2, k_3, k_4, k_5 \) and \( k_6 \) are parameters to be estimated.

Component (2) of the framework involves rolling optimization, the indoor comfort level and system energy consumption are taken into account in the optimization problem, achieving the indoor comfort degree while minimizing energy consumption. It is expressed in the form of Equation (7). In the objective function, a penalty coefficient and two factors are considered, one is the square of indoor temperature deviation, and another is the total energy consumption. The square of indoor temperature deviation represents the effect of the room temperature control. The larger the square of indoor temperature deviation is, the more the indoor temperature deviates from the set value. And the penalty coefficient is played as a weighting variable in the objective function. Then, based on the objective function, the internal point method is applied to optimize the air supply volume and air supply temperature, minimizing the objective function under the constraint enables optimal indoor temperature control and energy efficiency. In this study, the prediction horizon was chosen to be 24 hours with a control time step of 20 minutes.

\[
\min J(t) = \sum_{i=1}^{n} \zeta (T_{an}(t) - T_{set}(t))^2 + \sum_{i=1}^{n} E_{total}
\]

Where \( J(t) \) is objective function, \( T_{an} \) and \( T_{set} \) represent the actual value and the set value of indoor temperature respectively, °C. \( E_{total} \) is the total power of system. \( \zeta \) is the penalty coefficient.

In this study, the rolling optimization process in model predictive control was all done in Python, and then the optimized parameters were input into the air conditioning system simulation model in the form of a schedule to realize the data interaction.

Feedback correction with adaptive integral controller

Component (3) of the framework involves feedback correction. Parameters for feedback correction is room temperature and the feedback correction in this paper is divided into two main aspects. One is the feedback correction of the model prediction itself, the other is the feedback correction of the whole control process. Therefore, the actual output value of the model predictive control process is shown in Equation (8).

\[
u_r = u_{COMP} + u_{ref}
\]

where \( u_{COMP} \) is model prediction output value at time \( t \). \( u_{ref} \) is correction and compensation value calculated by integral controller and is expressed in Equation (9).

\[
u_{ref} = \frac{1}{\tau_i} \int (y_r - y_{ref}) d\tau_i
\]

where \( \tau_i \) is the gain of integral controller. \( y_r \) is the actual output value of the system simulation model. \( y_{ref} \) is set value. \( \tau_i \) is integral time, h.

Proportional Integral control strategy

In the Proportional Integral (PI) control strategy, sensors collect the operational data of the system and send control signals at a fixed time step. The recommended values from the commissioning engineers were used as the control parameters of PI in this study.

The PI control strategy is composed of two operation modes, constant air volume mode and variable air volume mode. In the initial state, the system operates in a variable air volume mode with a supply air temperature of 13 °C, and the air volume is adjusted through a variable frequency fan to maintain indoor comfort level. When the air supply volume is lower than 50% of the maximum air volume and the room temperature is under the temperature setting value, the operation mode is switched to constant air volume mode, and the air volume is stabilized at 50% of the maximum air volume. In the constant air volume mode, the air supply temperature is regulated by PI controller according to the room temperature deviation to maintain a stable room temperature.

CASE STUDY

Simulation model building and validation

The research baggage claim hall of airport terminal is located in Beijing, and it can be approximated as an inner region. The total area is about 19880 m², and interior walls, ceiling and floor are set to be adiabatic. In this region, the indoor environment is controlled by the method of mechanical ventilation only, and the indoor temperature is set at 25 °C. The air conditioning system, controlled by multiple air handling units (AHU), adopts the form of zone variable air volume (VAV), and the
terminal of VAV has no variable air volume box. The air conditioning water system adopts the two-pipe supply air treatment unit, and the water supply and return temperature is 4.5 °C/13.5 °C. The air handling unit adopts large temperature difference air supply with a supply air temperature of 13 °C and a temperature difference of 12 °C.

Based on Modelica language, this paper establishes a dynamic simulation model of variable air volume air conditioning system. The model mainly is composed of room model, heat and cold source model, heat and cold coil model, fan model, chiller model and other sub-models, and its dynamic operation is simulated by the joint operation submodule. To facilitate the development of optimized control strategies in subsequent research, this study simplified the air conditioning system by simplifying multiple AHU units responsible for indoor environmental control in the baggage claim hall into large single AHU unit.

In order to verify the accuracy of the model, the Normalized Mean Bias Error (NMBE) and the Coefficient of Variation of the Root Mean Squared Error, Cv(RMSE), were adopted to evaluate the error between results.

In this paper, indoor temperature and system cooling capacity during the operation of air conditioning system (7:00-24:00) on a day in the cooling season were selected for verification. The NMBE and Cv(RMSE) of room temperature are 0.98% and 1.22% respectively, which are within the acceptable range of ±15% and ±30%(Judkoff R., 2014). Furthermore, the NMBE and Cv(RMSE) of cooling capacity are 12.9% and 14.7% respectively, which meet the specified limit value requirements. Therefore, the simulation model of the air conditioning system in the baggage claim hall established in this paper is proved to be accurate.

**Prediction model parameter estimation**

The parameter estimation is responsible for estimating parameters for the MPC models for the room temperature, cooling capacity, fan and chiller established in the previous section. In this section, the parameter estimation problem is formulated as an optimization problem, according to Equation. (10)–(12), and genetic algorithm(GA) is used for optimization.

$$\min J = \sum_{i=1}^{N} (y_{i,m} - y_{i,s})^2 \quad (10)$$

$$\text{S.t. } f = 0 \quad (11)$$

$$\theta_{\text{min}} \leq \theta \leq \theta_{\text{max}} \quad (12)$$

where \(y_{i,m}\) is measured value, \(y_{i,s}\) is simulation value, \(f\) is corresponding model expressions. \(\theta_{\text{min}}\) is estimated parameter lower limits. \(\theta_{\text{max}}\) is estimated parameter upper limits.

Both the orders of room temperature prediction model, \(p\), \(q\) and \(r\) were selected based on the Akaike Information Criterion(AIC)(Suneral., 2016). The median of selected model orders are \(p = 1\), \(q = 1\) and \(r = 1\). Genetic algorithm is used to find the optimal value of parameters by using 504 groups of data from the “Simulation Model Database”. The model parameters determined are \(a = -0.1766\), \(b = -0.00245\), \(c = 0.00281\), \(h = 29.46\).

**Figure 1: Room temperature prediction error**

In order to verify the accuracy of the room temperature prediction model, 216 groups of data were selected and compared with the predicted values of the model. As shown in Fig 1, The predicted value of room temperature was basically consistent with the actual value. The absolute error of some data was greater than ± 0.5°C, and the absolute error of other data was within the range of ± 0.5°C. Meanwhile, it can be seen that the relative errors of room temperature are all within the range of ±4%. Therefore, the room temperature prediction model established in this paper is reasonable and correct.

Furthermore, the same method is used to optimize the parameters of cooling capacity model, fan model and chiller model. As for cooling capacity model, parameters estimated are \(d_1 = 0.003\), \(d_2 = 0\), \(d_3 = 0.005\), \(f_1 = 1.29\), \(f_2 = 1.29\), \(f_3 = 0\), \(g = -0.05\). The parameters estimated of fan energy consumption model are \(u_1 = -0.862\), \(u_2 = 0.015\), \(u_3 = 12.042\), \(u_4 = 0.418\), \(u_5 = 0.009\), \(u_6 = 7.079\), and the parameters estimated for chiller consumption model are \(k_1 = -0.0526\), \(k_2 = 0.000017\), \(k_3 = 34.582\), \(k_4 = 1.48\), \(k_5 = 0.007987\), and \(k_6 = 441.26\). Similarly, 216 groups of data were selected and compared with the predicted values of the corresponding model. These relative errors between the predictive and the actual value of the corresponding models are always within 5%, except for a few points. Therefore, the energy consumption model of the fan, the energy consumption model of the chiller, and the cooling capacity model of system established in this paper are correct and can be used in subsequent research.

**Optimization problem and constraints**

According to Equation (8), the penalty coefficient in objective function is finally determined to be 50 based on the Pareto optimality(Nagaretal., 2023). The objective function and constraints in this paper are finally written in Equation (13). The objective function is built taking into account the control objective of the regulation model, ensuring the comfort level of indoor environment by minimizing energy consumption. The rolling optimization problem in this paper can be written in

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Equation (14), GA is employed to deal the above rolling optimization problem.

\[ J(t) = \sum_{i=1}^{N} w_i (T_N(t) - T_w(t))^2 + \sum_{i=1}^{N} E_{\text{total}} \]

\[ s.t. \begin{cases} 
24^\circ C \leq T_N \leq 26^\circ C \\
13^\circ C \leq T_e \leq 21^\circ C \\
50kg / s \leq G_i \leq 100kg / s 
\end{cases} \]

RESULTS AND DISCUSSION

To evaluate the performance of the MPC based on the dynamic passenger flow for zone VAV air-conditioning systems and the PI control system, the operational performance and thermal comfort during a typical day and cooling seasons were compared and analyzed based on simulation. Air supply volume , air supply temperature and energy consumption of the system are selected to evaluate the operational performance of system. As for thermal comfort, two evaluation indicators, Temperature Cumulative Deviation (\( \Delta T_{\text{CD}} \)) and Temperature Cumulative Deviation in the Uncomfortable Interval (\( \Delta T_{\text{CDUI}} \)), were proposed to evaluate stability of room temperature and the level of indoor comfort respectively. The greater \( \Delta T_{\text{CD}} \), the worse the room temperature stability. Similarly, the greater \( \Delta T_{\text{CDUI}} \), the worse the indoor comfort level.

\[ \Delta T_{\text{CD}} = \sum_{i=1}^{N} \int_{t_0}^{t_i} |T_N - T_{\text{set}}| dt \]  \hspace{1cm} (14)

\[ \Delta T_{\text{CDUI}} = \sum_{i=1}^{N} \int_{t_0}^{t_i} |T_N - T_{\text{limit}}| dt \]  \hspace{1cm} (15)

where \( T_{\text{limit}} \) is limit values for comfort interval temperature, lower limit is 24 °C, upper limit is 26 °C. \( t_0 \) is start time, h. \( \Delta t \) is end time, h. \( I \) is the number of samples. \( N \) is the number of samples located in the uncomfortable interval.

The 2nd of August is selected the typical day. During the cooling season, the average system load rate

\[ \text{figure 2: Load rate in the cooling season} \]

of the baggage claim hall is 34.6%. On the whole, the proportion of low load conditions [0,33%] during the cooling season is 39.6%, and the proportion of medium and high load conditions [34,100%] is 60.4%, with most of them located in the [34,50%] range of medium load.

Analysis of indoor comfort comparison

Hourly room temperature distribution box plot, in the typical day, with two control strategies is plotted in Fig.3. It can be seen that the overall cabinet size of the room temperature box plot under the MPC based on dynamic passenger flow is relatively small compared to PI control strategy, and the room temperature is always stable within the comfort interval, while room temperature deviates from comfort interval several times with PI control strategy. The MPC introducing dynamic passenger flow can quickly respond to the rapid changes in indoor passenger flow and immediately provide the indoor cooling required, which eliminates the accumulation of the impact caused by multiple continuous passenger flow changes.

\[ \text{Figure 3: Box plot of room temperature distribution under different control strategies} \]

Furthermore, the room temperature stability and comfort level of the room under the two control strategies can also be evaluated using \( \Delta T_{\text{CD}} \) and \( \Delta T_{\text{CDUI}} \) proposed for a typical day. The \( \Delta T_{\text{CDUI}} \) under the MPC is 0, indicating that the room temperature is almost always within the comfort interval and the room temperature control is better than the PI strategy. Meanwhile, it can be seen that the \( \Delta T_{\text{CD}} \) under two control strategy are 3.50 °C·h and 5.86 °C·h respectively, which is 40.3% lower than the PI control strategy. It is an indication that the room temperature stability under PI control strategy deviates from the set point to a more serious extent, and the room temperature stability is poorer than MPC strategy.

The daily distribution of \( \Delta T_{\text{CD}} \) and \( \Delta T_{\text{CDUI}} \), in the cooling season, under different strategies is plotted in Fig. 4. Compared with the control strategy of PI, the cumulative value of \( \Delta T_{\text{CDUI}} \) under MPC strategy reduces 62%, which indicates that the overall indoor comfort level has been significantly improved during the cooling season, and the indoor comfort level is better than the PI control strategy. At the same time, in the blue region, the distribution of \( \Delta T_{\text{CD}} \) under the two control strategies almost coincides, while in the orange region, the majority of \( \Delta T_{\text{CD}} \) under the MPC strategy is lower than the corresponding value of the PI control strategy. In contrast, in the orange area, as most of the system load is in a medium-high load state, the MPC can cope with load fluctuations caused by short-term passenger flow changes, making room temperature fluctuations

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relatively small and improving stability. The cumulative value of $\Delta T_{CD}$ for MPC strategy decreased by 37.1%.

![Figure 4: The daily distribution of $\Delta T_{CD}$ and $\Delta T_{CD\text{avr}}$ under different strategies](image)

**Analysis of operation performance**

**Analysis of supply air volume and supply air temperature**

The supply air volume and supply air temperature, in the typical day, are shown in Fig. 5 with different control strategies. The orange area represents the optimal control of air supply volume, and the blue area is the optimal control of air supply temperature. It can be seen that in the orange area, the air supply volume of PI control strategy has an obvious lag compared with MPC. Based on the analysis of supply air volume distribution under the two control strategies and personnel density changes, it is found that the corresponding adjustment is immediately done under the MPC strategy to cope with the changes of regional passenger flow, while the PI control strategy has an adjustment lag of about 15-20 minute. The preliminary analysis is that the MPC strategy introducing dynamic passenger flow makes the air conditioning system can quickly respond to the dynamic change of passenger flow and timely change the air supply volume of the system. While the PI control strategy adopting temperature feedback control, due to the sensitivity of the temperature sensor and the influence of the thermal inertia of the air in large space, is difficult to adjust the air conditioning system in time to respond to the demand response brought by the change of passenger flow. Therefore, it makes the system air volume regulation is not synchronized with the change of passenger flow.

In the blue area, the difference of supply air temperature distribution under the two control strategies is not significant enough, and the difference in system lag time is small. Combined with the analysis of the change in personnel density, the main reason is that the personnel density is very small during the period, indoor disturbances mainly come from lights and equipment, and the indoor load changes more smoothly, which lead to poor optimization effect of air supply temperature under MPC.

![Figure 5: Variation of air supply volume and air supply temperature under different control strategies in a typical day](image)

During the cooling season, the air supply volume and air supply temperature distribution status of the air conditioning system under the two control strategies are shown in Figures 6. As can be seen from Figure 6(a), during the optimization control process of air supply volume, the distribution status of the average of air supply volume under the two control strategies in the area before the dotted line almost coincide. Based on the analysis of the distribution status of load rates during the cooling season, it is found that the system load rates in the blue area are relatively low, and most of them are under low load conditions. As a result, during this period, room temperature control is dominated by air supply temperature control, and there is no significant difference in the average distribution of air supply volumes under the two control strategies. On the contrary, in the area behind the dotted line, the average value of most of the air supply volumes under the MPC is smaller than the PI control strategy, and the difference is relatively large. The reason for the above phenomenon is that the MPC can adjust the system air volume in a timely manner, and avoid the problem of excessive or low air supply caused by room temperature overshoot in the medium-high load state, resulting in a low overall air volume of the system.

Furthermore, as can be seen from Fig. 6(b), during the optimization control process of supply air temperature, the average value under the MPC is generally higher than that under the PI control strategy. At the same time, it can be found that in the area before the dotted line, during the optimization control process of air supply temperature, the average supply air temperature under the two control strategies is generally higher. Combined with the distribution status of the load rate during the cooling season in Fig 4, it is found that the system load rate in this area is relatively low, the system adjustment is mainly based on supply air temperature control, coupled with the impact of low load conditions, resulting in a relatively high average supply air temperature during this period. In the area behind the dotted line,
most of the system is under medium-high load conditions, and the system adjustment is mainly based on air supply volume control, resulting in relatively low average supply air temperature under both control strategies. Especially in the green solid line area, the system load rate is at a peak. In order to eliminate the impact of high loads and maintain indoor comfort, the average value of air supply temperature remains at a relatively low state when the average value of air supply volume is relatively high.

Figure 6: Average distribution under different control strategies during cooling season(a) supply air volume and(b) supply air temperature

Analysis of energy consumption

Distribution of system energy consumption on a typical day is shown in Fig. 7. Compared with the PI control strategy, the MPC reduces the energy consumption of fan and chiller by 11.25% and 13.34% respectively, and the total energy consumption is reduced by 13.0%, which has a good energy-saving potential.

Figure 7: Energy consumption under different control strategies on a typical day

Energy consumption of each device in different months under two control strategies is shown in Fig. 8, it can be seen that the itemized energy consumption and total energy consumption in each month of the cooling season are lower than those of the PI control strategy. Among them, the energy saving rates in May, June, July, and August are 8.96%, 10.5%, 9.2%, and 10.6%, respectively. Compared to the PI strategy, the MPC strategy can bring about 10% energy saving effect in the cooling season.

Figure 8: Energy consumption under different control strategies during the cooling season

CONCLUSION

Aiming at the problems that the existing feedback control mode of air conditioning system in large space of airport terminal is difficult to quickly respond to the dynamic changes of regional passenger flow, the lag of air conditioning system adjustment leads to poor indoor comfort and poor actual operation effect of the system, based on model predictive control theory, a model predictive control strategy considering the dynamic passenger flow is proposed in this paper. In the strategy, indoor comfort level caused by large lag under traditional control method is improved and the energy consumption of system is reduced. This paper verifies the feasibility and effectiveness of the strategy through simulation experiments. The conclusions of this paper are as follows.

1. The MPC based on the dynamic passenger flow can effectively solve the problem of system adjustment lag, and compared to PI control strategy, it can achieve rapid response of the air-conditioning system to changes in passenger flow.

2. The MPC strategy not only shows a better indoor temperature control effect but also reduces the total energy consumption of the system operation. The room temperature stabilities of the MPC method are 40.3% and 37.1% higher than that of PI control strategy in a typical day and cooling season respectively. Similarly, compared with PI control strategy, total energy consumption can be reduced by 13% and 10% in a typical day and cooling season respectively.

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REFERENCES

Dai B, Tong Y, Hu Q, Chen Z (2022). Characteristics of thermal stratification and its effects on HVAC energy...


Xianliang G, Jingchao X, Zhiwen L, Jiaping L (2021). Analysis to energy consumption characteristics and influencing factors of terminal building based on airport operating data. *Sustainable Energy Technologies and Assessments* 44, 101034


Comstock MC, Braun JE, Bernhard R. Development of analysis tools for the evaluation of fault detection and diagnostics in chillers: Purdue University; 1999.
