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A control strategy for cabin temperature of electric vehicle considering health ventilation for lowering virus infection

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Keywords: HVAC system for EVs, COVID-19, Cabin temperature, Cooperative control strategy, Energy consumption, Control accuracy

A cooperative control strategy is proposed for the air conditioning (AC) system and ventilation system to reduce the risk of COVID-19 infection and save the energy of the AC system. This strategy integrates the dynamic model of the AC-cabin system, infection risk assessment, model predictive control (MPC) of the thermal environment inside the cabin, and ventilation control that considers passengers’ sneezing. Unlike other existing AC system models, the thermal-health model established can describe not only the system performance but also the virus concentration and risk of COVID-19 infection using the Wells-Riley assessment model. Experiments are conducted to verify the prediction accuracy of the AC-cabin model. The results prove that the proposed model can accurately predict the evolution of cabin temperature under different cases. The cooperative control strategy of the AC system integrates the MPC-based refrigeration algorithm for the cabin temperature and intermittent ventilation strategy to reduce the risk of COVID-19 infection. This strategy well balances the control accuracy, energy consumption of the AC system, and the risk of COVID-19 infection, and greatly reduces the infection risk at the expense of a little rise in the energy consumption.

1. Introduction

HVAC (Heating, Ventilation and Air Conditioning) system is a key auxiliary system of the vehicle due to the comfort and health requirements in the cabin. However, the HVAC system consumes a lot of energy and increases the fuel consumption of vehicles powered by internal combustion engines. With the inevitable trend of powertrain electrification in the automotive industry [1], electric vehicles (EVs) are faced with huge energy consumption of HVAC systems, which reduces the driving range of EVs. It is reported that the HVAC system may reduce the driving range of EVs by about 30% and more in extreme cold or hot conditions [2,3]. Thus, energy management is crucial for the HVAC system of EVs to maintain thermal comfort for passengers and improve driving range. In recent years, epidemics like H1N1 and COVID-19 this year have caused huge loss of life and economy across the world and are spreading rapidly, especially in the indoor environment via airborne transmission [4–6]. As the most common means of transportation, vehicles occupy a lot of time in people’s daily life, and narrow cabins are ideal places for disease transmission.Ventilation is proved to be an effective method to reduce the risk of indoor disease infection [7,8]. Reasonable ventilation by the HVAC system is particularly important for the health of passengers, but it brings extra energy consumption. Therefore, an intelligent, cooperative control strategy integrating the compressor control and ventilation control together is needed by the HVAC system of electric vehicles in order to improve the thermal comfort of passengers, reduce the infection risk and save energy.

The cabin temperature control in vehicles have been widely studied [9–23]. The on-off control, as one of the rule-based control strategies, is widely used for the air conditioner (AC) system in vehicles due to the simple control logic. However, the poor control accuracy of on-off control makes it difficult to achieve precise temperature control, which limits its application [10,11]. As another widely used rule-based control strategy, the feedback proportion integration differentiation (PID) control provides more precise and continuous control, especially for a linear system. Therefore, it is widely used in vehicles [12]. Because the HVAC-cabin system is complex and nonlinear, the PID control is

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hard to achieve the desired result under the changing condition which is common in the driving process [13]. To further improve the control performance, advanced control strategies based on black-box models of the system are used for cabin temperature control. Fuzzy logic control and data-based control strategy like artificial neural networks (ANNs) are the representatives of this kind of strategy. Because of their good robustness and quick response for the nonlinear characteristics, they are used for the AC system in vehicles [14–18]. Khayyam et al. [14] built a look-ahead system based on fuzzy logic control which improves the AC system efficiency and reduces energy consumption. For the thermal comfort control in the cabin, Farzaneh et al. [16] adjusted the cabin temperature and the PMV (predicted mean vote) index to enhance the performance of fuzzy controller. The result shows that the PMV-based control strategy not only provides the passengers with better thermal comfort but also consumes less energy than the temperature-based strategy. To adapt the target cabin temperature to the thermal preferences of different passengers, Xie et al. [17] embedded the predictor of the passenger’s thermal habit into the fuzzy PID controller. For the application of the control method based on the neural network, Ng et al. [19] established a predictive control strategy for the AC system by employing the online ANN training. In contrast with the classic rule-based controllers, the ANN-based controller has a smaller control overshoot and lower error.

The feedback control methods mentioned above perform well in the control process for simple-input and simple-output (SISO) system, but for the multiple-input and multiple-output (MIMO) system, it is difficult to prescribe the control logic and coordinate the different input and output parameters of controller. In the literature about the feedback control applied to the HVAC system for vehicles, the controller usually sets the compressor speed as a single output and the cabin temperature as a single input. In fact, the evaporator fan speed also needs to be controlled in conjunction with the compressor speed for the high load. The coordination requirement turns the SISO problem of the HVAC control into a MIMO problem, which is difficult for the conventional feedback control. Thus, control strategies with optimization algorithms, for example, model predictive control (MPC), are popular in the field of MIMO systems [20,21]. In previous studies, Huang et al. [22] used the MPC algorithm to control the vehicle AC system and compared it with the traditional feedback on-off control. The result indicates that the MPC method can do better in balancing different inputs and outputs and saves energy compared to the conventional feedback control approach. He et al. [23] used the MPC to automatically adjust the HVAC system in a city bus by estimating the passenger number. The result shows that the energy consumed by the AC system is 5.8% smaller than that controlled by the rule-based strategy. At present, the optimization-based strategies already focus on both the energy consumption of the AC system and the control error of the temperature in the vehicle cabin. However, they usually ignore the ventilation inside the cabin, making the air quality poor. Moreover, when the ventilation system is on, the fresh air enters the cabin. Cooling it by the AC system produces the extra energy cost and bigger fluctuation of cabin temperature. Therefore, it is necessary to integrate the ventilation strategy into the control strategy of the AC system for the low energy cost and good thermal comfort. However, the issue about energy saving and accurate control of cabin temperature under the condition of the dynamic ventilation has not been studied in the references mentioned above.

Although cabin temperature control is the main task of the HVAC system, the air quality also needs to be carefully controlled for the health of the passengers. In the previous studies on the air quality inside the vehicle cabin, the control of air composition has attracted wide attention [24–29]. Heejung et al. [24] and Chang et al. [25] researched the effect of the ventilation method on the CO2 concentration in the vehicle cabin. Ding et al. [26] analyzed the distribution of PM2.5 (particulate matter with an aerodynamic diameter of 2.5 μm or smaller) in the vehicle cabin under different ventilation modes. Yan et al. [27] discussed the effectiveness of a cloud-based smart control strategy in the air quality management of vehicle cabins. Because the cabin is small and ventilation is poor, it is easy for the virus to spread and infect passengers. However, to the best of our knowledge, there are few studies on the effect of ventilation in the vehicle cabin on the risk of infection, although it has been studied in buildings or planes [28,29]. As the COVID-19 pandemic goes on, it is urgently needed to reduce its infection risk in the car cabin, and the management of the cabin ventilation is very important to protect passengers from COVID-19. However, there is no such a control strategy of AC system focusing on both thermal management and reduction of virus infection inside the vehicle cabin. Therefore, this study proposes an intelligent, cooperative control strategy for the temperature and air quality in the cabin. This strategy integrates the model predictive control for the thermal environment inside the cabin and the ventilation control focusing on passengers’ sneezing that is one of the most important transmission paths for COVID-19. In contrast with the previous studies, four main contributions are made in this study. Firstly, a dynamic model integrating ventilation system, AC system and cabin is built and verified by the test data. Secondly, the Wells-Riley assessment model is applied to estimating the risk of COVID-19 infection in the vehicle cabin in the case of a COVID-19 infected passenger sneezing. Thirdly, the ventilation strategy is established to make the virus infection risk low by optimizing ventilation time inside the cabin. Finally, a cooperative control strategy integrating the model predictive control (MPC) and the optimal ventilation control is established for cabin temperature control and passenger health protection. This strategy balances control error, risk of COVID-19 infection, and energy cost of the HVAC system. It can reduce the risk of COVID-19 infection, save the energy of the system, and provide passengers with the good thermal environment.

2. Thermal model of HVAC-cabin system and verification

In this section, the thermal model of HVAC-cabin system is built. The evaporator and condenser are modeled based on the first law of thermodynamics and theory of heat transfer; the whole AC system is modeled according to the theory of the refrigeration cycle; the thermal model of cabin is established according to the energy conservation. Then thermal model is verified by the experiment at the component level and system level to show the prediction precision of the thermal model.

2.1. AC-cabin system

Fig. 1 provides the schematic diagram of the coupled system, including the ventilation system, air conditioning system and cabin (AC-cabin system). The whole system has six main parts, including the evaporator, condenser, expansion valve, electric compressor, ventilation system, and cabin. In Section 2.1, a control-oriented lumped-parameter model is built for the coupled system. Table 1 shows the modeling process based on the assumption in Ref. [30], and the nomenclature presents the meanings of the variables in the equations. Moreover, R134a is used as the refrigerant. As the core component of the AC system, the compressor propels the refrigerant to flow in the refrigeration process. For the electric compressor used in EV, its rotation speed Ncomp determines the power of the AC system. Thus, it is chosen as one of the control variables. The flow of R134a in the expansion valve is simplified as the adiabatic process, and Eq. (3) shows the relationship between the mass flow rate and the pressure drop. The moving boundary method (MBM) [22,31] is applied to the condenser and evaporator due to its simplicity and accuracy. Because the heat exchange in the two-phase region of R134a is much larger than that in the single-phase region, the heat transfer in the single-phase region of the condenser and evaporator is ignored. Eqs. (4)-(12) in Table 1 are used to describe the heat transfer process in the condenser and evaporator. Fig. 2 presents the heat load of the cabin. Based on the first law of thermodynamics, the development of air temperature inside the cabin can be described by Eq. (16). The detailed modeling process of the AC-cabin system can be found
3.3. Verification of AC-cabin system model

An experiment is carried out to verify the prediction accuracy of the AC-cabin model, and Fig. 4a presents the experiment setup. An environment chamber is used to simulate the real environment for an SUV (sport utility vehicle), and the ambient temperature, solar radiation power, and airflow are kept constant. Thermocouples are attached to the dashboard, front seats, and back seats to obtain the temperature, and the cabin temperature is calculated by their average value. The dynamic thermal model is verified under four cases. The test lasts for 1800s in each case, the initial temperature is 60°C, and the compressor and evaporator work at a constant speed of 6000 rpm and 2000 rpm, respectively. The other experiment parameters are given in Table 4. Fig. 4b gives the cabin temperature obtained by the proposed model and test. The predicted temperature fall is similar to the measured one, and their average error is no more than 3.69%, which proves that the proposed dynamic thermal model is accurate enough for predicting the system performance.

3. Assessment model for the risk of COVID-19 infection

The vehicle cabin is a narrow indoor environment that is easy for virus to spread. To reduce the risk of virus infection in the cabin, a risk assessment model for the infection is required. Although computational fluid dynamic can obtain the spatio-temporal profile of virus particles, it needs a lot of computational resources and is not suitable for the on-line control. For the quick assessment of infection risk, there are two popular risk prediction models for the virus infection. One is Wells-Riley model, and the other is Dose-Response model. The Wells-Riley model is based on the indoor premise and does not need the interspecies extrapolation in our previous work [32]. Moreover, the AC-cabin model shown in Table 1 is solved by the Matlab/Simulink program that is developed by the authors to obtain the performance of the AC system and the development of the cabin temperature.

The modeling of the AC-cabin system in this paper is similar with our previous work given in Ref. [32], but the control target and relative method are totally different. In Ref. [32], the temperature control in the cabin and the energy consumption of the AC system are focused on, and there is no ventilation strategy. The main goal of this study is to reduce the infection risk of passengers in the cabin. Therefore, the ventilation strategy is studied in detail. Then, it is coupled with the control strategy for the cabin temperature to reduce the energy consumption of the AC system and improve the control accuracy of the cabin temperature in the context of the low infection risk of virus.

2.2. Ventilation system

It is assumed that the cabin is fully sealed. Therefore, air exchange between the cabin and the environment is decided only by the intake air flap inside the HVAC. In the process of thermal modeling for the ventilation system, the ventilator in the HVAC system is assumed to be adiabatic, and air exchanges heat with the environment in the evaporator. Thus, the air temperature $T_{\text{ae}}$ near the evaporator wall is:

$$T_{\text{ae}} = \begin{cases} T_{\text{a}} & \text{Intake air flap open} \\ T_{\text{ac}} & \text{Intake air flap closed} \end{cases} \quad \text{(17)}$$

where $T_{\text{a}}$ is the air temperature in the cabin, and $T_{\text{ac}}$ is the ambient temperature.

Based on the AC-cabin system model, seven independent state variables are chosen as the state variables $x$ for the MPC strategy in Section 4 and $x$ is:

$$x = [l_x, P_s, T_{ac}, P_e, T_{ae}, T_s, T_a]^T. \quad \text{(18)}$$

2.3. Verification of AC-cabin system model

2.3.1. Verification of condenser and evaporator models

The model of AC-cabin is verified at two levels. At first, the component models of the AC system are validated. Then, the vehicle experiment is implemented to show the prediction precision of the AC-cabin system. Fig. 3 shows the experiment devices for the condenser and evaporator. Table 2 gives their experiment conditions, and Table 3 presents the heat transfer rates obtained by experiment and simulation, respectively. According to Table 3, the predicted heat transfer rates are similar with experimental results, and the prediction errors of the models for the condenser and evaporator are below 5%. When the inlet velocity of air is 3.5 m/s and the mass flow rate of R134a is 248.6 kg/h, the prediction error of the condenser model reaches the maximum, and it is 3.6%. When the inlet velocity of air is 10.5 m/s and the mass flow rate of R134a is 100.1 kg/h, the prediction error of the evaporator model reaches the maximum, and it is 4.5%. Therefore, the models of the condenser and evaporator can accurately predict their performance.
of infectivity [33,34]. Thus, it can quickly calculate the risk of virus infection. According to Refs. [29,34], it is used to predict the infection risk in epidemics like influenza, H1N1, and SARS in the indoor environment, and is proven to have a good reliability [29,34]. The

Dose-Response model needs the virus dose that causes the infection for the calculation of the infection risk [34,35]. Because it is difficult to get the dose of the pathogens in practice, the Dose-Response model is not applicable. Therefore, the Wells-Riley model [33,36] is adopted to

| Components       | Equations | Equation No. | Ref. |
|------------------|-----------|--------------|------|
| Electric compressor | \[ m_{\text{comp}} = n_s \rho_s N_s V_d \] | (1) | [22] |
|                  | \[ h_{s,v} - h_{i,v} = \frac{h_{s,v} - h_{i,v}}{\eta} \] | (2) | |
| Expansion valve  | \[ m_r = \frac{C_p A_s \sqrt{\Delta P}}{\Delta P} \] | (3) | [22] |
| Evaporator       | \[ \rho_s h_{i,v} A_k \left(1 - \tau_1\right) \frac{dh_{i,v}}{dt} = m_{\text{comp}} (h_{s,v} - h_{i,v}) - a_s \pi D_m (T_{ac} - T_{vc}) \] | (4) | [32] |
|                  | \[ A_k \frac{dP_{\text{in}}}{dP_{\text{out}}} = m_{\text{comp}} (h_{s,v} - h_{i,v}) - a_s \pi D_m (T_{ac} - T_{vc}) \] | (5) | |
|                  | \[ (C_p m_r) \frac{dT_{ac}}{dt} = a_w A_c (T_{ac} - T_{vc}) - a_s \pi D_m (T_{ac} - T_{vc}) \] | (6) | |
|                  | \[ a_w = f_{21}(N_{\text{in}}) \] | (7) | |
| Condenser        | \[ \rho_s h_{i,v} A_k \left(1 - \tau\right) \frac{dh_{i,v}}{dt} = m_{\text{comp}} (h_{s,v} - h_{i,v}) + a_s \pi D_m (T_{ac} - T_{vc}) \] | (8) | [32] |
|                  | \[ A_k \frac{dP_{\text{in}}}{dP_{\text{out}}} = m_{\text{comp}} \cdot a_s \pi D_m (T_{ac} - T_{vc}) \] | (9) | |
|                  | \[ (C_p m_r) \frac{dT_{ac}}{dt} = a_s \pi D_m (T_{ac} - T_{vc}) + a_s \pi D_m (T_{ac} - T_{vc}) \left(\frac{T_{ac} + T_{vc}}{2} - T_{vc}\right) - a_w A_c (T_{ac} - T_{vc}) \] | (10) | |
|                  | \[ A_c \left[ \rho_s h_{i,v} \left(1 - \tau\right) + \rho_s h_{i,v} \tau + \rho_s (L_v - L_i) \right] + A_r \left[ \rho_s h_{i,v} \left(1 - \tau\right) + \rho_s h_{i,v} \tau + \rho_s (L_v - L_i) \right] = \text{constant} \] | (11) | |
|                  | \[ a_w = f_{21}(N_{\text{in}}) \] | (12) | |
| Vehicle cabin    | \[ Q_{\text{vac}} = Q_{\text{vac}} + Q_{\text{ac}} + Q_{\text{r}} + Q_{\text{ac}} \] | (13) | [32] |
|                  | \[ Q_{\text{vac}} = h_{(\text{vac})} S(T_{ac} - T_{i}) \] | (14) | |
|                  | \[ \frac{dT_c}{dt} = \frac{h_{(v)} S(T_{ac} - T_{i}) - h_i S(T_{ac} - T_{i})}{M_{\text{corr}}} \] | (15) | |
|                  | \[ \frac{dT_c}{dt} = \frac{Q_{\text{vac}} - Q_{\text{ac}}}{M_{\text{corr}}} \] | (16) | |

Table 1
Dynamic modeling of AC-cabin system.
estimate the risk of COVID-19 infection inside the cabin. Fig. 5 introduces the transmission routes of COVID-19 in the cabin. The risk of infection is related to the exposure time $t$ of the healthy passenger in the virus environment, and it is expressed as [37]:

$$ R = e^{-IR \int_{0}^{T} C_q(t) dt} $$

(19)

where $R$ is the risk of infection from 0 to 1, $IR$ is the inhalation rate of passengers, $T$ is the total exposure time of passengers, and $C_q$ is the quanta concentration of virus in the cabin. Because the passenger in the cabin is less active, he/she is in an activity level between rest and light activity. Thus, the inhalation rate is set to 0.96 m$^3$/h [37]. $C_q$ is calculated by Ref. [37]:

$$ V \frac{dC_q}{dt} = ER_q - (R_d + R_i)C_qV - AER \cdot C_q $$

(20)

where $R$ is the risk of infection from 0 to 1, $IR$ is the inhalation rate of passengers, $T$ is the total exposure time of passengers, and $C_q$ is the quanta concentration of virus in the cabin. Because the passenger in the cabin is less active, he/she is in an activity level between rest and light activity. Thus, the inhalation rate $IR$ is set to 0.96 m$^3$/h [37]. $C_q$ is calculated by Ref. [37]:

$$ V \frac{dC_q}{dt} = ER_q - (R_d + R_i)C_qV - AER \cdot C_q $$

(20)

where $V$ is the cabin volume, $ER_q$ is the quanta emission rate of infectors, $R_d$ is the particle deposition rate of aerosol exhaled by infectors, $R_i$ is the viral inactivation rate, and $AER$ is the air exchange rate in the cabin. According to Refs. [37–39], $R_d$ and $R_i$ are set to 0.36/h and 0.63/h, respectively. $ER_q$ depends on the epidemic type, the infecter physical feature, and his/her activity level. Based on Buonanno et al.’s research [37], $ER_q$ of a COVID-19 infector reaches 100 quanta/h when he/she rests. Because the passenger infected by COVID-19 is in a state of rest, $ER_q$ is set to 20 quanta/h when he/she breathes normally [37]. According to the study on the respiratory droplets exhaled by people, the droplet number

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**Table 2**

| Component | Inlet temperature of R134a (°C) | Inlet temperature of air (°C) | Inlet velocity of air (m/s) | Mass flow rate of R134a (kg/h) |
|-----------|---------------------------------|-------------------------------|-----------------------------|--------------------------------|
| Condenser | 25 (degree of superheat)        | 35                            | 2.5                         | 202.7                          |
|           |                                 |                               | 3.5                         | 248.6                          |
|           |                                 |                               | 4.5                         | 284.4                          |
| Evaporator| 5 (degree of supercooling)      | 27                            | 10.5                        | 100.1                          |
|           |                                 |                               | 14                          | 126.9                          |
|           |                                 |                               | 17.5                        | 149.6                          |

**Table 3**

| Component | Inlet velocity of air (m/s) | Mass flow rate of R134a (kg/h) | Measured heat transfer rate (kW) | Predicted heat transfer rate (kW) |
|-----------|-----------------------------|--------------------------------|----------------------------------|----------------------------------|
| Condenser | 2.5                         | 202.7                          | 10.34                            | 10.67                            |
|           | 3.5                         | 248.6                          | 12.83                            | 13.29                            |
|           | 4.5                         | 284.4                          | 14.8                             | 14.99                            |
| Evaporator| 10.5                        | 100.1                          | 3.54                             | 3.7                              |
|           | 14                          | 126.9                          | 4.47                             | 4.66                             |
|           | 17.5                        | 149.6                          | 5.27                             | 5.46                             |
of the sneeze is much larger than that of the normal breath. The droplet number is about 250 for the normal breath, while it reaches $10^6$ for the sneeze [37–39]. Thus, $ER_q$ is set to 80000 quanta/h when the infector sneezes, and each sneeze is assumed to last for 1 s. Table 5 shows the parameters for the risk assessment model of COVID-19. It is known from the model that $AER$ is the most important parameter to reduce the infection of COVID-19 inside the cabin. This parameter is adjusted by controlling the intake air flap of HVAC and the evaporator fan speed. In the vehicle HVAC system, there are two modes of ventilation. One is the internal air circulation, and the other is the external air circulation. In this paper, $AER$ is set as 0 if the mode of “internal air circulation” is on, while it is calculated according to the evaporator fan speed if the mode of “external air circulation” is on.

### Table 4

| case | Vehicle speed $V_c$ (km/h) | Ambient temperature $T_{ae}$ (°C) | Solar radiation power $P_s$ (W/m²) |
|------|--------------------------|---------------------------------|-------------------------------|
| 1    | 40                        | 38                              | 1000                           |
| 2    | 40                        | 30                              | 1000                           |
| 3    | 0                         | 38                              | 1000                           |
| 4    | 40                        | 38                              | 800                            |

Fig. 4. Verification for the AC-cabin model: (a) Experiment setup and thermal sensor placements, (b) evolution of cabin temperature.

There are three main tasks for the proposed control strategy. The first one is the accurate control of cabin temperature for passenger thermal comfort; the second one is the energy saving of the AC system; the third one is the control of the air quality inside the cabin in order to reduce the virus infection and protect passenger health. To achieve these goals, the cabin temperature and risk of COVID-19 infection are regarded as the control targets. For temperature control, the cabin temperature can be easily measured by the temperature sensor, and it is used to guide the model predictive control (MPC) and guarantee the control accuracy. Because there is no sensor that can get the real-time virus concentration in the cabin, the virus concentration cannot be obtained online. This
makes the control strategy with measured virus concentration inapplicable to the air flap. Moreover, lack of real-time virus data also makes it impossible to add the healthy ventilation strategy based on the risk of COVID-19 infection to the MPC for cabin temperature. In order to overcome the problem, a cooperative control strategy for the AC-cabin system is established, and its structure is shown in Fig. 6. The MPC part in the strategy is to control the compressor power and fan speed and achieve the precise control of cabin temperature and energy saving. A control strategy based on the assessment model for the risk of COVID-19 infection is used for the ventilation system to bring the fresh air as much as possible to the cabin in the allowed time and reduce the risk of COVID-19 infection. This healthy ventilation strategy is activated through the voice recognition of the continuous sneezing of an infected passenger.

### Table 5

| Parameter | Value               | Parameter | Value               |
|-----------|---------------------|-----------|---------------------|
| IR        | 0.96 m³/h           | Rₐ        | 0.63/h              |
| Brₐ       | normal breathing: 20 quanta/h; sneezing: 80000 quanta/h (lasting 1s) | AER       | 0.560 CMH (m³/h)    |
|           |                     |           | (control variable)  |
| Rₐ        | 0.36/h              | V         | 3 m³                |

**4.1. Model predictive control for the cabin temperature**

**4.1.1. State estimator**

The state estimator is embedded into MPC to predict the future system behavior according to the current state \( x \) in Eq. (18), control variables, and disturbance. It is known from Section 2 that the AC-cabin system is nonlinear and needs to be linearized to make the computational cost low. The first-order differential approximation is employed to linearize the integrated system [40,41]. After linearization, the estimator in \( p \) estimation horizon at the time step \( k \) becomes:

\[
x(k+i|k) = Ax(k+i-1|k) + Bu(k+i-1|k) + Bv(k+i-1|k)
\]

\[
y(k+i|k) = Cx(k+i-1|k)
\]

where \( i \) is the successive step from 1 to \( p \), \( u \) and \( v \) are defined by Eqs. (23) and (24), \( A, B_u \) and \( B_v \) are the constant matrices related with \( x \), and \( C \) is the coefficient connecting the output value of the AC-cabin system \( y \) and its current state \( x \). \( y \) defined by Eq. (25) is used as feedback to adjust the estimator.

\[
u = [N_{comp}, N_{fan}]^T
\]

\[
v = [V_{car}, T_{ac}, P_{Solar}]^T
\]
\[ y = \left[ T_o \right] \] (25)

### 4.1.2. Optimizer

The optimizer is another important component of MPC. It is used to find the most suitable output to minimize the cost function. The quadratic programming method is employed as the optimizer in the MPC strategy. The optimization goal \( J(Z_k) \) defined in Eq. (26) contains three components. The first component is \( J_1(Z_k) \), which makes the cabin temperature approach the set temperature. The second one \( J_2(Z_k) \) is used for energy saving by controlling the speed of compressor and fan. In this paper, it only includes the energy consumed by the compressor and fan. The last one \( J_{\Delta u}(Z_k) \) is to reduce the speed fluctuation of the compressor and fan for the stable working of the AC system when the car speed changes.

\[
J(Z_k) = J_1(Z_k) + J_2(Z_k) + J_{\Delta u}(Z_k)
\] (26)

\( J_i(Z_k), J_2(Z_k) \) and \( J_{\Delta u}(Z_k) \) in the control horizon of \( c \) at the time \( k \), are:

\[
J_1(Z_k) = \sum_{i=1}^{n_c} \sum_{j=1}^{c} \left\{ w_{ij}^c [r_j(k+i|k) - y_j(k+i|k)] \right\}^2
\] (27)

\[
J_2(Z_k) = \sum_{i=1}^{n_c} \sum_{j=1}^{c} \left\{ w_{ij}^c [u_j(k+i|k) - u_j(k+i-1|k)] \right\}^2
\] (28)

\[
J_{\Delta u}(Z_k) = \sum_{i=1}^{n_c} \left\{ \sum_{j=1}^{c} w_{ij}^c [u_j(k+i|k) - y_j(k+i|k)] \right\}^2
\] (29)

where \( n_c \) is the control output index, \( n_{\Delta u} \) is the manipulated input index, \( w_{ij}^c \) is the non-dimensional weight coefficient for the \( j \)th control output at the \( i \)th prediction horizon step, the superscript \( c \) and \( u \) means the coefficient used for \( y \), \( u \), and \( \Delta u \), and \( Z_k \) is the decision value from the optimizer. The goal and the restricted conditions of the optimization algorithm are:

\[
\text{Goal : } \min \left| J(Z_k) \right|
\]

Restricted conditions : \( 0 \leq N_{\text{comp}} \leq 6000 \frac{r}{\text{min}} \), \( 0 \leq N_{\text{fan}} \leq 3000 \frac{r}{\text{min}} \), \( 0 \leq T_{\text{we}} \leq 10 \text{ } ^\circ \text{C}. \) (30)

Solving Eq. (30) by the quadratic programming method \([42]\) gives the successive output \( Z_k \) in the control horizon of \( c \), and its expression is:

\[
Z_k = \left[ u(k|k)^T, u(k+l|k)^T, \ldots, u(k+c|k)^T \right].
\] (31)

In Eq. (31), the first term \( u(k|k)^T \) is used as the actual manipulated output of the MPC to ensure the accuracy of the adjustment.

### 4.2. Ventilation strategy for the cabin

Ventilation is an effective method to reduce the risk of infection of a virus transmitted via air, for example, COVID-19. The ventilation mode (“internal circulation mode” or “external circulation mode”) in the cabin is decided by the intake air flap. When the external circulation mode is on, fresh air comes into the cabin, and the risk of COVID-19 infection falls. However, if this mode is on all the time, extra energy is consumed by the AC system, which reduces the driving range of EVs. Therefore, this paper establishes a balanced ventilation strategy to reduce the risk of infection and save energy. The strategy is divided into two parts, namely the regular ventilation strategy for normal driving and the forced one for the passenger sneezing. Because it is difficult to get the real-time virus concentration in the cabin via sensors, the direct feedback control based on the virus concentration is not applicable. The

**Table 6**

| Condition for the ventilation strategy. | Regular ventilation | Forced ventilation |
|----------------------------------------|---------------------|--------------------|
| Driving condition WLTC × 4            | WLTC               |
| Initial cabin temperature (°C)        | 50                 | 50                 |
| Simulation time (s)                   | 7200               | 1800               |
| Sneezing moment (s)                   | No sneezing        | 500                |
| Ambient temperature (°C)              | 38                 | 38                 |
| Target cabin temperature (°C)         | 25                 | 25                 |

The infector’s sneezing greatly increases the virus concentration, and sneezing can be detected through sound signal and video signal. Thus, sneezing is used as the trigger signal of the forced ventilation. The ventilation strategy is off-line, and made in advance. In order to obtain the best opening frequency and time of the air flap for the regular and the forced ventilation, the control accuracy of cabin temperature, energy consumption of the AC system, virus concentration, and risk of infection are considered and optimized in the off-line ventilation strategy. Sections 4.2.1 and 4.2.2 show how these ventilation parameters are achieved. Once the ventilation strategy is determined, its control parameters are fixed. Moreover, when it is applied to the AC-cabin system, it calculates only the fresh air flux and sends it to the MPC. Table 6 introduces the scenario used for the AC-cabin system. WLTC (worldwide light-duty test cycle) is applied. The concentration of COVID-19 is increased by sneezing and normal breathing of the infector. Sneezing increases the virus concentration sharply, and normal breathing of the infector increases it gradually. Because the whole process of sneezing does not last long, a single WLTC is long enough to describe the development of the virus concentration. Moreover, the infector sneezes at 500 s which is selected randomly. WLTC is repeated by four times to show the effect of the normal breathing of the infector on the virus concentration. In the cabin, there are two persons. One is healthy, and the other is infected by COVID-19. The environment temperature is 38 °C. According to Ref. [43], the comfortable temperature for majority of people is between 22 °C and 26 °C. People living in the temperate zone prefers a warmer environment [44]. Because the control strategy is planned to be tested in Chongqing, China that belongs to the north temperate zone, 25 °C is selected as the target temperature. The Wells-Riley model is applied to estimate the risk of COVID-19 infection. Because the off-line strategy is adopted for the ventilation system, the Wells-Riley model is used to calculate the quanta concentration of COVID-19 offline. Thus, it has a good robustness.

### 4.2.1. Forced ventilation strategy for sneezing

Because sneezing greatly increases the virus concentration, sneezing is assumed to be the only source of COVID-19 when the forced ventilation strategy is designed. Once sneezing occurs, the intake air flap opens immediately. Because the COVID-19 virus floats in the air, it is hard to completely expel it from the cabin to the environment through ventilation. When the virus concentration is low, ratio of the energy consumption of the AC system to the fall of virus concentration becomes very large, which means a lot of energy is needed to make the concentration fall only a little. Therefore, a suitable FAFR (fresh air flow rate) and ventilation duration are needed to reduce the risk of infection and save energy. Nine flow rates of fresh air and twenty durations form the matrix \( \text{FAFR} \times T_{\text{we}} \), which is used to find the most suitable FAFR and ventilation duration. The FAFR is from 80 CMH to 560 CMH (maximum...
flow rate of the fan) with an interval of 60 CMH. The ventilation duration is from 10 s to 200 s with an interval of 10 s. The matrices of FAFR and the ventilation duration $T_{f,v}$ are

$$ FAFR = [80, 140, \ldots, 560]^T, \; T_{f,v} = [10, 20, \ldots, 200]. $$

180 cases in the matrix $FAFR \times T_{f,v}$ are used for the AC-cabin system controlled by the MPC established in Section 4.1. The average control error of cabin temperature over the whole cycle $Cost_{f, tc}$, energy consumption $Cost_{f, ec}$, quanta concentration of COVID-19 $Cost_{f, q}$ and infection risk $Cost_f$, at the end of the cycle are adopted as the cost to evaluate the performance of the ventilation parameters. These costs are calculated based on the working process of the AC system under the condition of the forced ventilation shown in Table 3. In order to ensure that the various costs can be equally treated, the costs are normalized by

$$ Cost' = \frac{Cost}{\max(f_i)(Cost)} $$

where $Cost'$ is normalized cost and $\max(Cost)$ is the maximum among the cases. In order to balance the control accuracy, energy cost, and infection risk, the total normalized cost $Cost_{f, total}'$ is used, and it is defined by

$$ Cost_{f, total} = Cost'_{f,r} + Cost'_{f, tc} + Cost'_{f, ec} + Cost'_{f, q}. $$

Fig. 7 shows the influence of the FAFR and ventilation duration on the five costs mentioned above. A large FAFR and medium ventilation duration can increase the control accuracy of cabin temperature, reduce the energy consumption and keep the virus concentration and infection risk low. When the flow rate of fresh air is 560 CMH and the ventilation duration is 100 s, $Cost_{f, total}'$ reaches the minimum. Therefore, the parameters for the forced ventilation are:

$$ [FAFR', T_{r,v}]^T = [560, 100]^T $$

where $FAFR'$ is the optimal flow rate of fresh air and $T_{f,v}'$ is the optimal ventilation duration.

4.2.2. Regular ventilation strategy

Because the breathing and talking of the infector gradually increase the virus concentration, regular ventilation is needed to keep the infection risk low. Intermittent ventilation is used as the regular ventilation strategy, since it has low energy consumption. The maximum flow rate of the fan can expel the COVID-19 from the cabin quickly. Thus, 560 CMH is selected as the FAFR for the regular ventilation, just like the forced ventilation. The open frequency of the intake air flap and ventilation duration are the parameters that need to be optimized for regular ventilation. In order to bring down the energy cost of the AC system and risk of COVID-19 infection, thirty open frequencies and eight durations of intake air flap form the matrix $F_{r,v} \times T_{r,v}$ which is used to find the most suitable open frequency and ventilation duration. The open frequency is from 1 times/h to 30 times/h with an interval of 1 times/h. The ventilation duration is from 40 s to 180 s with an interval of 20 s. The matrices of $F_{r,v}$ and $T_{r,v}$ are

$$ F_{r,v} = [1, 2, \ldots, 29, 30]^T, \; T_{r,v} = [40, 60, \ldots, 160, 180]. $$

240 cases in the matrix $F_{r,v} \times T_{r,v}$ is applied to the AC-cabin system with regular ventilation. Because the COVID-19 virus in the air exhaled by the infector is limited, the virus concentration in the cabin is small, and it is easily affected by the breathing if the virus comes only from the normal breath. Thus, the virus concentration is not used as the cost for the evaluation of the regular ventilation. In order to find the optimal open frequency and ventilation duration for the regular ventilation, the average control error of cabin temperature over the cycle $Cost_{r, tc}$, energy consumption $Cost_{r, ec}$ and infection risk $Cost_r$ at the end of the cycle are selected as the cost. The condition of the regular ventilation shown in Table 5 is used for the calculation of the costs mentioned above. Like the costs in the forced ventilation, those for the regular ventilation are also normalized by Eq. (33). The total normalized cost $Cost_{r, total}'$ shown in Eq. (37) is used to comprehensively evaluate the influence of the open frequency of intake air flap and ventilation duration on the behavior of the AC system.

$$ Cost_{r, total} = Cost_{r,r} + Cost_{r, tc} + Cost_{r, ec}. $$

Fig. 8 shows the influence of the open frequency $F_{r,v}$ and ventilation duration $T_{r,v}$ on the costs mentioned above. Frequent ventilation with a small duration can decrease the control error of cabin temperature and energy consumption. Moreover, frequent ventilation, even with a small duration, can even reduce the risk of COVID-19 infection. When the open frequency of the air flap is 25 times/h and the duration for each ventilation is 40 s, the total cost $Cost_{r, total}'$ reaches the minimum, which is 1.19. Therefore, the parameters for the regular ventilation are:

$$ [F_{r,v}', T_{r,v}]^T = [25, 40]^T $$

where $F_{r,v}'$ is the optimal open frequency of the intake air flap and $T_{r,v}'$ is the optimal duration for every ventilation.

4.2.3. Ventilation strategy for the cabin

Fig. 9 shows the cooperative control strategy of cabin thermal environment, which includes the control strategy of cabin temperature.
and ventilation strategy. The AC system detects the sneezing of the infector by the image and voice signal. Once sneezing occurs, the controller opens the intake air flap immediately and keeps it open for the next 100 s. If there is no sneezing, intermittent ventilation with a frequency of 25 times/h and a duration of 40 s for each time is applied. When regular or forced ventilation is used, the fan speed reaches the maximum (560 CMH) in order to reduce the virus concentration as soon as possible. At other times, it is controlled by the MPC. The compressor speed is always controlled by the MPC so as to maintain the cabin temperature accurately and save energy.

5. Performance of the proposed control strategy

In this section, the control performance of the proposed control strategy for the AC-cabin system is examined under the condition shown in Table 7. WLTC is chosen for the driving condition. Because WLTC with a duration of 1800 s is short to evaluate the proposed strategy, the test condition is extended to 7200 s by repeating the WLTC four times. The initial cabin temperature is set to 50 °C to simulate the sunlight exposure in summer, and the air conditioner is on once the passengers get into the car. The ambient temperature and solar radiation are set to 38 °C and 800 W which are normal in the summer of Chongqing, China. The target cabin temperature is set to 25 °C which is regarded as a comfortable temperature for the human body. In the simulation, it is assumed that there are two people without the mask in the car, and one of them has COVID-19. Because it is difficult to get the frequency and times of sneezing, three random times at 1473 s, 2852 s, and 4989 s are assumed to be the sneezing times of the infector. To show the superiority of the proposed control method in the fields of control precision of cabin temperature, risk reduction of COVID-19 infection, and energy-saving, the traditional MPCs with full ventilation/without ventilation are used as the control groups. In the MPC with full ventilation, the intake air flap is always open, and the ventilation fan reaches its maximum speed. In the MPC without ventilation, it is closed.
Fig. 10. Intake air flap controlled by three strategies.

Fig. 11. Speeds of compressor and evaporator fan controlled by three strategies.

Fig. 12. Cabin temperature and energy consumption.
5.1. Control performance comparison for different strategies

5.1.1. Action of AC system

Fig. 10 shows the control strategy for the intake air flap, and Fig. 11 shows the speeds of the evaporator fan and compressor. When the AC system is controlled by the MPC with full ventilation, the intake air flap is always open and the evaporator fan works at its top speed, 3000 rpm. Therefore, a lot of hot fresh air is sent into the cabin to reduce the concentration of COVID-19. In order to cool the fresh air, the controller runs the compressor always at high speed, namely 6000 rpm, which leads to large energy consumption. When the AC system is controlled by the MPC without ventilation, the intake air flap is closed, and the cool circulating air, instead of the hot fresh air, comes into the cabin. Therefore, the MPC without ventilation uses a low compressor speed and a relatively high speed of the evaporator fan to maintain the cabin temperature. This strategy is executed to make the AC system cost low energy. From 1000 s to 7200 s, the compressor speed of the MPC without ventilation rises or falls around 4000 rpm. However, because the circulation air is from the cabin, it may contain the COVID-19 exhaled by the infector in the car. Different from the two strategies mentioned above, the cooperative control strategy proposed in this paper uses intermittent ventilation. As shown in Fig. 10, the intake air flap opens intermittently, and the hot fresh air is sent into the cabin at a given time interval. When the intake air flap is closed, the speed of the evaporator fan falls down, and it rises to the top speed once the intake air flap is open. Moreover, the forced ventilation is on and lasts for 100 s to cope with the temporary rise of the COVID-19 concentration, if the AC-cabin system detects the sneezing of the infector. When the hot fresh air enters the AC system, the compressor increases its speed to cool the air. According to Fig. 11, the cooperative control strategy has a lower compressor speed than the MPC with full ventilation, while its compressor speed is higher than that of the MPC without ventilation.

5.1.2. Cabin temperature and energy consumption of AC system

Fig. 12 shows the evolution of cabin temperature and energy consumed by the AC system. Because the thermal load from the environment is big and the temperature of the fresh air is 38 °C which is very high, the MPC with full ventilation cannot provide enough refrigeration power to cool the cabin, even with the maximum power of the compressor. Therefore, the cabin temperature falls down slowly and the balanced cabin temperature is over the target temperature by about 2.7 °C, indicating that the MPC with full ventilation cannot reach the target cabin temperature. Because the circulating air is used by the MPC without ventilation, its temperature falls down quickly. When the cabin temperature reaches the target temperature (25 °C in this paper), it moves up and down a little bit around 25 °C and the maximum fluctuation is only 0.5 °C, indicating that the cabin temperature can be precisely controlled by the strategy. The cabin temperature controlled by the cooperative strategy falls at almost the same rate as that controlled by the MPC without ventilation. Unlike the MPC with full ventilation, the cooperative control strategy can achieve the target cabin temperature. Although the intermittent ventilation increases the fluctuation of the cabin temperature, the fluctuation is no more than 1.6 °C which has little impact on the thermal comfort of the passengers. In the whole control process of the cabin temperature, the forced ventilation brings greater fluctuation to the cabin temperature than the regular ventilation. This is because the forced ventilation lasts longer than the regular ventilation and more fresh air with high temperature needs to be cooled by the AC system.

According to Fig. 12, the MPC with full ventilation has the highest energy consumption among the three strategies because the compressor always works at the top speed. When the cycle is over, its energy consumption is 10.35 kW h. Due to the intermittent ventilation, the proposed cooperative control algorithm has a larger compressor speed than the MPC without ventilation. However, the compressor speed is not raised too much in time short ventilation time. In the whole cycle, the average compressor speed of the cooperative control strategy is 4803 rpm and the one of the MPC without ventilation is 4147 rpm, which makes the energy consumption of the proposed strategy a little higher than that of the MPC without ventilation. When the cycle finishes, the energy cost of the cooperative strategy is 3.99 kW h which is 0.81 kW h higher than that of the MPC without ventilation and 6.36 kW h lower than that of the MPC with full ventilation.

5.1.3. Risk of COVID-19 infection

Fig. 13 shows the virus quanta concentration and infection risk of COVID-19 in the cabin. With the effective ventilation, both of the cooperative control strategy and the MPC with full ventilation can obviously reduce the quanta concentration. However, the quanta concentration is high, if there is no ventilation. Because of the forced ventilation in the cooperative control strategy, the quanta concentration falls down quickly once the infector sneezes, which reduces the infection risk of COVID-19. In the whole driving process, the average quanta concentrations are 0.11 quanta/m^3 for the MPC with full ventilation, 0.22 quanta/m^3 for the cooperative control strategy and 12.9 quanta/m^3 for the MPC without ventilation. Therefore, like the full ventilation, the proposed intermittent ventilation strategy can greatly reduce the infection risk of COVID-19.

Fig. 13. Quanta concentration and infection risk of COVID-19 in the cabin.
With the help of ventilation, the infection risk of COVID-19 is greatly reduced. If there is no ventilation, the infection possibility rises to 99.4%, which means that the passenger has a great possibility of catching COVID-19 after 3000 s. With the help of ventilation for the cabin, the quanta concentration of COVID-19 falls greatly, bringing the infection risk down. At 3000 s, the infection risk of the intermittent ventilation in the proposed strategy is 18.6% which is 80.8% lower than that of no ventilation and only 7% higher than the full ventilation. When the driving cycle ends, the infection risks are 100% for no ventilation, 19.2% for the full ventilation and 34.1% for intermittent ventilation. Therefore, the cooperative control strategy can greatly reduce the infection risk of COVID-19.

5.1.4. Comprehensive performance

Table 8 shows the comprehensive performance of three control strategies. Although the cooperative control strategy does not have the best single performance, its comprehensive performance is the best. For the control accuracy of cabin temperature, the cooperative control strategy has a mean temperature control error of 0.75 °C which is 0.21 °C higher than the MPC without ventilation and 2.75 °C lower than the MPC with full ventilation. For the energy saving, the cooperative control strategy has an energy consumption of 3.99 kW h which is only 20% higher than the MPC with full ventilation but 159.6% lower than the MPC with full ventilation. For the risk of COVID-19 infection, the cooperative control strategy has an infection risk of 34.1% at the end of the driving cycle which is only 43.7% higher than the MPC with full ventilation but 193.3% lower than the MPC without ventilation. According to Table 5, the cooperative control strategy can balance the control accuracy, energy consumption and infection risk and reduces the risk of infection greatly at the cost of a small fall in the control accuracy and an acceptable rise in the energy consumption. Therefore, the cooperative control strategy has the best comprehensive performance.

5.2. Necessity of forced ventilation after sneezing

In order to prove that it is necessary to include the forced ventilation after sneezing in the strategy, the performance of the cooperative control strategy is compared with that of the control strategy with only regular ventilation. Fig. 14 shows the two different ventilation strategies. The first ventilation strategy (called FRV for short) has both forced and regular ventilation, and it is included in the proposed control strategy, while the second one (called RV for short) has only regular ventilation. The regular ventilation is the same in both of the strategies: the intake air flap opens every 104 s and it lasts for 40 s for each opening. Fig. 15 presents the action of the intake air flap. The regular ventilation makes it open at a fixed frequency, and there is no feedback of the air flap for sneezing. Therefore, it cannot send the extra virus produced by the sneezing to the environment in time, which may raise the concentration of COVID-19. When the forced ventilation is added, the intake air flap is opened once sneezing is detected. Thus, the rise in the concentration of COVID-19 can be immediately reduced. Fig. 16 shows the development of virus concentration and risk of COVID-19 infection. According to the MPC given in Section 4, there is no control target about virus. The regular ventilation with the fixed parameters and the forced ventilation following the sneezing are used to reduce the virus concentration. Although the development of virus concentration and risk of COVID-19 infection looks like the results from the continuous feedback control, it is the results based on the sneezing detection and fix ventilation parameters. According to Fig. 16, with the help of the forced ventilation, the high virus concentration after sneezing falls down sharply, which greatly reduces the risk of COVID-19 infection. The infection risk of FRV at 3000 s is 18.6% and that of RV is 37.5%. When the driving cycle finishes, the infection risk of FRV is 34.1%, and it falls by 19.2% compared with that of RV.

Fig. 17 gives the energy consumption and cabin temperature of different ventilation strategies. Although the FRV has a bigger fluctuation of cabin temperature than the RV after the infector sneezes, the maximum fluctuation of FRV is only 0.84 °C bigger than that of RV. Therefore, the FRV affects the thermal comfort of passengers little. Because the forced ventilation brings extra fresh air into the cabin, extra energy is needed to cool them. When the driving cycle ends, the FRV has an energy consumption of 3.99 kW h which is only 0.15 kW h higher than that of RV.

Table 8

| Evaluation item         | MPC with full ventilation | MPC without ventilation | Cooperative control strategy | Compared with MPC with/without ventilation |
|-------------------------|---------------------------|-------------------------|------------------------------|----------------------------------------|
| Mean temperature control error (°C) | 3.5                       | 0.54                    | 0.75                         | -366.7% / +28%                        |
| Infection risk At 3000 s | 11.6%                     | 99.4%                   | 18.6%                        | +37% / -434.4%                        |
| At the end of driving cycle | 19.2%                     | 100%                    | 34.1%                        | +43.7% / +193.3%                      |
| Energy consumption (kW h) | 10.36                     | 3.18                    | 3.99                         | -159.6% / +20%                        |

Fig. 14. Control strategies of FRV and RV.
Fig. 15. Action of intake air flap.

Fig. 16. Quanta concentration and risk of COVID-19 infection for two ventilation strategies.

Fig. 17. Cabin temperature and energy consumption for two ventilation strategies.
than the RV. It is concluded that the forced ventilation following sneezing has little effect on the temperature control accuracy and energy consumption.

6. Conclusion and future works

A cooperative control algorithm integrating the dynamic model of AC-cabin system, MPC, and intermittent ventilation is proposed for the AC-cabin system in order to accurately maintain the cabin temperature, reduce the risk of COVID-19 infection and save the energy of the AC system. The Wells–Riley model has been used to predict the infection risk in vehicle cabin based on the virus quanta emission of infector’s breath and sneeze. And the cooperative control strategy is applied to the WLTC and compared with the MPC with/without ventilation to show its superiority in terms of control accuracy, energy-saving, and risk reduction of COVID-19 infection. Based on the above analysis, the following conclusions can be made:

1. The proposed control-oriented dynamic thermal model can accurately describe the thermal behavior of the AC-cabin system with average relative error of 3.69% compared to the cooling experiment.

2. The forced ventilation after sneezing reduces the risk of COVID-19 infection greatly at the expense of a small decrease in the temperature control accuracy and a small increase in energy consumption, and it should be included in the ventilation strategy. Compared with the regular ventilation, the strategy integrating the forced and regular ventilation reduces the infection risk of COVID-19 by 19.2%, while it increases the energy consumption and maximum fluctuation of cabin temperature by only 0.15 kW h and 0.84 °C.

3. Compared with the MPC with full ventilation which has the lowest infection risk, the proposed strategy reduces the mean temperature control error by 2.75 °C and energy consumption by 366.7% (6.37 kW h), while it increases the infection risk by only 14.9% at the end of the driving cycle. Compared with the MPC without ventilation which has the lowest energy consumption, it reduces the infection risk by 65.9% at the end of the driving cycle at the expense of a little increase of 0.21 °C for the mean temperature control error and 0.81 kW h for the energy consumption. Thus, the cooperative control strategy for the AC system has a better comprehensive performance than the MPC with full ventilation or without ventilation.

Because the hardware of the AC controller is being developed, the HIL (hardware in loop) test and on-vehicle experiment will be implemented to verify the performance of the proposed cooperative control strategy in the future works. Moreover, the control strategy based on the framework of MPC will be further studied in order to reduce the calculation amount of the algorithm and improve its execution efficiency, which makes the strategy more suitable for the single chip microcomputer. As for the ventilation strategy, the algorithm of virtual sensor will be applied to the strategy for the calculation of the virus concentration which is considered as the feedback, and then the control strategy with the feedback will be developed for the ventilation system.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Nomenclature

| Acronym | Description |
|---------|-------------|
| AC | air conditioning |
| AER | air exchange rate |
| ANN | artificial neural network |
| CMH | cubic meter per hour |
| EV | electric vehicle |
| FAFR | flow rate of fresh air |
| HVAC | heating, ventilation and air conditioning |
| IR | inhalation rate |
| MBM | moving boundary method |
| MIMO | multiple-input and multiple-output |
| MPC | model predictive control |
| PID | PM2.5 proportion integration differentiation particulate matter that has an aerodynamic diameter of 2.5 μm or smaller |
| PMV | predicted mean vote |
| SISO | simple-input and simple-output |
| SUV | sport utility vehicle |
| WLTC | worldwide light-duty test cycle |
| $D_h$ ($D_y$) | hydraulic diameter of the flat tube in the evaporator (condenser) |
| $l_e$ ($l_c$) | length of liquid-vapor mixing zone in evaporator (condenser) |
| $M_a$ | mass of air in cabin |
| $M_s$ | mass of cabin closure structure |
| $m_{comp}$ | mass flow rate of refrigerant |
| $m_{vap}$ ($m_{vac}$) | evaporator (condenser) mass |
| $N_{comp}$ | compressor speed |
| $N_{fan}$ | speed of evaporator fan |
| $\Delta P$ | pressure fall of refrigerant through the expansion valve |
| $P_e$ ($P_c$) | refrigerant pressure in evaporator (condenser) |
| $Q_d$ | heat produced by mechanical and electronic devices |
| $Q_{conv}$ | heat convection between ambient air and car |
| $Q_{cab}$ | total heat of cabin |
| $Q_p$ | heat generated by passenger |
\[ Q_{AC} \] refrigeration power of air conditioning system
\[ Q_{solar} \] power of solar radiation
\[ Q_{vent} \] heat load of the ventilation system
\[ h_{v,0} \] enthalpy of the refrigerant at compressor exit (entrance)
\[ \dot{h}_1 \] heat exchange coefficient between air and internal surface of the cabin
\[ \dot{h}_{v,0} \] isentropic enthalpy of refrigerant inside compressor
\[ h_{v,0} \] vapor refrigerant enthalpy inside evaporator (condenser)
\[ \dot{h}_{v,0} \] liquid refrigerant enthalpy in the evaporator (condenser)
\[ \dot{h}_c \] refrigerant enthalpy at evaporator (condenser) entrance
\[ \dot{h}_e \] heat exchange coefficient between car and environment
\[ \dot{h}_{v,e} \] refrigerant latent enthalpy for evaporation (condensation)
\[ L_v \] length of flat tube in the evaporator (condenser)
\[ S \] cabin closure surface area
\[ T_a \] temperature of air in cabin
\[ T_{ac} \] environment temperature
\[ T_{we} \] air temperature near evaporator
\[ T_{re} \] refrigerant saturation temperature for evaporation (condensation)
\[ T_s \] temperature of closure surface
\[ T_{we} \] (T_{ac}) evaporator (condenser) temperature wall
\[ V_{car} \] car velocity
\[ V_d \] displacement of compressor
\[ \rho_r \] refrigerant density in compressor
\[ \rho_{v,0} \] refrigerant density in the expansion valve
\[ \rho_{v} \] density of vapor refrigerant in the evaporator (condenser)
\[ \rho_{l} \] density of liquid refrigerant in evaporator (condenser)
\[ \tau_{e} \] void fraction in the liquid-vapor mixing zone region of the evaporator (condenser)
\[ \eta_r \] compressor isentropic efficiency
\[ \eta_v \] compressor volume efficiency

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