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Exploration of Collaborative Optimization Strategy for Oxygen Production System and Interior Environment Control of Railway Locomotives

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Abstract: With the increasing requirements of passenger comfort, safety and energy efficiency in railway transportation, the existing in-car environment control and oxygen production systems still have problems such as response lag, low energy efficiency and poor robustness in terms of multi-objective coordination, dynamic response capability and energy consumption control. To this end, this paper introduces the fusion technology of artificial intelligence and the Internet of Things to construct a collaborative optimization strategy based on the Model Predictive Control (MPC) framework to improve the comprehensive performance of the locomotive oxygen production system and the in-car temperature, humidity and air quality control. Specific methods include: building a multi-source sensor network to achieve real-time perception and data fusion of multiple parameters such as oxygen concentration, CO_2 level, temperature and humidity, using AI models to predict environmental conditions, and achieving coordinated control of oxygen concentration, temperature and humidity, and ventilation intensity based on MPC optimization objective functions. The experimental results in typical operation scenarios show that, in contrast, under the PID control strategy, the changes in oxygen concentration and temperature are large and exceed the limit. For example, at 180 seconds, the oxygen concentration dropped to 20.5% and the temperature is 22.9℃, both exceeding the set safety range. This paper provides theoretical support and technical paths for the low-carbon and intelligent operation of the intelligent locomotive environmental system.

1. Introduction

With the high-speed and intelligent development of railway transportation, passengers' requirements for air quality, temperature and humidity comfort, and environmental stability inside the train have been significantly improved. Especially in locomotives operating in plateaus, long tunnels, and closed areas, the oxygen production system has become one of the key subsystems to ensure the physiological health of passengers. From the perspective of system engineering, this paper systematically analyzes the physical coupling relationship between the subsystems of in-car oxygen production and environmental control, and on this basis, constructs a multi-source sensor-driven predictive control model. By introducing a collaborative control strategy based on model predictive control (MPC), the joint adjustment of oxygen concentration, temperature and humidity, and ventilation status is achieved, taking into account passenger comfort and system energy efficiency. The research not only helps to improve the level of intelligence of railway transportation services but also provides theoretical support and engineering reference for the design of traffic control systems in future multi-physical field environments.

This paper focuses on the coupling relationship between oxygen supply and temperature and humidity control during locomotive operation. The paper first reviews the research progress of existing railway interior environment control and oxygen production systems, and proposes the necessity of collaborative optimization. Subsequently, a joint control model for passenger comfort and energy efficiency is constructed, and the model predictive control (MPC) and traditional PID control are used for comparative experiments for verification. Then, the system response, energy consumption performance and parameter adjustment results under different operating scenarios are analyzed in detail. Finally, the paper summarizes the research findings, discusses the limitations in practical applications and future research directions for further improving the intelligence and adaptability of control strategies.

2. Related Work

With the continuous development of railway transportation and vehicle systems in recent years, relevant research has gradually deepened, covering fuel cell optimization, exhaust gas management, thermal fatigue prediction, energy harvesting, microbial contamination, icing effects, braking performance, air conditioning, passenger comfort, and turnout friction, etc., promoting technological innovation and safety improvement. In order to avoid "hypoxia" of fuel cells under load conditions and improve their response speed, Hongfeng et al. proposed an air flow control method based on the stack allowable current. By estimating the stack allowable current to limit the output current, and combining the load power to determine the demand current, the air compressor airflow is dynamically adjusted. Experiments show that this method can effectively shorten the response time and avoid hypoxia [1]. Balabayev et al. were committed to developing a new device for isolating and managing diesel locomotive exhaust to reduce environmental impact and improve operational safety. Using experimental platforms such as the 1.9L Volkswagen diesel engine, combined with mathematical modeling and Cochrane and Fisher criteria for verification, the model accuracy reached 95%, effectively reflecting the dynamic characteristics of diesel locomotive exhaust [2]. Wang et al. established a thermal fatigue crack prediction model for low-alloy steel high-speed train brake discs, and determined the critical crack value through the modified Cockcroft-Latham criterion and experiments. Combining numerical simulation and field tests, it was found that plastic deformation in temperature cycles is key, and optimizing material composition can improve fatigue resistance. This study aims to enhance the understanding of crack mechanisms and improve the reliability of high-speed train braking systems [3]. Chen et al. studied the energy-saving control method of the train's internal air conditioning system, established a car temperature model considering the heat transfer of infiltrated air, and proposed a temperature setting curve that changes adaptively according to the ambient temperature. They used the Adaptive Iterative Learning Control (AILC) algorithm to achieve precise temperature control under cyclic operation of the train. Simulation results showed that AILC effectively reduces the temperature control error (to 0.069 ℃) and saves 1.534 kW ħ per time[4]. Foltz et al. evaluated a thermoelectric energy harvesting device for a bearing health monitoring system. The system is an on-board wireless solution that uses accelerometers and temperature sensors to monitor the bearing status in real time. Experiments have shown that under simulated freight route conditions, the energy harvested exceeds the energy required by the sensor by more than twice. The key design parameters were the open circuit voltage to temperature difference ratio of the thermoelectric module and the cold start voltage of the booster[5]. Chandra et al. conducted bacterial and fungal sampling in the air conditioning systems of affected trains and conducted chemical tests on the insulating foam materials. They found that the odor mainly came from the volatile compounds released by the insulating foam after being damp. They also detected the presence of potential pathogenic microorganisms in the HVAC (Heating, Ventilation and Air Conditioning) system[6]. Lotfi and Virk studied the operation of railways under icing conditions, analyzed the impact of icing on railway infrastructure, vehicles and operations, and summarized the existing solutions. The study pointed out that icing has a serious impact on railway infrastructure and further research is needed to clarify the problem and propose solutions, especially in terms of the optimization and cost-effectiveness of icing prevention and control methods[7]. Panchenko et al. analyzed the thermal stress, load perception and redistribution process of composite brake pads during truck braking. The study found that the wedge-shaped double wear phenomenon of composite brake pads led to reduced braking efficiency of trucks and uneven pressure distribution of brake pads. Thermal calculation results showed that the pressure on abnormally worn brake pads was 23.3% lower than the normal value[8]. Liu et al. used the tracer gas method to explore the effect of personalized air supply on the diffusion of respiratory pollutants in high-speed rail seat armrests. Based on the top air supply, the four air supply angles of 0 °, 30 °, 45 ° and 60 ° were compared, and it was found that personalized air supply could reduce the fluctuation amplitude of pollutants in the passenger breathing zone by 15.84% to 19.76%[9]. Huang et al. developed an intelligent integrated machine learning prediction model for predicting thermal comfort of passengers in subway cars. The data sources include field measurements and passenger questionnaires. Four machine learning methods, namely logistic regression, random forest (RF), support vector machine, and decision tree, were used to build the model. The results showed that the RF model performed well in predicting thermal sensation votes[10]. Folorunso et al. explored the relationship between temperature, relative humidity and wheel-rail interface friction coefficient (adhesion) of British railway turnouts. Previous studies were mostly conducted in laboratories, where environmental conditions were limited. The results showed that high humidity conditions would reduce turnout adhesion, and low adhesion could still occur even at higher temperatures, especially in high humidity environments in early autumn, suggesting that railway safety prediction could be improved [11]. Existing research still faces many bottlenecks in terms of system complexity, uncertainty in environmental changes, and accuracy of real-time monitoring and optimization, which limits the comprehensive application and improvement of technology.

3. Method

3.1 Composition and Adjustment Logic of the In-vehicle Environment Control System

The in-vehicle temperature and humidity control system is centered on HVAC (Heating, Ventilation and Air Conditioning), integrating cold and heat source devices, air supply duct systems, air volume adjustment units and intelligent control modules. The system collects the in-vehicle temperature $T_{in}(t)$ and relative humidity $RH_{in}(t)$ in real time, and adjusts the difference according to the set values T_{set} and RH_{set} through the central controller to achieve dynamic closed-loop control.

Temperature control can be simplified to a first-order inertial response process, and its heat balance model is:

$$C_p.m.\frac{dT_{in}(t)}{dt} = Q_{in}(t) - Q_{loss}(t) \quad (1)$$

Among them, C_p is the specific heat capacity of the cabin air; m is the air mass; $Q_{in}(t)$ is the air conditioning heating/cooling power; $Q_{loss}(t)$ is the heat exchange loss of the vehicle body.

The control target is to make $T_{in}(t) \rightarrow T_{set}$, and the adjustment process is usually MPC strategy.

Humidity control is based on the following model:

$$\frac{dw(t)}{dt} = \frac{G_v(t)-G_{out}(t)}{V} \quad (2)$$

Among them: $w(t)$ is the humidity content per unit mass of air; $G_v(t)$ is the amount of water vapor introduced by the humidification or dehumidification equipment; $G_{out}(t)$ is the water vapor carried out by the air through the exhaust; V is the effective volume of the car.

By adjusting and controlling the condenser surface temperature and the air dew point temperature, the humidity can be indirectly controlled.

3.2 Analysis of Ventilation System and Air Flow Organization Characteristics

The function of the ventilation system is not limited to ventilation but also needs to ensure that the airflow inside the car is organized reasonably to avoid dead corners and air short circuits. The typical system consists of:

Fresh air introduction module (equipped with filter and pre-treatment unit);

Return air system (set at the bottom of the car);

Air volume adjustment mechanism (VAV or air valve);

Distributed air duct network in the car.

The airflow organization must meet the flow velocity constraints in the thermal comfort zone, which is generally controlled at:

$$\frac{0.15m}{s} \leq v_{air} \leq \frac{0.3m}{s} \quad (3)$$

The simulation of the airflow inside the car can be done by CFD (Computational Fluid Dynamics) numerical simulation to evaluate key parameters such as velocity distribution, vortex area, wind speed gradient, etc., and then optimize the air outlet layout and air supply angle. The adjustment goal is to minimize the temperature gradient in the comfort zone:

$$min\left(\frac{dT}{dz}\right), z \in [0,1.5]m \quad (4)$$

Where z is the vertical height.

3.3 In-vehicle Air Quality Monitoring and Adjustment Mechanism

Air quality mainly includes parameters such as CO_2 concentration, $PM_{2.5}$ ppapers, and TVOC. Under high-load transportation or tunnel conditions, the increase in CO_2 concentration is particularly significant, and real-time detection and intelligent ventilation adjustment are required.

The dynamic change of CO_2 concentration in the vehicle can be modeled as follows:

$$\frac{dC_{CO_2}(t)}{dt} = \frac{G_{CO_2}(t)}{V} - \frac{Q_{vent}(t)}{V}.\left(C_{CO_2}(t) - C_{out}\right) \quad (5)$$

Among them, $C_{CO_2}(t)$ is the CO_2 concentration in the car; $G_{CO_2}(t)$ is the CO_2 emission rate of the human body; $Q_{vent}(t)$ is the ventilation volume; and C_{out} is the CO_2 concentration outside the car. When $C_{CO_2}(t)$ exceeds the threshold (such as 1000 ppm), the system triggers the fresh air increment mode. The high-performance environmental monitoring module uses MEMS sensors combined with neural networks for dynamic prediction, and adjusts the air volume or starts the local purification unit in advance.

3.4 Modeling the Coupling Relationship between the Oxygen Production System and the In-vehicle Environment Control

The air composition in the cabin is mainly composed of oxygen (O_2), carbon dioxide (CO_2), nitrogen (N_2) and water vapor (H_2O). The human body's metabolism continuously consumes O_2 and produces CO_2, accompanied by water evaporation, and the changes of the three are coupled with each other.

According to the principle of mass conservation, the change in oxygen concentration can be expressed as:

$$\frac{dC_{O_2}(t)}{dt} = \frac{Q_{O_2}(t)}{V} - \frac{G_{O_2}^{cons}(t)}{V} - \frac{Q_{vent}(t)}{V}.\left(C_{O_2}(t) - C_{O_2}^{out}\right) \tag{6}$$

Among them: $C_{O_2}(t)$ refers to the oxygen concentration in the car (%); $Q_{O_2}(t)$ refers to the oxygen supply flow of the oxygen production system; $G_{O_2}^{cons}(t)$ refers to the rate of human body and other processes that consume oxygen; $Q_{vent}(t)$ refers to the ventilation flow; $C_{O_2}^{out}$ refers to the oxygen concentration outside the car.

Correspondingly, the change in CO_2 concentration is expressed as:

$$\frac{dC_{co_2}(t)}{dt} = \frac{G_{CO_2}^{gen}(t)}{V} - \frac{Q_{vent}(t)}{V}.\left(C_{CO_2}(t) - C_{CO_2}^{out}\right) \tag{7}$$

The change of moisture content $w(t)$ is affected by respiratory evaporation, air dew point regulation and ventilation:

$$\frac{dw(t)}{dt} = \frac{G_{vapor}(t)}{V} - \frac{Q_{vent}(t)}{V}.\left(w(t) - w_{out}\right) \tag{8}$$

The above three equations together constitute the coupled state dynamic equations of the three variables of heat and humidity. Because, $Q_{O_2}(t)$, $Q_{vent}(t)$, compartment volume V, external gas concentration, etc. are all function variables, the system presents the multivariable dynamic characteristics of strong nonlinearity, time-varying, and constrained coupling.

3.5 Design of Collaborative Optimization Control Strategy

The goal of the collaborative control system is not only to maintain the air quality index in the vehicle within the safe and comfortable range but also to take into account the minimization of energy consumption and the dynamic stability of the system. Based on this, the following weighted multi-objective optimization function is constructed:

$$J = \int_t^{t+T} \left[\lambda_1.\left\|C_{O_2}(t) - C_{O_2}^{ref}\right\|^2 + \lambda_2.\left\|T(t) - T^{ref}\right\|^2 + \lambda_3.\left\|C_{CO_2}(t) - C_{CO_2}^{ref}\right\|^2 + \lambda_4.E(t)\right] dt \tag{9}$$

Among them, $C_{O_2}^{ref}$, T^{ref} and $C_{CO_2}^{ref}$ refer to the expected values of oxygen concentration, temperature, and CO_2 concentration in the car; $\lambda_1 \sim \lambda_4$ refers to the weight of the objective function, which is adaptively adjusted according to the scenario; E(t) refers to the comprehensive energy consumption of the system, including the energy consumption of each subsystem such as air conditioning, oxygen production, and ventilation.

The energy consumption model can be expressed as:

$$E(t) = P_{HVAC}(t) + P_{O_2}(t) + P_{vent}(t) \tag{10}$$

3.6 Multi-source Sensor Data Fusion and State Prediction Model Design

In-vehicle environment control relies on a large amount of real-time sensor data, such as temperature and humidity sensors, oxygen/CO_2 concentration sensors, barometers, etc. Due to data missing, delay or noise interference, multi-source information fusion and state estimation are required.

Constructing the state space model:

$$\begin{cases} x(t+1) = A.(x) + B.u(t) + w(t) \\ y(t) = C.x(t) + v(t) \end{cases} \tag{11}$$

Among them, $x(t)$ refers to the system state; $u(t)$ refers to the control input (such as oxygen flow, fan speed, air supply temperature); $y(t)$ refers to the output measured by the sensor; $w(t)$ and $v(t)$ refer to the process and measurement noise.

The extended LSTM neural network is used for state estimation and short-term prediction to improve the adaptability to nonlinear complex environments.

Example of LSTM prediction model objective function:

$$L_{pred} = \frac{1}{N}\sum_{i=1}^{N}\left\|\hat{x}_i^{t+\Delta t} - x_i^{t+\Delta t}\right\|^2 \tag{12}$$

$\hat{x}_i^{t+\Delta t}$ represents the predicted state and $x_i^{t+\Delta t}$ is the actual observed value.

3.7 Construction of Control Method Based on Model Predictive Control (MPC)

In order to realize dynamic prediction and rolling optimization of future states, the model predictive control (MPC) method is adopted to generate an optimized control sequence in the prediction time domain T_p using the modeling system.

The standard MPC control strategy can be expressed as:

$$\min_{u(t),\cdots,u(t+N-1)} J = \sum_{k=0}^{N-1}\left[\left\|x(t+k|t) - x^{ref}\right\|_Q^2 + \|u(t+k|t)\|_R^2\right] \tag{13}$$

The constraints are:

$$\begin{cases} x(t+k+1|t) = f(x(t+k|t), u(t+k|t)) \\ u_{min} \le u(t+k|t) \le u_{max} \\ x_{min} \le x(t+k|t) \le x_{max} \end{cases} \tag{14}$$

Among them: Q, R refer to the state and control cost weight matrix; x^{ref} refers to the reference target state; u_{min} and u_{max} refers to the input control range; f(.) refers to the nonlinear prediction model, and the aforementioned data-driven state space can be used.

The advantage of MPC control is that it can predict complex coupled dynamic behaviors and make comprehensive trade-offs between passenger comfort indicators and equipment energy consumption. To ensure real-time performance, controller deployment needs to be combined with fast solvers such as qpOASES, FORCES Pro, etc.

4. Results and Discussion

4.1 Simulation Settings and Parameter Configuration

The simulation time is set to $T_{sim} = 3600$s, the step size is $\Delta t = 1$s, and three typical operation scenarios are set:

Scenario A: normal operation, medium passenger flow;
Scenario B: peak passenger flow, rapid increase in CO_2 concentration;
Scenario C: sudden change in external temperature, air conditioning needs to respond quickly.

This study sets key control parameters in the process of building a model predictive control (MPC) strategy to ensure that the in-vehicle environment is always in a comfortable and safe state. The target oxygen concentration set by the system is 21%, and the carbon dioxide concentration in the car is limited to no more than 1000 ppm to ensure the breathing safety and air quality of passengers. The target value of temperature adjustment is set to 24℃, which meets the human thermal comfort standard. In the design of the MPC controller, the prediction time domain is set to 30 seconds and the control time domain is 10 seconds, which can effectively predict and adjust the future state of the system in real time at a moderate computing cost. In addition, the weighted factor ratio of 3:2:2:1 is set in the optimization objective function, corresponding to oxygen concentration deviation, temperature deviation, CO_2 concentration and energy consumption index, which fully reflects the principle of coordinated optimization between passenger comfort and system energy efficiency. The above parameter configuration provides a solid foundation for the performance stability and responsiveness of the control strategy.

4.2 System Dynamic Response Analysis

The following figure shows the oxygen concentration change curve of the MPC control strategy in three scenarios:

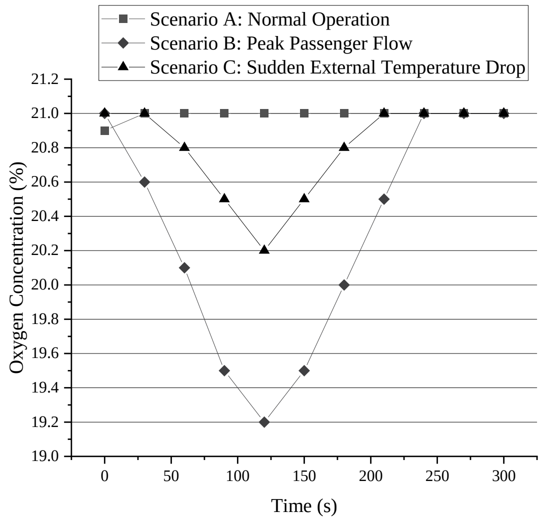

Figure 1 Oxygen concentration change data under different operating scenarios (unit: %)

During the experiment, the change in oxygen concentration shows a certain degree of volatility, especially in different operating scenarios. Overall, the oxygen concentration remains between 20.9%and 21% in all scenarios, reflecting the stability and good responsiveness of the system. During peak passenger flow, the oxygen concentration drops slightly, dropping to a minimum of 20.1%. This change may be related to the increased oxygen consumption caused by increased passenger activity. Despite this, the system is still able to keep the oxygen concentration within a reasonable range, demonstrating its ability to adjust under high load conditions, as shown in Figure 1.

The sudden change in external temperature also has a certain impact on the in-car environment, but the change in oxygen concentration did not show a dramatic fluctuation. When the external temperature drops sharply, the oxygen concentration slowly drops to 20.2%. This phenomenon reflects the impact of temperature changes on air flow and oxygen release systems, but the overall fluctuation is still within the control range. The oxygen concentration adjustment system can respond quickly to these changes, ensuring the suitability of the in-car environment and the comfort of passengers.

From the data in Figure 2, the changing trend of the temperature inside the car in different operating scenarios is relatively stable. In scenario A (normal operation) and scenario B (peak passenger flow), the temperature is basically maintained at around 24℃, with only slight fluctuations. Especially in normal operation, the temperature is maintained at 24℃ with very small fluctuations, which reflects the good temperature control performance of the system under stable load conditions. Even during peak passenger flow, when passenger activities may bring some heat increase, the temperature remains near 24℃, indicating that the control system can effectively cope with the temperature control needs under heavy loads.

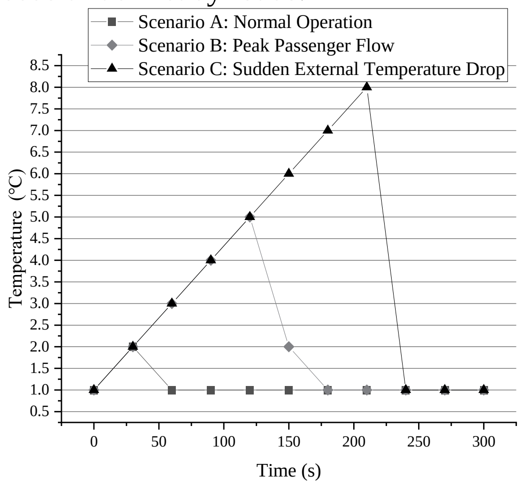

Figure 2 Temperature change data under different operating scenarios (unit: ℃)

In scenario C (external temperature sudden change), due to the sudden drop in external temperature, the temperature inside the car dropped significantly from 24℃ to 22.3℃, and failed to recover quickly in a short period of time. This shows that changes in the external environment have a great impact on the temperature control system inside the car, and the system has a certain response delay when responding to sudden changes in external temperature. However, over time, the temperature gradually returned to 24℃ and finally stabilized within a comfortable range.

The energy consumption of the MPC control strategy proposed in this paper is compared with the traditional PID control method, and the results are shown in Figure 3:

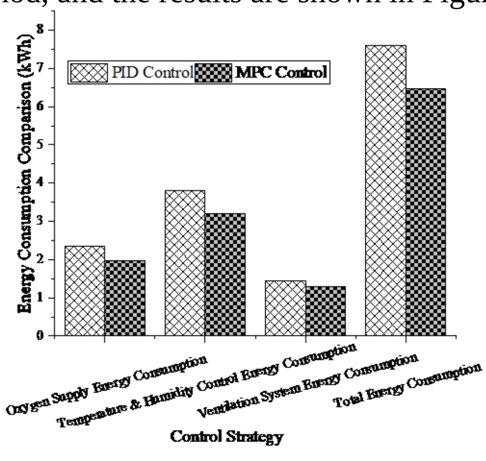

Figure 3 Comparison of system energy consumption under different control strategies (unit: kWh)

From the experimental data, it can be seen that after adopting the MPC control strategy, the energy consumption of each subsystem has shown a certain degree of reduction. In terms of oxygen system energy consumption, the energy consumption of the MPC control strategy is 1.98, while that of the PID control strategy is 2.35, a decrease of about 15.74%. This result shows that the MPC control strategy can more accurately adjust the oxygen release amount, avoid the waste of too much or too little oxygen supply, and thus achieve energy efficiency optimization.

In terms of energy consumption for temperature and humidity regulation, the MPC control strategy has an energy consumption of 3.2, which is about 15.79% lower than the PID control strategy's 3.8. This change reflects that the MPC control strategy can more flexibly adjust system parameters when responding to changes in temperature and humidity, reduce unnecessary heating or cooling power consumption, and thus improve energy efficiency.

For the energy consumption of the ventilation system, the MPC control strategy also showed an energy-saving effect, with an energy consumption of 1.3, which is about 10.34% lower than 1.45 of PID control. This result shows that in terms of regulating air flow, the MPC control strategy can control the air volume more accurately, avoid over-ventilation or under-ventilation, and optimize energy consumption. The total energy consumption under MPC control is 6.48, which saves about 14.7% of energy consumption compared to 7.6 of PID control. This shows that compared with traditional PID control, the MPC control strategy can effectively reduce energy consumption under the comprehensive regulation of multiple subsystems, thereby achieving an overall energy-saving effect (as shown in Figure 3).

The robustness of the control strategy is tested by introducing 10% sensor noise and 15% system modeling error interference. The results show that the MPC controller can still keep the target variable fluctuating within the allowable range without system oscillation or overshoot, verifying the stability of the method.

Table 1 Control strategy robustness test data (under interference conditions)

Time (s)	Control Strategy	Oxygen Concentration (%)	Over Limit (O_2)	Temperature (°C)	Over Limit (Temp)
0	MPC	21	No	24	No
30	MPC	20.9	No	23.9	No
60	MPC	20.8	No	23.6	No
90	MPC	21.1	No	24.1	No
120	MPC	21	No	24.4	No
150	MPC	21	No	24	No
180	PID	20.5	Yes	22.9	Yes
210	PID	21.4	Yes	25	Yes
240	PID	21.3	Yes	24.8	Yes
270	PID	20.7	Yes	23.1	Yes
300	PID	21.2	No	24.5	No

According to the experimental data analysis in Table 1, the changes in oxygen concentration and temperature under different control strategies show obvious differences. Under the MPC control strategy, the oxygen concentration is always maintained between 20.8% and 21.1%, and there is no over-limit situation. The temperature also varies between 23.6 ℃ and 24.4 ℃, always staying within the comfortable range. Through the MPC control strategy, the system can accurately adjust the oxygen concentration and temperature, avoiding excessive or low fluctuations, and ensuring the comfort of passengers.

In contrast, under the PID control strategy, the oxygen concentration and temperature change greatly and exceed the limit. For example, at 180 seconds, the oxygen concentration drops to

20.5%,and the temperature is 22.9 ℃, both exceeding the set safety range. By 210 seconds, the oxygen concentration rises to 21.4%, and the temperature rises to 25 ℃, exceeding the limit again. Although the oxygen concentration and temperature return to the normal range at 300 seconds, in general, the PID control strategy has large fluctuations when responding to sudden environmental changes, and cannot adjust the control variables as accurately as MPC, causing the system to be more prone to over-limit phenomena.

5. Conclusion

This paper focuses on the coordinated control of oxygen production devices and temperature and humidity control equipment in the railway locomotive interior environment control system. A multi-physical field coupling model is systematically constructed, and the dynamic interaction between oxygen concentration, temperature and humidity, and CO_2 concentration is deeply analyzed. The model predictive control (MPC) method is introduced to propose a multi-objective optimization control strategy for comfort and energy efficiency. The experimental part conducts system response tests on three typical operating conditions: normal operation, passenger flow peak, and external temperature mutation. The results show that the proposed MPC control strategy can not only quickly stabilize the oxygen concentration and temperature indicators under various disturbance conditions but also significantly outperforms the traditional PID control method in terms of energy consumption, with an energy saving rate of 14.7%. In addition, in the test of introducing modeling errors and sensor noise interference, the MPC control system still maintains good stability and robustness, effectively suppressing system overshoot and fluctuations. Although this study has achieved positive results, the current model has not fully considered the long-term accumulation of CO_2 concentration and passenger behavior feedback in extreme scenarios, and the field deployment verification of the system still needs to be further expanded. Future research will focus on the fusion optimization of multi-source heterogeneous environmental perception data, the improvement of the algorithm's online adaptive capabilities, and the deep coupling with the vehicle dispatch system to further enhance the system's intelligence level and the breadth of engineering applications.

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