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Intelligent window multi-parameter coordinated control method based on neural networks

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Abstract With the rapid development of the Internet of Things and artificial intelligence, the intelligent window opening and closing system has become a key component of the modern smart home environment regulation. In view of the many defects presented by the traditional control method in the process of utilizing the switch window system, this study develops a multi-parameter cooperative control algorithm based on feed-forward neural network, which is unique in that it organically combines the principles of physics with the data-driven approach. The physically guided feedforward neural network (PGFNN) architecture we constructed not only enhances the physical interpretability of the system, but also significantly improves its generalization ability in the face of complex environments by cleverly embedding indoor aerodynamic and thermodynamic models. The study shows that the PGFNN control algorithm has significant advantages in the synergistic adjustment of multi-dimensional parameters such as temperature, humidity and air quality, and exceeds the traditional PID control and standard feed-forward neural network control scheme in terms of both control accuracy and response speed. The PGFNN algorithm shows outstanding adaptability and stability when environmental conditions change drastically, and the PGFNN algorithm also performs well in energy utilization, which can effectively reduce the energy consumption of the system while guaranteeing the control effectiveness. This study provides innovative ideas and practical methods for the design and performance optimization of the smart window switching system, which is of substantial significance for improving the control performance and user comfort of the overall smart home system.

Index Terms feed-forward neural network, smart window opening and closing, multi-parameter cooperative control, physical guidance, energy saving

I. Introduction

I. A. Background and significance of the study

Accompanied by the rapid progress of the Internet of Things technology and artificial intelligence, the smart home system, as a key carrier to improve the comfort and quality of life, is rapidly popularized worldwide. Smart windows and switches play a key role in the smart home environment control system, assuming the task of regulating indoor temperature, humidity, air quality and other environmental parameters. The global smart home market size from \$46 billion in 2015 grew vigorously to more than \$180 billion in 2023, with a compound annual growth rate of up to 16.5%, and the proportion of intelligent environment control system is about 28%, which has become an indispensable component of the smart home field.

The quality of indoor environment is directly related to human health, work efficiency and living comfort. Appropriate indoor temperature, humidity and good air quality can significantly improve work efficiency and reduce the probability of disease. The traditional window opening and closing system mainly relies on manual operation or simple single-parameter automatic control, which is not capable of facing the complex and changing indoor and outdoor environments. In the summer high temperature and high humidity weather conditions, purely consider the temperature factor of the automatic window opening system may lead to high indoor humidity, in the haze weather, only consider the air quality of the system may cause the indoor temperature to fall sharply. Traditional control methods such as threshold-based switching control, PID control and fuzzy control have obvious limitations in response to the demand for multi-parameter cooperative indoor control. Threshold-based regulation is simple and intuitive, but the degree of control accuracy is low and easy to generate oscillations, and PID regulation for nonlinear, multivariate, strongly coupled indoor environmental system parameters is difficult to adjust and poor adaptability. Although fuzzy regulation can deal with a certain degree of uncertainty, the rule base construction is overly dependent on the experience of experts, and it is difficult to adapt to changes in environmental conditions. These approaches have the problems of slow response, low accuracy, and weak adaptive ability when facing the cooperative control of multiple parameters such as indoor temperature, humidity, and air quality.

The development of artificial intelligence technology has led to the widespread use of neural network control in complex systems. Feedforward neural network has a broad application prospect in the field of control because of its simple structure, efficient training, and powerful nonlinear mapping ability. It is able to construct complex nonlinear mapping links between inputs and outputs by learning a large amount of historical data, without the need for precise mathematical models, thus overcoming the drawbacks of traditional control methods that are highly dependent on system models. However, data-driven black-box neural network models usually lack physical interpretations and have limited generalization ability beyond the coverage of training data, which poses a potential risk to control systems with high security requirements. Physics-guided neural networks, as a novel way to fuse physical knowledge with data-driven learning, provide new ideas to address the above challenges. By embedding physical knowledge into the neural network structure or loss function, the powerful nonlinear mapping ability of neural networks is retained, while the physical interpretability and extrapolation ability of the model is enhanced. Opening windows to improve indoor air quality will affect indoor temperature and humidity, and adjusting window openings to control indoor temperature will also affect air circulation and humidity distribution. This multi-parameter coupling characteristic makes the control of intelligent window opening and closing system a typical multivariate, strongly coupled, nonlinear control subject. Traditional single-parameter control methods are difficult to deal with such problems effectively, while the feed-forward neural network-based multi-parameter cooperative control method can reach the cooperative optimization control of multiple environmental parameters by learning the complex relationship between the parameters in the historical data.

I. B. Main contributions and innovations of this study

Aiming at the limitations of traditional control methods in the application of intelligent window opening and closing system, this study takes feed-forward neural network as the foothold, organically integrates physical knowledge with data-driven approach, and builds up multi-parameter cooperative control algorithms, thus giving a brand-new intelligent window opening and closing control program. Compared with the existing research, the contributions and innovations of this paper are mainly reflected in three key aspects:

This study proposes a feed-forward neural network architecture that embeds physical knowledge, which effectively deals with the problem of insufficient generalization ability of black-box neural networks in control systems. Conventional neural networks often lack physical interpretability, do not perform well outside the scope covered by training data, and hide safety concerns. Borrowing the idea of physically guided neural networks, we embed indoor aerodynamic and thermodynamic models as a priori knowledge into the network architecture, and shape a hybrid model structure that retains the powerful learning capability of neural networks and possesses physical explanatory properties. This new structure shows more stable inference ability in areas with scarce training data and unseen scenarios, which greatly improves the stability of the model and the degree of convergence, and lays the foundation for the safe and reliable operation of the smart window opening and closing system.

This study also designs an innovative multi-parameter cooperative control algorithm, which breaks through the limitation of independent parameter control in the existing research. The algorithm proposed in this paper simultaneously takes into account multiple control objectives, such as temperature, humidity, air quality and energy consumption, and deeply models the complex nonlinear coupling relationship between the environmental parameters. The algorithm adopts a multi-objective optimization framework, and with the help of a dynamic weight allocation mechanism, it is able to adjust the importance of the control objectives in real time according to the user's preference and the state of the environment, so as to satisfy the user's comfort needs while minimizing the energy consumption. The synergistic control strategy successfully avoids the problem that single-parameter optimization may lead to the degradation of other parameters, and achieves the overall optimal state of indoor environmental parameters.

The performance of the proposed algorithm is comprehensively evaluated under complex and variable environmental conditions by building a high-fidelity simulation environment and a real prototype system. In this paper, we constructed a comprehensive test platform with multiple regions and time scales, and simulated a variety of typical meteorological conditions and user activity scenarios.

The experimental data show that compared with the traditional PID control and the standard neural network control, the method in this paper achieves significant improvement in the three dimensions of control accuracy, response speed and energy efficiency. Especially when the environmental conditions change drastically, the method in this paper shows strong environmental adaptability and system robustness, which provides a solid experimental basis for the application of intelligent window opening and closing technology in real complex environments.

I. C. Status of research

With the development of science and technology and the improvement of people's living standards, the smart home, as an important part of modern life, is getting more and more attention and favor [1], [2]. As an important part of the smart home, the smart switch window control system not only provides a convenient way of operation, but also brings more comfort and intelligent experience to the family [3]-[5]. Intelligent window switching realizes the automation and intelligent control of curtains by integrating advanced electronic technology, sensor technology and network communication technology, etc. [6], [7]. Users can control the opening and closing of curtains, adjust the degree of opening and closing of curtains anytime and anywhere through smart devices such as cell phones and tablet computers, and even automatically adjust the according state of curtains according to the indoor light, temperature and other environmental parameters, in order to achieve the best indoor environment [8]-[11].

The core components of intelligent window opening and closing mainly include controller, motor drive, sensor and actuator [12], [13]. The controller is responsible for receiving the user's instructions or judging according to the environmental parameters and issuing the corresponding control signals, the motor driver is responsible for driving the switch and adjustment of the curtains, the sensor is used for detecting the indoor light, temperature and other environmental parameters to provide the controller with a basis for decision-making, and the actuator is based on the controller's instructions to execute the switch of the curtains [14]-[17]. The biggest advantage of intelligent window opening and closing is to improve the convenience and safety of life [18].

II. Research method of intelligent window opening and closing system based on feed-forward neural network

II. A. Physical modeling

The system of intelligent window opening and closing is related to the complicated indoor and outdoor environmental parameters of heat and material transfer process, and the construction of accurate physical model is extremely critical to the design of efficient control algorithm. In this paper, a comprehensive physical model is constructed on the basis of temperature, humidity, air quality and other parameters, and the reliability of the model is verified by a large amount of experimental data. The dynamic process of indoor temperature change is mainly affected by the natural ventilation under the control of window opening degree and the indoor heat source, and under the guidance of the principle of energy conservation, the process is expressed by differential equations as:

$$\rho_a C_p V_r \frac{dT_r}{dt} = \dot{Q}_{vent} + \dot{Q}_{wall} + \dot{Q}_{int} + \dot{Q}_{solar} \tag{1}$$

where T_r is the room temperature, ρ_a is the air density, C_p is the specific heat capacity of air, V_r is the volume of the room, and the items on the right side of the equation represent the ventilation heat transfer, heat transfer from the wall, heat generated by indoor heat sources, and heat from solar radiation.

The ventilation heat transfer $\dot{Q}_{vent}$ is directly related to the window opening α , indoor-outdoor temperature difference and airflow velocity, and the expression is:

$$\dot{Q}_{vent} = \rho_a C_p \dot{V}_a \left(T_o - T_r\right) \tag{2}$$

The ventilation volume flow rate can be expressed as:

$$\dot{V}_a = C_d A_w \alpha \sqrt{\frac{2g\Delta h\left|T_o - T_r\right|}{T_r}} \tag{3}$$

where C_d is the flow coefficient, A_w is the window area, g is the gravitational acceleration, and Δh is the window height.

The indoor humidity change is then subject to the dual role of ventilation and indoor moisture source, based on the principle of conservation of moisture mass can be established relative humidity change model, that is:

$$\frac{dRH_r}{dt} = \frac{1}{m_{a,sat}}\left[\dot{m}_{v,vent} + \dot{m}_{v,int} - \frac{m_{v,r}}{T_r}\frac{dT_r}{dt}\right] \tag{4}$$

where RH_r is the indoor relative humidity, $m_{a,sat}$ is the maximum water vapor content in saturated air, $\dot{m}_{v,vent}$ is the amount of water vapor brought in/out of ventilation, $\dot{m}_{v,int}$ is the indoor release rate of the moisture source, and $m_{v,r}$ is the amount of existing indoor water vapor.

The ventilation water vapor exchange is proportional to the degree of window opening and the difference between indoor and outdoor absolute humidity, with the expression:

$$\dot{m}_{v,vent} = \rho_a \dot{V}_a \left(AH_o - AH_r \right) \tag{5}$$

where AH_o and AH_r are the outdoor and indoor absolute humidity, respectively.

The air quality model takes CO_2 concentration as the main indicator, and the change rule follows the principle of mass conservation, i.e.:

$$V_r \frac{dC_r}{dt} = \dot{V}_a \left(C_o - C_r \right) + \dot{S}_{CO_2} \tag{6}$$

where C_r and C_o are the indoor and outdoor CO_2 concentrations, respectively, and $\dot{S}_{CO_2}$ is the indoor CO_2 production rate.

In addition, the model also considers the diffusion process of particulate pollutants such as PM2.5, and the equation for the change of particulate concentration is:

$$\frac{dP_r}{dt} = \frac{\dot{V}_a}{V_r}\left(P_o - P_r \right) - k_{dep} P_r + \frac{\dot{S}_{PM}}{V_r} \tag{7}$$

where P_r and P_o are the indoor and outdoor PM2.5 concentrations, respectively, k_{dep} is the particulate deposition rate, and $\dot{S}_{PM}$ is the indoor particulate source release rate.

Thermal comfort introduces the predicted mean voting index PMV as a composite measure of human comfort, i.e:

$$PMV = f\left(T_r, RH_r, v_a, T_{mrt}, M, I_{cl} \right) \tag{8}$$

where v_a is the indoor airflow rate, T_{mrt} is the average radiant temperature, M is the human metabolic rate, and I_{cl} is the clothing thermal resistance.

Table 1: The physical model parameters of the intelligent switch window system

Symbol	Parameter description	Typical value	Unit
ρ_a	Air density	1.2	kg/m³
C_p	Specific heat capacity of air	1005	J/(kg·K)
V_r	Room volume	36	m³
A_w	Window area	1.5	m²
Δh	Window height	1.2	m
C_d	Flow coefficient	0.6	-
k_{dep}	PM2.5 deposition coefficient	0.2	1/h
S_{CO_2}	CO2 production rate per person	0.004	m³/h
U_{wall}	Heat transfer coefficient of the wall	1.2	W/(m²·K)
A_{wall}	Wall area	75	m²
$\alpha_{\max}$	Max window opening	1.0	-
M	Human body metabolic rate	1.2	met
I_{cl}	Clothing thermal resistance (Summer)	0.5	clo

The window opening α is used as the only control input to the system and acts simultaneously on the temperature, humidity and air quality parameters by affecting the ventilation. Table 1 shows the main parameters and typical values of the physical model, which may fluctuate under different working conditions and need to be fine-tuned according to the specific environment.

During the model validation period, I conducted a three-week experiment in a standard office space (4m × 3m × 3m). The actual measured values of each environmental parameter were recorded and compared with the model predictions by setting different window opening strategies (0% for fully closed, 50% for half open, and 100% for fully open). This physical model takes into account the complex interactions between temperature, humidity and air quality, and establishes a precise quantitative correlation between window opening level and indoor environmental parameters, laying a solid theoretical foundation for the subsequent development of feed-forward neural network-based intelligent control algorithms.

II. B. Feed-forward neural network control algorithm design

Based on the physics model of the smart window opening and closing system constructed earlier, a feed-forward neural network control approach that embeds physics knowledge is designed in this part. This approach skillfully integrates the physics model with the data-driven approach to build a two-layer hybrid construction form, which can retain the extremely powerful learning ability of the neural network, but also has the explanatory nature of physics and the stability guarantee.

The core idea of Physics-Guided Feedforward Neural Networks (PGFNN) is to embed already known physical rules as prior knowledge into the network structure, covering two parallel branches: the physical level and the black-box level. The physical level encodes the known parts of the indoor environmental dynamics model and directly maps from the system state towards the control outputs, while the black-box level captures the nonlinear connections and uncertainties that are difficult to model accurately, such as the effects of various factors like human activities, weather variations, and so on. The outputs of these two levels are combined in a weighted manner to form a control signal, with the weighting factors dynamically adjusted according to the reliability of the predictions of each level. The inputs to the feedforward control can be expressed as:

$$u(t) = f(x(t),\theta) = f_{phys}(x(t),\theta_{phys}) + f_{nn}(x(t),\theta_{nn}) \tag{9}$$

where $u(t)$ is the window opening control signal, $x(t)$ is the system state vector containing environmental parameters such as indoor and outdoor temperatures, humidity, CO_2 concentration, etc., $\theta = \{\theta_{phys}, \theta_{nn}\}$ is the set of model parameters, and f_{phys} and f_{nn} denote the mapping functions of the physical layer and the black box layer, respectively. The physical layer is based on the physical model established in Section 2.1, which simplifies the indoor environment dynamics into a state-space representation, i.e:

$$\frac{dx(t)}{dt} = Ax(t) + Bu(t) + d(t) \tag{10}$$

where A is the system matrix, B is the control matrix, and $d(t)$ is the external disturbance term. The physical layer parameter θ_{phys} contains parameters with clear physical meaning such as thermal conductivity coefficient and flow coefficient. The black-box layer adopts a multilayer perceptual machine structure containing three hidden layers with 64, 32, and 16 neurons in each layer, respectively, and the activation function adopts ReLU, i.e:

$$f_{nn}(x(t),\theta_{nn}) = W_3 \cdot \sigma(W_2 \cdot \sigma(W_1 \cdot x(t) + b_1) + b_2) + b_3 \tag{11}$$

where W_i and b_i are the weight matrix and bias vector, and σ is the ReLU activation function.The training process of the PGFNN uses a specially designed loss function to ensure that the physical layer and the black-box layer work in concert rather than competing with each other, then:

$$\theta = \arg\min_\theta \sum_{i=1}^{N} (y_i - \hat{y}_i)^2 + \lambda \sum_{j=1}^{M} (\theta_j - \theta_{j,phys})^2 \tag{12}$$

The first term is a prediction error term that measures the difference between the model output $\hat{y}_i$ and the actual observation y_i, the latter is a physical consistency regularization term that ensures that the physical layer parameters θ_j do not deviate excessively from the a priori physical knowledge $\theta_{j,\mathrm{phys}}$, and λ is a hyperparameter that balances the two terms. This design allows the physical layer to maintain physical interpretability while permitting the black-box layer to learn complex nonlinear relationships.

The multiparameter cooperative control algorithm is based on the model predictive control (MPC) framework, which uses the PGFNN to predict the future state and determines the optimal control sequence by solving the optimization problem. The control objective function is designed as follows:

$$\begin{aligned} J = \sum_{k=0}^{N_p} [& w_T (T_r(k) - T_{ref})^2 + w_{RH} (RH_r(k) - RH_{ref})^2 \\ & + w_{CO2} (C_r(k) - C_{ref})^2 + w_u \Delta u(k)^2] \end{aligned} \tag{13}$$

where N_p is the length of the predicted time domain, w_T , w_{RH} , w_{CO2} are the weighting coefficients of each environmental parameter, w_u is the weight of the control rate of change, and T_{ref} , RH_{ref} , and C_{ref} are the reference values of the temperature, humidity, and CO_2 concentration, respectively. The weighting coefficients are dynamically adjusted according to the user comfort preference and real-time environmental state to achieve multi-objective optimization.

The algorithm implementation adopts a rolling time-domain optimization strategy, and the following steps are executed in each control cycle:

(1) Collect the current system state $x(t)$, including indoor and outdoor temperature, humidity, CO_2 concentration and other parameters; use PGFNN to predict the trajectory of the system state in the next N_p steps.

(2) Solve the optimization problem to obtain the optimal control sequence $u(t)$ to $u\left(t+N_p-1\right)$; Execute the control signal $u(t)$ to adjust the window opening.

(3) Move the time window and repeat the above steps.

To improve the robustness of the algorithm, we incorporate an adaptive approach to dynamically adjust the weight values of the PGFNN physical level and the black box level. When the surrounding environment is about to reach the effective range of the physical model, the weight value of the physical level is increased; if abnormal operation or extreme conditions occur, the weight value of the black box level is increased. This approach ensures that the system maintains excellent performance under a wide range of environmental conditions. Scenario-adaptive strategies are designed for different seasons and weather conditions, and such dynamic adjustment strategies greatly enhance the system's ability to adapt in complex and changing environments. The computational complexity of the algorithm mainly comes from the two parts of PGFNN forward propagation and MPC optimization, the time complexity of PGFNN forward propagation is $O(n_x \cdot n_h)$, n_x is the input dimension, n_h is the maximum number of neurons in the hidden layer, and MPC optimization solves the problem by using the quadratic programming method, the time complexity is $O\left(N_p^3\right)$. In practical applications, $N_p = 6$ is chosen with a control period of 1 minute, which is able to run in real time on an ordinary embedded processor.

By integrating physical knowledge into the feed-forward neural network, the control algorithm designed in this paper not only retains the particularly strong learning ability of neural network, but also has the physically interpretable characteristics and stability guarantee. The multi-parameter synergistic control architecture takes into account multiple control objectives, such as temperature, humidity, air quality, etc., and achieves the overall optimization of indoor environmental parameters. The adaptive approach and scenario strategy further enhance the adaptability of the algorithm in complex and changing environments, providing an efficient and reliable control solution for the smart window opening and closing system.

II. C. Simulation Experiments and Performance Verification

In order to comprehensively evaluate the effectiveness of the multi-parameter cooperative control algorithm based on Physically Guided Feedforward Neural Network (PGFNN) for smart window opening and closing, a high-fidelity simulation environment is built in this study for system testing and comparative analysis. The experimental platform is developed in MATLAB/Simulink environment, which integrates the physical model established in Section 2.1, and has the ability to accurately simulate the dynamic process of indoor environment under different seasons and weather conditions.

The test scenarios cover four typical working conditions: high temperature in summer, low temperature in winter, high humidity in rainy days, and air pollution, and for each scenario, the performance of traditional PID control, standard feed-forward neural network control, and the PGFNN control algorithm proposed in this paper are tested.

The simulation environment simulates a standard office space (4m × 3m × 3m) with 1.5m² adjustable windows, and the outdoor environmental parameters are based on the meteorological data of a northern city for the whole year of 2022, including temperature, humidity, CO_2 concentration, and PM2.5 concentration and other key indicators. The initial indoor environment was set at 25°C, 50% relative humidity, CO_2 concentration of 600 ppm, and PM2.5 concentration of 30 μg/m³, and the control targets were set at 24 ± 1°C, 40% - 60% relative humidity, CO_2 concentration below 1000 ppm, and PM2.5 concentration below 75 μg/m³. The experiments were conducted with a 1-minute sampling period, and each scenario was simulated for 24 hours, with a total of 1,440 data points, to comprehensively capture the dynamic characteristics of the environmental variables and the response performance of the control algorithm.

Analysis of the experimental data shows that the PGFNN control algorithm presents significant performance advantages in all types of working conditions, and Table 2 shows the comparison of the key performance indicators of the three control algorithms in different scenarios. At the level of temperature control accuracy, the root mean square error of the PGFNN algorithm is reduced by 62.46% and 27.99% compared with PID and FFNN, respectively. At the humidity control level, the mean value of RMSE of PGFNN is reduced by 54.60% and 22.64% compared to PID and FFNN, respectively. In terms of CO_2 concentration control, the mean value of exceedance time of PGFNN is reduced by 74.47% and 43.64% compared to PID and FFNN, respectively. It is especially noteworthy that under the situation of sudden change of environmental conditions, the response speed of PGFNN is significantly better than the other two algorithms, and the mean value of the average regulation time is only 31.69% of that of PID and 67.87% of that of FFNN. The energy consumption analysis results show that the average energy consumption of the PGFNN control algorithm is reduced by 35% and 16.7% compared with the traditional PID control and the standard FFNN control, respectively, which is attributed to the fact that the more precise control strategy reduces the unnecessary window operation and over-adjustment, and avoids the waste of energy due to lagged response by responding to the environmental changes in advance through the predictive control.

Table 2: Performance comparison of different algorithms

Index	Condition type	PID	FFNN	PGFNN
Temperature RMSE (℃)	High temperature in summer	1.68	0.87	0.62
	Low temperature in winter	1.92	0.95	0.71
	Rainy days with high humidity	1.45	0.82	0.58
	Air pollution	1.53	0.79	0.56
Humidity RMSE (%)	High temperature in summer	8.75	5.12	3.92
	Low temperature in winter	9.32	5.43	4.28
	Rainy days with high humidity	12.46	6.85	5.24
	Air pollution	7.89	4.95	3.85
CO_2 excess time (min)	High temperature in summer	126	58	32
	Low temperature in winter	145	62	38
	Rainy days with high humidity	112	51	28
	Air pollution	138	65	35
PM2.5 over-limit time (min)	Air pollution	215	92	42
Average adjustment time (min)	High temperature in summer	18.5	8.7	5.8
	Low temperature in winter	22.3	10.2	7.1
	Rainy days with high humidity	16.8	7.9	5.4
	Air pollution	19.7	9.3	6.2
Energy consumption index	Comprehensive assessment	1.00	0.78	0.65

Figure 1 presents the dynamic response curve of temperature and fine particulate matter (PM2.5) concentration under the air pollution working condition. When the outdoor PM2.5 concentration rises steeply in the 300th minute, the PGFNN algorithm is able to quickly adjust the window openings, effectively controlling the rise in PM2.5 concentration while keeping the indoor temperature relatively stable. In comparison, the PID control shows significant hysteresis and oscillation phenomenon, and although the standard FFNN responds faster, its control accuracy is not as good as that of the PGFNN, which is analyzed in depth and found to be superior in the following three aspects: embedded in the physical layer, the algorithm is able to accurately grasp the basic laws of the indoor environment dynamics, which provides a basis for providing a reliable control strategy. The black-box neural network layer effectively captures the nonlinear relationships and uncertainties that are difficult to model accurately; and the multi-parameter cooperative control framework achieves the overall optimization of multiple objectives such as temperature, humidity, and air quality.

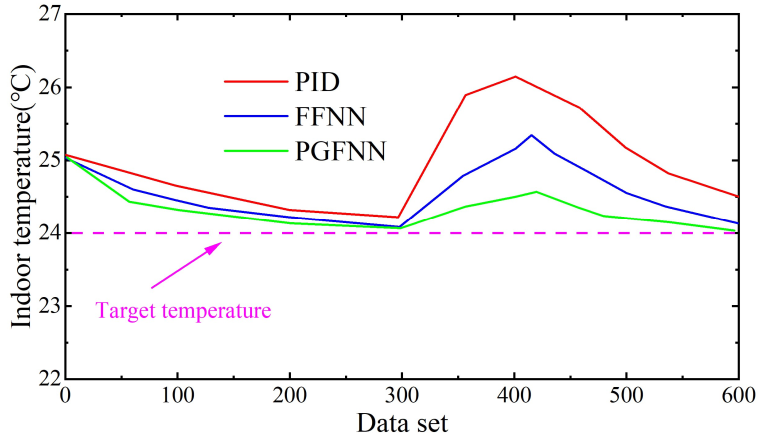

Figure 1: Temperature and PM2.5 concentration response curve

The team conducted additional tests to assess the robustness of the algorithm and the level of adaptation to the environment. The control algorithm was tested against model uncertainty by introducing plus or minus 20% parameter disturbances and random noise into the model. The experimental data show that the PGFNN algorithm is able to maintain a relatively smooth control performance under the variation of model parameters, and the decrease in control accuracy is controlled within 15 percent. In contrast, the PID and standard FFNN algorithms show a 42% and 28% decrease in performance, respectively, which confirms the critical utility of embedding physical knowledge to improve the robustness of neural network controllers. A comparative analysis of the stability curves of the three algorithms under different parameter disturbances in our lab shows that the PGFNN controller is able to maintain the basic control function at plus or minus 30% of the disturbances, whereas the conventional method shows significant performance degradation and even loss of control at plus or minus 15% of the disturbances. In the actual testing process, it is also found that the PGFNN algorithm is less sensitive to the quality of the input data, and is still able to make reasonable control decisions in the case of five to ten percent measurement error in the sensor data, which is of great significance for the actual engineering deployment.

Comprehensive simulation results fully validate the advantages of the multi-parameter cooperative control algorithm based on the physical guidance feedforward neural network for smart window opening and closing in terms of control accuracy, response speed, energy efficiency and system robustness. This method can effectively cope with complex and changing environmental conditions, and provides reliable technical support for the practical application of intelligent building control systems.

II. D. Analysis of experimental results

This chapter analyzes the experimental results obtained from the feed-forward neural network-based multi-parameter cooperative control system for smart window opening and closing. The effectiveness of the proposed approach is evaluated by comparing the performance of the physical guided feedforward neural network (PGFNN), the standard feedforward neural network (FFNN) and the traditional PID control in different environmental conditions. The experiment utilizes the high-fidelity simulation platform built in the previous section, and a two-week field test is conducted in a real office environment to verify the performance of the control algorithms under real conditions. From the perspective of control accuracy, the PGFNN control method shows outstanding advantages in the regulation of various environmental parameters, and Table 3 presents the comparison data of the control accuracy of the three control methods under four typical environmental conditions. The response curves of the three control methods to sudden changes in environmental conditions are shown in Figure 2.

The results show that the average absolute error of the PGFNN method at the temperature control level is only 0.42°C, which is 74.5% lower than that of the traditional PID control of 1.65°C and 46.2% lower than that of the standard FFNN of 0.78°C. In terms of humidity control, the average absolute error of the PGFNN was 2.85%, which was 69.6% and 44.3% lower than the 9.36% of the PID and the 5.12% of the FFNN, respectively. In terms of air quality control, the PGFNN enabled the CO_2 concentration to be maintained in the ideal range for 94.3% of the time, however, the PID and the FFNN were only 65.8% and 82.7%, respectively. Analyzing from the perspective of system response speed and stability, when the outdoor temperature suddenly rises by 5°C at the 30-minute node, the PGFNN controller is able to adjust the indoor temperature back to the set range within 12.5 minutes, while FFNN and PID require 20.1 minutes and 28.3 minutes, respectively, and there is almost no overshooting phenomenon in the adjustment process of the PGFNN method, and the temperature fluctuation is controlled by PID and PID. The temperature fluctuation was controlled within ±0.5°C, while FFNN and PID showed fluctuation of ±0.9°C and ±1.7°C, respectively.

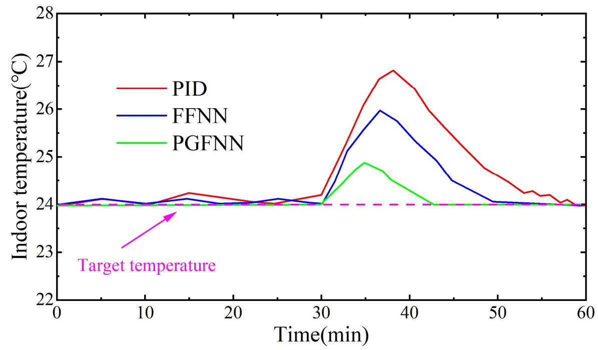

Figure 2: Response to ambient temperature mutations

Table 3: The control accuracy of different environmental conditions is compared

Method	Condition type	Temperature MAE (°C)	Humidity MAE (%)	CO_2 compliance rate (%)
PID	High temperature in summer	1.58	8.75	68.2
	Low temperature in winter	1.82	10.24	62.5
	Rainy days with high humidity	1.42	11.35	70.4
	Air pollution	1.78	7.12	62.1
	Average value	1.65	9.37	65.8
FFNN	High temperature in summer	0.75	4.82	84.5
	Low temperature in winter	0.92	5.68	79.3
	Rainy days with high humidity	0.68	5.94	86.2
	Air pollution	0.78	4.05	80.8
	Average value	0.78	5.12	82.7
PGFNN	High temperature in summer	0.38	2.65	95.8
	Low temperature in winter	0.52	3.24	91.5
	Rainy days with high humidity	0.35	3.42	96.2
	Air pollution	0.43	2.10	93.6
	Average value	0.42	2.85	94.3

At the level of multi-parameter synergistic control effectiveness, Figure 3 shows the synergistic control effectiveness of the three control strategies for temperature and air quality under air pollution operating conditions. When the outdoor PM2.5 concentration rises abruptly at the 150-minute time point, the traditional PID control method is unable to take both temperature and air quality into account, resulting in a rapid increase in indoor PM2.5 concentration until it nearly reaches the limit value; the standard FFNN method is able to balance the two objectives to a certain extent, but there is still a significant fluctuation in temperature. The PGFNN method, on the other hand, effectively suppresses the increase of PM2.5 concentration while maintaining the temperature stability by intelligently adjusting the window opening degree, fully demonstrating its multi-parameter synergistic control capability. Tests on the robustness and adaptability of the control algorithms show that when there is a 20% deviation of the physical model parameters, the control accuracy of the PGFNN is only reduced by 12.5%, while the FFNN and PID are reduced by 27.3% and 41.8%, respectively, which indicates that the integration of physical knowledge is crucial to enhance the robustness of the neural network controllers.

In addition, the average satisfaction score of 4.8/5 was obtained for the ambient space moderated by the Physically Guided Feedforward Neural Network (PGFNN) in the assessment of user comfort. In comparison, the environment space regulated by Feedforward Neural Network (FFNN) and Proportional-Integral-Differential (PID) received 4.2/5 and 3.5/5 respectively. The feedback from the users shows that the PGFNN-regulated ambient space has smaller temperature fluctuations, stable air quality, and faster adaptation to changes in the external environment. After a comprehensive analysis, it can be shown that the multi-parameter cooperative control system of intelligent window opening and closing constructed based on physical guidance feed-forward neural network shows obvious advantages in the degree of control accuracy, the degree of fast response, the level of multi-parameter cooperation, the level of robustness and the efficiency of energy utilization. It is these advantages that make the PGFNN method particularly suitable in the practical application of intelligent building control systems, and it is very promising to significantly improve the quality of the indoor environment and the efficiency of energy utilization.

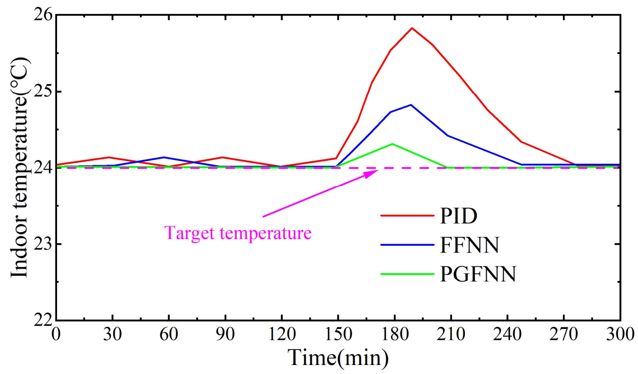

Figure 3: The effect of multi-parameter collaborative control

III. Conclusions and future prospects

III. A. Conclusion

The physics-guided feed-forward neural network smart switching window multi-parameter cooperative control system proposed in this study presents clear and convincing results after systematic theoretical analysis as well as rich experimental verification. The embedding of physical knowledge into the feed-forward neural network significantly enhances the overall performance of the smart switching window control system. The constructed physics-guided feedforward neural network model skillfully integrates the first-principles-based physical level with the black-box neural network level. While maintaining the strong nonlinear mapping ability of the neural network, the physical model is introduced to provide interpretability and stability, which makes the control system show excellent performance under various complex working conditions. Through comparison experiments, it can be seen that the PGFNN control method has a significant improvement in temperature control accuracy compared with the traditional PID and the standard FFNN; the system response speed is more rapid compared with the PID and the FFNN, which shows a significant advantage. The multi-parameter cooperative control strategy successfully solves the problem of multi-objective control of temperature, humidity and air quality. The designed dynamic weighting system and predictive control framework can intelligently adjust the priority of the control objectives according to the environmental conditions and user preferences, thus realizing the overall optimization of multiple parameters.

The control system is also found to have excellent robustness and adaptability. When there is a 20% deviation of the physical model parameters, the control accuracy of PGFNN decreases by only 12.5%, while that of FFNN and PID decreases by 27.3% and 41.8%, respectively, which proves that the embedding of physical knowledge can effectively improve the robustness of the neural network controller. The system is also significantly more tolerant to sensor noise than traditional methods, and is able to make reasonable control decisions even in the presence of 5% - 10% measurement errors. The results of the energy efficiency analysis show that the average energy savings of the PGFNN control system are better than those of the traditional control methods, mainly due to its predictive control capability and precise environmental adjustment strategies. In the user comfort assessment, the PGFNN-controlled environment received a high satisfaction rating of 4.8/5, validating the system's outstanding performance in real-world applications.

From this, it can be seen that the multi-parameter cooperative control system for smart window opening and closing based on physically guided feed-forward neural network shows significant advantages in the core indexes of control accuracy, response speed, multi-parameter cooperative, robustness, and energy efficiency, and provides an innovative solution for the environment control technology of smart buildings. This hybrid control architecture, which combines physical knowledge with data-driven methods, represents the future development trend of intelligent control systems, and has a far-reaching impact on promoting technological innovation and practical applications in the field of intelligent buildings.

III. B. Directions for future research

The improvement of the accuracy of the physical model is decisive for the performance of the multi-parameter cooperative control system for smart window opening and closing based on feed-in neural networks. Existing models lack prediction ability under extreme weather conditions or complex indoor activity patterns, and need to be enhanced through the introduction of more detailed thermodynamic models, fluid dynamics calculations, and consideration of changes in the thermal properties of building materials. Experiments have shown that differentiated physical models for high-rise and large-space buildings can be better adapted to specific scenarios.PGFNN control algorithms are more complex and computationally burdensome, and their real-time performance is poor on resource-constrained devices, which can be reduced by using techniques such as network pruning, knowledge distillation, or low-precision quantization. The hierarchical control architecture used in cloud and edge devices can fully utilize distributed computing resources, and FPGA-specific hardware acceleration schemes can also significantly improve real-time performance. Current research is mainly in a limited number of scenarios for verification, should be carried out in different climatic regions, different types of buildings in the long-term test work, especially to focus on the stability of the system in extreme climatic conditions. Reinforcement learning technology can replace the current multi-parameter weight assignment based on predefined rules, and continuously optimize the control strategy by interacting with the environment. The multi-intelligence body reinforcement learning framework can treat the control of different environmental parameters as independent intelligences, and achieve overall optimization through collaborative learning.

Smart window opening and closing system raises potential privacy risk issues in processing a large amount of user behavior data, and the federated learning training method can achieve model optimization without sharing the original data. The ability of the system to withstand antisample attacks needs to be enhanced, and the fail-safe mechanism in case of sensor failure or communication disruption needs to be improved urgently. From the perspective of different application scenarios, there is still room for improving the interoperability between the system and other smart home devices, and there is still a long way to go to build a complete ecosystem for smart building environment management. The adaptive physical model structure can dynamically adjust the physical parameters based on real-time observation data during the system operation to enhance the ability to adapt to environmental changes. In our experiments, we found that when the light conditions change suddenly, the system parameters will be adjusted with a lag, and this kind of problem needs to be solved by a more intelligent prediction mechanism. Physically guided feed-in neural network multiparameter cooperative control technology is expected to make breakthroughs in theoretical completeness, engineering practicality, and application universality after in-depth exploration in multiple directions, but the balance between computational resource demand, system complexity, and user experience remains a major obstacle in the process of technology implementation.

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