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# Delay Compensation Strategy of Networked Control System Based on Neural Network Predictive Control

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**Abstract**: The transmission delay of information in the network environment degrades the performance of networked control system, so it is necessary to compensate the delay in networked control system. This paper proposes a delay compensation strategy for networked control system based on neural network predictive control. Firstly, the back propagation neural network is optimized by the Cuckoo search algorithm to establish a delay prediction model to identify the transmission delay. The comparative experiment of actual delay data shows that the prediction accuracy of the optimized back propagation neural network has improved from 93.49% to 97.81%. Next, the multi-step delay prediction model is combined with the implicit generalized predictive control algorithm to solve the control increment at future sampling times. Finally, a delay compensation strategy is proposed, which improves control accuracy and achieves delay compensation by setting a buffer in the actuator and selecting an appropriate control increment based on the predicted delay value. The networked gas boiler control system is used as the validation object and compared with several strategies such as implicit generalized predictive control, generalized predictive control, and self correcting control. The simulation results show that compared with these delay compensation strategies, under normal working conditions, the rise time is reduced by 15.9, 22 and 21.3 seconds, the steady-state error of the system decreased by 10% to 15% after stable operation. Under disturbance, the settling time reduced by 4.7, 28.9, and 8.5 seconds, respectively. At the same time, under both working conditions, the other indicators such as initial overshoot, stable overshoot, etc., of the proposed delay compensation strategy are also minimized. The simulation results verify the effectiveness of the proposed delay compensation strategy for networked control system.

*Keywords*: networked control system, delay compensation, back propagation neural network, generalized predictive control, Cuckoo search algorithm.

## 1. INTRODUCTION

### 1.1 Background

Unlike traditional point-to-point control system, in networked control system (NCS), components are interconnected on a shared network. Specifically, even if the locations of sensors, controllers, and actuators are different, these components can still transmit shared information through the network, and the cost of installation and maintenance is lower (Liang et al., 2022). NCS has been widely applied in many fields. However, with the introduction of communication networks, due to the limited bandwidth of the network, when a large amount of data needs to be transmitted, it will lead to network congestion, queuing, and waiting. Although the remote information transmission problem in modern industrial intelligence has been successfully solved by NCS, there are also many uncertain factors in NCS itself, among which the most common problem is network communication delay. In the fields of home and office, the impact of delay is not significant, but in areas such as manufacturing and remote control that require high real-time performance, network induced delay has a significant impact on the performance of NCS, and in severe cases, it may cause incalculable losses.

From the perspective of control theory, the occurrence of delay can disrupt multiple dynamic performance indicators, such as causing an increase in overshoot, longer settling time, and so on. Even if a control system with deteriorating dynamic performance returns to stability after a period of fluctuation, its performance will still decline, and when the delay reappears, the overall stability of the control system will also decrease (Mu et al., 2024). In addition, due to the presence of network delay, it is also possible to cause packet loss or empty sampling. The current data cannot be collected, and the controller will process it based on the previous data, resulting in a lack of real-time performance in the system and seriously affecting the performance of NCS. Considering the randomness of network delay, when performing NCS delay compensation, it is necessary to treat the system with random delay as a complex nonlinear system, which undoubtedly increases the difficulty of controller design. Therefore, it is necessary to compensate for the negative effects of delay in NCS through effective strategies (Wu et al., 2022). This study conducts corresponding research on the delay compensation of NCS. Establish a delay compensation scheme based on neural network predictive control for the delay problem of nonlinear NCS.

### 1.2 Literature review

As the most intuitive issue in NCS, effective delay compensation strategies are of great significance for promoting the development of control theory and industrial practical applications. Researchers have made some efforts in both communication and control aspects.

*A. Research on communication networks*

There is a certain correlation between the control effect of NCS and the nodes in the network. In the study of communication networks, careful consideration should be given to the actual bandwidth situation, and the selected network protocol can serve as a theoretical basis for analyzing the delay phenomenon in NCS. Generally speaking, the probability of network delay occurring is directly related to the transmission scale of data packets. Analyzing the generation of delay phenomenon requires considering multiple factors in NCS, among which the upper limit of network bandwidth and the compatibility between communication protocols and networks will have a certain impact on delay in NCS. Therefore, reducing delay from a communication perspective is particularly meaningful for maintaining the stability of NCS. Some common strategies include variable sampling period (Truong and Ahn, 2015), dead band feedback (Phu and Mien, 2020), variable sampling period and dead band (Lian, 2023) and co-design control (Lu and Guo, 2023).

However, there is a certain contradiction between communication protocols and control performance. From a control perspective, it is hoped that the network bandwidth will be large and the information transmission rate will be high, but these will lead to an increase in data transmission, thereby increasing the probability of network congestion. From a communication perspective, it is hoped that sensors and controllers will send as little data as possible to alleviate network bandwidth pressure.

*B. Research on control theory*

From the perspective of control theory, analyzing delay requires assuming that other parameters in NCS, such as packet loss rate, are fixed and unchanged. Design controllers in a network environment to compensate for NCS delay and packet loss. Common delay compensation strategies include the following strategies.

Deterministic control strategy. The design concept of this strategy is the delay shaping method. Before designing the controller, set up data buffers in the actuators and controllers in NCS. Then, the data readout mode is changed to directly read data from the data buffer based on the clock. The original uncertain communication delay can be converted into a common fixed delay, thereby reducing the uncertainty of the system and reducing the design difficulty of the system controller. The authors proposed a distributed linear Kalman filter with the memory principle to determine the uncertainty of data transmission. Simulations involving abrupt fault and degradation datasets of networked aircraft engines are carried out to numerically evaluate and compare the performance of the proposed approach with dual-channel uncertainty (Jin et al., 2023). In their study (Zhang et al., 2015), for the delay in the forward channel, the buffer and packet-based delay compensation approaches are presented, respectively. A servo motor control system is used to demonstrate the effectiveness of the proposed new design scheme. The disadvantage of this strategy is that the set data buffer is difficult to adapt to rapidly changing delay, and excessive fixed delay can cause a decrease in NCS performance.

Stochastic control strategy. The main idea of stochastic control is to idealize network delay into some known random distributions, and model and analyze NCS according to the distribution law of network delay. Therefore, in many studies, network delay is modeled as a jumping stochastic sequence, and random theory is used to compensate for the delay. In their study, the random interval delay is considered to obey a certain uncorrelated Bernoulli distribution white noise sequence. Then, an improved time continuous delay system model for NCS is constructed by using input delay method. The effectiveness of the proposed method is verified by two simulation examples (Wang et al., 2022). Similarly, the authors considered network induced delay as Gaussian distribution (Deng et al., 2013). The delay in actual NCS is influenced by many factors, and it is difficult to conform to a specific mathematical distinction. The delay presents more random characteristics. Delay exhibits more random features, which leads to inaccurate estimation of delay by the model and has a significant impact on the performance of NCS.

Robust control strategy. The Robust control strategy can be used to solve the problems of random delay and data packet loss in networked control systems. The design of the controller makes the system more robust. Steinberger and Horn proposed a Robust filtered Smith predictors for NCS with packet-based data transmission. Three network protocols, which use different packet selection and hold mechanisms, are considered to state criteria for the robust stability of the networked feedback loops with filtered Smith predictors (Steinberger and Horn, 2022). In the literature, the authors proposed a discrete predictor-based control method for a class of linear time-invariant NCS with a sensor-to-controller time-varying delay and a controller-to-actuator uncertain constant delay. The simulation results illustrated the effective of the study (Deng et al., 2022). Robust control methods typically rely on the mathematical model of the system, and the design process is relatively complex. When there are errors in the model, the control effect may decrease. Meanwhile, for highly nonlinear systems, the steady-state accuracy of robust control is poor.

Predictive control strategy. When there is network delay in the system, the controller predicts current and future output information based on the model information of the control object and previous sampling information. By predicting the output value to replace the actual data generated due to delay or loss, the system can operate stably. Predictive control strategies that can be applied to NCS delay compensation include generalized predictive control (Ye et al., 2017; Kong and Zhang, 2020), model predictive control (Li et al., 2022; Bahraini et al., 2022), dynamic matrix control (Tian et al., 2021), etc. Predictive control requires iterative solving of optimization problems at each time step, and solving optimization problem is often time-consuming. The actions of the controller may have stronger real-time requirements, which can lead to conflicts.

Sliding mode control strategy. Sliding mode control (SMC) is a nonlinear control method, which can make the system have strong robustness on the sliding mode surface. These characteristics of SMC can effectively solve the delay problem of NCS. In the study, based on the derived sliding mode function, a reduced-order networked sliding mode dynamics with communication delay is established. Simulation results illustrated the effectiveness and merit of the developed method (Li and Peng, 2022). The authors reviewed the SMC application for NCS. The results of the SMC applied to NCS with basic constraints, including packet dropouts, time delays and signal quantization are given in details (Zhou et al., 2022). In their study, the authors designed a novel SMC method to address the robust stabilization problem for uncertain time-varying NCS. The simulation results show that the designed SMC can make the NCS gradually stable (Hou et al., 2022). Considering SMC for a class of uncertain switched systems with state and input delays, by employing a weighted sum of the input matrices, a common sliding surface is designed. A numerical example is given to demonstrate the effectiveness of the proposed method (Liu and Niu, 2018). The main drawback of SMC is the chattering phenomenon. The chattering phenomenon is caused by the frequent switching of control signals on the switching surface, which leads to the system traversing back and forth on the sliding surface, resulting in chattering. The introduction of network delay can exacerbate the chattering phenomenon, which greatly affects the stability and control accuracy of NCS.

Neural networks. Neural networks have excellent modeling capabilities and are therefore used for delay compensation in NCS. Ma and Wang designed an adaptive compensation control method based on multiple neural networks. Considering the nonlinear systems with time-varying delays, a neural network method is adopted to approximate the unknown nonlinear structure with time-varying delays. Simulation results demonstrate the effectiveness of the designed scheme (Ma and Wang, 2023). In their study, the authors proposed a time-delay prediction control system based on the PSO-RBF neural network for NCS. The results from the true-time simulation platform show that the delay prediction control system based on the PSO-RBF network is effective (You et al., 2023). In recent years, some deep learning models have also been used in NCS, such as long short-term memory (Kim et al., 2022), reinforcement learning (Redder and Quevedo, 2019), etc. However, deep learning models typically require a large amount of sample data, high computational complexity and cost, and low real-time performance. Therefore, many NCS scenarios are not suitable for using deep learning models for control or delay compensation. At present, the neural networks applied in NCS are still mainly based on traditional models.

Neural network predictive control. This strategy combines the advantages of predictive control and neural networks, namely the approximation ability of neural networks to nonlinear models and the traditional advantages of predictive control in multi-step prediction and rolling optimization. Sharma et al. designed an intelligent feedback controller based on an artificial neural network. The predicted feedback gain parameters with the learning mechanism ensure the NCS stable (Sharma et al., 2023). In their study, the authors proposed a model predictive control scheme incorporating integral sliding mode to deal with a class of uncertain nonlinear systems. In the proposed approach, two deep neural networks are employed to estimate the drift dynamics and control effectiveness matrix of the system. The proposal is assessed in simulation on the classical Duffing oscillator with satisfactorily results (Sacchi et al., 2024). In the literature (Han et al., 2023), based on a Fuzzy neural network, an iterative learning model predictive control is designed for complex nonlinear systems. The experimental results verify the effectiveness and superiority of the designed controller. Based on the above overview of neural network predictive control, researchers have proposed many control strategies and solutions for control problems in industrial production, which have been widely applied in various engineering applications with delays, such as nuclear power plant (Lv et al., 2024), autonomous underwater vehicle (Zhao et al., 2024), heating systems (de Giuli et al., 2024) and so forth.

*1.3 Contributions of the paper*

Most current strategies have certain limitations in the delay compensation problem of NCS, such as excessive reliance on accurate mathematical models, constraints on the controlled object under assumed conditions, or long online calculation time. Considering that the generalized predictive control (GPC) uses rolling optimization to predict the output of NCS, it is effective to solve the problem of delay in NCS, and it is worth further studying. Considering the complexity of the system and the excellent approximation ability of neural networks to nonlinear systems, this paper proposes a NCS delay compensation strategy combining implicit generalized predictive control (IGPC) and back propagation (BP) neural network prediction model. The main innovations of this paper are as follows.

(1) A delay prediction model based on Cuckoo search algorithm optimized BP (CS-BP) neural network is proposed to predict delay samples. The trained prediction model can be used to accurately model random delays, replacing the controlled auto regressive integral moving average (CARIMA) model in GPC. CS-BP directly identify parameters based on input and output to improve computational efficiency

(2) The CS-BP model is combined with IGPC to solve the control increment sequences. Set a buffer in the actuator, select appropriate control increments based on the relationship between predicted delay and sampling period, and then achieve delay compensation.

(3) The effectiveness of the proposed delay compensation strategy is tested using a networked gas boiler control system that is close to the actual industrial background. Many performance indicators demonstrate the effectiveness of the proposed strategy.

(4) The proposed delay compensation strategy solves the problem that NCS cannot provide high-precision models in industrial backgrounds, and has low computational complexity, which has certain application prospects.

*1.4 Structure of the paper*

The rest content of this paper is arranged as follows. The preliminaries of delay in NCS are introduced in Section 2. Section 3 gives the implementation process of the developed CS-BP model for NCS delay. Section 4 gives the implementation process of the designed delay compensation strategy. Section 5 shows the verification of the effectiveness of the proposed delay compensation strategy. The conclusions and future work are summarized in last Section 6.

## 2. PRELIMINARIES

The structure of a NCS is as shown in Figure 1. As shown in Figure 1, the delay of the NCS can be seen from different time-delay generation processes include $\tau_{sc}$ - delay from the sensor to the controller (feedback delay), $\tau_{ca}$ - delay from the controller to the actuator (forward delay), $\tau_c$ - delay for the controller to calculate the control law. From the delay in Figure 1, it can be seen that the difference from traditional control systems is that the presence of forward delay and feedback delay can change the performance of the control system and also have some negative effects on the stability of the system. In severe cases, the system performance cannot meet practical requirements, and even the system is unstable.

With the rapid progress of technology and the rapid improvement of hardware development, the delay $\tau_c$ required for the controller to calculate the control law can be ignored. Therefore, the total delay of NCS studied in this paper is as follows equation (1).

$$\tau = \tau_{sc} + \tau_{ca} \tag{1}$$

Select an appropriate compensation strategy to process total delay $\tau$ , so that the control law calculated by the controller minimizes the impact of delay in NCS on control performance.

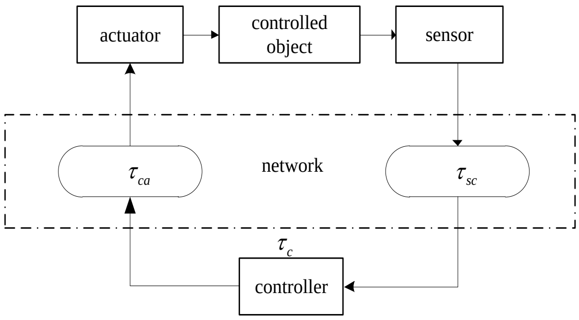


Fig. 1. The structure of a NCS.

## 3. DELAY PREDICTION BASED ON CS-BP

This section designs a delay prediction model based on CS-BP, which compensates for future delays by combining prediction with control algorithm. As a classic feed-forward network, BP neural network has been widely applied in many fields. Although BP neural network has many advantages, its convergence effect is closely related to the initial weights and bias. The parameters of BP neural network are usually configured through random initialization. In order to avoid falling into local optimal due to unreasonable parameters and achieve global fast convergence, the parameter settings of weights and bias should avoid using random generation. Research has shown that using Meta heuristic algorithms to optimize and assign values to BP neural network is currently a common approach (Cao et al., 2023; Du et al., 2023).

As a Meta heuristic algorithm, CS algorithm has many advantages such as simple structure and fewer required parameters (Zheng et al., 2023). By using the CS algorithm to solve the initialization problem of BP parameters, it is possible to predict the delay in NCS.

The CS algorithm is inspired by the nest parasitism of Cuckoos in nature. Unlike other types of position update strategies, this algorithm updates its position through Levy flight and random walking. Cuckoo lays eggs in public nests or other bird nests, increasing the success rate of hatching by disguising and removing eggs from other birds. CS algorithm follows the following three ideal rules.

(1) The Cuckoo only hatches one egg at a time and randomly selects a parasitic host's nest to lay the eggs.

(2) Compare all randomly selected bird nests and preserve the best nest for the next generation.

(3) The number of bird nests available for random selection is fixed, and the host of the nest discovers the eggs parasitized by the Cuckoo based on a certain probability. If the host discovers it, they either discard the Cuckoo eggs or abandon the current nest and choose a new one.

Let the i-th candidate solution of the evolution of the CS algorithm to the t-th generation be $X_i^t$ , and the update expression for generating new individuals using Levy flight is as follows.

$$X_i^{t+1} = X_i^t + \alpha \otimes levy(\beta) \tag{2}$$

where $X_i^t$ represents the i-th solution of the t-th generation, $\alpha$ represents the step size factor of the random search range, and $\otimes$ represents point-to-point multiplication. Levy flight is a type of flight that consists of more short distance update steps and fewer long distance update steps, which can reduce the risk of falling into local optima during the optimization process. The Mantegna method is an approximate method of Levy flight, and the mathematical expression for step size *s* is as follows.

$$s = \frac{u}{|v|^{1/\beta}} \tag{3}$$

where $u \sim N\left(0, \sigma^2\right)$, $v \sim N(0,1)$, $\sigma = \left\{ \frac{\Gamma(1+\beta)\sin\frac{\pi\beta}{2}}{\beta\Gamma\left(\frac{1+\beta}{2}\right)2^{\frac{\beta-1}{2}}} \right\}^{\frac{1}{\beta}}$.

The nesting bird abandons its nest with a certain probability, and in the preferred random walk method, after discarding some candidate solutions according to the discovery probability *Pa*, generates the same number of new solutions as follows.

$$X_i^{t+1} = X_i^t + \varnothing\left(X_k^t - X_s^t\right) \quad (4)$$

where $\varnothing$ is the coefficient for controlling scaling of the algorithm. The steps of the CS algorithm are as follows:

Step 1 Assuming the number of bird nests is *n*, initialize population $X = [x_1, x_2, ..., x_d]^T$, search space dimension is *d*, initialize the position of bird nests as $X_i = [x_1^{(0)}, x_2^{(0)}, ..., x_d^{(0)}]^T$, and find the optimal position $X_{best}, i \in (1, 2, ..., n)$ and optimal solution $f_{\min}$.

Step 2 Loop body

(1) Retain the position of the previous generation's best nest and update the positions of other nests using equation (2).

(2) Utilize Levi's flight to obtain the position of a new set of bird nests.

(3) Compare the current generated nest position with the previous set of nest positions and select the nest position with better fitness to replace the position with poorer fitness value. Finally, obtain a set of better performing bird's nest locations. After updating the position, first compare a random number with *Pa*. If the random number is less than *Pa*, then move the corresponding bird at the position randomly. This ensures obtaining a set of better positioned bird nests.

Step 3 After Step 2, identify the optimal nest position $X_{best}$ and the corresponding optimal value $f_{\min}$. If the preset iteration criteria are met, output the global optimal solution $Gf_{\min}$ and the optimal position $GX_{best}$. If it is not met, return to Step 2 to continue optimizing and finding a better solution.

Based on the advantages of the CS algorithm, this paper uses the CS algorithm to optimize the parameters of the BP neural network. Figure 2 shows the flowchart of the CS-BP prediction model.

For CS algorithm, parameter selection is very important. For Levy fly, $\beta$ is usually set to 1.5 and $\alpha$ is set to 0.01. For *Pa*, the larger the value, the lower the probability of randomly discovering the position of a new bird's nest. Conversely, a value that is too small can lead to randomness in the algorithm. Generally, *Pa* is set to 0.25. For the maximum number of iterations, the larger the value, the higher the possibility of finding the optimal solution, but it will increase the search time and decrease the real-time performance of the algorithm. However, maximum number of iterations that is too small may increase the efficiency of the algorithm, but it can lead to a decrease in optimization capability. The setting of population size is the same.

Generally speaking, the number of nodes in the input and output layers of a BP neural network is determined by the actual predicted data, while the number of nodes in the hidden layer is usually given based on the empirical formula $l = \sqrt{m-n} + k$ of the hidden layer nodes, where *m* and *n* represent the number of nodes in the input and output layers, and *k* is positive integers between 1 and 10.

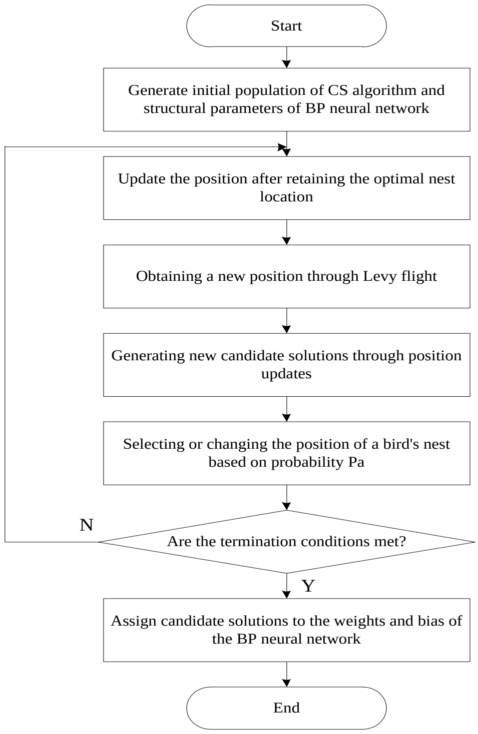


Fig. 2. The flowchart of the CS-BP prediction model.

In this paper, the number of input nodes and output nodes of the BP neural network are 4 and 1, respectively. The delay data of the previous 4 time steps before the current time step of the neural network is used as input to predict the delay at the current time step. Based on $l = \sqrt{m-n} + k$, the hidden layer nodes is set as 11. Therefore, this paper adopts a structure of 4-11-1 for configuration.

In order to determine the optimal and suitable parameters for the CS algorithm, 500 sets of delay data are collected from industrial environments to train the network delay prediction model. The first 450 sets are used for training the delay prediction model, and the last 50 sets are used for testing. For the weights and biases of the BP neural network to be optimized, set their value ranges to [-3, 3]. Set the preset error accuracy to 0.000001. In the process of optimizing BP by CS algorithm, the fitness function is taken as the root mean square error (RMSE) between the predicted value of delay and the actual value, as shown in the following formula.

$$fitness(k) = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \bar{y}_i)^2} \quad (5)$$

where *k* is the number of iterations, *N* is the number of samples, $y_i$ is actual value of delay, $\bar{y}_i$ is the predicted value of delay.

Table 1 compares the RMSE and optimization time of the training set when the CS algorithm is set with different population sizes and maximum number of iterations. From the results in Table 1, it can be seen that as the population size and maximum number of iterations increase, RMSE decreases, but the decreasing value decreases, while training time increases significantly. Therefore, based on the results in

Table 1 and considering that the structure of the BP neural network in this paper is not particularly complex, the population size is set to 20 and maximum number of iterations is set to 50. This ensures both predictive performance and a certain level of real-time performance.

**Table 1. Performance comparison of CS algorithm under different parameter settings**

| Population size | Maximum iterations | RMSE (ms) | Training time (s) |
|---|---|---|---|
| 5 | 10 | 23.86 | 1.18 |
| 10 | 20 | 12.19 | 4.90 |
| 20 | 50 | 10.62 | 8.83 |
| 50 | 100 | 8.41 | 37.45 |
| 100 | 200 | 7.22 | 80.63 |

Figure 3 shows the comparison of prediction errors between the BP model and the CS-BP model. For 50 test sets, the prediction results of the BP model and the CS-BP model are shown in Figure 4 and Figure 5, respectively. The RMSE, mean absolute error (MAE) and mean absolute percentage error (MAPE) are used as performance evaluation indicators. Table 2 shows the performance evaluation indicators comparison results of BP model and CS-BP model.

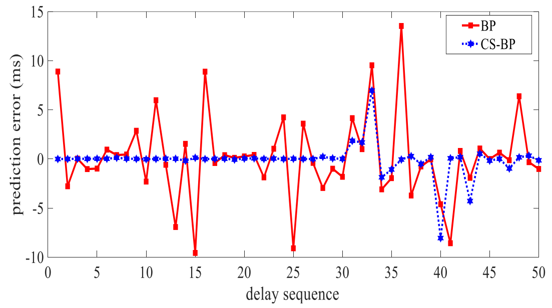


Fig. 3. The comparison of prediction errors between the BP model and the CS-BP model.

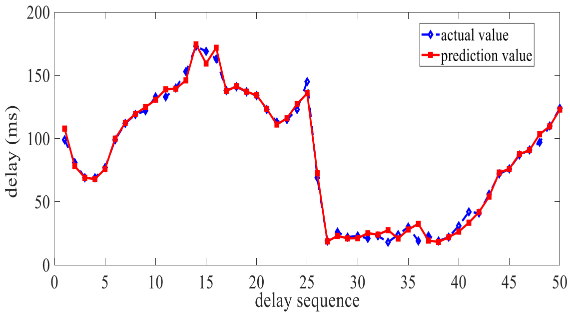


Fig. 4. The prediction results of the BP model.

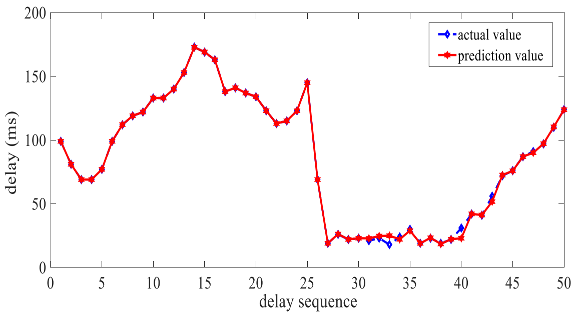


Fig. 5. The prediction results of the CS-BP model.

**Table 2. The performance evaluation indicators comparison results of BP model and CS-BP model**

| Model | MSE (ms) | MAE (ms) | MAPE (%) |
|---|---|---|---|
| BP | 4.39 | 2.91 | 6.51 |
| CS-BP | 1.72 | 0.61 | 2.19 |

It can be clearly seen from Figure 3 that the BP neural network prediction model optimized by CS has effectively reduced the prediction error compared to a single BP neural network. In the fitting comparison between Figure 4 and Figure 5, the prediction accuracy of CS-BP for 50 test sets of time delay data is better than that of the BP model. Based on the results in Table 2, it can be seen that the prediction accuracy of the BP model is 93.49%, and the prediction accuracy of CS-BP is 97.81%. Based on simulation experiments and performance index calculations, it can be inferred that the CS-BP neural network proposed in this paper has achieved a certain degree of improvement in prediction performance. Compared to a single BP, CS-BP is more suitable as a delay prediction model for NCS.

## 4. DELAY COMPENSATION STRATEGY

In this section, the design process of the proposed compensation strategy for NCS random delay is given.

### *4.1 IGPC based on CS-BP*

Combining the CS-BP model with IGPC, the structural diagram of the control system is shown in Figure 6. Through multi-step prediction, IGPC based on CS-BP provides the predicted output for the future time. During this period, the IGPC uses rolling optimization to provide the optimal control sequence for the current time based on past control inputs, reference trajectories, and model predicted outputs. By utilizing the real-time characteristics of predictive control, IGPC based on CS-BP (CSBP-IGPC) can optimize and correct the output errors in the control system. Finally, based on the optimal control sequence and the current delay situation of the system, an appropriate control signal is selected to act on the controlled object to achieve optimal control at the current time, continuously cycling until the system terminates.

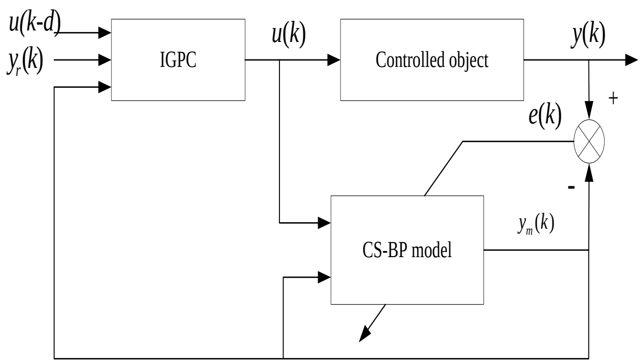


Fig. 6. The structure of IGPC based on CS-BP.

### *4.2 CS-BP delay prediction model*

Establish a nonlinear prediction model for time delay based on CS-BP, as shown in equation (6).

$$y_m(k) = f_N\left[y(k-1),\ldots,y\left(k-n_y\right),u(k-d),\ldots,u\left(k-n_u\right)\right] \quad (6)$$

The prediction model of j-step advance is obtained by multi-step strategy. And, the corresponding system structure diagram is shown in Figure 7.

$$y_m(k+j) = f_N\left[y(k+j-1),\cdots,y\left(k+j-n_y\right),u(k+j-d),\cdots,u\left(k+j-n_u\right)\right]$$
(7)

In Figure 7, the input to the neural network is

$$X_j(k) = \left[y(k+j-1),\cdots,y\left(k+j-n_y\right),u(k+j-d),\cdots,u\left(k+j-n_u\right)\right] \quad (8)$$

The output of the neural network is $y_m(k+j)$, where *m* is the number of input layer nodes, the hidden layer selects the Sigmoid function $\sigma(x) = \dfrac{1}{1+e^{-x}}$, the number of hidden layer nodes is *p*, the output value of the j-step prediction model is

$$y_m(k+j) = W^{\mathrm{T}} R(k) \quad (9)$$

where $R(k) = \left[R_1(k), R_2(k),\ldots,R_p(k)\right]^{\mathrm{T}}$ is the output value of the hidden layer, $W = \left[W_1, W_2,\ldots,W_p\right]^{\mathrm{T}}$ is the weight between the hidden layer and the output layer.

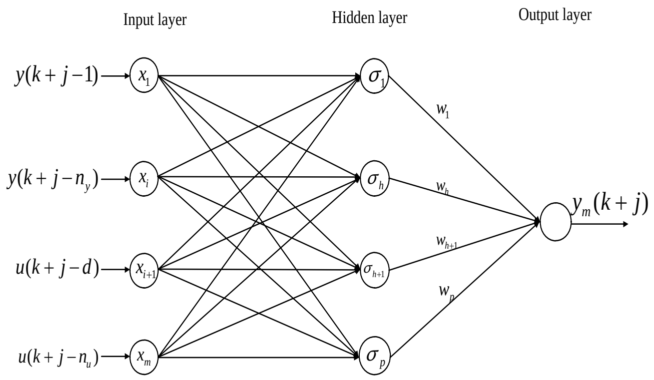


Fig. 7. The prediction model of j-step advance.

### *4.3 CSBP-IGPC controller*

In general, GPC needs to obtain the control input law by calculating the Diophantine equation online, which takes a long time and is complex to solve, so the IGPC controller is introduced to NCS (Tian and Wang, 2022). Compared with GPC, the most significant advantage of IGPC is that after identifying the correlation matrix according to the input and output data, the control increment at the current moment can be solved, which saves time and improves the control efficiency significantly.

In order to obtain the optimal control sequence of the controlled object, the optimal control vector calculation of the objective function is performed.

$$J(k) = \sum_{j=1}^{N}\left[y(k+j) - w_r(k+j)\right]^2 + \sum_{j=0}^{M-1}\lambda(j)\left[\Delta u(k+j)\right]^2 \quad (10)$$

where $N$ is prediction horizon, $M$ is control horizon. The predicted value of the $k$ moment can be obtained by the CS-BP output.

$$y_m(k+j) = f_N\left[y(k+j-1),\ldots,y\left(k+j-n_y\right),u(k+j-d),\ldots,u\left(k+j-n_u\right)\right]$$
(11)

Subtract the predicted output obtained by equation (11) from the actual output $y(k)$, i.e. $e(k) = y(k) - y_m(k)$ is the error. The prediction control feedback correction shown in equation (12) below is used to find the prediction vector *f*.

$$f = \begin{bmatrix} \hat{y}(k+2|k) \\ \hat{y}(k+3|k) \\ \vdots \\ \hat{y}(k+n+1|k) \end{bmatrix} + \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix} e(k+1) \quad (12)$$

In order to further improve the stability of the system so that the system does not produce large fluctuations, the output tracks the pre-designed reference trajectory. The reference trajectory is designed according to equation (13) ensures a smooth tracking state of the system.

$$w_r(k+j) = \alpha^j y(k) + \left(1-\alpha^j\right) y_r(k),\ j = 1,\cdots,N \quad (13)$$

where $\alpha$ is softening factor. The optimal control law of CSBP-IGPC is

$$\Delta u(k) = \left(G^T G + \lambda I\right)^{-1} G^T \left(w - f\right) \quad (14)$$

The system control input is

$$u(k) = u(k-1) + [1,0,\ldots,0]\left(G^{\mathrm{T}} G + \lambda I\right)^{-1} G^{\mathrm{T}}\left(w - f\right) \quad (15)$$

In summary, the implementation process based on CSBP-IGPC control is as follows.

Step 1 Parameter initialization. Initialize the parameters of the neural network and optimization algorithm, as well as the parameters of the control horizon *M*, prediction horizon *N*, softening factor $\alpha$ and forgetting factor $\lambda$ of the required inputs in the controller.

Step 2 Obtain the multi-step prediction output value $y_m(k+j)$ identified by CS-BP and the reference trajectory input $w_r(k+j)$, and assign them to the controller.

Step 3 Obtain the controller parameters, and use the least squares method with forgetting factor to identify the relevant parameters of the IGPC controller.

Step 4 The control increment $\Delta U$ is solved by equation (14) and the control sequence $u(k)$ is obtained by equation (15). Return Step 2 to continue control.

### *4.4 Delay compensation scheme*

Using the previously established delay prediction model for parameter identification, the IGPC algorithm is used to calculate the control increment, and a delay compensation scheme for neural network predictive control is designed. The specific solution is to set a buffer in front of the actuator to store the control sequence calculated by IGPC. The CS-BP model is used to predict future delay. At the same time, based on historical delay data and current input, the optimal control law in the control sequence is selected based on the predicted delay. The designed delay compensation structure diagram is shown in Figure 8.

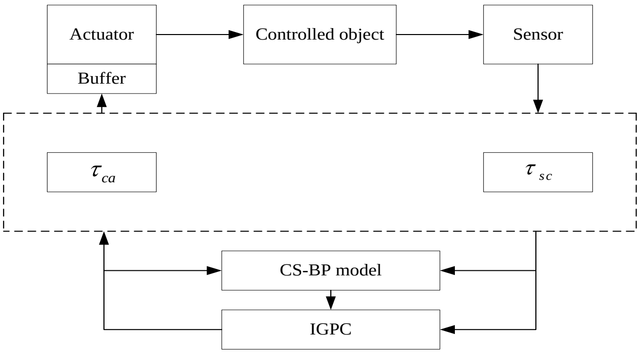


Fig. 8. The designed delay compensation structure diagram.

The implementation steps of the designed NCS delay compensation controller are as follows.

Step 1 Obtain delay samples and pre-process the data.

Step 2 Parameter initialization of BP neural network. Train BP neural network and predict test data through processed data.

Step 3 Replace the predicted delay of CS-BP with the actual delay, and solve the control increment $\Delta u(k)$ through the IGPC control algorithm combining historical inputs and reference trajectories.

Step 4 Select the appropriate $\Delta u(k)$ and transfer it to the actuator, apply it to the controlled object, and return to Step 2.

The flowchart of the designed delay compensation strategy is shown in Figure 9.

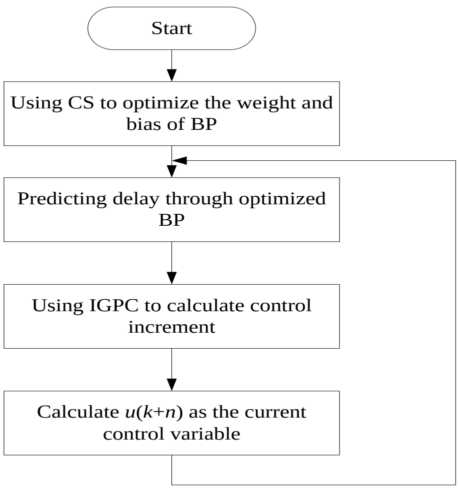


Fig. 9. The flowchart of the designed delay compensation strategy.

Relying on the advantage of ICPG multi-step prediction, the buffer at each time can obtain the current control sequence. For example, the control sequence at time $k$ should be $\Delta u_M = [\Delta u(k), \Delta u(k+1), ..., \Delta u(k+M-1)]$, and the control sequence contains $M$ future control increments. Choosing an appropriate control sequence is related to the network delay at the current time. The specific implementation process is to directly select the first control increment from the latest control sequence when there is no induced delay at the current time of the network, and apply the updated control quantity to the controlled object. If there is a network delay at the current time $k$, and the control sequence cannot reach the buffer within the pre-set period, the current predicted delay of CS-BP is taken as the true delay. Combined with the system input, IGPC is used to solve the control increment sequence. By selecting the appropriate control increment from the previous time control sequence through the relationship between the predicted delay and the sampling period, the optimal control law is updated. The specific strategy is as follows.

Step 1 By using the trained CS-BP neural network prediction model to predict the current time delay, denoted as $\tau_k$, calculate the ratio $n$ of the delay to the sampling period using the following equation (16).

Step 2 Calculate the current control increment $\Delta u(k)$ through IGPC.

Step 3 Based on the $n$ value calculated in Step 1 and the control increment sequence $\Delta u(k)$ calculated in Step 2, select the appropriate control increment to update $u(k+n)$ and transmit it to the actuator.

Step 4 Let $k$=$k$+1, go to Step 1.

$$n = \begin{cases} \tau / T, & \tau / T \text{ is an integer} \\ \tau / T + 1, & \tau / T \text{ is not an integer} \end{cases} \tag{16}$$

## 5. SIMULATION VERIFICATION

In order to verify the effectiveness of the proposed time delay compensation scheme for random delays in NCS, a type of networked gas boiler control system with nonlinear delay in actual production is selected for research to discuss the compensation effect for time delays. Considering that the networked gas boiler control system uses Industrial Ethernet as the communication medium to realize information collection and exchange, this paper takes the networked gas boiler control system as a whole, and introduces random delay to verify the effectiveness of the proposed delay compensation scheme. The working principle of a networked gas boiler is shown in Figure 10.

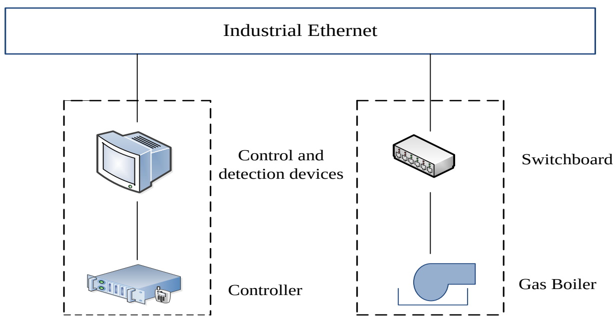


Fig. 10. Working principle of a networked gas boiler.

The switches in the networked gas boiler system package and classify different types of data before transmitting them to the workstation. The workstation receives the data packet and analyzes the boiler operation based on the provided information. Through control and detection devices, feedback information is transmitted to the boiler, thereby achieving remote control. Due to the common problems of nonlinearity, large delay, and low modeling accuracy in industrial production, this paper selects the single input single output nonlinear time delay system shown in equation (17) as the simplified model of the networked gas boiler control system.

$$y(k)=0.4u^3(k-\tau-2)+0.3u^3(k-\tau-3)+\frac{0.9+1.9y^3(k-1)}{1.4+y^2(k-1)+y^3(k-2)} \tag{17}$$

where $\tau$ is the random delay in the networked gas boiler system. The proposed delay compensation scheme is applied to the networked gas boiler system. For the system shown in equation (17), establish a CS-BP neural network model to predict delay and complete the establishment of a multi-step prediction model. Among them, the network input layer and output layer are set to 4 and 1, respectively, with input parameter $x(k)=[y(k-1),y(k-2),u(k-2),u(k-3)]$ and output parameter $y(k)=[\hat{y}(k)]$. Select the control input signal as $u(k)=0.8\sin(0.004\pi k)$.

Save the nonlinear delay data generated by $y(k)$ and $u(k)$, and set the training and testing sets of the CS-BP neural network model to 5000 and 1000 sets, respectively. The input layer, hidden layer, and output layer of the BP neural network have a 4-9-1 structure, where the hidden layer neuron function uses a Sigmoid function. The nonlinear delay system is identified through the CS optimized BP neural network, where the set parameters of CS are as follows: population size is 20, iteration number is set to 50, and *Pa* is 0.25. The identification effect of the established delay prediction model is shown in Figure 11 and Figure 12.

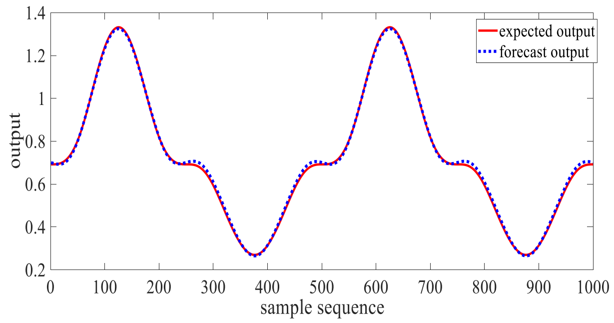


Fig. 11. CS-BP identification result of networked gas boiler model.

From the above two figures, it can be seen that the CS-BP model has smaller errors and higher identification accuracy. The model has achieved identification of nonlinear delay system and successfully completed the task of replacing the CARIMA model to establish a multi-step model. The comparison of delay prediction in the system is shown in Figure 13, and the fitness curve in the process of optimizing the BP neural network using the CS algorithm is shown in Figure 14.

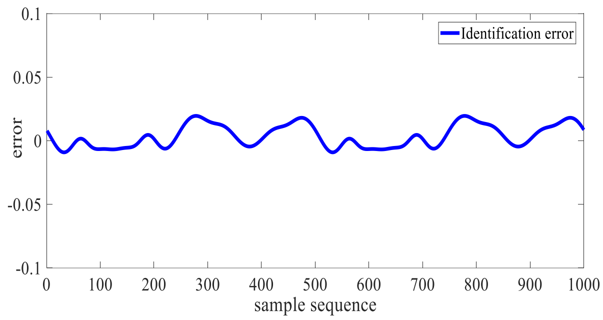


Fig. 12. Identification error of CS-BP model.

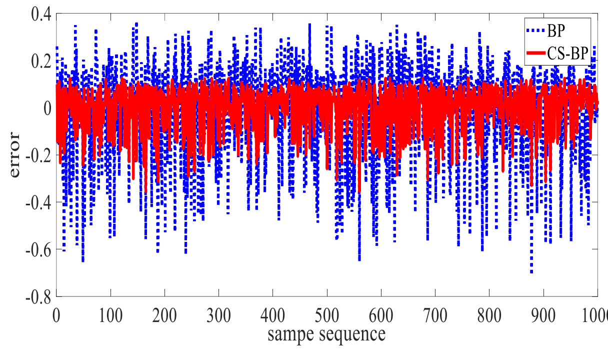


Fig. 13. The comparison of delay prediction in the system between BP and CS-BP.

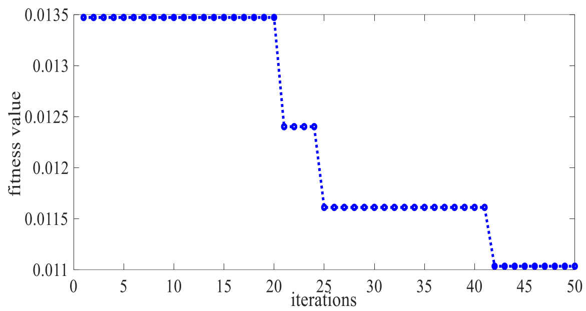


Fig. 14. The fitness curve of CS algorithm optimized BP neural network.

For the networked gas boiler system (17) used in the simulation, delay historical data is introduced to provide samples for the delay predictor. A CS-BP neural network prediction model is established based on 4000 sets of delay historical data, with a training set of 3000, a testing set of 1000. The RMSE of the BP neural network prediction model without optimization is 8.94 $\times 10^{-2}$, the CS-BP neural network MSE optimized by CS algorithm is $3.02\times 10^{-2}$, it can be seen that the CS-BP prediction model established in this paper has higher prediction accuracy and smaller prediction error. In the face of random delays in NCS, accurate prediction can be achieved, which improves the robustness of NCS and lays the foundation for selecting appropriate control increments in control sequences to achieve delay compensation in the future.

In order to verify the effectiveness of the delay compensation strategy in this paper, simulation verification is conducted on the delay compensation of networked gas boilers under normal operating conditions and external disturbances caused by adding materials. Firstly, the predicted delay in the CS-BP delay predictor is considered as the current delay, and the neural network predictive control method proposed in this paper is used for tracking the reference signal. Set as reference trajectory as $w$=0.3sign(sin(0.003$\pi k$))+0.7. The parameters of IGPC are set as follows: control time horizon $M$ is 2, prediction horizon $N$=6, control weight 0.4, and softening factor $\alpha$ is 0.6. In order to better validate the effectiveness of the method proposed in this paper, self correcting control based on PID and RBF (Shi et al. 2019), IGPC and GPC are selected for comparison. The parameters of self correcting control are set as follows: the learning rate is 0.2, the momentum factor is 0.05, the momentum factor and the learning rate of PID are 0.1 and 1, respectively, and the number of hidden layer nodes of RBF neural network is 6. The parameters of GPC are set as follows: control time horizon $M$ is 2, prediction horizon $N$ is 6, control weight 0.4, and softening factor is 0.6. The compensation effects of the four delay compensation strategies under normal working conditions are shown in Figure 15.

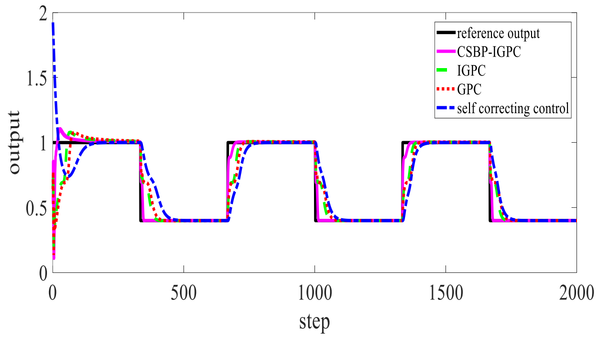


Fig. 15. Comparison of tracking effects under normal working conditions.

From Figure 15, it can be seen that for networked gas boilers, in addition to significant overshoot in the initial stage of self correcting control, CSBP-IGPC, IGPC, and GPC all have relatively small overshoot. And when the networked gas boiler enters a stable operating state, these control strategies can achieve tracking of the reference trajectory. Compared to other control strategies, CSBP-IGPC is clearly the optimal one. The reason is that self correcting control is based on PID control and cannot achieve the best compensation effect. However, neither IGPC nor GPC can accurately predict the changing network delay, thus unable to achieve the best compensation effect.

The performance comparison of the four compensation strategies is shown in Table 3. From Table 3, it can be seen that the CSBP-IGPC strategy proposed in this paper performs well in terms of rise time and settling time, with a decrease of 15.9 seconds, 22 seconds and 21.3 seconds in rise time compared to IGPC, GPC and self correcting control, respectively. Meanwhile, compared with the other three control strategies, the steady-state error of the system decreased by 10% to 15% after stable operation, and the model accuracy and stability are improved. Although the proposed delay compensation scheme has a small overshoot after stable operation, it has significantly improved performance compared to the other three delay compensation strategies, namely better control effect, smaller error, and faster response speed.

**Table 3. The performance comparison of the three compensation strategies under nornal working conditions**

| Strategy | Rise time (s) | Settling time (s) | Initial overshoot (%) | Steady-state overshoot (%) |
|---|---|---|---|---|
| CSBP-IGPC | 22.3 | 52.2 | 11.7 | 1.2 |
| IGPC | 38.2 | 60.9 | 10.8 | 1.3 |
| Self correcting control | 43.6 | 61.6 | 80.2 | 0.4 |
| GPC | 44.3 | 62.4 | 10.4 | 1.1 |

Considering that the working conditions of gas boilers are dynamically changing under networked control, it is a very common problem for the gas boiler system to experience disturbances when adding materials. In order to verify the robustness of the proposed strategy in the actual Industrial control system, when $k$ is 400 and $k$ is 600, disturbances of 0.2 and -0.2 are applied to the system, respectively. The parameters of the four delay compensation strategies remain unchanged. The comparison of the effects of four delay compensation strategies is shown in Figure 16, and the performance indicators of different control strategies under disturbance state are shown in Table 4.

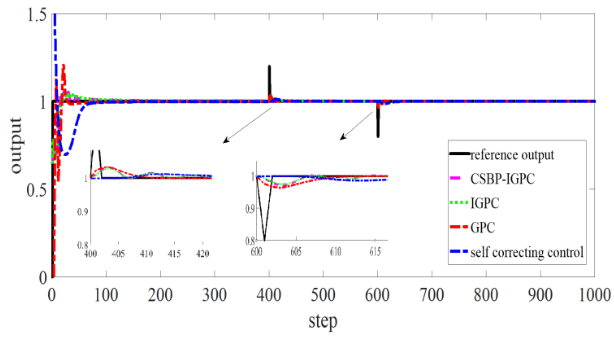


Fig. 16. Comparison of tracking effects under disturbance.

**Table 4. The performance comparison of the three compensation strategies under disturbances**

| Strategy | Rise time (s) | Settling time under disturbance (s) | Initial overshoot (%) | Disturbance overshoot (%) |
|---|---|---|---|---|
| CSBP-IGPC | 5.2 | 21.7 | 8.6 | 2.5 |
| IGPC | 5.4 | 26.4 | 11.1 | 2.8 |
| Self correcting control | 10.9 | 50.6 | 50.3 | 2.1 |
| GPC | 7.8 | 30.2 | 21.2 | 3.7 |

From Figure 16 and Table 4, it can be seen that when disturbances occur in the networked gas boiler system, all four delay compensation strategies generate a certain degree of overshoot, which returns to a stable state after a period of time. Among them, although the self correcting control has the lowest overshoot of the output curve of the system, there is lag when disturbance occurs, and the system response speed is slow and the settling time is long. Among the three delay compensation strategies based on GPC, GPC has the largest overshoot, followed by IGPC, and the smallest is CSBP-IGPC. When the system is disturbed, the settling time of CSBP-IGPC is also the shortest, compared with IGPC, self correcting control and GPC, reduced by 4.7 seconds, 28.9 seconds, and 8.5 seconds, respectively. Therefore, the proposed CSFP-IGPC strategy has smaller steady-state error, shorter rise time and stabilization time, and can quickly restore the system to a stable state when disturbances occur. For actual industrial equipment based on networked control, disturbances often occur, which requires the control strategy of the system to have a certain ability to suppress disturbances. On the premise of ensuring stability, the overshoot and setting time of the system should be as small as possible. And the proposed CSBP-IGPC is more suitable for practical control processes with interference.

In summary, in the networked gas boiler system, whether under normal working conditions or in the presence of disturbances, the delay compensation effect of the proposed CSBP-IGPC compensation strategy is better than that of IGPC, GPC and self correcting control strategy in the above cases, and has certain engineering application value.

## 6. CONCLUSIONS

Aiming at the delay problem in NCS, a neural network predictive control strategy is proposed to compensate the delay in NCS. The CS algorithm is used to optimize the BP neural network and establish a prediction model for delay in NCS to predict future delays. The IGPC control algorithm utilizes the predicted delay to select the appropriate control law to be applied to the controlled object in the buffer set in front of the actuator. Taking networked gas boilers as the research object, the proposed delay compensation strategy is analyzed and discussed. Compared with strategies include GPC, IGPC, and self correcting control, the proposed CSBP-IGPC exhibits excellent performance under both normal operation and disturbance conditions. The designed CSBP-IGPC strategy can be applied to similar networked industrial control systems with time delays.

This paper only considers the design of a delay compensator in the case of single packet transmission, while in real NCS, both delay and packet losses are high-frequency issues. If the data packet is long, multi packet transmission is also an inevitable situation. Converting multi packet transmission into a switching system is a feasible solution. The networked feedback control laws can be obtained by solving some matrix inequalities. On the other hand, the controller proposed in this paper has been validated for its effectiveness in numerical simulations, but in the practical industrial applications of NCS, communication technology is the most critical. It is worth conducting in-depth research on how to expand network channels, improve network transmission rates, and reduce the impact of the network on the system when resources are limited. The co-deign of communication and control is an effective solution, which comprehensively considers communication performance and control performance to improve the performance of NCS. Among them, robust H-infinity and stochastic optimal control are feasible and worth studying solutions.

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