ARTICLE IN PRESS

Alexandria Engineering Journal (2020) **xxx**, xxx–xxx

HOSTED BY

ELSEVIER

Alexandria University

Alexandria Engineering Journal

www.elsevier.com/locate/aej
www.sciencedirect.com

Stepped generalized predictive control of test tank temperature based on backpropagation neural network

Qinglei Zhao, Qiang Liu, Nailiang Cao, Fengwei Guan, Shuxin Wang *, Hang Wang

Changchun Institute of Optics, Fine Mechanics and Physics, Chinese Academy of Sciences, Changchun 130033, China

Received 31 July 2020; revised 20 August 2020; accepted 24 August 2020

KEYWORDS

Temperature control;
Backpropagation Neural Network (BPNN);
Generalized Predictive Control (GPC);
Test tank

Abstract It is significant to ensure the temperature stability of the test tank, which has a direct impact on reducing production energy consumption, improving tank quality and ensuring experimental results. However, the high nonlinearity and long delay of the temperature control process in the test tank make it difficult to satisfactorily control the temperature by traditional control methods. To solve the problem, this paper designs a temperature prediction model for the test tank based on backpropagation neural network (BPNN), which has a good fitting ability for nonlinear systems. The proposed model was coupled with improved generalized predictive control (GPC) into a new test tank temperature control method, namely, BPNN-based stepped GPC. Simulation results show that the new control method could reduce the prediction error of the BPNN and effectively control the temperature of the test tank.

1. Introduction

The mathematical modelling of the temperature control system in the test tank is hampered by the long lag, high nonlinearity, and large inertia of the temperature control process. If the tank temperature is controlled stably, it is possible to carry out high-quality and energy-efficient tests at a low cost, and extend the service life of the test tank. Thus, the temperature control of the test tank is conducive to sustainable green development. The test tank mainly provides temperature control function for high and low temperature environment test. Through the description of the overall structure and process flow of the test tank, the research object is determined as the temperature control of the heating process of the test tank. Through the analysis of the key factors affecting the temperature of the test tank, the temperature can be effectively controlled (see Table 1)

The heating system in the test tank is often controlled by computer. There are three possible control modes: feedforward control, feedback control, and feedforward-feedback control [1,2]. In feedforward control, the computer collects the relevant data in the early phase, and formulates the heating instructions for different periods and temperatures. Then, the test indices are adjusted in the light of humidity, temperature, calorific value, and other parameters.

In feedback control, the temperature is determined empirically by experts based on relevant data. Then, the temperature

* Corresponding author.
E-mail address: wangsx@ciomp.ac.cn (S. Wang).

Peer review under responsibility of Faculty of Engineering, Alexandria University.

https://doi.org/10.1016/j.aej.2020.08.032
1110-0168 © 2020 Faculty of Engineering, Alexandria University. Production and hosting by Elsevier B.V.

Table 1 Results of correlation analysis.

	Nitrogen pressure	Gas collector pressure	Tank pressure	Air flow	Pipe temperature	Pipe suction	Test temperature
Pearson correlation coefficient	−0.115**	−0.621**	0.323**	0.266**	0.712**	−0.010**	0.825**
Significance	0.007	0.000	0.000	0.000	0.000	0.0021	0.000
Number of samples	2,000	2,000	2,000	2,000	2,000	2,000	2,000

Note: ** stands for sig < 0.01, i.e. the correlation is highly significant; * stands for 0.01 < sig < 0.05, i.e. the correlation is significant.

curve is drawn and transmitted to the computer. Meanwhile, the thermocouple keeps measuring the actual temperature, and transmitting the measured data to the computer. Based on the difference between empirical and measured data, the computer will adjust the test indices.

In feedforward-feedback control, the temperature control object is optimized by feedforward control, and the auxiliary control object is optimized by feedback control, which converts the regulated temperature into optimal temperature supply. The feedforward-feedback control combines the merits of feedforward and feedback controls, and achieves satisfactory control effect.

To effectively control the test tank temperature, this paper puts forward a novel control approach based on backpropagation neural network (BPNN) [3,4] and improved generalized predictive control (GPC). The proposed approach, known as BPNN-based stepped GPC, was proved effective through simulations on an actual high and low temperature test tank.

2. Literature review

In the test tank, the temperature control process is a highly nonlinear phenomenon, which involves multiple distributed parameters, and an intermingle of fast and slow subprocesses. Therefore, the temperature in the test tank is too complicated to be controlled well by traditional modes. Fortunately, the recent boom of artificial intelligence (AI) technologies [5], namely, neural network (NN) [6], fuzzy control [7], and predictive control [8], sheds new light on the temperature control of the test tank.

With the advent of new AI technologies, many intelligent temperature control algorithms have emerged [9–11]. The fuzzy control stands out for its excellent effect in temperature control: this technology refines the knowledge and experience of operators and experts, eliminating the need for mathematically modelling of the control object.

Based on expert control and fuzzy control, Hong [12] regulated the gas flow in a furnace, and successfully stabilized the furnace temperature. Wang and Pan [13] proposed an intelligent furnace temperature control algorithm, drawing on the proportional–integral–derivative (PID) controller. Nomura et al. [14] summarized the features of coke oven, and designed a hybrid controller for coke oven heating process, which couples dynamic matrix with PID cascade control. Based on orthogonal NN, He et al. [15] realized the predictive control of the flue temperature in the coke oven. Yabanova et al. [16] regulated the intermittent heating and gas flow in the test tank by modelling the heating system with NN and fuzzy control.

If accurate mathematical models are available, modern control technologies can achieve desirable effect. However, it is difficult to obtain an accurate mathematical model, because actual industrial production is a time-varying process with multiple nonlinear and strongly coupled parameters. In the industrial background, the control object has a high uncertainty, and the control task becomes a multi-objective optimization problem. To solve the problem, the intelligent strategy of predictive control has been developed. The early forms of predictive control include model predictive heuristic control (MPHC) [17] and dynamic matrix control (DMC) [18].

Tian et al. [19] combined the GPC in nonlinear control system and fuzzy NN to identify object, and implemented the predictive control using the local weighted model. Based on multilayer feedforward network, Muir [20] designed a generalized predictive controller through dynamic modelling; the designed controller operates as a linear system, and performs online learning by least squares (LS) method. Karmakar et al. [21] identified the control system and parameters by the NN, determined the optimization direction through iterative learning, and built a stable and fast control algorithm by quasi-Newton method. Cao and Kuang [22] developed a predictive control algorithm by extending the orthogonal NN and linearizing the nonlinear model, and successfully applied the algorithm to control the vertical flue temperature of coke oven. Plett [23] identified the control system by the NN and inverse dynamic network, conducted weight training with the optimization performance index of multi-step prediction, and put forward a NN-inverse dynamic control method with that index. Bououden et al. [24] introduced particle swarm optimization (PSO) to the NN-based predictive control, and proved the good performance of the optimization predictor model and PSO-based nonlinear controller.

3. Temperature prediction model for test tank

3.1. Temperature control scheme

The tank structure and heating process of the test tank make its temperature affected by many aspects, mainly including heating mode, operation plan, energy and airflow, heating time, gas pressure and other factors, which is very suitable to be described by BP neural network model.

As shown in Fig. 1, the temperature control scheme for test tank includes optimizing preset temperature, temperature prediction and modelling, and GPC structuring. Based on the scheme, the backpropagation neural network (BP) was introduced to predict the temperature in the test tank. Then, a simulation model was established for the temperature control

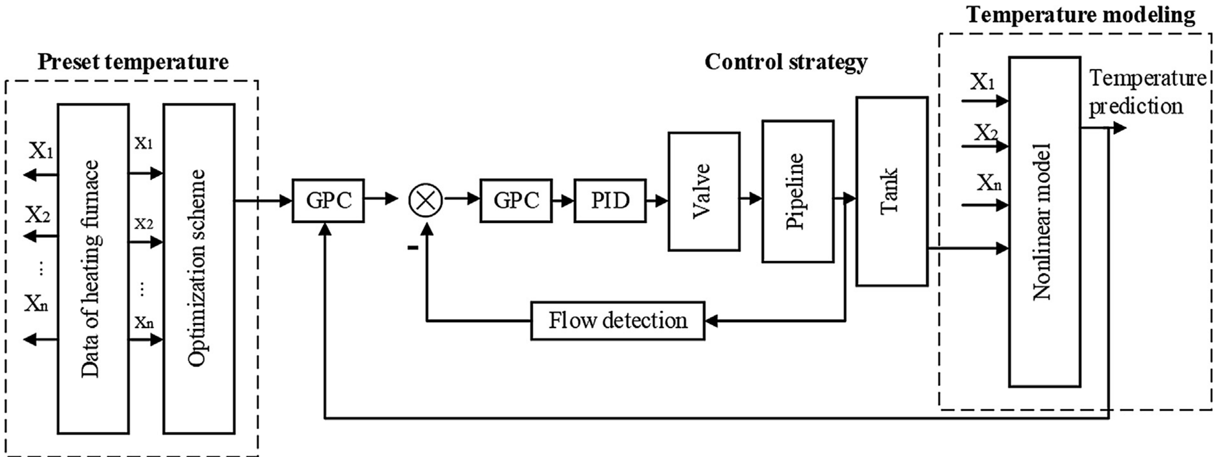

Fig. 1 Temperature control scheme for test tank.

process of the control object. Besides, the GPC was combined with the improved stepped predictive control algorithm into a stepped GPC algorithm. Specifically, the NN-based predictive model was linearized into a difference equation, the predictive control of temperature was discussed under the environment of the test tank, and the effects of key parameters on the control effect of the stepped GPC algorithm were investigated. Finally, the proposed algorithm was simulated under various working conditions.

3.2. Data collection and preprocessing

The research data were collected from a high and low temperature test tank over half a year. During the test, the main parameters of the high and low temperature test tank include air flow, tank pressure, Pipe suction, pipe temperature, nitrogen pressure, gas collector pressure, and test temperature. The sampling period of each parameter was determined, for the sampling rate with working conditions.

The collected data contain some abnormal or missing items, which arise from noises, device errors, and human factors. These items should be filtered out before model construction. To eliminate the abnormal items, each data sample $X = \{x_1, x_2, \cdots, x_n\}$ was processed by the 3σ criterion, where σ is the standard deviation:

$$\sigma = \sqrt{\sum_{i=1}^{n} \left(x_i - \bar{x}\right)/(n-1)} \tag{1}$$

where, x_i is the measured value. If the residual error $v_i = \left|x_i - \bar{x}\right|$ satisfies $|v_i| > 3\sigma$, then x_i is an abnormal item to be eliminated.

The missing data could be supplemented by various methods, such as regression, mean value padding, continuous mean value padding, to name but a few [25,26]. To obtain smooth and diverse data, this paper completes the missing items with continuous mean values, producing a time series of modelling data.

Then, the dimensionality of data sampled in different periods was standardized. In this way, over 2,000 high-quality datasets were obtained for modelling. 80% data is used as training set, and 20% data is used as test set.

After that, the data on all parameters were subject to correlation analysis, aiming to provide a scientific reference for parameter selection. The correlation coefficients reflect the magnitude of the linear correlation between parameters. The correlation is stronger if the coefficient is greater, and the inverse is also true.

The analysis results show that the temperature at the next moment is significantly affected by six parameters: air flow, tank pressure, pipe temperature, nitrogen pressure, gas collector pressure, and test temperature.

3.3. BPNN-based temperature prediction

To accurately predict the temperature of test tank, air flow, tank pressure, pipe temperature, nitrogen pressure, gas collector pressure, and test temperature were selected as the input parameters of the BPNN, while the tank temperature was taken as the output parameter.

The learning algorithm of the BPNN relies on gradient descent method to optimize the training process. The network function iteratively reduces the error based on the constantly updated network weights. The specific process is as follows:

Step 1. After the model is constructed, initialize the relevant parameters, namely, network weight, and the number of hidden layer nodes.

Step 2. Read the training set, and set the input and output vectors as $x = (x_1, x_2, \cdots, x_n)$ and $\widehat{y} = \left(\widehat{y}_1, \widehat{y}_2, \cdots, \widehat{y}_j\right)$, respectively.

Step 3. Calculate the output by the weighted sum of each node, and express the hidden layer and output layer functions as $f_1(\cdot)$ and $f_2(\cdot)$, respectively:

$$z_i = f_1\left(\sum_{k=1}^{n} \omega_{kj} \cdot x_k\right) \tag{2}$$

$$y_j = f_2\left(\sum_{k=1}^{i} \omega_{kj} \cdot z_k\right) \tag{3}$$

Step 4. Calculate the error between actual and expected results, and define the objective function as:

$$f_o = \frac{1}{2}\sum |y - \hat{y}|^2 \tag{4}$$

Step 5. Obtain the derivation of the objective function:

$$\frac{\partial f_o}{\partial \omega} = \sum_{t=1}^{n} \frac{\partial f_t}{\partial \omega} \tag{5}$$

Step 6. Correct network weight:

$$\omega(\mathrm{t}+1) = \omega(\mathrm{t}) - \tau \frac{\partial f_o}{\partial \omega(\mathrm{t})} \tag{6}$$

Step 7. Return to Step 3 and repeat the following steps until the maximum number of iterations is reached.

BPNN involves two simultaneous processes: forward propagation and backpropagation. As the signal is transmitted from the input layer to the output layer, the error propagates backwards to optimize the output. In our BPNN, the input layer, hidden layer, and output layer have six, eight, and one node(s), respectively.

The preprocessed data were imported to the BPNN as training samples. Once the parameters were configured, the learning algorithm was simulated by simulation software. The training was terminated under one of the following conditions: the maximum number of iterations is reached, and the loss function no longer changes despite the growing number of iterations.

The prediction effect of the trained BPNN was verified on the test set. As shown in Fig. 2, the tank temperature predicted by the BPNN deviated slightly from the actual temperature, which meets the requirements of the objective function.

4. BPNN-based temperature control

4.1. Gpc

Predictive control, also known as model predictive control, aims to predict the operation at a future moment according to the current control effect and data. In general, the predictive control system contains a reference trajectory, a predictive model, an object model, an online correction module, and an optimization calculation model. The basic process of predictive control is shown in Fig. 3, whereω is the preset value; $y_r(k)$ is

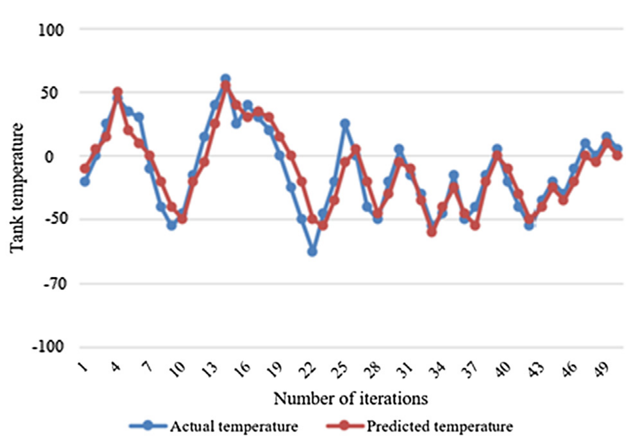

Fig. 2 Predicted temperature vs. actual temperature.

the reference trajectory; $y(k)$ is the control output; $y_m(k)$ is the control input; $e(k)$ is the prediction error; $y_p(k)$ is the predicted output.

However, the input and output of the predictive control process might not be stable, especially when the environment changes greatly. In this case, the control parameters will vary synchronously, reducing the system stability. To solve this problem, the set value should be flexible so that the system could gradually approximate the value. According to the preset temperature $y(k)$ of the test tank, the reference trajectory of the input can be obtained as:

$$y_r(k) = \beta y(k+j-1) + (1-\beta)c \tag{7}$$

where, $j = 1, 2, \cdots, N$ (N is the number of optimization parameters); $\beta \in [0,1]$ is the flexibility parameters; c is a user-defined constant. The trajectory of the control object must be consistent with the reference trajectory, that is, $y(k) = y_r(k)$.

Rolling optimization is the defining feature of predictive control. By rolling optimization, the future control strategy can be obtained, and the future behavior can be controlled through prediction with suitable parameters. The only defect with rolling optimization is the inability to optimize the global solution.

In actual temperature experiment, the working conditions are extremely complex, involving numerous time-varying factors and diverse interferences. Under this background, it is impossible to illustrate the control process with a simple linear system. The interferences can be effectively solved by rolling optimization. The optimal control parameters help to improve the control effect of actual models.

The performance function of predictive control can be defined as:

$$f_o = \min\left\{\sum_{s=1}^{N} e^2(k+s) + \sum_{t=1}^{L} r_i \Delta u^2(k+t-1)\right\} \tag{8}$$

where, r_i is the control coefficient; N is the number of optimization parameters; L is the control duration.

Then, the model deviation can be obtained as:

$$e(k+s) = y_r(k+s) - y_p(k+s) \tag{9}$$

The control quantity was introduced as a constraint of the objective function, with the aim to control the drastic change of control parameters, enhance the robustness of the control object, and ensure the stability of control output. Despite being similar to nonparametric model, the control effect can be ensured by using the impulse response with unstable zero point. Hence, the objective function can be defined as:

$$\min f_o(k) = E\left\{\sum_{s=1}^{N} [y(k+s) - y_r(k+s)]^2 + \sum_{s=1}^{N_u} \theta_s [\Delta u(k+s-1)]^2\right\} \tag{10}$$

where, $E\{\cdot\}$ is mathematical expectation; N is the optimal prediction length, whose order is greater than $B(z^{-1})$; N_u is control length; θ_s is the weight coefficient of control quantity; $y_r(k+s)$ is the input reference trajectory.

To realize flexible control, the reference trajectory needs to be tracked gently, without any sudden change. It is usually achieved by the first-order equation below:

$$y_{ref}(k+s) = \beta y_{ref}(k+s+1) + (1-\beta) y_{ref} \tag{11}$$

Please cite this article in press as: Q. Zhao et al., Stepped generalized predictive control of test tank temperature based on backpropagation neural network, Alexandria Eng. J. (2020), https://doi.org/10.1016/j.aej.2020.08.032

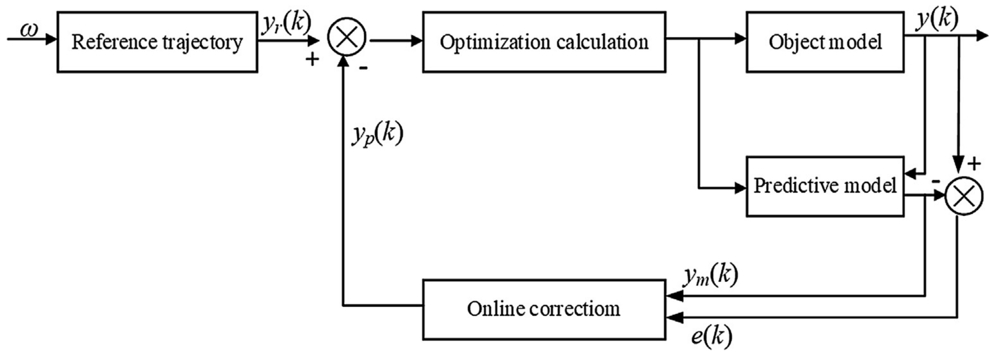

Fig. 3 Basic process of predictive control.

where, y_{ref} is the preset value; $y_{ref}(k+s)$ is the reference trajectory; β is the flexibility parameter.

The objective of the GPC can be summarized as acquiring the $\Delta u(k), \Delta u(k+1), \cdots, \Delta u(k+m-1)$ that minimizes the value of the objective function.

Unlike the traditional optimal control, the GPC optimizes the objective function in a rolling manner, along with the elapse of sampling time. The optimization objective is not invariable, but changes over time. At any moment, the objective function has a local optimal value.

Without reflecting the closed loop and feedback, the predictive control algorithm guarantees the consistency between the actual system and the base point of rolling optimization. In each step of control, the measured value is compared with the predicted value, and the incorrect predicted value is corrected.

To eliminate the field interference, time variance and error, the self-tuning was incorporated into the GPC algorithm. After detecting the relevant field data, the prediction parameters were updated online, such that the control law could be updated in time.

The GPC model is a discrete difference equation with nonstationary noise and random step disturbance:

$$A(z^{-1})\Delta y(k) = B(z^{-1})\Delta u(k-1) + e(k) \tag{12}$$

Then, the following equation can be obtained:

$$\Delta y(k) = -A'(z^{-1})\Delta y(k) + B(z^{-1})\Delta u(k-1) + e(k) \tag{13}$$

where, $A(z^{-1}) = A'(z^{-1})$.

The data and model parameters can be written as vectors:

$$\vartheta = [u_1, \cdots, u_n, v_1, \cdots, v_m]^T \tag{14}$$

$$\varphi(k) = [-\Delta y(k-1) \cdots - \Delta y(k-n)\Delta u(k-1) \cdots \Delta u(k-m+1)]^T \tag{15}$$

Then, formula (13) can be redefined as:

$$\Delta y(k) = \varphi^T(k)\vartheta + e(k) \tag{16}$$

The recursive LS method with genetic factors was used to estimate the parameters of the correlation model:

$$\hat{\vartheta}(k) = \hat{\vartheta}(k-1) + M(k)\left[\Delta y(k) - \varphi^T(k)\hat{\vartheta}(k-1)\right] \tag{17}$$

$$M(k) = Q(k-1)\varphi(k)\left[\varphi^T(k)Q(k-1)\varphi(k) + \epsilon\right]^{-1} \tag{18}$$

$$Q(k) = \frac{1}{\epsilon}\left[1 - M(k)\varphi^T(k)\right]Q(k-1) \tag{19}$$

where, $0 < \epsilon < 1$ is forgetting factor; $M(k)$ is weight factor; $Q(k)$ is covariance matrix.

Before executing the GPC algorithm, the covariance matrix Q and parameter vector ϑ must be configured. In general, $\hat{\vartheta}(0) = 0$, and $Q(0) = \alpha^2 I$. After the data vectors were constructed, $\hat{\vartheta}(k)$ and $Q(k)$ were solved by formulas (17)–(19).

4.2. BPNN-based GPC

The effectiveness of predictive control on nonlinear systems hinges on how well the nonlinear prediction model reflects the dynamic features of the object. To demonstrate such features, it is necessary to establish a prediction model for the nonlinear system, and incorporate rolling optimization in the prediction algorithm.

In this paper, the nonlinear prediction model is constructed based on the BPNN, which is good at nonlinear fitting and generalization. To realize rolling optimization, the nonlinear model was transformed by linearization method into a linear time-varying model. In this way, a BPNN-based GPC process was established (Fig. 4).

The nonlinear model can be defined as follows:

$$y(k) = f(y(k-1), \cdots, y(k-n), u(k-1), \cdots, u(k-m)) \tag{20}$$

where, $y \in R^n$ and $u \in R^n$ are the output and input of control object, respectively; n and m are the orders of the output and input, respectively; $f(\cdot)$ is the nonlinear function of the model.

The above model is a time varying system equivalent to linearization [27] under the following conditions: (1) $f(0, \cdots, 0) = 0$; (2) $f(\cdot)$ is continuously differentiable with a bounded derivative.

After linearizing formula (13) and adding disturbance term, the following formula can be obtained:

$$A(z^{-1})y(k) = B(z^{-1})u(k-1) + Y_c(k-1) + C(z^{-1})\rho(k)/\Delta \tag{21}$$

Then, the model was solved by the GPC algorithm. To improve the predictive control, the Diophantine equation was introduced:

$$E_j(z^{-1})A(z^{-1})\Delta + z^{-j}F_j((z^{-1})) = 1 \tag{22}$$

The predicted value of $k+s$ time can be optimized as:

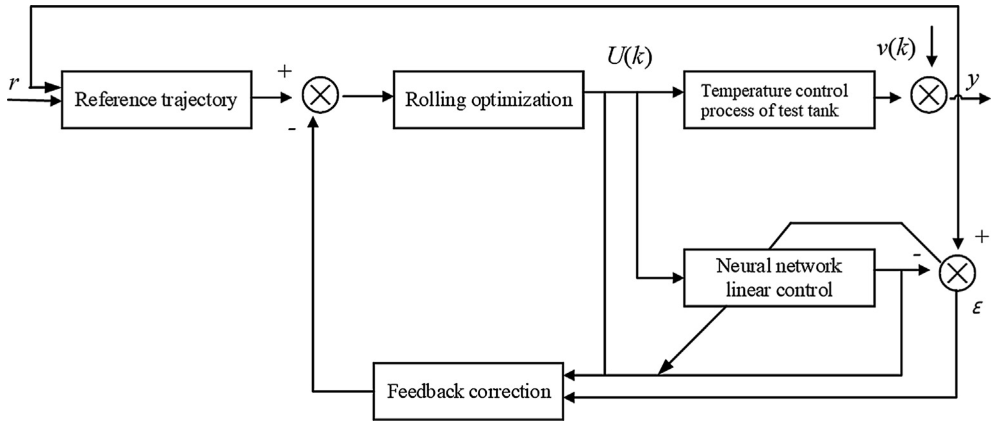

Fig. 4 Basic structure of BPNN-based GPC process.

$$y^{*}(k+s) = G_j \Delta u(k+s-1) + F_j(z^{-1}) y(k) + H_j \Delta u(k-1) \tag{23}$$

5. Simulation and results analysis

In the high and low temperature test tank, the temperature control process is a complex system with heat absorption and heat release. Besides, the system features strong nonlinearity, long lag, and high time variation, making it difficult to establish an accurate mathematical model. In general, the temperature control of environmental experiment can be described as a first-order delay system. Hence, the temperature control process in the test tank can be simplified as a first-order inertial link with time delay:

$$H(s) = Ke^{-\tau s}/Ts + 1 \tag{24}$$

where, T and τ are time constant and pure delay time, respectively; K is the static gain.

Since computer simulation mainly processes discrete signals, the continuous signal was discretized through z-transform of impulse transfer function $G(z)$. Then, the difference equation of the discrete system was obtained for simulation and control.

Before simulation, the prediction length N, control length N_u and flexibility coefficient β of the GPC were set to 9, 3 and 0.6, respectively. BP neural network model adopts 6–8-1 structure, there are 6 nodes in input layer, 8 nodes in hidden layer and 1 node in output layer. Moreover, the test temperature was set as 50 °C, for the actual temperature of the test tank falls between 48 and 52 °C.

Firstly, the GPC was applied to control the normal heating process. The GPC curve in Fig. 5 shows that, the control object tracked the preset object excellently, indicating that the GPC algorithm can control the heating process in the test tank well.

In addition, both the GPC and stepped GPC were simulated. As shown in Fig. 5, the stepped GPC improved the control effect and dynamic response, and kept the change directions of control parameters the same, such that the heating process would not fluctuate.

Next, the preset temperature was adjusted from 50 °C in the first 300 s to 52 °C in the next 300 s and to 48 °C in the last 600 s. The control curves of GPC and stepped GPC are displayed in Fig. 6 below.

Next, the change of the given temperature value is simulated. In the process of simulation, it is necessary to set the temperature reasonably, in which the temperature is 50 °C in the first 300 s, then 52 °C in 300 s and 48 °C in 600 s. The control strategy curve is shown in Fig. 6.

As shown in Fig. 6, despite the variation in the preset temperature, the control object could timely track the changing value. Judging by dynamic features, the stepped GPC responded faster than the general GPC. Moreover, with the change of the preset temperature, the control quantity of the stepped GPC moved smoothly in the same direction. When the sampling time is too large, it will lead to a very small change of control variables, which makes the controlled process can not be adjusted in time and will lead to poor dynamic performance of the system.

6. Conclusions

In the test tank, the temperature control process is a very complex system with heat absorption and heat release. It is difficult to control the process satisfactorily with a simple control method. To overcome the difficulty, this paper introduces the BPNN to predict temperature. After analyzing predictive control, a prediction model for the heating process in the test tank was established based on the BPNN. Then, the stepped GPC was integrated into the model, and the effects of important parameters on the model algorithm were studied in details. Simulation results show that our control method improved the dynamic response of the control system, and adjusted the parameters easily and intuitively. To sum up, this paper provides an effective tool to control the complex temperature control process in the test tank. In this paper, BP neural network method is used in temperature modeling. In the process of input variable increasing, the number of units will show exponential growth law, which will significantly reduce the training speed, or data over fitting problem, so we should continue to study in this field.

Declaration of Competing Interest

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

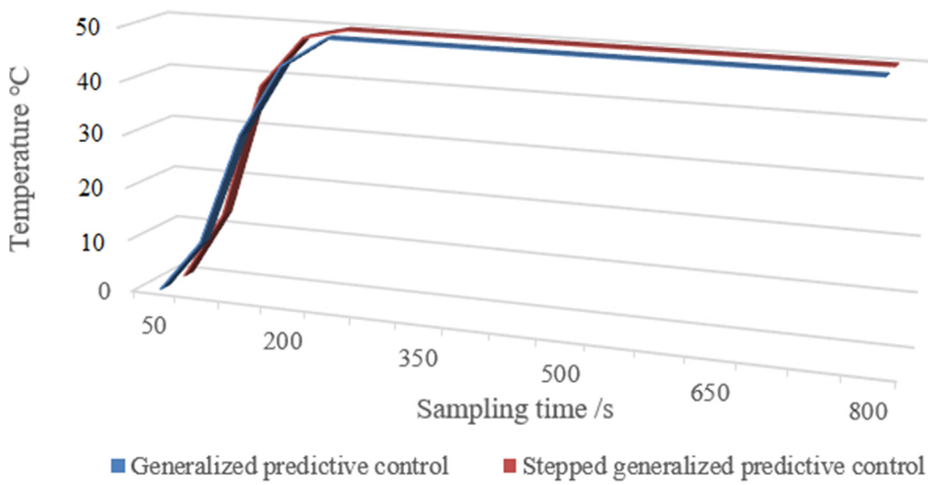

Fig. 5 Control curves of normal heating process.

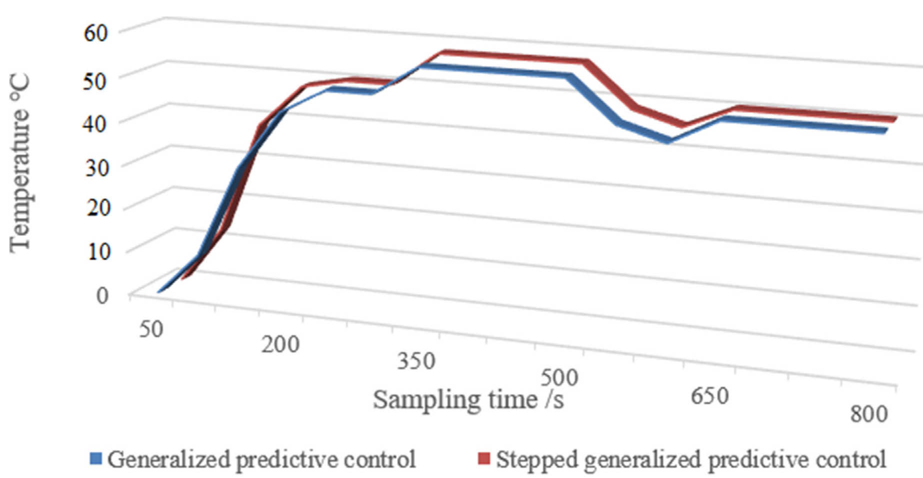

Fig. 6 Control curves of heating process with variable preset temperature.

Acknowledgements

This work was supported by the National Natural Science Foundation of China (Grant No. 11873046).

References

[1] Z.H. Zuo, Y. Wang, Design and simulation of a temperature control system for a heating furnace based on the quantitative feedback theory, J. Eng. Therm. Energy Power 25 (6) (2010) 663–1462.
[2] J. Zhong, J. Dieckhoff, M. Schilling, F. Ludwig, Influence of static magnetic field strength on the temperature resolution of a magnetic nanoparticle thermometer, J. Appl. Phys. 120 (14) (2016) 1559–1564.
[3] Q. Huang, L.M. Cui, Design and application of face recognition algorithm based on improved backpropagation neural network, Revue d'Intelligence Artificielle 33 (1) (2019) 25–32.
[4] B.H. Zheng, Y.F. Zhong, Study on the impacts of urban network evolution on urban wind and heat environment based on improved genetic algorithm, Ingénierie des Systèmes d'Information 23 (5) (2019) 105–119.
[5] S. Ouchtati, A. Chergui, S. Mavromatis, B. Aissa, D. Rafik, J. Sequeira, Novel method for brain tumor classification based on use of image entropy and seven Hu's invariant moments, Traitement du Signal 36 (6) (2019) 483–491.
[6] M.A. Wajeed, V. Sreenivasulu, Image based tumor cells identification using convolutional neural network and auto encoders, Traitement du Signal 36 (5) (2019) 445–453.
[7] S.J. Wang, Design and simulation of a fuzzy controller for automatic train driving based on multi-swarm optimization, Journal Européen des Systèmes Automatisés 52 (3) (2019) 495–500.
[8] A.E.H.M. Elbeltagy, A.M. Youssef, A.M. Bayoumy, Y.Z. Elhalwagy, Fixed ground-target tracking control of satellites using a nonlinear model predictive control, Mathematical Model. Eng. Probl. 5 (1) (2018) 11–20.
[9] A.A.M. Madkour, M.A. Hossain, K.P. Dahal, Intelligent learning algorithms for active vibration control, IEEE Trans. Man Cybernet. Part C 37 (5) (2007) 1022–1033.
[10] G. Sun, S. Bin, C. Chen, Reliability analysis of complex brain networks based on chaotic time series, Microelectron. Reliab. 99 (2019) 295–301.
[11] F. Lozano Santamaría, J.M. Gómez, An algorithm for tuning NMPC controllers with application to chemical processes, Ind. Eng. Chem. Res. 55 (34) (2016) 9215–9228.
[12] Y.Y. Hong, An enhanced expert system with fuzzy reasoning for line flow control in power systems, Electr. Power Syst. Res. 39 (1) (1996) 1–8.

[13] X. Wang, H. Pan, System of annealing furnace temperature control based on neural network, Adv. Mater. Res. 1044 (2014) 881–884.
[14] S. Nomura, T. Arima, The cause of the uneven carbonization process in wet coal charging in coke oven chamber, Fuel 87 (15–16) (2008) 3240–3246.
[15] Y. He, G. Li, Y. Sun, G. Jiang, J. Kong, D. Jiang, H. Liu, Temperature intelligent prediction model of coke oven flue based on CBR and RBFNN, Int. J. Comput. Sci. Math. 9 (4) (2018) 327–339.
[16] I. Yabanova, A. Kecbas, Development of ANN model for geothermal district heating system and a novel PID-based control strategy, Appl. Therm. Eng. 51 (1–2) (2013) 908–916.
[17] C.D. Townsend, T.J. Summers, R.E. Betz, Multigoal Heuristic Model Predictive Control Technique Applied to a Cascaded H-bridge StatCom, IEEE Trans. Power Electron. 27 (3) (2012) 1191–1200.
[18] S. Bin, G. Sun, Optimal energy resources allocation method of wireless sensor networks for intelligent railway systems, Sensors 20 (2) (2020) 482.
[19] Z. Tian, S. Li, Y. Wang, X. Wang, Q. Zhang, The time-delay compensation method for networked control system based on improved fast implicit GPC, Int. J. Control Automat. 9 (1) (2016) 231–240.
[20] D.R. Muir, Feedforward approximations to dynamic recurrent network architectures, Neural Comput. 30 (2) (2018) 546–567.
[21] S. Karmakar, G. Shrivastava, M.K. Kowar, Impact of learning rate and momentum factor in the performance of back-propagation neural network to identify internal dynamics of chaotic motion, Kuwait J. Sci. 41 (2) (2014) 151–174.
[22] Z. Cao, Y. Kuang, Process control of dense medium separation based on improved implicit generalized predictive control algorithm, J. Info. Comput. Sci. 11 (16) (2014) 5957–5968.
[23] G.L. Plett, Adaptive inverse control of linear and nonlinear systems using dynamic neural networks, IEEE Trans. Neural Networks 14 (2) (2003) 360–376.
[24] S. Bououden, M. Chadli, F. Allouani, S. Filali, A new approach for fuzzy predictive adaptive controller design using particle swarm optimization algorithm, Int. J. Innovat. Comput. Info. Control 9 (9) (2013) 3741–3758.
[25] G. Sun, S. Bin, A new opinion leaders detecting algorithm in multi-relationship online social networks, Multimedia Tools Appl. 77 (4) (2018) 4295–4307.
[26] G. Sun, S. Bin, Router-level internet topology evolution model based on multi-subnet composited complex network model, J. Internet Technol. 18 (6) (2017) 1275–1283.
[27] K. Nam, A. Arapostathis, K.K. Lee, Some numerical aspects of approximate linearization of single input non-linear systems, Int. J. Control 57 (2) (1993) 463–472.

Please cite this article in press as: Q. Zhao et al., Stepped generalized predictive control of test tank temperature based on backpropagation neural network, Alexandria Eng. J. (2020), https://doi.org/10.1016/j.aej.2020.08.032