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Research Article

Model Reference Adaptive Control Based on GANN for Vertical Electric Furnace

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Abstract: The vertical electric furnace is a multi-variable complex system, conventional control methods are used to control it, to need modelling and decoupling. In this study, a model reference adaptive control using the Neural Network with Genetic Algorithm (GANN) for the temperature control of the vertical electric furnace is proposed. The neural model of the system is identified by the genetic algorithm. Another neural network is trained to learn the inverse dynamics of the system so that it can be used as a nonlinear controller. Because of the limitation of BP algorithm, the genetic algorithm is used to find the fitness weights and thresholds of the neural network model and the simulation results show that the model is satisfied and the control is effective.

Keywords: Adaptive control, genetic algorithm, multi-variable system, neural network, vertical electric furnace

INTRODUCTION

The vertical electric furnace is a multi-variable control system. It is used to test the mechanical properties of the high temperature alloys with the aviation in the steel. The internal structure of the vertical electric furnace is shown as Fig. 1. According to the technical requirements, the test temperatures of different materials are not the same. Generally, the test temperature is in 100 to 980°C range. We demand that the test temperature stably rise from room temperature to the setting point and long-term stability in the settings and the errors are ±2°C.

The outside wall of the ceramic bushing in the vertical electric furnace is heated by the upper and the lower resistance wires. Then, the steel specimen and clamp in the centre of the ceramic bushing are heated by multi-thermodynamic process. Two outcrop sheathed thermocouples of K (EU-2) type are installed two points that is away from 25 mm in the steel specimen surface. According to the technical requirements, the temperature error of the two points on the steel specimen surface must be less than ±4°C in 400 to 900°C range. This means the steel specimen has a small temperature gradient in the length of 25 mm, or there is a symmetrical temperature field.

The temperature of the vertical electric furnace is heated and kept by the resistance wires, but the drop in temperature depend on natural cooling. When the temperature of the vertical electric furnace has overshoots, it will not be able to use control method to cool. Thus, the vertical electric furnace only has a heating input control phase and large time delay yet. It is more difficult to control than two phase plant to obtain good control performance. Besides, the upper and the lower temperature regions of the vertical electric furnace exist in the characteristic of mutual coupling. In addition, the temperature control is non-linear, so it is very difficult to obtain satisfactory control effect by using the conventional control methods and estimate an appropriate dynamic model for model-based controller design. Especially, the temperature control problem with heating input only has time-delay and asymmetric control behavior. How to design a practical temperature controller with good response speed, smaller steady-state error and without overshoot for industrial implementation is still a challenge in the control research field.

Hornik *et al*. (1989) reported that Artificial Neural Networks (ANNs) have shown an excellent ability to model any nonlinear function to a desired degree of accuracy. Because of this property, they are suitable for the identification and control of nonlinear plants.

Genetic Algorithms (GAs) are a parallel global search technique that emulates natural genetic mechanics and biological evolution theory. Because they exploit strategies of genetic information and survival of the fittest to guide their search, it needs not calculate the gradient and assume that the search space is differentiable or continuous. Besides, they simultaneously evaluate many points in the parameter space, so it is more likely to converge toward the global solution. Genetic algorithms are very suitable for searching discrete, noisy, multimodal and complex space (Goldberg, 1989). They have been successfully applied to engineering in search and optimization problems because it has many remarkable features,

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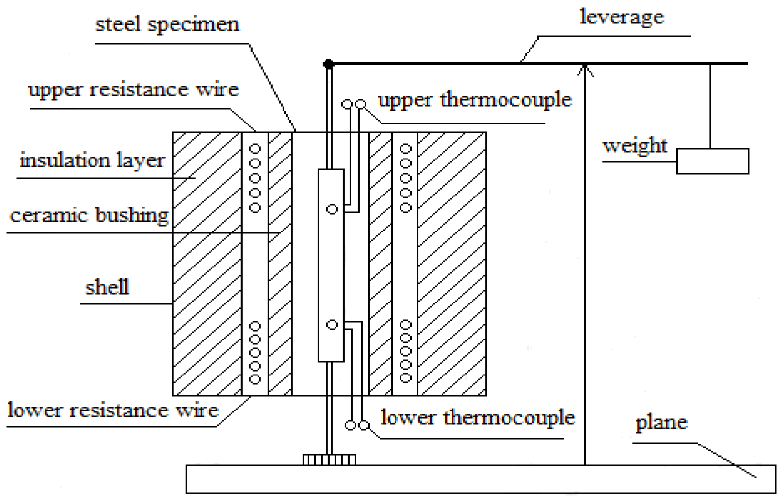

Fig. 1: The internal structure diagram of the vertical electric furnace

which are reported by Goldberg (1989), Li *et al*. (2005), Teng *et al*. (2003) and Sharma *et al*. (2005).

The hybrid control methods of the genetic algorithm and neural network are used for the complex system. In this study, the Model Reference Adaptive Control (MRAC) strategy is considered, due to its excellent robustness and stability (Wang *et al*., 2003; Araz and Salum, 2010). The MRAC strategy based on ANN consists in training a network to learn the process dynamics of the vertical electric furnace. Another ANN is trained to learn the inverse dynamics so that it can be used as a nonlinear controller.

In general the inversion of nonlinear models is not an easy task and analytical solutions may not exist, so solutions have to be found numerically. One important point is that the inversion of the process model may lead to unstable controllers when the plant has unstable zeros.

In this study, the Back-Propagation (BP) neural network is used to identify the model and inverse model of the vertical electric furnace. The power of the BP network has been demonstrated by a number of workers and research has indicated that a BP neural network has the potential to approximate any continuous nonlinear function with arbitrary accuracy, provided that there are enough hidden neurons. In order to overcome the disadvantage of BP algorithm, the improved genetic algorithm is used to train the neural network and present an interesting alternative to optimize the weight and threshold of BP structure. It is very efficient that the genetic algorithms are used to train the NN (Sharma *et al*., 2005). Based on the model and inverse model of the neural network, an effective MRAC method is proposed for the temperature control of the vertical electric furnace.

NEURAL NETWORK MODELLING

The NN modeling for the vertical electric furnace: Artificial neural networks have been increasingly used in many aspects of controlling and modelling in the industry (Hsu *et al*., 2005). The traditional use of neural network modelling is a black-box approach; i.e., a neural network is trained on the available process data. However, in the real world, quite often the available process data are not sufficient to develop a good neural network model. The main difficulties arise from lack of excitation in the training data, uneven distribution of the data samples, significant noise in the modeling data, etc. They will result in the inaccurate neural network model and the not converged process of learning algorithm.

A normal network contents input layer, hidden layer, output layer, the hidden layer may not be only one. In BP network the output of every nodes in one layer only affect the output of the next layer. The nodes of different layers are connected by the weights.

The BP NN is trained to learn the dynamics of the temperature of the vertical electric furnace using the genetic algorithm, as shown in Fig. 2.

The output of the neural network is denoted by:

$$y_k^m(x) = \sum_{j=0}^{m} f\left(\sum_{i=0}^{n} x_i w_{ji}\right) v_{kj}$$

$$= \sum_{j=1}^{m} f\left(\sum_{i=1}^{n} x_i w_{ji} + w_{j0}\right) v_{kj} + v_{k0}, \quad k = 1, \cdots, l \tag{1}$$

where, w_{ji} and v_{kj} are the input-hidden weight and hidden-output weight respectively and f is activation function that it is used in the hidden layer and the output layer, as follows:

$$f_{ij}(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{2}$$

In the training scheme of the neural network, the determination of parameters usually involves the

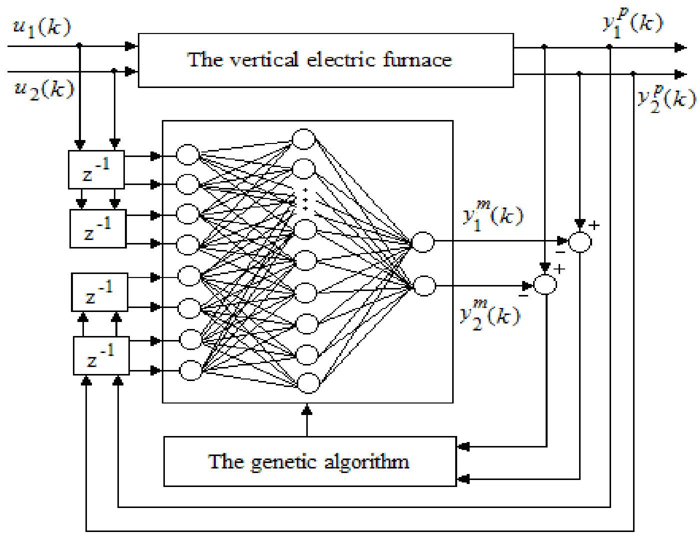

Fig. 2: BP NN is trained to learn the dynamics of the vertical electric furnace

minimization of an error function that, typically, is the Mean Squared Error (MSE) between the actual outputs and the targets for the whole training set. For a multi-output system, MSE is calculated using all the training examples over each network output, denoted by:

$$MSE = \frac{1}{nl}\sum_{i=1}^{n}\sum_{j=1}^{l}(y_{ij}^{p} - y_{ij}^{m}) \tag{3}$$

where,
l, n = The number of NN outputs and the number of training data respectively
y^p_{ij} = The actual output of the vertical electric furnace
y^m_{ij} = The output of NN model

Since GA is usually applied to maximize a fitness function, a transformation is required to convert the error function into a suitable fitness function. A common method for this purpose is given by:

$$f = \frac{1}{MSE + a} \tag{4}$$

where, a is a small positive constant ($0<a<1$) that is used to avoid dividing by zero. Thus, f can now be treated as the absolute fitness function of the genetic algorithm.

The parameter vector θ of the genetic algorithm is described as:

$$\Theta = [W, V] \tag{5}$$

where,
$W = (w_{ij})^T$ (i = 1, …, 8, j = 1, …, 16) is the weights between input layer and hidden layer
$V = (v_{ij})^T$ (i = 1,…, 16, j = 1, 2) is the weights between hidden layer and output layer

Each real parameter of the vector θ needs to be given a specified interval [$\theta_{j\min}$, $\theta_{j\max}$] so that the L_j-bit substring of the binary code is interpreted as the binary integer on the interval [0, 2^{L_j}] and this integer can be mapped to this interval according to the following:

$$\theta_j = \theta_{j\min} + \frac{binrep}{2^{L_j} - 1}(\theta_{j\max} - \theta_{j\min}) \tag{6}$$

where,
$binrep$ = The integer value represented by an L_j-bit string
θ_j = j^{th} real parameter of the vector θ

In this study, the reproduction is implemented using stochastic remainder without replacement. Expected string count values are calculated as $NF_i / \sum_{i=1}^{N} F_i$ and integer parts are assigned the reproduction numbers of the strings and the fractional parts of the expected number values are treated as probabilities. One by one, whether the fractional parts will be able to reproduce one string is decided by the stochastic probability. This process continues until the population is full.

An effective method of adaptive probabilities of crossover and mutation is used in the study. In this method, the crossover probability P_c and the mutation probability P_m are varied with the fitness values of the solution. Therefore, low values of P_c and P_m are assigned to high fitness solutions, while low fitness solutions have very high values of P_c and P_m. The method can maintain diversity in the population and sustain the convergence capacity of the GA. The expressions for P_c and P_m are given as:

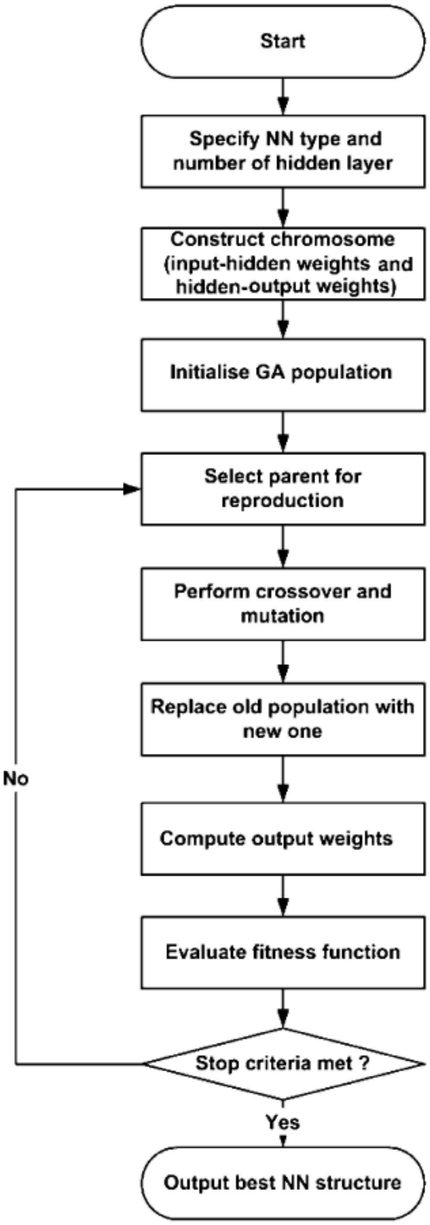

Fig. 3: Flowchart of neural network training by the GA

$$P_c = \begin{cases} k_1(f_{\max} - f')/(f_{\max} - \bar{f}), & f' \geq \bar{f} \\ k_2, & f' < \bar{f} \end{cases} \tag{7}$$

and

$$P_m = \begin{cases} k_3(f_{\max} - f)/(f_{\max} - \bar{f}), & f \geq \bar{f} \\ k_4, & f < \bar{f} \end{cases} \tag{8}$$

where, k_1, k_2, k_3, $k_4 \leq 1.0$, $f_{\max}$ is the maximum fitness value, $\bar{f}$ is the average fitness value, f' is the largest of the fitness values in the two stings to be crossed and f is the fitness value of the string to be mutated.

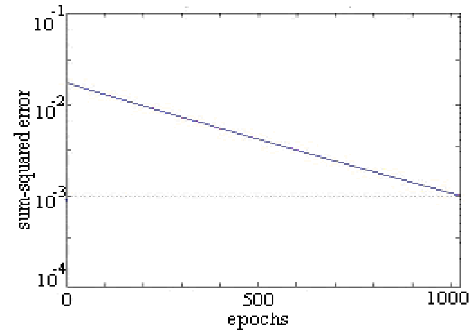

Fig. 4: Error curve of the NN model

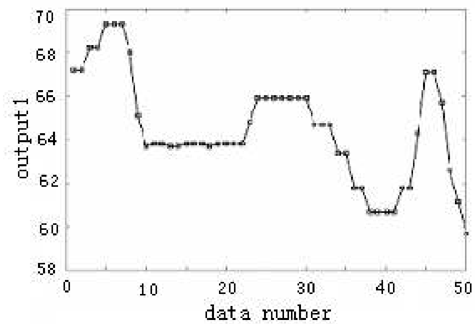

Fig. 5: Actual output 1 versus model output 1

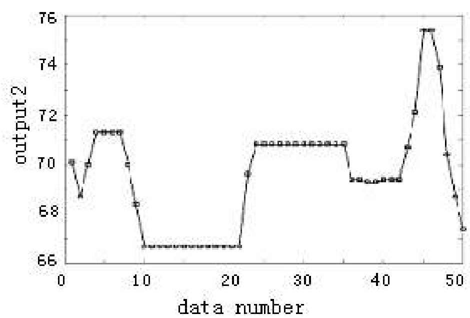

Fig. 6: Actual output 2 versus model output 2

The procedure of the NN model training by the GA is described as Fig. 3.

SIMULATION RESULTS

Once the model structure has been defined, the next step is to train this particular NN by the proposed method. In experiment, the data of inputs and outputs are acquired from the actual temperature of the vertical electric furnace, i.e., gather once data from the two inputs and outputs every 10 sec, collected a total of 5 sets of data, each consisting of 720 data. After they are pretreated, the two sets of data are selected, which one set of data is used to train the NN, another is employed to enhance its generalization capabilities. Our method can automatically choose the best weights and thresholds for each generation. We set the initial weights between -1 and 1. The goal of error is 0.001,

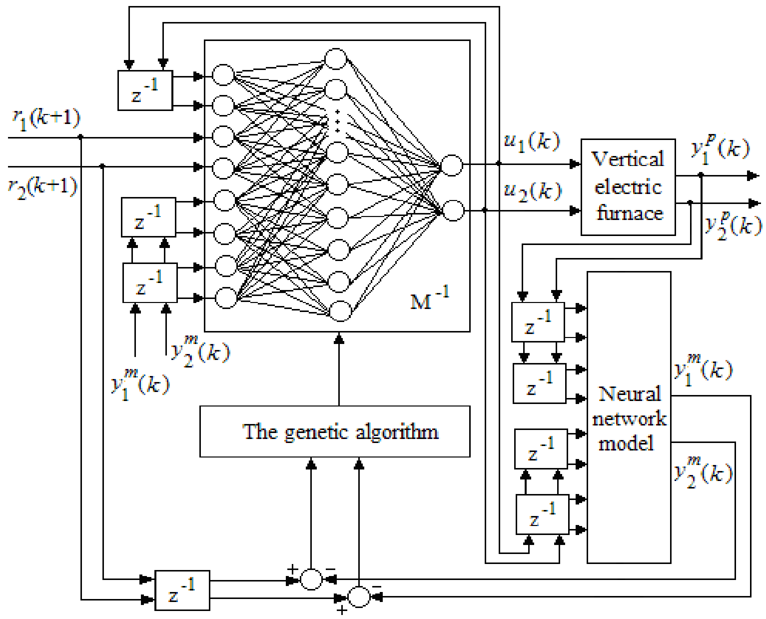

Fig. 7: BP NN is trained to learn the inverse dynamics of the vertical electric furnace

learning rate is 0.005 and the largest training time is 3000.

The genetic parameters for the NN model training are chosen as follows:

Population size N = 80
Coefficients of crossover probability k_1 = 0.9 and k_2 = 1.0
Coefficients of mutation probability k_3 = 0.02 and k_4 = 0.1

After the NN model training algorithm is implemented, the error curve is obtained in the Fig. 4, the dotted line is shown as the error-goal and the solid line is shown as error-trained. From the Fig. 4, we can see that about 1024 epochs the sum-squared error reached error-goal.

In the Fig. 5 and 6, '-o-' stands for the actual temperature of the vertical electric furnace, '-*-' stands for the model output. It is clearly seen that the NN model obtained by the proposed method produces a good approximation to temperature of the vertical electric furnace, the MES is 0.00019.

The inverse NN modelling for the vertical electric furnace: In the model reference adaptive control strategy, another ANN needs to be trained to learn the inverse dynamics of the vertical electric furnace so that it can be used as a nonlinear controller.

The BP NN is trained to learn the inverse dynamics of the vertical electric furnace using the genetic algorithm, as shown in Fig. 7.

The output of the neural network for the inverse model is denoted by:

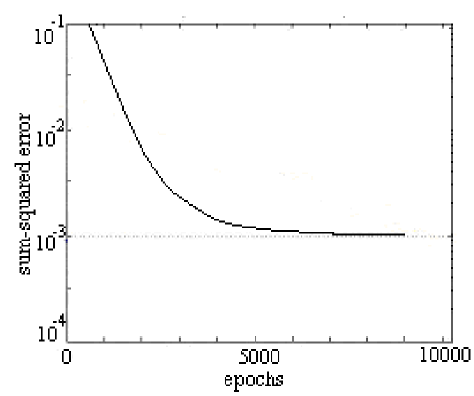

Fig. 8: Error curve of the NN inverse model

$$u_k(x) = \sum_{j=0}^{m} f\left(\sum_{i=0}^{n} x_i w_{ji}\right) v_{kj}$$

$$= \sum_{j=1}^{m} f\left(\sum_{i=1}^{n} x_i w_{ji} + w_{j0}\right) v_{kj} + v_{k0}, \quad k = 1, \cdots, l \tag{9}$$

The input vector of the neural network is denoted by:

$$\begin{aligned} X(k) = [&y_1^m(k), \cdots, y_1^m(k-n), r_1(k+1), \\ &u_1(k-1), \cdots, u_1(k-m), \\ &y_2^m(k), \cdots, y_2^m(k), r_2(k+1), \\ &u_2(k-1), \cdots, u_2(k-m)]^T \end{aligned} \tag{10}$$

where $r_t(k+1)$ (t = 1, 2) is the input of the controller, replace with y^m_t (k + 1) because it can be not measured in the actual plant.

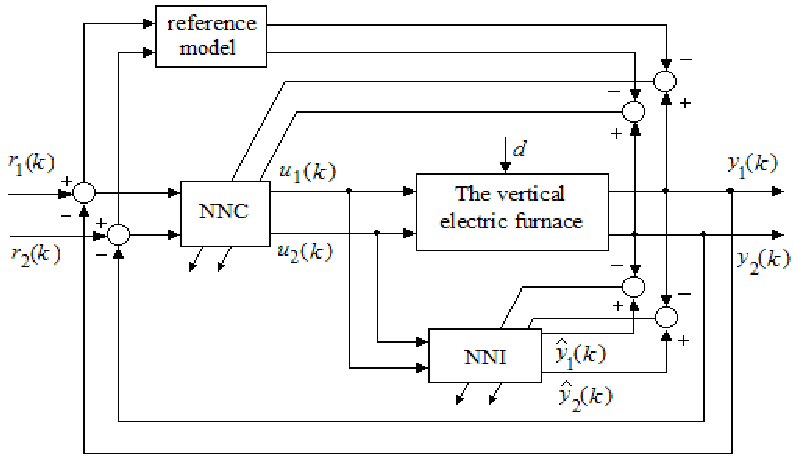

Fig. 9: The configuration of MRAC for the vertical electric furnace

The other parameters are the same with the aforementioned those. The NN inverse model is trained by using the proposed genetic algorithm.

After the NN model training algorithm is implemented, the error curve of the inverse model is obtained in the Fig. 8, the dotted line is shown as the error-goal and the solid line is shown as error-trained. From the Fig. 8, we can see that about 5160 epochs the sum-squared error reached error-goal. It is clearly seen that training time of the NN inverse model needs longer by the proposed method.

THE MODEL REFERENCE ADAPTIVE CONTROL

The model and the inverse model using the neural network have been identified by above section. A model reference adaptive control based on the GA-NN is presented in this study.

MRAC for temperature of vertical electric furnace: In the MRAC strategy, the model of the neural network is used as the estimator of the vertical electric furnace and the inverse model is employed as the controller. The configuration of MRAC for the temperature control the vertical electric furnace is shown as Fig. 9. The d is disturbance of the system. The reference model is selected as:

$$y_m(k+1) = ay_m(k) + r(k) \qquad (11)$$

where, a is constant.

In Fig. 9, $y_1(k)$, $y_2(k)$, $u_1(k)$ and $u_2(k)$ are the two output and input of the vertical electric furnace respectively. $r_1(k)$ and $r_2(k)$ are the input of the control system.

Simulation result: The traditional PID control is employed in order to compare with the proposed method MRAC in the study. In all disturbances d = 0, the parameter of the reference model is selected as a = 0.56. The input of the temperature is 500°C, a plot of the response of the system appears in Fig. 10. The green line and purple line are the output of the MRAC, which they denote the upper and the lower temperature regions of the vertical electric furnace respectively. The red line and blue line are the output of the PID control. It is clearly seen that the transient and steady-state

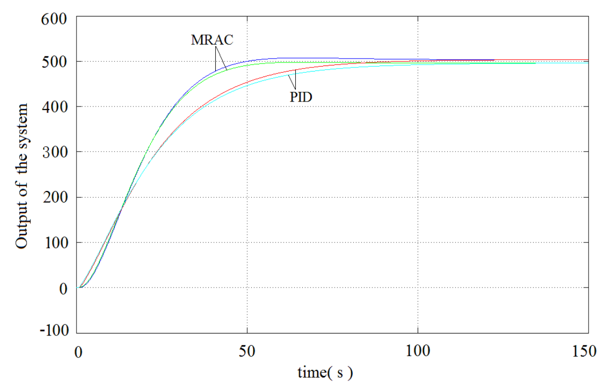

Fig. 10: The response of the temperature control system

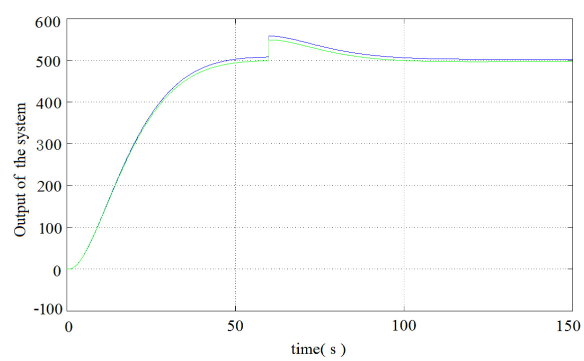

Fig. 11: The response of the MRAC under the disturbance signal d = 60

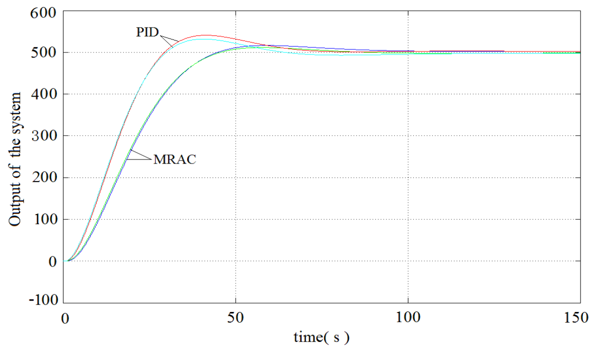

Fig. 12: The response of the system in parameters of the vertical electric furnace is increased by 25%

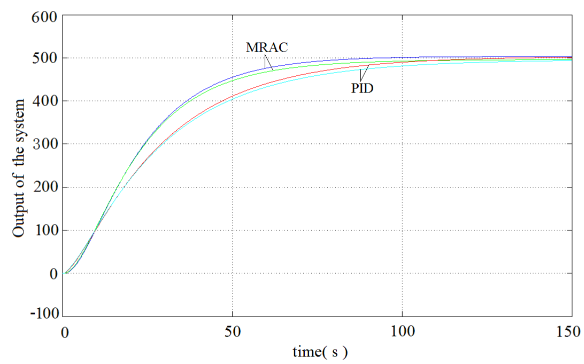

Fig. 13: The response of the system in parameters of the vertical electric furnace is decreased by 25%

response of the system has the advantage of the MRAC method over the traditional PID control. Thus, the response parameters of the system, as the overshoot, the settling time and the steady-state value is very satisfied. We now consider that the system has disturbance. Assume that the disturbance signal d is 10% of the system input, i.e., d = 60, the plot of the response of the system is shown in Fig. 11. It is clearly seen that the MRAC system proposed has a good capability of resisting disturbance.

When the parameters of the temperature model of the vertical electric furnace is increased by 25%, the response of the system of the two control methods is shown in Fig. 12. After the parameters of the temperature model of the vertical electric furnace is decreased by 25%, the response of the system of the two control methods is shown in Fig. 13. It is clearly seen that the MRAC is robust.

CONCLUSION

The temperature of the vertical electric furnace is strongly coupled and disturbed, nonlinear and slow time-variant. It is difficult to control the temperature of the vertical electric furnace with conventional methods. The model reference adaptive control strategy based on the GA and NN is considered to control the temperature of the vertical electric furnace in this study. The model of the neural network of the system is identified. Another NN is trained to learn the inverse dynamics of the system. In order to overcome the disadvantage of BP learning algorithm, the genetic algorithm is used to train the neural networks to learn the dynamics and inverse dynamics of the system. The simulation results show that the method proposed for controlling the temperature of the vertical electric furnace is effective.

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