Application of PID Controller Based on BP Neural Network in Export Steam′s Temperature Control System

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Abstract — **By combining the Back-Propagation (BP) neural network with conventional proportional Integral Derivative (PID) controller, a new temperature control strategy of the export steam in supercritical electric power plant is put forward. This scheme can effectively overcome the large time delay, inertia of the export steam and the influence of object in varying operational parameters. Thus excellent control quality is obtained. The present paper describes the development and application of neural network based controller to control the temperature of the boiler′s export steam. Through simulation in various situations, it validates that the control quality of this control system is apparently superior to the conventional PID control system.**

Key words — *PID controller based on BP neural network*; *supercritical power unit*; *export steam temperature*; *large time delay*

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1 Introduction

The control system of thermal power planted boiler export steam′s temperature is an important part to improve efficiency and ensure the safe operation of the unit thermal. There are many complex factors interfere the export steam′s temperature, under the various disturbance, the dynamic characteristics of the export steam′s temperature are large delay, large inertia, time-varying and nonlinear, which is particular in the supercritical units.

Using conventional fixed parameters PID to control the object is difficult to balance between the stability and quality, and even if this system could set relatively good parameters, as the object properties change, the control quality is also difficult to guarantee. In view of this situation, we need such a PID controller whose bias of output control related not only to the deviation of size, but also the state of the controlled object. So it requires the PID control parameters K_P, K_I K_D can alter the size and object state according to the changes in auto-correction, and keep the quality of the control system stable. The neural network has the nonlinear representation capabilities. Just right through learning system performance we can find the best combination of PID control parameters K_P, K_I, K_D, which can adapt the practical conditions.

Artificial neural networks have been the focus of a great deal of attention during the last three decades, due to their capabilities to solve the nonlinear problems by learning from data. Although a broad range of neural networks architectures can be found, Multilayer Perceptions (MLP′s) and Radial Basis Function Networks (RBFN′s) are the most popular models[1]. Neural Networks (NNs) could be thought of as a nonlinear mapping between a set of inputs and outputs. In a neural network the inputs and outputs are connected through a series of nodes arranged in some layers (Fig. 1). Because of this complex connectivity the NN model is able to perform the mapping with excellent accuracy[13].

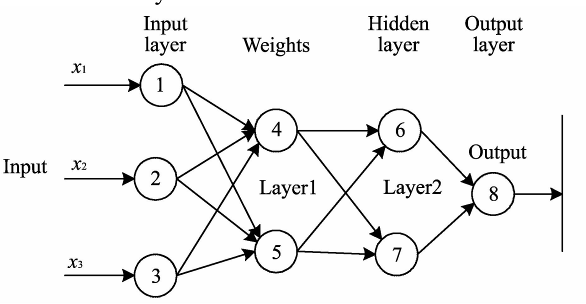

Fig.1 Feed forward neural network

There are no hard rules about the choice of the number of nodes and the number of hidden layers to be used in an application. Usually some trial and error is required to determine the best combination to minimize the error. Before a neural network model can be used it must be trained yet[2]. During the training the best values of the weights are determined by an optimization technique. In the present works a standard method of optimization called Generalized Delta Rule (GDR) was used for training the networks. In the GDR′s algorithm we begin with an initial assumed set of weights which can all be unity. For all data sets in the training set we determine the calculated outputs using the NN and compare it with the actual required outputs. The errors between the two are used to change the weights such that the summations of the squared errors are minimized. In the present study the Levenberg Marquardt method was used for the optimization[3].

This article combines the BP neural network with conventional PID controller, through learning from the system performance to find the best combination of PID control parameters, and sent directly to the conventional PID controller. So we can get a controller based on BP neural network used to control the export steam′s temper-

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ature. Simulation results show that PID controller based on BP neural network has strong adaptability, whose control quality is better than conventional PID controller too[6].

2 The control system of the export steam's temperature

In this article, the natural circular boiler widely used in the areas of industrial is selected as the object controlled. The fuel burns in the furnace and water in the drum is heated by the radiation. Then the gas with high temperature produced by the burning of the fuel enters the convection chamber and transfers the energy to the water by convection. The industrial boiler mainly constitutes with the radiation chamber, convection chamber and the ventilation system. The radiation chamber is the part of transferring energy by the flame radiation. This part directly affected by the flame with the highest temperature. The radiation chamber is the main place for the heat exchange and the most important part of the whole furnace. The ultimate goal of the control system is that make the temperature of the outlet steam reach the expectations. Therefore, the temperature control is the most important part of the system.

In theory the single-loop control system with the steam's temperature as the volume charged and the amount of fuel as the control volume can overcome most of the disturbance. However, to the boiler object, the control channel's large time constant volume delayed and its large control action is not timely, the system cannot overcome the disturbance or meet the requirements of the production process. Therefore, the system selects the cascade control of boiler steam's (temperature-temperature of the boiler) to achieve steam's temperature control. Cascade control system uses the output of a regulator to change the settings of another regulator and the two controllers are linked together[4]. The control system is shown in Fig. 2.

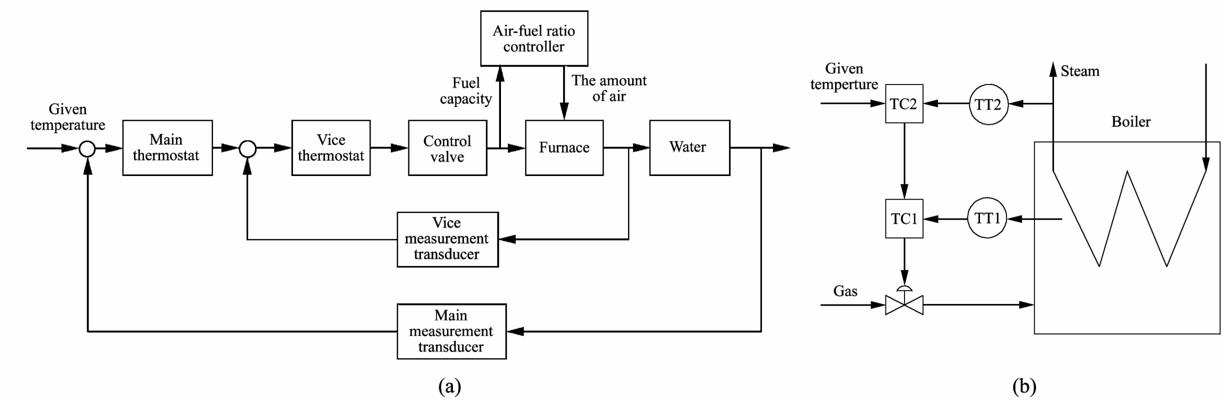

Fig. 2 (a) the block chart of steam's temperature control; (b) the process chart of steam's temperature control

The features of the cascade control are: ①Improve the dynamic characteristics and the control quality of the process. ②Greatly enhances the ability of overcoming the secondary disturbance. ③Have a good ability of overcoming the firstly disturbance. ④Have some adaptive capacity against the parameters change in the vice-loop.

As shown in Fig. 2, in the cascade control system, temperature system which is the cascade control system of the deputy circuit is primarily used to provide the right amount of air and fuel flows according to the output requirements of the primary loop temperature controller, to respond to the furnace changes in the output of the main loop as soon as possible. Steam outlet temperature controller is the main controller; its output is the settings of the deputy controller, through the temperature controller to determine the fuel valve opening. The fluctuation of fuel pressure disturbance and other rapid changes, which included in vice loop, using the excellent dynamic performance of deputy circuit to suppress these disturbances on the outlet temperature of materials. When the steady state is destroyed, the outlet controller and the furnace temperature controller work together[14].

Cascade conventional outlet steam temperature control system, its main loop adopts the control law of PID; the deputy circuit adopts the control law of PID. The interference of factors of the outlet steam temperature is very much, very often, and has a great disturbance, the steam temperature's dynamic characteristicunder various disturbance has characteristics of large delay, large inertia, time-varying and nonlinear. Therefore, traditional control methods are difficult to meet the high accuracy requirement.

In order to maintain the advantages of cascade control system and maintain the deputy circuit's *P* controller unchanged, while change the main circuit of the conventional PID controller to BP neural network tuning PID controller, this constitutes a steam temperature control device system with BP neural network and PID Controller[5].

3 Introduction of the neural networks

3.1 Neural Networks

Artificial Neural Networks (ANNs) are biologically inspired and mimic the human's brain. They are consisting of large numbers of simple processing elements called as neurons[7].

The schematic diagram for an artificial neuron model is given in Fig. 3.

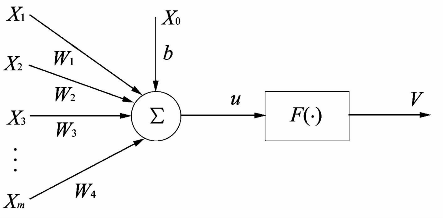

Fig. 3 Artificial neuron model

Let $x = (x_1, x_2, \cdots, x_n)$ represent the n inputs applied to the neuron. While w_i represents the weight for the input x_i and b is a bias, then the output of the neuron is given by Eq. (1).

$$u = \sum_{j=0}^{m} x_j w_j - b,\ v = f(u). \tag{1}$$

3.2 Improved three-layer BP Neural Network framework

BP network is a typical way for altering errors. It sets each quantified index as the network's input, x. and the result as output, o. After training enough samples and amending repeatedly connection weight values (w, v) and threshold values between neurons, final weight values and threshold values are obtained to indicate correct knowledge[9] (Fig. 4). In this study, the improved three layer BP network algorithm is applied. Extra momentum and self-adaptation's gradient-descending method are used in the network training.

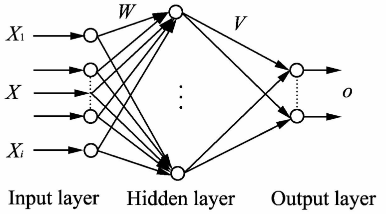

Fig. 4 Three-layer BP Neural Network framework

3.3 Controller learning

The first control strategy which has been proposed is to train the neural network to behave like the inverse of the process, and then use it as a controller (see Fig. 5). For a Single-Input and Single-Output (SISO) nonlinear process to be controlled, with input U and output Y, it is assumed that this model can be expressed by Eq. (2)[10].

$$\begin{aligned} y(t+1) = f(&y(t), \cdots, y(t-n+1), \\ &u(t), \cdots, u(t-m)). \end{aligned} \tag{2}$$

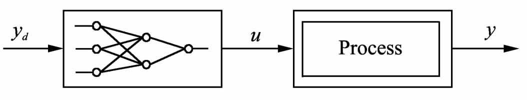

Fig. 5 Direct inverse control(open loop)

Therefore, the model of the system can be built by using a neural network

$$\begin{aligned} \hat{u}(t) = \hat{f}^{-1}(&y(t+1), y(t), \cdots, y(t-n+1), \\ &u(t-1), \cdots, u(t-m)). \end{aligned} \tag{3}$$

The latter model could be used for control by replacing the actual system's output at time $t+1$, $y(t+1)$ by the reference $y_d(t+1)$[11].

In the case where the direct model is stable and one-to-one, learning of the inverse model can be done directly from the system only (see. Fig. 6(a)). The inverse model can also be taught to be configured as a process controller c by a recursive gradient-based algorithm. This "specialized" learning requires the process Jacobian (gradient), which can be obtained from the physical knowledge of the process, if available, or approximated by[12]

1) applying small variations (Δu) to the process input;

2) observing the output (Δy);

3) calculating the approximate gradient ($\Delta y / \Delta u$).

Alternatively, the process can be approximated by a (direct) linear model M or by a nonlinear neural one, from which the gradient can be derived (see Fig. 6(b)). Note that the latter approach is quite close to the conventional adaptive control.

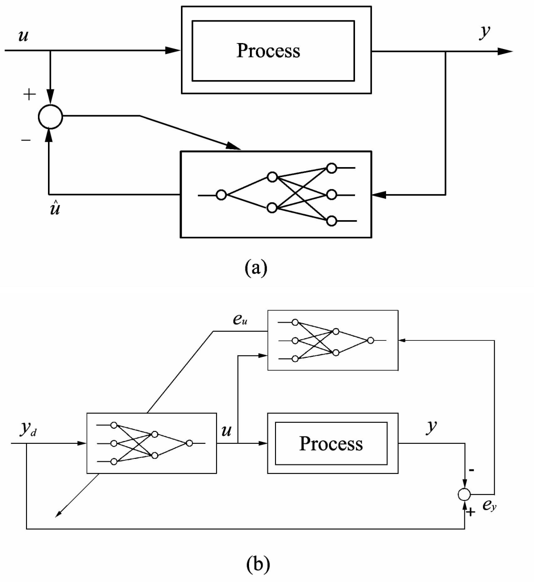

Fig. 6 (a) direct learning; (b) specialized learning through direct neural model

4 The simulation of the system

Choose the model between the fuel valve and the outlet temperature as follows[12]:

$$G(s) = \frac{1.64 e^{-120s}}{493s + 1}. \tag{4}$$

The model of PID controller based on BP neural network is shown in Fig. 7. As the neural network learniog algorithm can not be directly used to describe the transfer function, we cannot use the simulink simply, and then we have to introduce the S function. The S function has a fixed format procedure. We must form an S function module and use the language and embed it into the system' s simulation model. The Simulation waveform can be seen in Fig. 8. From these simulation results we can see that the simulation curve of conventional PID controller have a large overshoot, while the PID controller based on BP neural network have better Static characteristics than the conventional PID controller. The parameters of the controller based on BP neural network have self-tuning features; it also has better dynamic characteristics than the conventional regulator.

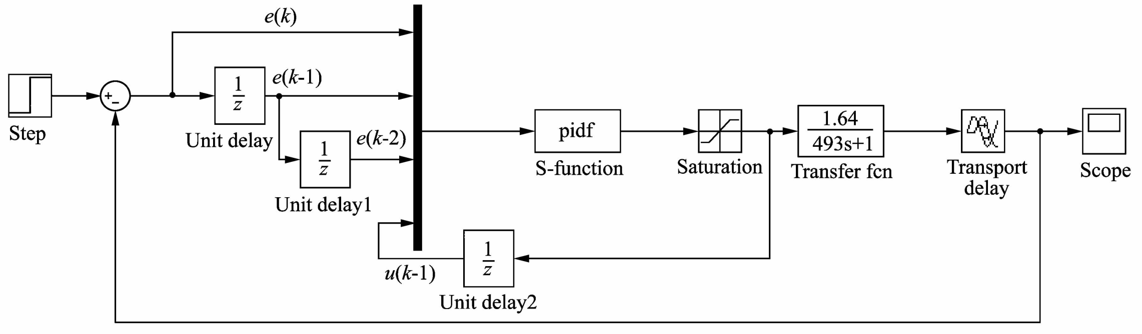

Fig. 7 Simulink model of PID controller based on BP neural network

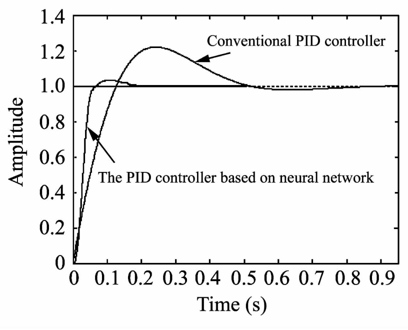

Fig. 8 Response diagram under the PID controller based on BP neural network and the conventional PID controller

5 Conclusion

The steam′s temperature control system is an object with large delay, large inertia, time variability and nonlinear. The conventional PID control system is difficult to meet the control quality. In this paper we combine the BP neural network and PID controller together, using BP network′s strong self-learning ability to make the PID controller with the function of parameter self-tuning, and make up the conventional PID controller′s shortage in solving the nonlinear, parameter varying system. This method have the features of simple, high accuracy and steady-state, short transition process and it is worth extending to the practical applications. As can be seen from the simulation results the PID controller based on BP neural network have better Static and dynamic characteristics than the conventional PID controller. To improve the performance of the system furthermore, we need to acquire more deep knowledge about the process of blast furnaces, and explore efficient methods for representing and processing qualitative knowledge as well.

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