

Research of the Electro-hydraulic Servo System Based on RBF Fuzzy Neural Network Controller

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Abstract—This article describes the composition and working principle of electro-hydraulic position servo control system, and establishes a systematic mathematical model. This article presents a controller which is based on Fuzzy neural networks for an electro-hydraulic speed governor. The design process of the RBF Fuzzy neural network control is introduced in detail. This controller which combines the advantages of the Fuzzy control and Neural networks control can get the best PID parameters by self-adjustment on line. The simulation study proves that this control system has a better adaptability and can improve the control effect greatly.

Index Terms—RBF neural network, electro-hydraulic servo system, PID controller, fuzzy control.

I. INTRODUCTION

Conventional PID controller is a kind of controller with the most basic and widest application. It has advantages of simple algorithm, good stability, and high reliability and so on. The regulation law of conventional PID controller is very effective to quite a number of control objects, especially to linear time-invariant system, and the quality of its regulation process depends on tuning of all parameters of PID controller. However, the traditional PID control algorithm is tuned and finished under certain specific condition, the actual control system often has nonlinearity and time-varying uncertainty, thereby it is difficult to establish accurate mathematical model. Thus, when conditions change, a group of PID parameters is difficult to adapt to different working conditions, so the conventional PID controller often can not achieve the desired design performance. In order to overcome the shortcomings of conventional PID controller, the control field has proposed a number of programs of improving PID controller, such as self-tuning PID controller, generalized predictive PID controller, fuzzy PID controller, expert PID controller, intelligent PID controller, etc..

Although the theoretical basis for the different programs is difference with different methods, they are common in aiming at how to select and tune PID parameters, and they adopt new methods to confirm three

parameter values of PID control in on-line or off-line mode on the basis of keeping conventional PID controller structure.

Electro-hydraulic servo system has the advantages of fast response, high control precision, dynamic position, steady-state stiffness, anti-interference ability, etc., it is widely used in various industrial process control fields. However, the electro-hydraulic servo system also has its disadvantages, such as friction, dead zone, gap and other non-linear factors. The performances of all mechanical, electrical and hydraulic components of the hydraulic system are greatly changed along with the increase of use time. In addition, since the piping, servo valves and servo-hydraulic cylinder of the electro-hydraulic system have dynamics during operation process, and the dynamics directly affect the state parameters of the system, thereby allowing the performances of system to be completely different in different running times. Some parameters of the system can be changed along with different temperature, pressure and work status, thereby it is commonly focused to design a controller which has good control effect and strong robustness, and can eliminate the impact of system uncertainty signal [1].

In this paper, intelligent control is applied to electro-hydraulic servo system, and more importance is attached to control method for the sake of proceeding real-time control. Seeking a feasible control method is useful to settle a practical problem.

It is set up of the mathematical model of position servo electro-hydraulic system, relevant parameters of the system are selected, and simulation models are set up using simulink software package. Two self-tuning PID different strategies of conventional PID and neural network control are used separately to get theoretical analysis and experimental study of the performance of the system. While RBF (radial basis function) neural network control is also adapt to system, and it has high accuracy, the self study ability and fast calculation. We combines with expert knowledge, and uses control error and its change trend to design the fuzzy controller RBF based on neural network. It decides the control role of the controller according to the size of the absolute value of control error and change direction of control error absolute value, thereby rapidly decreasing the control error, and greatly improving the dynamic performance of electro-hydraulic servo control system [2-3].

II. MATHEMATICAL MODEL DESCRIPTION

The composition of electro-hydraulic position servo system is shown as in Fig.1:

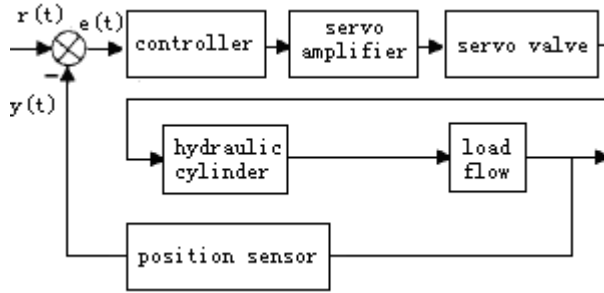


Figure1. The structure of electro-hydraulic system

The control system is mainly composed of a controller, an amplifier, a servo valve, a hydraulic cylinder and a position sensor. $r(t)$ in the figure refers to the given value, $y(t)$ refers to output displacement of the hydraulic cylinder, and error signals are generated after the position sensor is compared with a given value.

The control algorithms pre-arranged in the controller are used to operate the error signals, the output signals can be used to control the servo valve after being amplified by the amplifier, the servo valve is used to convert the electric signals conveyed from the amplifier into valve core displacement of the servo valve through an electric-to-mechanical switching device, thereby controlling the telescopic displacement of the hydraulic cylinder piston through the flow change of the servo valve, driving the control platform to move to the direction of eliminating errors, and enabling the position of the work platform to change according to the rule of the given valve of the instruction[4-5].

In general, the power of the servo valve is a zero-opening four side valve, and the load flow equation of the valve is:

$$Q_L = C_d W_d x_v \sqrt{\frac{1}{\rho} \left(P_l - \frac{x_v}{|x_v|} p_L \right)} \quad (1)$$

In the equation, the load flow is Q_L , C_d refers to the orifice flow coefficient, x_v refers to the valve core displacement, W_d refers to orifice area gradient, ρ refers to the liquid density, P_l refers to oil supply inlet pressure, and p_L refers to the load pressure.

The hydraulic cylinder flow continuous formula is:

$$Q = A_p \frac{dx_p}{dt} + C_{tp} p_L + \frac{V_t}{4\beta_e} \frac{dp_L}{dt} \quad (2)$$

A_p refers to the effective area of the cylinder piston, C_{tp} refers to the total leakage coefficient of hydraulic cylinder, V_t refers to the total volume of the two oil cavities of the hydraulic cylinder, and β_e refers to comprehensive elasticity modulus of the system.

The force balance equation of the hydraulic cylinder under the action of external forces is:

$$F_R = A p_L = M \frac{d^2 x_p}{dt^2} + B_p \frac{dx_p}{dt} + K x_p + F_L \quad (3)$$

In the equation, F_R refers to drying force of the hydraulic cylinder, M refers to the total mass of the piston and load, B_p refers to the damping coefficient of the piston and the load, K refers to elastic stiffness of the load, and F_L refers to load force of the piston.

From above equations, the transfer function of the hydraulic cylinder can be deduced:

$$\frac{x_v}{y} = \frac{Q}{I} = \frac{K_h}{s \left(\frac{s^2}{\omega_h^2} + \frac{2\xi_h}{\omega_h^2} s + 1 \right)} \quad (4)$$

In the formula, Y refers to the piston displacement, K_h refers to the speed amplifier, ω_h refers to the hydraulic natural frequency, and ξ_h refers to the damping ratio.

III. TRADITIONAL PID CONTROL ALGORITHM

Traditional PID control refers to proportional, integral and derivative control, and the continuous representation form of the algorithm is as follows:

$$u = k_c \left(e + \frac{1}{T_i} \int_0^t e dt + T_d \frac{de}{dt} \right) \quad (5)$$

In the equation, u is output, k_c is the proportional gain, e is the error, T_i is the integration time constant, and T_d is the differential time constant. The position digital PID algorithm used in the computer control system is expressed as follows:

$$u(k) = k_p e(k) + k_i \sum_{j=0}^k e(j) + k_d [e(k) - e(k-1)] \quad (6)$$

In the equation, $e(k)$ and $e(k-1)$ are respectively revised values in the sampling time k and $(k-1)$; k_p , k_i and k_d are proportional gain, integral gain and differential gain of the controller[6].

The algorithm has simple structure and easy implementation, when it is used in occasions with more stable working conditions and less interference, the control effect is more ideal.

However, the traditional PID control algorithm adopts linear time-invariant combination mode, and can not coordinate the contradiction between fastness and stability, its robustness is not good enough under the condition with changes in parameters and external interference.

Along with continuously improved requirements on system performance, traditional PID control often can not meet the requirements. In this case, the basic ideas of self-adaptive control and fuzzy control should be learned, advantages of computer technology should be utilized to reconstruct traditional PID control, thereby forming the fuzzy RBF adaptive control algorithm studied by the paper.

IV. RESEARCH AND DESIGN OF RBF FUZZY ADAPTIVE CONTROLLER

A. Design of RBF Fuzzy Adaptive Controller

The fuzzy RBF control algorithm is the control method with fast development speed in recent years, and these two methods do not rely on accurate mathematical model of control object, and have good control effect and interference resistance [7]. However, the fuzzy rules, membership functions and other design parameters of the fuzzy system only can be selected through relying on experience, and can not be automatically designed and adjusted easily, and thereby it is lack of self-learning ability and adaptability.

Although the neural network control has strong adaptation and learning capabilities, it does not have the function of dealing with uncertainty information. Fuzzy neural network control is combined with advantages of fuzzy control and neural network control, the neural network is used to construct fuzzy systems, namely, the learning method of neural network is used to automatically design and adjust the design parameters of the fuzzy system according to the input and output samples, the controller not only can adjust the k_p , k_i and k_d parameters of PID online, but also can find out a group of optimal controller parameters through self-learning ability.

Compared with the traditional PID control, although electro-hydraulic speed servo system adopts fuzzy controller for controlling, the method is simple and reliable, the accuracy is not high with no adaptive capacity, the method is difficult to adapt to requirements of modern technology and control. Next, we analyze the use of combination between self-learning ability of neural networks and fuzzy control, thereby building RBF fuzzy adaptive controller.

B. Fuzzy Logic Analytic Expression

A fuzzy logic analytic expression replaces conventional fuzzy controller, and improves the fuzzy inference engine part of conventional fuzzy controller, when single value fuzzy, Gaussian membership functions, product inference rule and centroid method solving fuzzy are adopted, the fuzzy logic controller can be expressed as follows through the analytic expression:

$$f(x) = \frac{\sum_{l=1}^m y^l [\prod_{i=1}^n \exp[-(\frac{x_i - x_i^l}{\delta^l})^2]]}{\sum_{l=1}^m [\prod_{i=1}^n \exp[-(\frac{x_i - x_i^l}{\delta^l})^2]]} \quad (7)$$

In the equation, $x = (x_1, x_2, \dots, x_n)^T$ is the fuzzy logic controller input, $f(x)$ is the output of fuzzy logic controller, y^l is the central value of one rule output fuzzy set, x_i^l is the central value of fuzzy set selected by the No. i linguistic variable input by the No. 1 rule, δ^l is its width, wherein $l = 1, 2, \dots, m$ refers to the rule number, $i = 1, 2, \dots, n$ refers to the quantity of input variables input by the fuzzy controller. The above expression can uniformly

approximate any non-linear function defined on the dense set in any accuracy, namely, there is the following universal approximation theorem: as for any continuous function g and any $\epsilon > 0$ defined on the dense set $U \in R^n$, the fuzzy logic system f of the upper expression must be available, thereby:

$$\sup_{x \in U} |f(x) - g(x)| < \epsilon \quad (8)$$

This ensures that it can be widely used in modeling and control field; it has universal significance to use the above expression in the electro-hydraulic speed servo system as resolution fuzzy controller [8].

C. Fuzzy RBF Control Algorithm Requirements

Aiming at the shortcomings of traditional PID control strategy, the selected RBF control strategies of electro-hydraulic servo system should consider and meet the following aspects due to its characteristics:

(1). Since the system has complex dynamic characteristics, the designed controller should meet the dynamic property of the system, thereby reducing the steady-state error, and making the system quick without overshoot.

(2). As for the uncertainty caused by system nonlinearity, parameter change and external interference, the control system should have strong robustness.

(3). The selected control strategy should have strong intelligence, thereby the system have good self-learning adaptive capacity.

(4). The control law or control algorithms should be simple and feasible in order to meet the system's real-time requirements.

Electro-hydraulic servo control system commonly has strong nonlinearity, large time-varying parameters, external load disturbance and cross-load disturbance, the factors have critical influence on the control system of the system, and has important guidance significance to the application of electro-hydraulic control system and the establishment of theory system and control method integral system of electro-hydraulic control system.

D. Fuzzy RBF Neural Network Control Structure

With the development of science and technology, the performance demand for electro-hydraulic servo system is higher. Considering that the system is nonlinear and its parameters are uncertain, an accurate mathematical model is difficult to establish, so traditional PID control is hard to meet the control demand, in this aspect, intelligent control represented by fuzzy RBF neural network control has the superiority in nonlinear system.

While RBF function neural network control is also adapt to nonlinear system, and it has high accuracy, the self study ability and fast calculation. Thus combining the advantages of fuzzy and neural network control[9]. The parameters of fuzzy controller are modified continuously in the real-time control using RBF neural network self study ability, and then electro-hydraulic servo system is better controlled. This paper adopts RBF neural network for online identification modeling of electro-hydraulic servo system, thereby accurately tracking system model changes. On this basis, the PID control parameters are

adjusted on line in real time based on single neuron PID controller according to system dynamic network identification information provided by the identification network, thereby realizing self-tuning of PID parameters, and realizing intelligent control of the system. Fuzzy RBF neural network control structure chart is shown in Fig. 2:

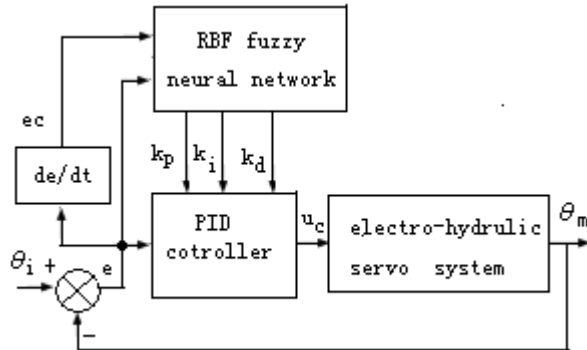


Figure2. Fuzzy RBF neural network control structure chart

In figure 2, θ_i is the system given input angle, θ_m is the system output angle, e is the deviation between given input and actual output, ec is the error rate of change, k_p , k_i and k_d refer to three parameters of fuzzy neural network output, they are inputted to the PID controller, and u is the PID controller output.

The whole fuzzy RBF neural network control structure diagram has the following working principle: according to angle deviation e and its deviation change rate ec which are sampled and measured in real-time, the suitable parameter k is calculated on-line through fuzzy treatment and decision-making treatment, they are output motor drive servo system through the PID controller, the system can continuously optimize the controller parameter according to the changes in the operation condition, thereby achieving the purpose of improving system control performance.

E. RBF Neural Network Inference

RBF neural network has arbitrary function approximation ability, ability to automatically optimize the neural network structure, fast training and convergence ability and better learning ability. The network inference design concept is as follows.

If a pattern classification problem is mapped to high dimensional space, it can be linearly divided than being mapped to a low-dimensional space, so the RBF neural network hidden space dimensions are usually higher. RBF neural network design can be seen as a curve fitting matter in a high-dimensional space, he's learning is equivalent to looking for a curve surface which can best fit the training data in the multi-dimensional space, generalization is equivalent to using this multi-dimensional curved face for test data interpolation. Through the design concept, RBF network structure is a two-story feed forward neural network with single hidden layer, and can finish non-linear mapping from input layer to hidden layer, and linear mapping is finished from hidden layer to output layer.

RBF neural network learning algorithm adopts hybrid learning methods and includes two stages: the one is the

nearest neighbor clustering algorithm and aims at estimating a suitable position for the center of hidden layer radial basis function, mean dynamic cluster is adopted to determine the center position and width of hidden layer RBF as for the self-organizing learning process, the other is to monitor the learning stage to estimate the weight of the output layer through the least mean square algorithm.

When the training error reaches a predetermined value, the neural network design is completed.

F. Structure of Fuzzy RBF Neural Network Control Algorithm

The basic idea of RBF neural network is as follows: RBF composes the hidden layer space as the base of middle layer hidden units, thereby the input vector can be directly mapped to the hidden space. When the RBF center is determined, the mapping relation is also determined, the mapping from the hidden layer space to the output solution space is linear, namely, network output is the linear weighted sum output by the hidden unit, the parameters adjustable in the network is the weight of the linear combination. Parameter adjustment adopts linear adjustment technology, and thereby RBF neural network has faster learning characteristics than the BP algorithm neural network with strong ability to close.

Fuzzy RBF network is algorithm of realizing fuzzy control through network structure, and the structure is shown in Fig.3. The network consists of input layer, fuzzification layer, fuzzy inference layer and output layer. Network output comprises k_p , k_i and k_d [10-11].

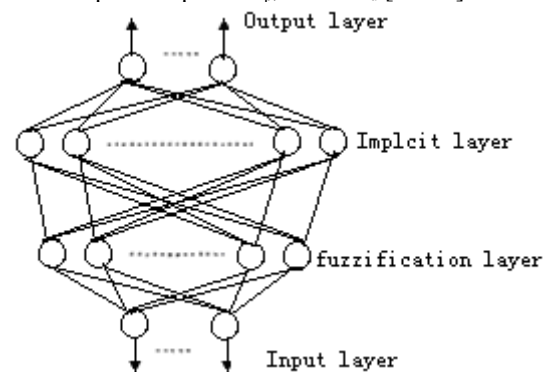


Figure3. Fuzzy RBF neural network structure

Here, signal transmission in the RBF neural network and function of each layer are expressed as follows:

The first layer: input layer.

Each node in the input layer is directly connected with various components of input quantity, and input quantity is passed to the next level. Input and output of each node i in the level are expressed as follows:

$$f_1(i) = X = [x_1, x_2, \dots, x_n] \quad (9)$$

The second layer: fuzzification layer.

Gaussian function is adopted as membership function, c_{ij} and b_{ij} are respectively mean and standard deviation of membership function of No. j fuzzy set in No. i input variable.

$$f_2(i, j) = \exp \left\{ -\frac{(f_1(i) - c_{ij})^2}{(b_{ij})^2} \right\} \quad (10)$$

Wherein, $i=1, 2, \dots, n$; $j=1, 2, \dots, n$.

The third layer: fuzzy inference layer.

Fuzzy inference layer finishes matching of fuzzy rules through connecting with fuzzification layer, and fuzzy operation is realized among various nodes, namely, corresponding firing strength can be obtained through combination of various nodes. Output of each node j is product of all input signals of the node, namely:

$$f_3(i, j) = \prod_{j=1}^N f_2(i, j) \quad (11)$$

Wherein, $N = \prod_{j=1}^n N_j$.

The fourth layer: output layer.

Output layer outputs f_4 as k_p , k_i and k_d tuning results, and the layer is constituted by three nodes, namely:

$$f_4(i) = w \cdot f_3(i) = \sum_{j=1}^N w(i, j) \cdot f_3(j) \quad (12)$$

Wherein, w_{ij} forms connection weight matrix $i=1, 2, 3$ between output node and all nodes in the third layer. Controller is:

$$\Delta u(k) = f_4 \cdot xc = k_p xc(1) + k_i xc(2) + k_d xc(3) \quad (13)$$

Wherein,

$$k_p = f_4(1), k_i = f_4(2), k_d = f_4(3) \quad (14)$$

$$xc(1) = e(k) \quad (15)$$

$$xc(2) = e(k) - e(k-1) \quad (16)$$

$$xc(3) = e^2(k) = e(k) - 2e(k-1) + e(k-2) \quad (17)$$

Incremental PID control algorithm is adopted:

$$u(k) = u(k-1) + \Delta u(k) \quad (18)$$

The Delta learning rule is adopted to modify the adjustable parameters, and the objective function is defined as:

$$E = \frac{1}{2} (rin(k) - your(k))^2 \quad (19)$$

Wherein, $rin(k)$ and $your(k)$ respectively represent the actual output and desired output of network, and the control error of each iteration step k is $rin(k) - your(k)$. Network weights learning algorithm is as follows:

$$\begin{aligned} \Delta w_j(k) &= -\eta \cdot \frac{\partial E}{\partial w_j} \\ &= \eta \cdot (rin(k) - your(k)) \cdot \frac{\partial your}{\partial \Delta u} \frac{\partial \Delta u}{\partial f_4} \frac{\partial f_4}{\partial w_j} \\ &= \eta \cdot (rin(k) - your(k)) \cdot \frac{\partial your}{\partial \Delta u} xc(j) f_3(j) \end{aligned} \quad (20)$$

Wherein, w_j refers to connection weight between network output nodes and all nodes of the upper layer, $j=1, 2, \dots, N$, η refers to learning speed.

If momentum factor is considered, the output layer weight is:

$$w_j(k) = w_j(k-1) + \Delta w_j(k) + \alpha(w_j(k-1) - w_j(k-2)) \quad (21)$$

Wherein, k refers to iteration steps for the network, α refers to the learning momentum factor.

Nonlinear function of RBF neural network most commonly used is Gauss function:

$$O_i = \exp \left[-\left(\frac{\|x - c_i\|}{\delta_i} \right)^2 \right] \quad (22)$$

Among them, it has two adjustable parameters, namely the function of center point c_i and function of width parameter δ_i which is known as variance, using this kind of adjustable parameters for the training in entire network has three groups, namely each basis function center point c_i , variance δ_i , and output unit weights w_{ij} .

There are three ways about variances selection in RBF network center point c_i and variance δ_i :

(1).According to the selected center experience. As long as the training sample distribution can represent a given issue, according to the experience of selected uniformly distributed M centre at a distance of d , Gauss uncton variance is:

$$\delta_i = \frac{d}{\sqrt{2M}} \quad (23)$$

Where M is the number of centers.

(2).Using k mean clustering method for real-time adjust to the minimum distance clustering center. The input data set is divided into k class and k center. When the RBF itself parameter is selected, because the output unit is a linear unit, so it can be directly calculated weight least square method.

(3).Supervised learning method. Above three parameters are used supervised learning called error correcting algorithm. We must calculate each error B to the partial derivative of parameters, and then use following equation to correct it.

$$w(n+1) = w(n) - \beta \frac{\partial \xi(n)}{\partial \theta} \quad (24)$$

Wherein, $\partial \theta$ is parameter waiting for learning.

V. CONTROL ALGORITHM IMPLEMENTATION

A. Neural Networks Training

Neural network training refers to the process of adopting appropriate learning algorithm to determine neural network weight based on input and output data. If the identification network structure is confirmed, and the data samples are given, appropriate learning algorithm can be adopted for training the system until meeting the requirements. The purpose of network training is to utilize the nonlinear mapping ability of the neutral network, and thereby the trained network can simulate the input-output relationship of actual control system.

Appropriate noise can be added into the data collected by the experiment during network training, the learning method relaying on rote in the network can be avoided, the flexibility of the sample learning can be improved, which is conducive to accelerating the network online learning speed and improving the anti-jamming capability.

In addition, learning allows errors, when the difference between the network output and samples is less than the given error range, amendment on the network weights can be stopped, the method of network tolerance can be adopted, and the network learning speed can be accelerated.

B. Acquisition of Identification Input Signal and Data Samples

As for dynamic systems, in order to get the system identification model, the input signal must meet certain conditions. It is usually required that the input signal can continuously inspire the dynamic process of the system in the identification time, namely, all system modes can be fully inspired by the selected input signals. The system identification input signal should meet the following requirements:

(1). The system dynamics must be fully inspired in the identification time, namely, the input signal must inspire all modes of the system.

(2). The inspiration time must be sufficiently long.

C. Sample Data Analysis and Treatment

Information necessary for neural network identification is completely obtained from learning samples, which decides that the system identification effect depends on sample quantity and quality. It is very important to preprocess the samples, thereby accelerating the training speed of the network [12].

When the data samples are processed offline, the key point is to eliminate defect error or random error in the samples. Defect error is caused by interference and the like in the system, and can be easily eliminated through amplitude limiting method. Random error is generally treated through filtering method of weighted averaging. Normalization process aims at meeting the requirements of neural network input and output, being convenient for training, and improving the identification precision. Standardization process refers to dividing each group of data into data with the mean of 0 and deviation of 1. The main principal component analysis is orthogonal treatment, thereby reducing the dimensions of input data. If normalized treatment is within $[0, 1]$ interval, the formula is as follows:

$$x_t = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \quad (25)$$

Wherein, x_t represents the sample data, $x_{\max}$ represents the maximum value in sample data, and $x_{\min}$ represents the minimum value in sample data.

D. Concrete Steps for Adopting

Concrete steps for adopting fuzzy RBF neural network PID controller:

(1). Network initialization sets network structure, network initial weights of each layer, network-based wide-vector, the center vector of network nodes, learning rate and momentum factor; Determine the fuzzy RBF neural network structure, that is, set the number n of input layer nodes, number m of fuzzy layer and fuzzy inference layer, provide the initial value of each layer weight

coefficient $w_{ij}^{(2)}(0)$ and $w_{ij}^{(3)}(0)$, learning rate η and inertia coefficient.

Determine input node and number n , and hidden number m of RBF identifying network, provide central vector $C_i(0)$ of hidden layer nodes, based broadband, initial parameters $b_j(0)$, initial weights $w_j(0)$, learning rate η , inertia coefficient; $k = 1$.

(2). Obtain $y(k)$ and $r(k)$ through sampling, and calculate $e(k)$.

(3). Calculate input and output of each layer of neurons of fuzzy RBF network according to formula, calculate output $u(k)$ of PID controller, send $u(k)$ into the control object and the RBF identification network, and generate next step output $y(k+1)$ of control object.

(4). According to the formula, calculate input and output of nerves of each layer of RBF identification network, identify the network output $\frac{\partial y_{\text{out}}}{\partial \Delta u}$.

(5). Correct identification network output weight coefficient, hidden layer point center vector and the hidden layer point base width parameter with formula.

(6). Correct Fuzzy RBF neural network weight coefficient;

(7). Enable $k = k + 1$, return to (1), and then continue.

VI. CONTROL SOFTWARE FLOW STRUCTURE

Fig.4 is the main program flow structure figure of the control software, when the main program starts running, firstly, the variables and parameters used in the program should be necessarily initialized. Next, data should be collected, the data should be pretreated, finally, the data should be calculated by the RBF fuzzy adaptive controller based on the processed data, and corresponding signals can be output to control the electro-hydraulic servo valve.

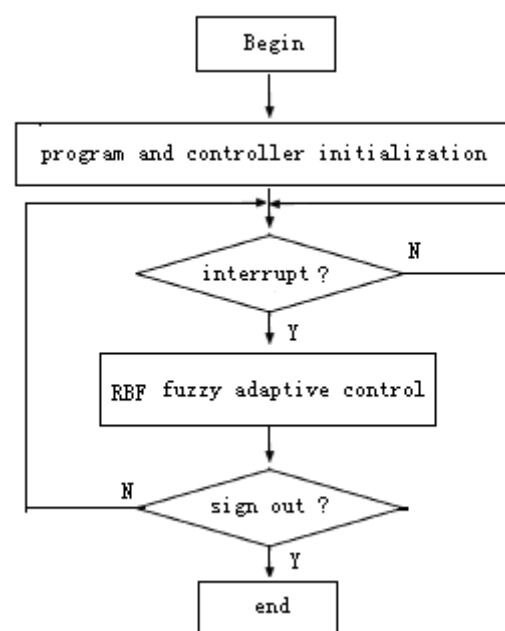


Figure4. Main program flow structure figure

VII. SYSTEM SIMULATION

A. Determination of Controller Initial Parameters

According to the system theoretical model, PID parameter tuning method is adopted to provide initial value of single neuron PID controller, as the initial weight parameter when the model is used for system simulation, which is beneficial for regulating other parameters. When system experiment is carried out, the method can be adopted to determine the initial weight parameter basically, which is beneficial for accelerating the learning speed of single neuron controller, reducing the response process overshoot, and shortening the adjustment time[13-14].

The determination method of weight parameters k_p , k_i and k_d of single neuron PID controller is to adopt Ziegler-Nichols method, and the initial weight parameter of single neuron PID controller is determined according to theoretical models. The method is as follows: firstly, making $k_i=k_d=0$, and making the closed-loop system poles in the J axis, and then increasing the scale factor until the system starts to oscillate, then getting k_c and ω , and obtaining the weight parameters according to the following tuning formula:

$$k_p = 0.6k_c, k_i = 0.318\omega k_c, k_d = 0.785k_p / \omega \quad (26)$$

Wherein, k_c represents adjustment coefficient, ω represents polar angle. After the initial weight parameters of the controller are determined, the learning speed of the parameter can select one small initial value. During simulation, suitable adjustment is available through observing the simulation curve: If the curve time from overshoot to stability is too long, the role of the integral term can be increased. If the overshoot is rapidly declined to be less than a given value, then the rising time to the stability state is too long, the role of the integral term can be increased [15].

B. Matlab Simulation

Set controlled object as follows:

$$y(k) = \frac{-0.1y(k-1) + u(k-1)}{1 + y(k-1)^2} \quad (27)$$

In the simulation process, input signals of the fuzzy RBF neural network are two, namely, the error signal of control systems and identification signals of RBF network, five fuzzy sets are obtained for fuzzification aiming at each input, namely, $n=2$ and $N=5$, 2-5-5-3 form is obtained for fuzzy RBF neural network structure, $\eta=0.20$ and $d=0.022$ are obtained for network learning parameters, and the network's initial weights and initial value of membership function parameters are obtained through test[16-17]. RBF identification network structure is taken as 3-6-1. The stimulation figure of RBF fuzzy neural network electro-hydraulic servo control system is shown in Fig.5 and Fig.6. Curve 1 of Fig.5 represents normal PID control, while Curve 2 represents fuzzy RBF network optimizing control:

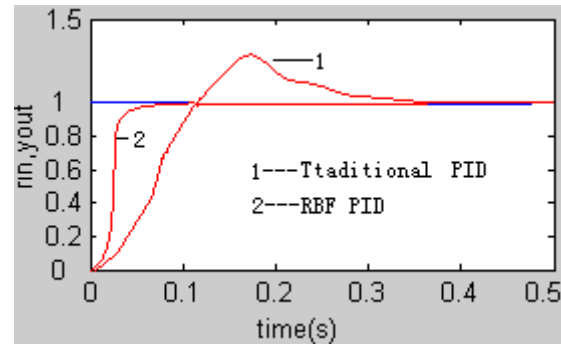


Figure5. The step response curve

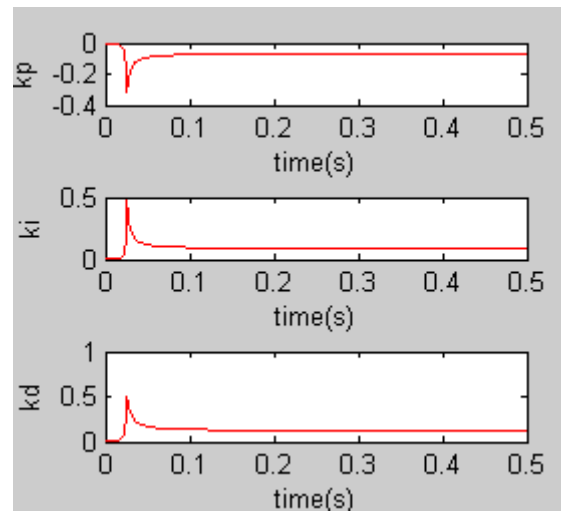


Figure6. Tuning process of RBF PID

It can be seen from above figures that compared with traditional PID controller, the fuzzy RBF neural network control has small overshoot, less oscillation frequency, and more smooth curve, when the system is disturbed, the control system is not affected and can be fast recovered to the steady state, which better solves the problem that charged objects have variability and more disturbance factors, and the control effect is more ideal. Theoretical analysis and experimental results show that, neural network self-turning PID control system can effectively improve the dynamic quality of the system, highlighting the advantages of improving dynamic quality of the control system under the control strategy.

VIII. CONCLUSION

Electro-hydraulic servo control system, with the characteristics of high precision, quick response, easy to adjust, can control large inertia and make high power output, therefore it have a wide range of applications in the field of industrial control. But the electro-hydraulic servo control system is essentially non-linear, it have the feature of multivariate, strong coupled and nonlinear. When using traditional PID control, the control feature of system is sensitive on model error. When the behavior of the system changes in more big range, the accuracy of the total system controlling is not high and is dissatisfactory with the need of system controlling. The high nonlinear

adaptive feature of neural network controller is effective in solving this problem.

The RBF fuzzy neural network servo control system designed by the paper has prominently-reduced transition time, steady-state error and overshoot are prominently improved compared with conventional PID method, and the robustness is strong through adding interference. The controller not only has self-learning and adaptive capacity of neural network, but also has the advantage of processing fuzzy information with fuzzy logic, and thereby it has good anti-interference ability and adaptive ability. Meanwhile, the controller has simple structure, easy realization, higher result precision, wide application field and application value.

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