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INTELLIGENT NEURAL NETWORK CONTROL STRATEGY OF HYDRAULIC SYSTEM DRIVEN BY SERVO MOTOR

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Abstract: A novel intelligent neural network control scheme which integrates the merits of fuzzy inference, neural network adaptivity and simple PID method is presented in this paper. This control method overcomes the defects existed in the traditional variable frequency induction motor driven hydraulic source, such as slow response, poor control precision, easy to overshoot. Permanent magnet synchronous motor driven constant pump hydraulic system is designed instead of common motor, energy saving, fast response and easy to realize closed loop control. System uses the structure of the combination of neural network control and RBF network online identification. The parameters of the controller are optimized by PSO algorithm offline and error back propagation (BP) algorithm offline, and a RBF network is built to identify the system online. The hydraulic power system's control simulation experiments are conducted, and the experimental results at the typical working conditions of the hydraulic source show that the controller and its optimization algorithm can effectively improve the system performance, and the system has no steady-state error, good dynamic performance and good robustness, superior to conventional fuzzy controller and PID controller.

Index terms*:* particle swarm optimization; Intelligent Neural Network; hydraulic system; PID;

I. INTRODUCTION

This paper takes the permanent magnet servo motor-driven hydraulic system as the research object. The hydraulic system uses high-performance permanent magnet AC servo motor drive dosing pumps as hydraulic power source, overcomes the shortages of traditional valve control hydraulic system complex structure, high energy consumption and higher requirements for hydraulic oil. Hydraulic power system driven by a servo motor has the advantages of compact structure, wide speed range, high precision control, high mechanical efficiency, and easy to achieve closed-loop control. The traditional PID control method is more suitable for linear, single variable deterministic control system. Due to the strong coupling characteristics of flow and pressure in the hydraulic system when the load changes, control object is still uncertain, nonlinear, time-varying. For this reason, appear intelligent control methods to deal with nonlinear problems. Such as fuzzy control[1-3], fuzzy PID control[4,5] , expert control[6], learning control[7,8], neural networks control[9-11], fuzzy neural network control[12,13] and the integration of intelligent control methods[14,15]. Accurate mathematical model of the object is not needed to effectively control objects, so that open up a new way of thinking for intelligent control of hydraulic systems.

However, heuristic adjustment limited to rules exists in fuzzy control, lack of adaptability; neural network control can not make full use of expert experience. Parameter optimization algorithm is easy to fall into local extreme or unable to meet real-time, etc. Thus, neural networks and fuzzy control should be combined to form fuzzy neural network, it will have better control performance than a single neural network control [16-18].

To effectively improve the above mentioned defect, a new control scheme is proposed in this paper: Combining the fuzzy neural network and PID neural network to form a new intelligent neural network as a controller. The controller parameters are adjusted using optimization particle swarm（PSO）offline and error back propagation(BP) offline methods. At the same time using RBF network system identification online. The new hydraulic power source is tested to control flow of hydraulic system in different conditions in this paper, and verify the feasibility of this new control scheme.

II. HYDRAULIC POWER SYSTEM STRUCTURE AND MODEL

2.1 Hydraulic power system structure

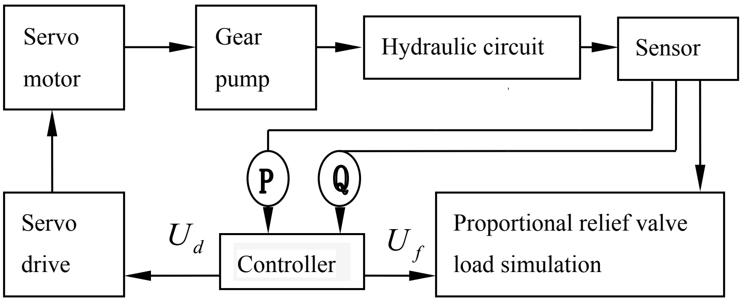

Fig.1 Hydraulic power system diagram

The hydraulic system is driven by a permanent magnet motor, proportional relief valve simulate actual load, simple, convenient, avoid the inconvenience of installing the actual load. Hydraulic flow is detected directly by the flow sensor, the system pressure is detected by the pressure sensor and sent to the controller, forms a closed-loop control with load simulation system of proportional relief valve. The hydraulic source can provide exactly matching pressure and flow according to the desired pressure and flow of the simulated load, and avoids the overflow and throttling energy loss brought by the traditional valve controlled hydraulic circuit. Because the system uses a high response speed of the servo motor, the control accuracy and response speed has been greatly improved compared with ordinary valve control hydraulic system.

2.2 hydraulic power source model

Mathematical model of permanent magnet motor is complex, we usually chose dq rotating vector control mathematical model based on park transformation [19,20]. It can be expressed as:

$$u_d = r_s i_d + p\psi_d - \omega_r \psi_q \tag{1}$$

$$u_q = r_s i_q + p\psi_q - \omega_r \psi_d \tag{2}$$

$$\psi_d = L_d i_d + \psi_f \tag{3}$$

$$\psi_q = L_q i_q \tag{4}$$

$$T_e = 1.5p(\psi_d i_q - \psi_q i_d) \tag{5}$$

Where u_d、u_q—— d, q axis stator voltage component

i_d, i_q——d, q axis stator current component

ω_r——Rotor angular velocity

r_s——Stator winding resistance

L_d, L_q——Stator direct axis and quadrate axis inductance

ψ_f——Flux generated by the permanent magnets of the rotor

ψ_d ,ψ_q——d, q axis stator flux

T_e——Electromagnetic torque

The main gear pump model:

The flow equation is:

$$Q_p = \omega D_p/(2\pi) - P_p C_p - P_p \omega D_p/(2\pi\beta_e) \tag{6}$$

where Q_p——Actual flow

$\omega D_p/(2\pi)$——theoretical flow of the pump

$P_p C_p$——amount of leakage of the pump

$P_p \omega D_p/(2\pi\beta_e)$——Fluid volume amount of compression

The torque balance equation of pump drive shaft:

$$T_L = J_p d\omega/dt + B_p\omega + D_p P_p/(2\pi) \tag{7}$$

Where T_L——The input torque of the pump (the load torque of the motor)

$J_p d\omega/dt$——Inertia torque

$B_p\omega$——The damping torque of the pump

$D_p P_p/(2\pi)$ ——The torque generated by the oil pressure

Ⅲ. INTELLIGENT NEURAL NETWORK CONTROL SYSTEM STRUCTURE AND PRINCIPLE

Control system block diagram is shown in Figure 2, RBF network is used for online identification, and controller (Neural network controller, NNC) is composed of FNN and PIDNN intelligent neural network. Many parameters and weights need to be adjusted when network training, and convergence speed of neural network depends on learning algorithm and initial weights. The combination of PSO offline and BP offline is the controller's optimization algorithm.

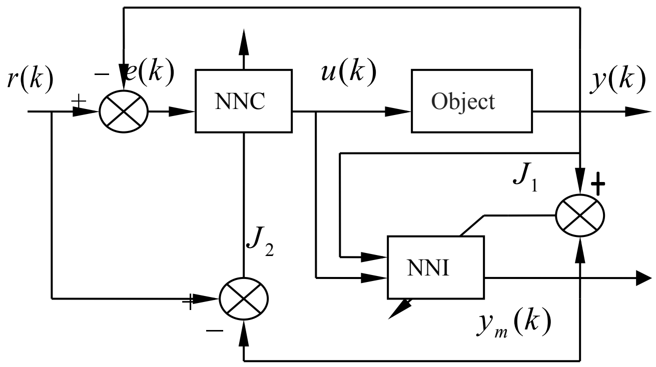

Fig.2 Intelligent neural network control system diagram

$r(k)$ is desired output, $y(k)$ is system actual output, $y_m(k)$ is identification output of RBF network, $e(k)$ is the error of desired output and actual output. The error J_1 of the system actual output $y(k)$ and RBF network output $y_m(k)$ is optimization goals, and make the J_1 minimum value. The main task of the controller is to optimize J_2 based on the identification of RBF network, and provide gradient information to make the $e(k)$ minimum value. Criteria function is the optimization objective.

$$E_1(k) = \frac{1}{2}[y(k) - y_m(k)]^2 = \frac{1}{2}e_1^2(k) \le \varepsilon_1 \qquad (8)$$

$$E_2(k) = \frac{1}{2}[r(k) - y_m(k)]^2 = \frac{1}{2}e_2^2(k) \le \varepsilon_2 \qquad (9)$$

The proposed intelligent neural network controller consists of two neural network controllers. Front part of the network is a fuzzy neural network (FNN), and it is to replace the fuzzy controller, using neural network to adjust the fuzzy control rules. After part of the network is a PID neural network (PIDNN), and it is to replace the PID controller. Combine the two parts can improve the transient, steady-state performance and tracking accuracy.

3.1 Intelligent neural network controller designs

Intelligent neural network controller composed of two neural network controller, that is fuzzy Neural Network（FNN）[21] and PID Neural Network （PIDNN）[22].The main role of the (FNN) is to adjust fuzzy control rules adaptively, the main role of the（PIDNN）is to substitute PID parameter. In this paper, improved the structure and learning algorithm of network. First, PID neural network became an input instead of two inputs, and then combined with the fuzzy neural network, constituted Fuzzy PID Neural Network. Not only possess the function of Fuzzy PID controller function, but also have the ability of self-learning and adaptive. The specific structure is shown in Figure 3.

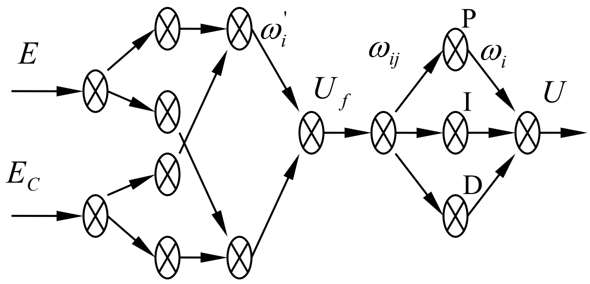

Fig.3 Intelligent neural network topology diagram

The specific structure of the neural network controller is shown as follows:

FNN is a 4-layer network: input layer, fuzzy layer, rule layer, defuzzification layer. The input layer has two nodes, the inputs are error and its rate of change，that is the error of expectations and the actual value of the hydraulic system flow. Fuzzy layer nodes are divided by number of fuzzy subset, membership function is Gaussian function. Rule layer nodes are divided by the number of rules. Output of defuzzification layer is indirect control variables, at the same time it is the input of the first layer of PIDNN. PIDNN is three layer network composed of five neurons: input layer, PID layer, output layer. There is only one node in the input layer which output equal to the input. There are three nodes in PID layer, they are proportional neurons, integral neurons and differential neurons, play a regulatory role of conventional PID controller. Consider the actual system output is limited, so limiter processing is necessary. There is one node in output layer; it is the weighted value of P, I, D. The input-output relationship of PIDNN network is shown as follows:

① Input layer

$$I_1(k) = U_f(k) \tag{10}$$

$$O_1(k) = I_1(k) \tag{11}$$

② PID layer

$$I_{Hi}(k) = \sum_{j=1}^{1} \omega_{ij} I_j(k), \quad i = 1,2,3 \tag{12}$$

The proportion neurons

$$O_{H1} = \begin{cases} -1, & I_{H1}(k) \le -1 \\ I_{H1}(k), & -1 \le I_{H1}(k) \le 1 \\ 1, & I_{H1}(k) \ge 1 \end{cases} \tag{13}$$

The integral neurons

$$O_{H2} = \begin{cases} -1, & I_{H2}(k) \le -1 \\ I_{H2}(k) + I_{H2}(k-1), & -1 \le I_{H2}(k) \le 1 \\ 1, & I_{H2}(k) \ge 1 \end{cases} \tag{14}$$

The differential neurons

$$O_{H3} = \begin{cases} -1, & I_{H3}(k) \le -1 \\ I_{H3}(k) - I_{H3}(k-1), & -1 \le I_{H3}(k) \le 1 \\ 1, & I_{H3}(k) \ge 1 \end{cases} \tag{15}$$

③ Output layer

$$O(k) = I(k) = \sum_{i=1}^{3} \omega_i O_{Hi}(k) \tag{16}$$

The PIDNN neural network introduced above is a dynamic forward network, enhance the network's ability to process information, and it is beneficial for the control of complex nonlinear systems.

Intelligent neural network controller is a new kind of fuzzy neural PID controller composed of FNN and PIDNN, an improvement of the traditional fuzzy PID controller. FNN is used for adjusting rules of fuzzy PID controller adaptively, and achieve an effective adjustment error results. PIDNN is used to replace the static PID parameters of fuzzy PID controller, by adjusting the weights to further enhance the system transient performance and steady-state precision.

In this paper, a single-node structure of input layer in PIDNN is adopted, its input is the output of FNN, and it is used as an indirect control variables. It is input to the PID function layer of PIDNN in weighted form. After the role of P, I, D neurons generate PID control effect, and weighted again, then outputs the final control variables of the system. System control variables which limited to the fuzzy rules and the P, I, D static parameters are converted into dynamic adjustment, and the network is changed into a dynamic fuzzy neural network controller which integrating the advantages of fuzzy reasoning, adaptive neural network and simple PID control.

The control law is derived according to the neural network controller structure:

$$U(k)=\omega_1\omega_{11}U_f(k)+\omega_2\omega_{21}[U_f(k)+U_f(k-1)]+\omega_3\omega_{31}[U_f(k)-U_f(k-1)] \quad (17)$$

Where, U is output of controller, ω_1、ω_2、ω_3 is the coefficient weights of PID layer and the output layer, ω_{11}、ω_{21}、ω_{31} is the connection weights of PID input layer and the PID layer, $U_f(k)$ is the output of fuzzy neural network.

3.2 controller offline optimization algorithm

PSO algorithm is a bionic optimization algorithm based on Cluster proposed by Kennedy [23]. PSO optimization algorithm initialized a group of random particle，M is the total number of particles, D is the particle dimension. Particle’s position, velocity are expressed as: $X_i=(X_{i1},X_{i2},\cdots,X_{iD})$、$V_i=(V_{i1},V_{i2},\cdots,V_{iD})$. Then through several iterations find the optimal solution. In each iteration process, the particle is updated by two "extreme", one is the particle’s individual extreme $pBEST$, expressed as $P_i=(P_{i1},P_{i2},\cdots,P_{iD})$, another is the global extreme $gBEST$, expressed as $P_g=(P_{g1},P_{g2},\cdots,P_{gD})$. Particles update their speed and the new position according to equation (18), (19) speed position search model, until satisfying the maximum number of iterations K or PSO searching the best position meeting the minimum error standard, the final output $pBEST$ is the global optimal solution.

The standard PSO algorithm iterative formula is:

$$V_{id}(k+1)=\omega V_{id}(k)+c_1r_1((P_{id}(k)-X_{id}(k))+c_2r_2((P_{gd}(k)-X_{id}(k)) \quad (18)$$

$$X_{id}(k+1) = X_{id}(k) + V_{id}(k) \qquad (19)$$

Where, 1 ≤i ≤M ， 1 ≤d ≤D, K is number of iterations, ω is inertia weight, c_1 、 c_2 is learning factor, c_1 = c_2 usually taken as the number between 0 to 4, inertia weight usually uses linear decreasing weight[17], that is:

$$\omega(i_{ter}) = \omega_{\max} - (\omega_{\max} - \omega_{\min}) / i_{t\max} \cdot i_{ter} \qquad (20)$$

Where, $i_{t\max}$ is max generation, i_{ter} is generation, $\omega_{\max}$ is maximum inertia weight, $\omega_{\min}$ is minimum inertia weight. PSO algorithm's performance has been greatly improved due to the introduction of ω. It can adjust the global and local search capability; PSO algorithm can successfully solve many practical problems.

PSO algorithm fitness function adopt ITAE index. System using ITAE standards generally have the characteristics of fasting, stable and small overshoot, ITAE criterion is expressed as:

$$J = \int_0^t t|e(t)|dt \qquad (21)$$

Aiming the characteristics of hydraulic power system, strong coupling and nonlinear, the controller's optimization method is shown as follows: The offline optimization, as far as possible to use the standard sample data of typical working conditions，such as step, ramp, sine standard sample data. Using these samples the algorithm can find the optimal solution of the controller's parameters. The controller's parameters have been optimized approximately, and then use the BP algorithm to quickly adjust.

3.3 RBF network Identifier design

RBF network[22] is the 3 layer feed forward network with a single hidden layer, the mapping from input layer to hidden layer is nonlinear, and the mapping from hidden layer to output layer is linear, thus greatly improve the learning speed and avoid the local minimum problem. RBF network has the global optimal approximation properties, and the training method is fast and easy. Therefore, RBF network provides a powerful tool for modeling and control of nonlinear systems. The structure of RBF neural network is shown in Figure 4.

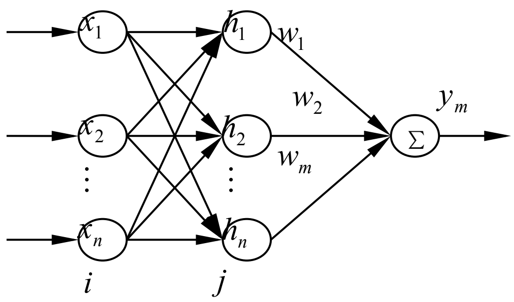

Fig.4 RBF neural network structure

$X = [x_1, x_2, \cdots, x_n]^T$ is the input vectors of the network, $H = [h_1, h_2, \cdots, h_j, \cdots, h_m]^T$ is the radial basis vector, h_j is Koski function:

$$h_j = \exp(\frac{\left\| X - c_j \right\|^2}{2\sigma_j^2}) \qquad (22)$$

Where, c_j is the center point of basis function, σ_j is the width of the basis function center and greater than zero. $W = [w_1, w_2, \cdots, w_j, \cdots, w_m]^T$ is the weight vector of network, output of identifier network is:

$$y_m(k) = w_1 h_1 + w_2 h_2 + \cdots + w_m h_m \qquad (23)$$

.The index function of identifier is:

$$J = \frac{1}{2}[(y(k) - y_m(k)]^2 \qquad (24)$$

The learning algorithm of the linear layer connection weights is

$$w_{ij}(l+1) = w_{ij}(l) + \beta[y_i^d - y_i(l)]h_j(x) / h^T(x)h(x) \qquad (25)$$

Ⅳ. SIMULATION STUDY

Permanent magnet servo motor-driven hydraulic power system is taken for the research object, and the system flow is control target. The power of 2.2kW permanent magnet synchronous motor and the displacement of 4.25ml / r gear pump are used as the hydraulic power source. Using proportional relief valve is to apply a load to the hydraulic system. Pressure depends on the size of the load, flow mainly depends on the motor speed. The control structure is shown in figure 5.

The system uses negative feedback of flow and pressure adaptive closed-loop control. In the pressure adaptive mode, the working pressure of the pump automatically adapt to the load pressure. System pressure increase when the load is increased, inside leakage of the pump increases，so that the output flow becomes small. The servo controller compares the flow signal Q with the set value Q_r , and controls the motor's speed to increase, so that the system flow reaches the set value, and adapts to the requirements of the load pressure. On the contrary when the load is reduced, the system pressure is reduced too. System pressure decreases when the load is decreased, inside leakage of the pump decreases，so that the output flow increases. Servo controller controls the motor speed reducing to adapt to the changes in load. This mode is suitable for larger changing of load and more stable speed occasion.

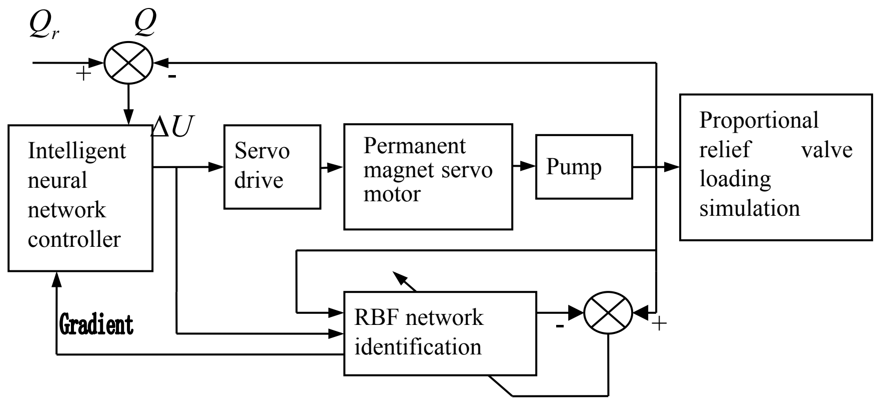

Fig.5 The hydraulic system control structure diagram

According to formula (1) ~ (7) using mat lab to establish the PWM space vector model of permanent magnet motor and the whole control system model. Use conventional PID control, fuzzy PID control, and the proposed intelligent neural network control to optimizing the system flow, and give simulation and comparison results. The tracking flow signals are sine, step and ramp.

Parameters of PID control are shown as follows: $K_p = 0.5$，$K_i = 1$，$K_d = 0.00008$；

The input E , Ec and the output $\Delta K_p, \Delta K_i, \Delta K_d$ of fuzzy PID control are divided into 7 fuzzy subsets, 49 rules.

The method in this paper: The structure of the intelligent neural network controller is 2-14-49-1-3-1, the second layer's activation function is Gauss function, using adaptive adjustment.

PSO algorithm parameter include these: population size M = 20, particle dimension D = 154, the evolution algebra K = 100, ω_{min} = 0.35， ω_{max} = 0.85, learning factor c1 = c2 = 2. 5.

The Fig.6 is the result of step load tracking sinusoidal signal flow of hydraulic system working condition; step load is applied to the system at 0.1 seconds. It can be seen from the simulation results in Fig.6, the control method proposed in this paper has good traceability, rapid response and resistance to load disturbance performance than traditional PID and fuzzy control method. Traditional PID control lags 0.02 seconds than neural networks control .The Fig.7 is the result of step load tracking step signal, step load is applied to the system at 0.1 seconds. From the simulation result also can be seen the superiority of the proposed method.

Fig.8 is the result of step load tracking ramp signal, PID control tracking ramp signal has a large steady-state error. In contrast, the proposed method has a very good tracking performance, almost has no steady-state error.

In summary, from fig.6, fig.7 and fig.8, the simulation results, the PID parameter is not adjusted, tracking dynamic alternating signal appears obviously lag, slow dynamic response, and the steady-state accuracy is not high. The fuzzy PID control effect is better than PID control, appears overshoot, and the adjusting time is long than the method proposed in this paper, the main reason is the variable initial domain is unreasonable, lacking adaptive adjustment of neural network. The method proposed in this paper is a combination of various intelligent methods and PID, based on the nature of the PID, reasonable using of expert knowledge and the adaptive adjustment of neural network, obtaining good initial parameters offline optimization, online control can be quickly adjusted in different conditions. The system has good robustness and good quality, short adjusting time, little overshoot, high steady-state accuracy.

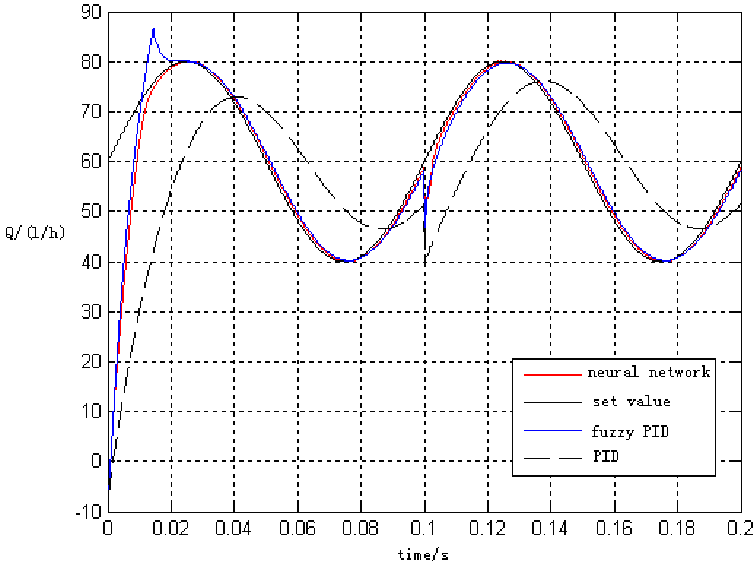

Fig.6 Step load tracking sinusoidal signals

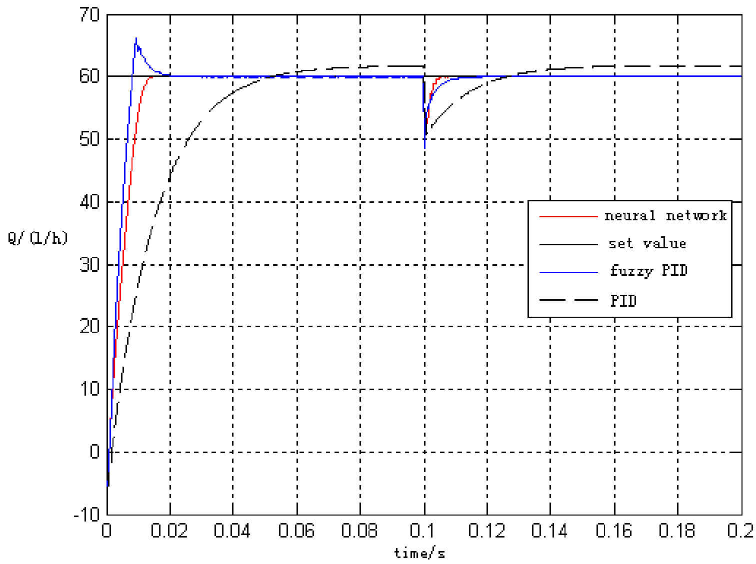

Fig.7 Step load tracking step signal

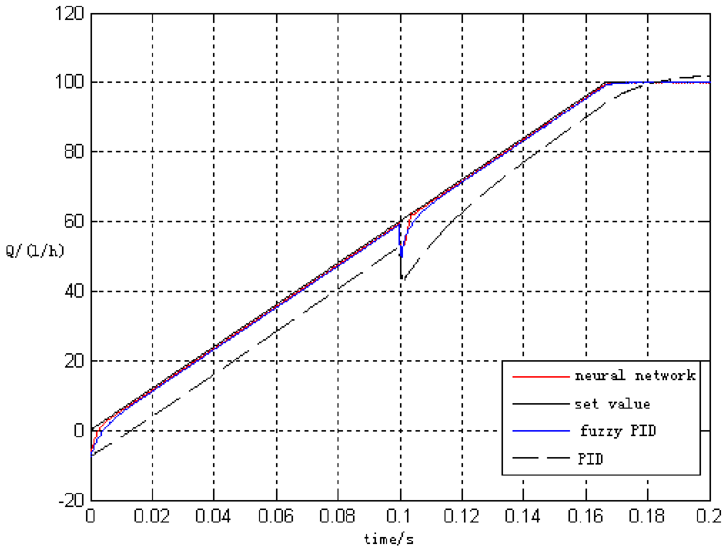

Fig.8 Step load tracking ramp signal

The Fig.9 is the result of sinusoidal load tracking sinusoidal signal flow of hydraulic system working conditions. In the case of dynamic loading, neural network method shows better superiority, PID control tracking performance becomes worse, lags 0.03 seconds. The Fig.10 is the result of sinusoidal load tracking step signal, the Fig.11 is the result of sinusoidal load tracking ramp signal, under the effect of sinusoidal load, and the system flow appears sinusoidal fluctuation using PID control.

It can be seen from figure 9 to figure 11 the simulation results, the condition of hydraulic system is complex, the control performance of the conventional PID is getting worse , such as slow dynamic response, low steady-state accuracy and serious load disturbance when adding dynamic alternating load. In contrast, fuzzy PID and the method proposed in this paper further improved the transient, steady-state performance and Tracking accuracy, and the latter has better control performance.

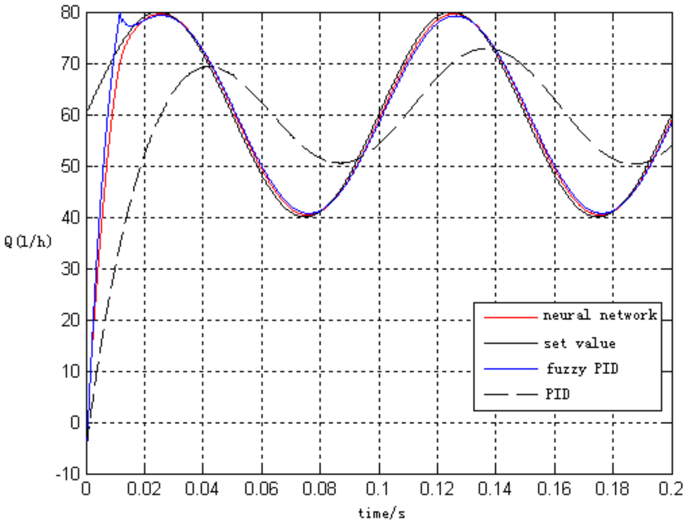

Fig.9 Sinusoidal load tracking sinusoidal signal

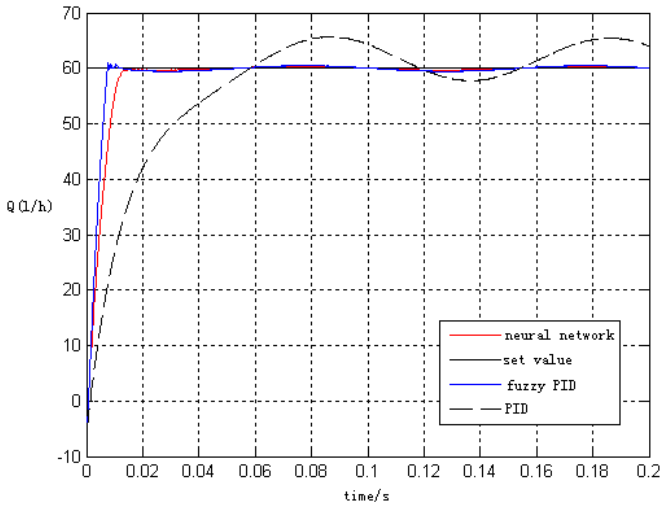

Fig.10 Sinusoidal load tracking step signal

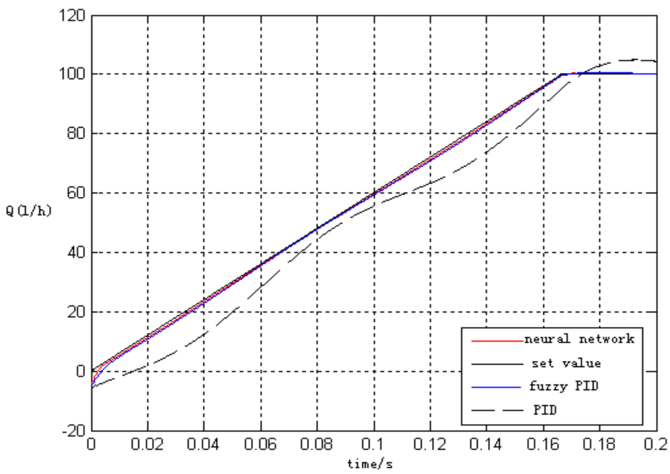

Fig.11 Sinusoidal load tracking ramp signal

IV. CONCLUSIONS

This paper uses the permanent magnet servo motor driven gear pump as a new type of hydraulic power source, the hydraulic power system has advantages of energy saving, rapid response, easy to realize control. In view of the nonlinear characteristics of large inertia, strong load disturbance and multi coupling of hydraulic power system, the conventional control method is difficult to achieve satisfactory control effect. This paper presents an intelligent neural network control scheme which integrated fuzzy inference, neural network adaptive and simple PID control advantages, uses the methods which combined PSO optimization offline with the error back propagation online to adjust the parameters of the controller. At the same time uses the advantages of online identification ability of RBF network, and provides gradient information to the controller.

It can been seen from the simulation results, the hydraulic system whether in static load or dynamic alternating loads, the method proposed in this paper tracking target flow has good response speed and control accuracy.

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