An Adaptive PID Neural Network for Complex Nonlinear System Control

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Abstract

Usually it is difficult to solve the control problem of a complex nonlinear system. In this paper, we present an effective control method based on adaptive PID neural network and particle swarm optimization (PSO) algorithm. PSO algorithm is introduced to initialize the neural network for improving the convergent speed and avoiding weights getting trapped into local optima. To adapt the initially uncertain and varying parameters in the control system, we introduce an improved gradient descent method to adjust the network parameters. The stability of our controller is analyzed according to the Lyapunov method. The simulation of complex nonlinear multiple-input and multiple-output (MIMO) system is presented with strong coupling. Empirical results illustrate that the proposed controller can obtain good precision with shorter time compared with the other considered methods. It provides a novel control approach for complex nonlinear systems.

Keywords: Complex Nonlinear System, Adaptive, PID Neural Network, PSO, Gradient Descent

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1. Introduction

In the industrial control field, the controlled system usually has great nonlinearity, including spacecraft system, vehicle system, robot system, power system, chemical reaction system, etc. PID control technique has been widely used in the real control system for its advantages such as simple mechanism and clear physical conception. It is hard to get a precise control performance even while researchers focus on other intelligent control methods, including adaptive control [1, 2], fuzzy control [3, 4, 5], neural network control [6, 7, 8] and decoupling control [9, 10, 11] etc.. And then, some mixed control methods are emerging, such as PID neural network. Due to the characteristics of self-learning, self-organizing and self-adaptation, PID neural network would automatically identify the controlled system parameters and automatically adjust the parameters according to the changes in the process parameters.

In this paper, we design a controller model based on an adaptive PID neural network. To prevent the weights of neural network falling into local optima, PSO algorithm is adopted to select initial weights. The parameters of PID neural network are self-regulating without intervention. The improved gradient descent method is used to optimize the weights of network.

2. Related Works

Since it is difficult to control a complex nonlinear system [12, 13, 14], neural network was introduced to solve the problem [15, 16, 17]. However, researches still confront some difficulties. For example, network parameters training is time-consuming and easily falls into local minimum. Particle swarm optimization (PSO) algorithm is a new globe optimization algorithm, which has the advantage of fast convergence speed [18, 19]. In [20], Selvakumaran et al. proposed a new design of decentralized load-frequency controller for interconnected power systems with ac-dc parallel using PSO algorithm. The experiment result illustrated that their method have rapid dynamic response ability. In [21], Hasni et al. used PSO algorithm to parameters selection, and used genetic algorithm (GA) to optimize the choice of parameters by minimizing a cost function. The study result was applied to a greenhouse environment with Continuous Roof Vents, and obtained satisfactory effect. In [22], Chen et al. designed a novel multi-objective endocrine particle swarm optimization algorithm. The method is equipped with the advantages of some multi-objective optimization problems. Nevertheless, these

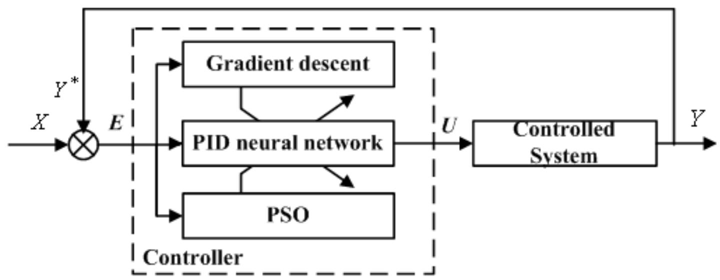

Figure 1: Structure of control system.

methods mentioned above can not be applied to complex nonlinear system with strong coupling.

Adaptive controller has the ability to adjust of control parameters without the help of human intelligence. It can tune complex systems better by combining nonlinear controlling methods and intelligent control technology [23, 24]. The results show that adaptive control has the advantage to solve effectively problems of nonlinear system with uncertain model and random disturbance.

3. Adaptive PID Neural Networks

3.1. Control system structure

The control system adopts close loop control, and it mainly consists of two parts: the controller and the controlled system, as shown in Figure 1. The controller is built based on adaptive PID neural network. In the whole control system, X is object vector, E is error vector, Y is output value of control system. And U is control law of the control system. The controlling algorithm is illustrated in Algorithm 1.

3.2. PID neural network controller

In the controller, three-layer PID neural network is built by combining PID and feedforward neural network, as shown in Figure 2. $X^* = [X\ Y]$ is input vector of the controller, $X = [x_1, x_2, \cdots, x_n]^T$ is object value of the whole control system, and $Y = [y_1^*, y_2^*, \cdots, y_n^*]^T$ is a feedback value from current system output.

Input layer have $2n$ neurons, n of them are used to input object values, the others are used to input values which returned from control system's output. The output of this layer at k is

Algorithm 1 Controlling algorithm for complex nonlinear system

1: Input the object value of controlled system into the controller.
2: Initialize weights of PID neutral network by PSO algorithm.
3: Use PID neural network to control the controlled system.
4: Feedback the output of the control system.
5: Adjust parameters of PID neural network by improved gradient descent method.
6: If the control error is small enough, algorithm is terminated. If not, return to Step 3.

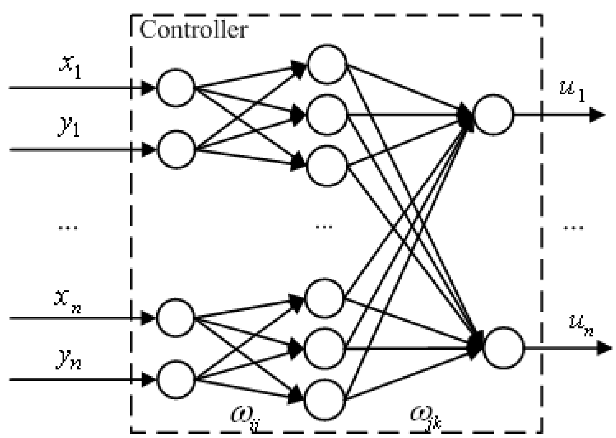

Figure 2: Structure of PID neural network

$$out_{q1}^{1}(k) = x_q(k) \tag{1}$$

$$out_{q2}^{1}(k) = y_q^{*}(k) \tag{2}$$

Hidden layer have $3n$ neurons, including n proportion neurons, n integration neurons and n differentiation neurons. The output of each neuron in this layer at k is

$$out_{q2}^{2}(k) = \phi_p \sum_{i=1}^{2} \omega_{i1} out_{qi}^{1}(k) \tag{3}$$

$$out_{q2}^{2}(k) = \phi_i \left[\sum_{i=1}^{2} \omega_{i2}(k) x_{li}(k) + out_{q2}^{2}(k-1) \right] \tag{4}$$

$$out_{q3}^{2}(k) = \phi_d \left[\sum_{i=1}^{2} \omega_{i3}(k) x_{li}(k) - \sum_{i=1}^{2} \omega_{i3}(k-1) x_{li}(k-1) \right] \tag{5}$$

where, ϕ_p, ϕ_i and ϕ_d are coefficient, usually larger than 1, which is used to balance output values from proportion neurons, integration neurons and differentiation neurons. Output layer have n neurons. The output of each neuron in this layer at k is

$$u_p(k) = out_p^{3}(k) = \sum_{l=1}^{n} \sum_{j=1}^{3} \omega_{jp}(k-1) out_{qj}^{2}(k-1) \tag{6}$$

where q is the number of subnets, that is, the number of output values. And j is the number of neurons in hidden layer, ω_{ij} is weight between input layer and hidden layer, ω_{jk} is weight between hidden layer and output layer.

3.3. Parameters initiation

PSO algorithm searches for the optimal solution by collaboration among individuals in the population [25, 26]. In the algorithm, weight initiation is done randomly. However, weights may fall into local optima during the process of optimization. In this paper, particle swarm optimization (PSO) algorithm is adopted to set initial weights in the controller. The main steps of PSO algorithm are showed in Algorithm 2.

Algorithm 2 Particle swarm optimization algorithm

1: Initialize a group of individuals by random algorithm (population size is m), including random position and velocity.
2: Calculate the fitness of each individual.
3: For each individual, compare the fitness with the fitness of its best historical position *bhp*. If the former is superior to the latter, *bhp* will be replaced with the current fitness, and the position of *bhp* will also be replaced with the current position.
4: For each individual, compare the fitness with the fitness of global best historical position *gbhp*. When the former is superior to the latter, *gbhp* will be replaced with the subscript and fitness of current individual.
5: Update the position and velocity of particles.
6: Check end condition. If satisfied, algorithm is over, otherwise, $k = k+1$, return to Step 2. The end condition is that a good enough fitness or the max desired evolution population *mdep* reaches.

In Step 5, the position and velocity of particles are updated according to Equ. (7) and Equ. (8).

$$v_{id}^{k+1} = v_{id}^{k} + a\psi_1(p_{id}^{k} - x_{id}^{k}) + b\psi_2(p_{gd}^{k} - x_{id}^{k}) \tag{7}$$

$$x_{id}^{k+1} = x_{id}^{k} + v_{id}^{k+1} \tag{8}$$

where $d \in [1, 2, \cdots, n]$, $i \in [1, 2, \cdots, m]$, k is current evolution population, ψ_1 and ψ_2 are random number between 0 and 1, a and b are acceleration constants. In order to prevent velocity of individual against great change, a max velocity is limited to a maximum of $V_{\max}$.

3.4. Adaptive parameters adjustment

Usually to get better control effect and close quickly to control object values, weights must be adjusted according to the error. The gradient descent method can be used to adjust the velocity. For function $f(X)$, $X = (x_1, x_2, \cdots, x_n)$, the gradient is shown in Equation (9).

$$\operatorname{grad} f(X) = \left[\frac{\partial f(X)}{\partial x_1}, \frac{\partial f(X)}{\partial x_2}, \cdots, \frac{\partial f(X)}{\partial x_n}\right]^T \tag{9}$$

Here the minus gradient direction is steepest descent direction. In this paper, an improved gradient descent method is designed considering the PID neural network. Gradient information is added into individual velocity with certain probability, which help particle to search the solutions more efficiently. The weights are changed by Equ. (10) and Equ. (11), which are presented as follows.

$$\omega_{ij}(k+1) = \omega_{ij}(k) - \mu \frac{\partial e(k)}{\partial \omega_{ij}(k)} + \sigma \left[\omega_{ij}(k) - \omega_{ij}(k-1)\right] \tag{10}$$

$$\omega_{jp}(k+1) = \omega_{jp}(k) - \mu \frac{\partial e(k)}{\partial \omega_{jp}(k)} + \sigma \left[\omega_{jp}(k) - \omega_{jp}(k-1)\right] \tag{11}$$

where μ and σ are the network learning rates, and $e(k)$ is control error calculated by Equ. (12).

$$e(k) = \frac{1}{2}\sum_{q=1}^{n} \left| y_q^*(k) - x_q(k) \right|^2 \tag{12}$$

In our neural network, the parameters are computed in each sampling period. The weights are automatically adjusted on line based on the errors of closed loop system, and the controller implements nonlinear and adaptive real-time online control for controlled system.

4. Stability Analysis

Let Lyapunov function be

$$V(k) = \frac{1}{2}\sum_{q=1}^{n} e_0^2(k) \tag{13}$$

where

$$e_0(k) = y_q^*(k) - x_q(k) \tag{14}$$

The change of Lyapunov function is

$$\Delta V(k) = V(k+1) - V(k) = \frac{1}{2}\sum_{q=1}^{n} \left((e_0^2(k+1) - e_0^2(k)) \right) \tag{15}$$

That is

$$
\begin{aligned}
\Delta V(k) &= \tfrac{1}{2}\sum_{q=1}^{n}\left(\left(e_0(k+1)-e_0(k)\right)\right)\left(e_0(k+1)+e_0(k)\right) \\
&= \tfrac{1}{2}\sum_{q=1}^{n}\Delta e_0(k)\left(2e_0(k)+\Delta e_0(k)\right) \\
&= \sum_{q=1}^{n} e_0(k)\Delta e_0(k)+\tfrac{1}{2}\sum_{q=1}^{n}\Delta e_0^2(k)
\end{aligned}
\tag{16}
$$

According to the Lyapunov method, when $\Delta V(k) \leq 0$ in any sampling period, the closed loop system is stable. That is,

$$
\sum_{q=1}^{n} e_0(k)\Delta e_0(k) \leq \frac{1}{2}\sum_{q=1}^{n}\Delta e_0^2(k) \tag{17}
$$

Based on Equ. (10) to Equ. (12), we can obtain Equ. (18).

$$
\begin{aligned}
\Delta\omega_{ij}(k) &= -\tfrac{\mu}{1-\sigma}\tfrac{\partial e(k)}{\partial\omega_{ij}(k)} \\
&\approx -\tfrac{\mu}{1-\sigma}e_0(k)\left(\sum_{q=1}^{n} e_0(k)\operatorname{sgn}\left(\tfrac{\Delta y_q^*(k)}{\Delta x_q(k)}\right)\right)
\end{aligned}
\tag{18}
$$

Then

$$
\begin{aligned}
\Delta e_0(k) &= \sum_{q=1}^{n}\left(\sum_{i=1}^{3}\left(\tfrac{\partial e_0(k)}{\partial\omega_{ij}(k)}\Delta\omega_{ij}(k)\right)\right) \\
&= -\tfrac{\mu}{1-\sigma}\left(\sum_{i=1}^{3}\tfrac{1}{\omega_{ij}(k)}\right)\sum_{q=1}^{n}\left(e_0\left(k\right)\operatorname{sgn}\left(\tfrac{\Delta y_q(k)}{\Delta x_q(k)}\right)\right)\sum_{q=1}^{n} e_0^2\left(k\right)
\end{aligned}
\tag{19}
$$

Let $h\left(k\right) = \sum_{q=1}^{n}\left(e_0\left(k\right)\operatorname{sgn}\left(\frac{\Delta y_q(k)}{\Delta x_q(k)}\right)\right)\sum_{q=1}^{n} e_0^2\left(k\right)$, Equ. (19) is simplified to

$$
\begin{aligned}
\Delta e_0(k) &= \sum_{q=1}^{n}\left(\sum_{i=1}^{3}\left(\tfrac{\partial e_0(k)}{\partial\omega_{ij}(k)}\Delta\omega_{ij}(k)\right)\right) \\
&= -\tfrac{\mu}{1-\sigma}\left(\sum_{i=1}^{3}\tfrac{1}{\omega_{ij}(k)}\right)h\left(k\right)
\end{aligned}
\tag{20}
$$

Substitute to Equ. (17), then

$$
-\frac{\mu}{1-\sigma}h\left(k\right)\sum_{q=1}^{n} e_0(k)\left(\sum_{i=1}^{3}\frac{1}{\omega_{ij}\left(k\right)}\right) \leq \frac{1}{2}\left(\frac{\mu}{1-\sigma}\right)^2 h^2\left(k\right)\sum_{q=1}^{n}\left(\sum_{i=1}^{3}\frac{1}{\omega_{ij}\left(k\right)}\right)^2 \tag{21}
$$

To ensure $\Delta V(k) \leq 0$,

When $\left(\sum\limits_{q=1}^{n}\sum\limits_{i=1}^{3}\frac{e_0(k)}{\omega_{ij}(k)}\right)h\left(k\right) < 0$, then

$$0 < \frac{\mu}{\sigma - 1} \leq -2\frac{\sum\limits_{q=1}^{n}\sum\limits_{i=1}^{3}\frac{e_0(k)}{\omega_{ij}(k)}}{\left(\sum\limits_{q=1}^{n}\left(\sum\limits_{i=1}^{3}\frac{1}{\omega_{ij}(k)}\right)^2\right)h\left(k\right)} \tag{22}$$

When $\left(\sum\limits_{q=1}^{n}\sum\limits_{i=1}^{3}\frac{e_0(k)}{\omega_{ij}(k)}\right)h\left(k\right) \geq 0$, then

$$-2\frac{\sum\limits_{q=1}^{n}\sum\limits_{i=1}^{3}\frac{e_0(k)}{\omega_{ij}(k)}}{\left(\sum\limits_{q=1}^{n}\left(\sum\limits_{i=1}^{3}\frac{1}{\omega_{ij}(k)}\right)^2\right)h\left(k\right)} \leq \frac{\mu}{\sigma - 1} \leq 0 \tag{23}$$

5. Simulation

A simulation is carried out to verify the proposed control strategy in this section. The controlled system is a complex nonlinear MIMO system with strong coupling of variables, described by Equ. (24).

$$\begin{cases} y_1(k+1) = 0.4 \times y_1(k) + 0.3 \times y_2(k) + \frac{u_1(k)}{1+u_1(k)^2} + 0.2 \times u_2(k)^3 \\ y_2(k+1) = 0.3 \times y_2(k) + 0.2 \times y_3(k) + \frac{u_2(k)}{1+u_2(k)^2} + 0.6 \times u_1(k)^3 \\ y_3(k+1) = 0.5 \times y_3(k) + 0.3 \times y_1(k) + \frac{u_3(k)}{1+u_3(k)^2} + 0.1 \times u_2(k)^3 \end{cases} \tag{24}$$

Where u_1, u_2, u_3 are control laws. The following parameters are set to the system:

- Initial values of control system is specified as [0 0 0].
- Object values of control system is specified as [0.7 0.4 0.8].
- Learning rates is specified as 0.006.
- Time interval is specified as 0.0001s.

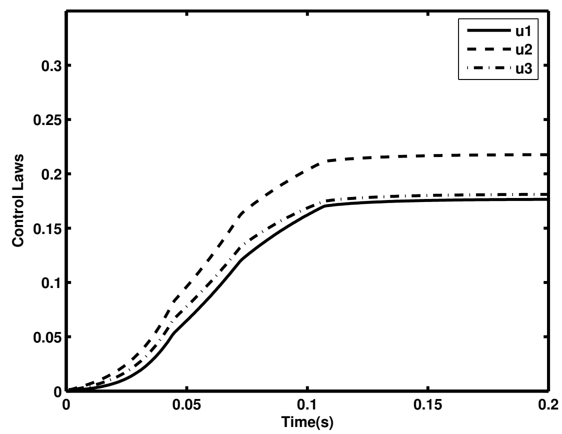

Figure 3: Control laws vary with time.

During the process of weights initiation by PSO, numbers of populations is specified as 50, and iteratiion number is specified as 40. To illustrate the advantages of our controller, three different methods are used to control the same system separately.

5.1. Control by traditional PID neutral network

The first simulation is controlling the system by traditional PID neutral network, and the results are shown from Figure 3 to Figure 5. Figure 3 shows the control laws changed with time. Figure 4 shows the contrast between the actual output values and the object output values. Figure 5 shows control error with time variation.

Simulation results show that the actual output is close to expect output, control law is gradually stabilized, and control error is close to 0. That is to say, this method has some effect on control the system.

5.2. Control by PID neutral network though standard PSO optimization

The second simulation is controlling the same system by PID neutral network which is optimized by standard PSO, and the results are shown from Figure 6 to Figure 8. Figure 6 shows the control laws changed with time. Figure 7 depicts the contrast between the actual output values and the object output values. Figure 8 illustrates the control error with time variation.

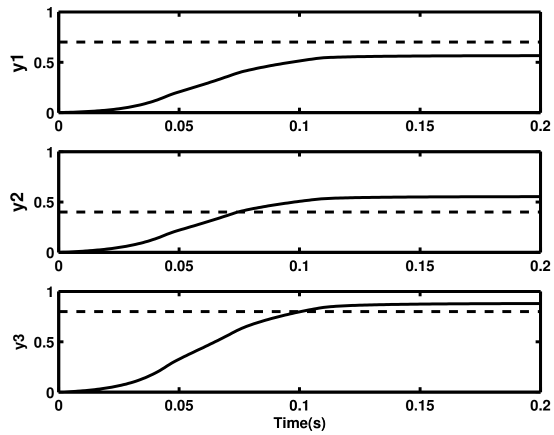

Figure 4: Actual output values vary with time.

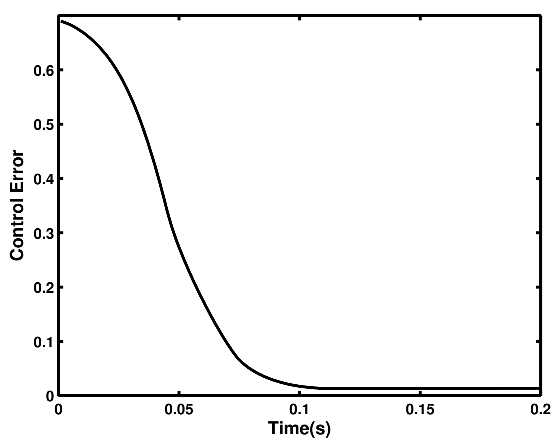

Figure 5: Control error vary with time.

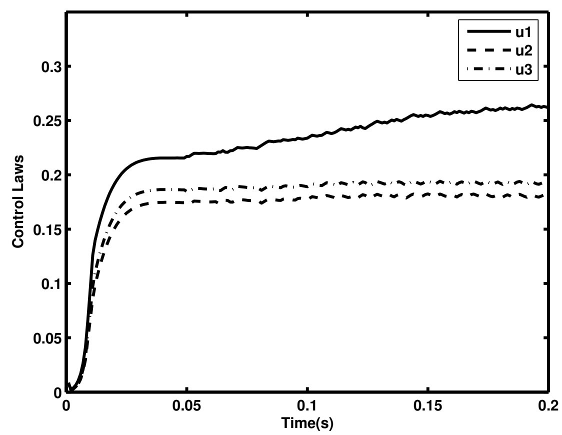

Figure 6: Control laws vary with time.

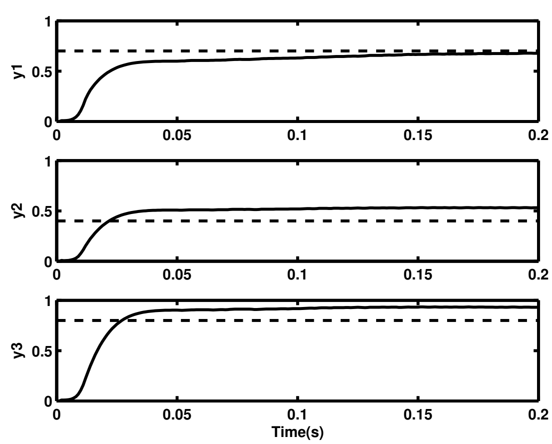

Figure 7: Actual output values vary with time.

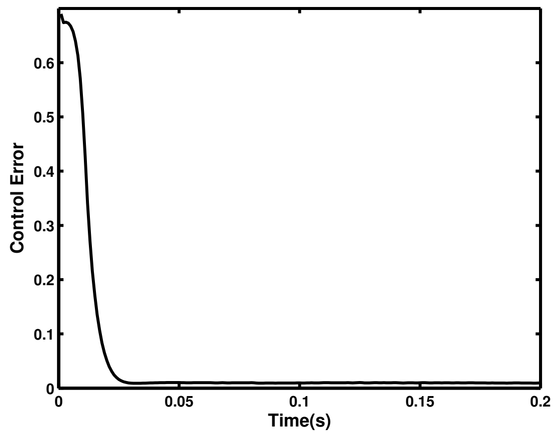

Figure 8: Control error vary with time.

Simulation results show that the actual output is close to the expected output, and the speed of convergence is faster than the previous method and the control law is gradually stabilized.

5.3. Control by the adaptive PID neutral network

The last simulation is controlling the same system by adaptive PID neutral network, which is proposed in this paper, and the results are shown from Figure 9 to Figure 11. Figure 9 shows the control laws changed with time. Figure 10 shows the contrast between the actual output values and the object output values. Figure 11 shows control error with time variation.

In order to compare the performance of three different control methods mentioned above, the control errors varied with time are shown respectively in Table 1. Due to the limit of space, the time interval of data is 0.001s, and 15 data groups is selected from 0.02s. Obviously, adopting the new method, the actual output values can most quickly approximate the object output values when compared with the previous two methods. The control error is falling faster before 0.02s, then tends to 0 gradually. The control laws are also quickly changed to constant within a short time. Therefore, the adaptive PID neutral network has high convergence speed, high accuracy and high stability for the control of a complex nonlinear system.

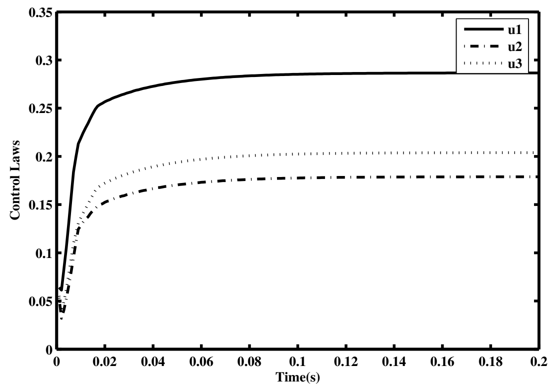

Figure 9: Control laws vary with time.

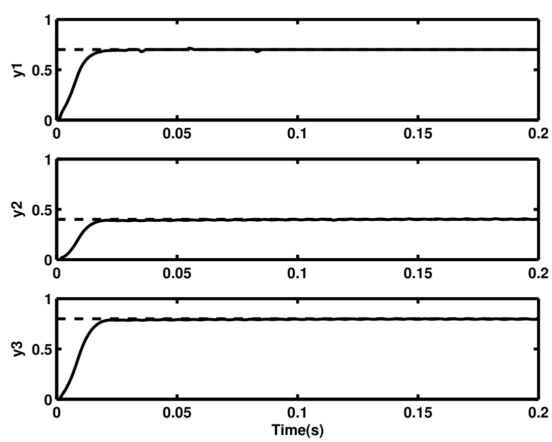

Figure 10: Actual output values vary with time.

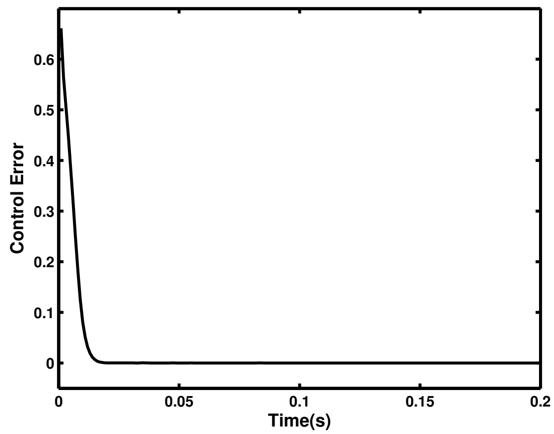

Figure 11: Control error vary with time.

Table 1: Control error vary with time using above three control methods.

Groups	Times	Control Error I [a]	Control Error II [b]	Control Error III [c]
1	0.020	0.626280	0.050725	0.000322
2	0.021	0.620422	0.039564	0.000204
3	0.022	0.614219	0.030990	0.000174
4	0.023	0.607665	0.024495	0.000165
5	0.024	0.600709	0.019648	0.000168
6	0.025	0.593351	0.016086	0.000221
7	0.026	0.585584	0.013522	0.000194
8	0.027	0.577358	0.011724	0.000158
9	0.028	0.568675	0.010503	0.000185
10	0.029	0.559526	0.009712	0.000234
11	0.030	0.549869	0.009237	0.000214
12	0.031	0.539705	0.008988	0.000165
13	0.032	0.529032	0.008897	0.000103
14	0.033	0.517811	0.008912	0.000103
15	0.034	0.506049	0.008997	0.000138
Mean	-	0.573084	0.018133	0.000183

[a] Control Error by 4.1.
[b] Control Error by 4.2.
[c] Control Error by 4.3.

6. Conclusion

In this paper, the design of an adaptive PID Neural Network controller is presented. The controller's model is established based on a PID Neural network. The PSO algorithm is adopted to select initial weights, solving the problem that influences the initial values in the training, improving the convergent speed, and preventing the weights getting trapped into local optima. In each sampling period, improved gradient descent method is used to change all weights in this network. With three main features such as self-correcting, on-line and real-time, the adaptive mechanism of parameters adjustment can compensate the drawbacks of the conventional methods. The stability is analyzed according to the Lyapunov method.

Empirical results illustrate that the adaptive PID Neural Network controller is significantly better than the traditional PID neutral network controller and PID neutral network optimized using PSO. Our controller can achieve better control results within less sampling periods and the error tends to 0 in a stable manner. During the weight initialization, PSO algorithm takes a long time and this requires more research and also to decide the number of iterations to have a nice balance between high efficiency and precision. The proposed control approach is available to some systems with complex nonlinear characteristics and it could also be extended to other nonlinear systems in natural and social sciences.

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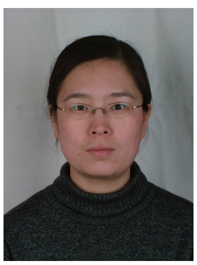

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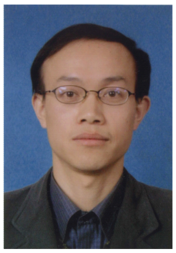

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