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A Neuron Model-free Controller with immune Tuning gain for Hydroelectric Generating Units

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Abstract—**A neuron model-free control method with immune scheme tuning gain for hydroelectric generating units is presented in this paper. Under the operating conditions of various guide vane opening, the characteristics of a hydroelectric generating unit show much difference in parameters. The influences of the time-varying parameters and the disturbances on the control system can be reduced by using the neuron model-free control method with immune scheme turning gain. With an example, the simulation results show that the neuron model-free controller has good control performance, fast transient response and strong robustness.**

I. Introduction

A hydroelectric generating unit is a complex controlled plant with non-minimum phase, nonlinear and time-varying parameters. Obviously, to design a controller for such a system is a difficult issue. The traditional control methods are using a PID controller under assuming that the plant is a time-invariant linear system with known structure and parameters [1]. However, the parameters of the plant usually could not be obtained in practice, and they will change in a large scale with the different operating conditions. In this case, it is impossible for the PID controller with fixed parameters to solve the problems caused by uncertain factors. With the development of artificial intelligence and process control theory, intelligent control methodology has been advanced greatly and widely applied in the various process fields, which provides a new possibility to solve the control problems of hydroelectric generating units. The application of fuzzy control in water turbine speed governing was investigated in [2], [3]. Due to the large variation within the parameters of the plant, it is not easy for fuzzy control methods to meet the requirements of all operating conditions. Therefore, Jing *et al* [4] developed the intelligent fuzzy controller with a neural network model of a hydroelectric generating unit. Qiao *et al* [5] presented a self-adaptive governing method with pole location and on-line identification of the model parameters. However, these methods are model-based, and there still exists the modeling problem. Once the structure and parameters of the plant are changed in large scale under the different operating points, the controller performance will be deteriorated. Based on the neuron model-free control method [6], this paper tries to improve the neuron model-free control performance with immune mechanism tuning neuron gain for controlling a hydroelectric generating unit under different operating conditions.

This paper is organized as follows. Section II gives a brief introduction of neuron model-free control methodology and the immune feedback law, and proposes the neuron model-free control method with immune scheme tuning gain. Section III describes the characteristics of a hydroelectric generating unit and presents the computer simulation results. Conclusions are summarized in section IV.

II. The Neuron Model-free Controller with Immune Feedback Law

A. The neuron model-free controller

In [6], in order to overcome the shorts of model-based control system, Wang *et al* developed an adaptive neuron model and its learning strategy for control, and presented the neuron model-free control method. Applied in several industrial processes ([7], [8]), the neuron model-free controllers show their advantages in treating with the uncertainties of the processes.

The adaptive neuron model-free control system is described in [6] as Fig. 1. Where, $p_i(t)$ stands for the learning strategy. The Transfer takes the charge of converting the output of the controlled plant and the set point into inputs of the neuron controller according to the designer.

On the base of the structure of the neuron model-free control system, the neuron output $u(t)$ can be formulated as

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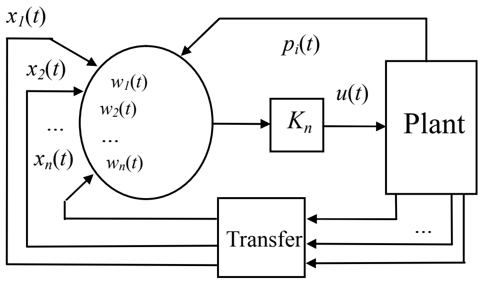

Fig. 1. The general neuron control system

$$u(t) = K_n \sum_{i=1}^{n} w_i(t) x_i(t) \tag{1}$$

where, K_n >0 is the neuron proportional coefficient; $x_i(t)(i = 1,2,\cdots n)$ denote the neuron inputs; $w_i(t)$ are the connection weights of inputs $x_i(t)$.

Following the associative learning strategy ($p_i(t) = z(t)u(t)x_i(t)$, $z(t)$ is the teacher signal), the neuron model-free control algorithm with normalization is presented as following in [6]

$$\begin{cases} u(t) = [K_n \sum_{i=1}^{n} w_i(t)x_i(t)] \Big/ [\sum_{i=1}^{n} w_i(t)] \\ w_i(t+1) = w_i(t) + d[r(t) - y(t)]u(t)x_i(t) \end{cases} \tag{2}$$

where, $u(t)$ is the control signal came from the output of the neuron controller; $r(t)$ is the set point; $y(t)$ is the plant output. n is the number of input variables. The inputs of the neuron $x_i(t)$ can be selected as ($n = 3$)

$$\begin{cases} x_1(t) = r(t), \\ x_2(t) = r(t) - y(t), \\ x_3(t) = x_2(t) - x_2(t-1) \end{cases} \tag{3}$$

Investigation has revealed that the control performance will be deteriorated when above neuron model-free controller with a fixed gain K_n is used in the plants with variable open-loop gain or severe nonlinearity. The control practice has also proved that the bigger K_n would lead to a faster system response and a bigger overshoot. However, a smaller K_n may result in a slower system response and longer settling time. Therefore, the value of K_n does significant influence on the performance of neuron control systems, special for the controlled plant with uncertainty in static gain. To the hydroelectric generating unit, the static gain is changed according to the value of the guide vane opening (α), this characteristics request that the controller gain must be self-adjustable for different guide vane opening (α). For this purpose, this paper proposed a method to tune the gain using immune feedback mechanism, and in order to achieve a fast response and small overshoot, the action of Transfer will be modified according to the system error.

B. Immune feedback law

The artificial immune system is extracted from the natural immune system, and is a current research hot in artificial intelligence ([9], [10]). The immune system has the ability to identify and eliminate foreign materials such as antigens and germ cells and also has memory as well as pattern recognition and learning abilities. Within the immune system, there is a feedback mechanism which simultaneously performs two diverse tasks: rapidly responding to the presence of foreign material while quickly stabilizing the immune system. According to the feedback mechanism of the immune system, one can draw out the immune feedback law as follows [11].

First, we define that $\varepsilon(k)$ is the amount of antigen at the kth generation, $T_H(k)$ is the output from the helper T-cells stimulated by the antigens, $T_S(k)$ is the effect of the suppressor T-cells on the B-cells, then, the total stimulation received by the B-cells $S(k)$ is

$$S(k) = T_H(k) - T_S(k) \tag{4}$$

where, $T_H(k) = k_1\varepsilon(k)$, $T_S(k) = k_2 f[\Delta S(k)]\varepsilon(k)$, $f(*)$ is a nonlinear function introduced to account for the effect of the reaction between the killer T-cells and the antigen at the (k-d)th generation.

Assuming that the amount of killer T-cells is given by the differentiation of the activity of the B-cells, the amount of killer T-cells $u_{kill}(k)$ is defined by [11]

$$\begin{aligned} u_{kill}(k) &= k_1\varepsilon(k) - k_2 f[\Delta u_{kill}(k)]\varepsilon(k) \\ &= K\{1 - \eta f[\Delta u_{kill}(k)]\}\varepsilon(k) \end{aligned} \tag{5}$$

where, $K = k_1$, $\eta = {k_2}/{k_1}$. In this equation, the parameter K governs the reactive speed, and the parameter η governs the stability of the system. The immune feedback mechanism provides a possible way to improve control system performance. Some research works on this topic have been reported in recent years [12]-[14]. In this paper, the immune feedback law is used to tune the neuron controller gain.

C. The neuron model-free controller with immune tuning gain

This section presents the developed neuron model-free control with immune algorithm. The immune feedback law is applied to regulate the gain of the neuron model-free controller, and the structure of the control system with immune tuning gain is set up and shown as in Fig.2. Where, IMF represents the immune feedback law used to determine the gain of the neuron controller. By considering the amount of foreign materials $\varepsilon(k)$ as the error of the system output, and treating

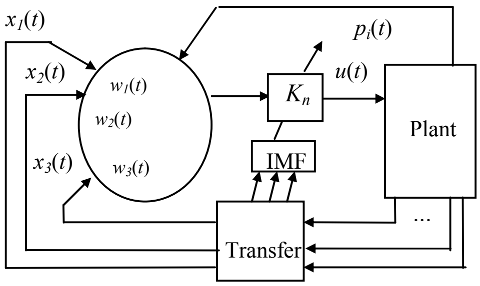

Fig.2. Neuron model-free control systems with immune turning gain

the neuron gain as the amount of killer T-cells, one can obtain the following tuning strategy

$$K_n(k) = K_n(k-1) + \alpha(1 - \eta f(\Delta y(k)))e(k) \tag{6}$$

where, the nonlinear function $f(\cdot)$ is selected as following format in this paper [11]

$$f(x) = 1 - \gamma \exp(-x^2/\beta) \tag{7}$$

where, γ *and* β are two constants determined by the user.

Thus, the control algorithm is presented as

$$\begin{cases} K_n(k) = K_n(k-1) + \\ \qquad \alpha(1-\eta(1-\gamma\exp((y(k)-y(k-1))^2/\beta)))e(k) \\ u(k) = K_n(k)[\sum_{i=1}^{3} w_i(k)x_i(k)] \Big/ [\sum_{i=1}^{3} w_i(k)] \\ w_i(k+1) = w_i(k) + d_i[r(k)-y(k)]u(k)x_i(k) \end{cases} \tag{8}$$

The action of the Transfer is to produce suitable inputs for the neuron controller. In order to make the developed controller run well, this paper selected the three inputs ($n = 3$) as

$$\begin{cases} x_1(k) = r(k) \\ x_2(k) = \lambda\sqrt{|r(k)-y(k)|}\,sign(r(k)-y(k)) \\ x_3(k) = x_2(k) - x_2(k-1) \end{cases} \tag{9}$$

where, the input $x_2(k)$ is different from the selection of Eq. (3), the reasons are two. First, this type of Transfer can enhance the system sensitivity to a smaller system error; Second, this Transfer will reduce the system sensitivity to a larger system error. λ is a proportional coefficient. Equation (8) and (9) constructer the neuron model-free controller with immune tuning gain.

III. THE SIMULATION RESULTS FOR A HYDROELECTRIC GENERATING UNIT

A. The dynamic characteristics of a hydroelectric generating unit

The governing system of a hydroelectric generating unit consists of servomotor, water turbine, diversion system, electric generator and external load, shown as in Fig. 3. Where, M_t is the turbine torque, Q_t is the flow, H is the

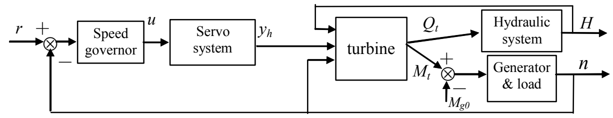

Fig.3. The control system for a hydraulic turbine generator unit

water head, n is the rotational speed. It is a complex controlled plant with non-minimum phase and variable structure and parameters under different operating conditions. Using the first principle modeling method, local linearization and simplification approach, this plant can be described with linearization model as follows.

The servomotor is represented as a following first order process

$$y(s) = \frac{1}{T_y s + 1} u(s) \tag{10}$$

where, T_y is the buffer time constant of the servomotor.

Similarly, the electric generator is also depicted as a first order process

$$v(s) = \frac{1}{T_a s + e_b}\left[m_t(s) - m_g(s)\right] \tag{11}$$

where, T_a is the time constant of electric generator, e_b is the load regulating coefficient.

The diversion system can be approximately denoted as an elastic water hammer model,

$$\frac{H(s)}{Q(s)} = -\frac{8T_w s}{T_r^2 s^2 + 8} \tag{12}$$

where, T_w is the inertia constant of water flow, T_r is the reflection time of pipeline.

To some work condition, the water turbine can be described as follows with local linearization method,

$$\begin{cases} m_t = e_h h + e_v v + e_y y_h \\ q_t = e_{qh} h + e_{qv} v + e_{qy} y_h \end{cases} \tag{13}$$

where, $e_h = \frac{\partial m_t}{\partial h}, e_v = \frac{\partial m_t}{\partial v}, e_y = \frac{\partial m_t}{\partial y_h}, e_{qh} = \frac{\partial q_t}{\partial h}$, $e_{qv} = \frac{\partial q_t}{\partial v}, e_{qy} = \frac{\partial q_t}{\partial y_h}$, they are all the transmission coefficients. m_t, q_t, h, v, and y_h are the amounts of relative deviation of turbine torque M_t, water flow rate Q, water head H, rotating speed n and guide vane opening a.

From the above, with the technology of local linearization, we can obtain the approximate transfer function of the hydroelectric generating unit as following,

$$G(s) = \frac{v(s)}{u(s)} = \frac{1}{1+T_y s} \cdot \frac{e_y - (e_{qy}e_h - e_{qh}e_y)T_w s}{1 + e_{qh}T_w s} \cdot \frac{1}{T_a s + e_b - e_v} \tag{14}$$

Table 1 Parameters of water turbine model under three special operating points [5]

α(mm)	T_y(s)	T_w(s)	T_r(s)	T_a(s)	e_v	e_y	e_h	e_{qv}	e_{qy}	e_{qh}	e_b
21.0	0.02	1.27	0.15	9.06	-0.761	1.190	0.835	-0.163	0.930	0.359	0.50
25.0	0.02	1.27	0.15	9.06	-1.026	1.041	1.162	-0.107	0.933	0.389	0.50
31.0	0.02	1.27	0.15	9.06	-1.220	0.656	1.431	-0.075	0.674	0.446	0.50

The table 1 gives the parameters of the linearization model under three special operating points [5]. Thus, it can be seen that the governing system is a high-order system with nonlinear and time varying parameters.

Substituting the parameter values of table 1 in Eq. (5), we can obtain the corresponding transfer functions as follows [5]

Case 1: for $a = 21.0$ mm,

$$G_{21}(s) = \frac{-0.3518s + 0.9437}{0.0655s^3 + 3.4286s^2 + 7.6607s + 1} \tag{15}$$

Case2: for $\alpha = 25.0$ mm,

$$G_{25}(s) = \frac{-0.5653s + 0.6822}{0.0587s^3 + 3.0617s^2 + 6.5511s + 1} \tag{16}$$

Case 3: for $\alpha = 31.0$ mm,

$$G_{31}(s) = \frac{-0.4961s + 0.3814}{0.0597s^3 + 3.1003s^2 + 5.8539s + 1} \tag{17}$$

Obviously, the open loop transfer function plant has a zero on the right hand of s plane, therefore, it is a non-minimal phase plant; the change of guide vane opening causes variations of the model parameters greatly. The unit step responses for the plant under the three cases are shown as in Fig.4-Fig.6. It is obvious that this process is an overdamped process. Along with the increasing of guide vane opening (α), the static gain is decreasing, and the response time is increasing. To this controlled process with such serious varying parameters, it is testified that the convention PID control method is hardly to obtain a satisfactory result.

B. Simulation and results

To verify the effectiveness of the proposed control method (equations (8) and (9)), the simulation tests for a hydroelectric generating unit under different operating conditions are performed. During the simulation experiments, we assumed that the normal operation point is set as 25mm of the guide vane opening, its characteristic is described as Eq. (16) and the controller parameters are selected for the previous neuron model-free method [6]. The corresponding parameters are selected as following: to the neuron controller of [6]: $K_n(0) = 2.5$, d_1 =50, d_2 =40, d_3 =10. To the proposed controller with the immune feedback law to tune the neuron gain, the following parameters are chosen as $K_n(0) = 0.7$, $\eta = 0.1$, $\beta = 10$, $\alpha = 0.3$, $\gamma = 1.0$, $\lambda = 2.0$, d_1=40, d_2=40, d_3=4. For different operating condition, the parameters of the controllers are not modified again. All of the simulation results of the previous neuron controller and the proposed controller are given in Fig. 7 – Fig. 12. From the above simulation results, one can draw the following conclusions: when the plant model changes from the normal case (Eq. (16)) to the other cases (Eqs. (15) or (17)), the robustness of the new controller is verified. The smaller overshoot, shorter settling time and stronger disturbance-rejection are achieved for the proposed neuron controller.

From those results, we can also conclude that the new modified neuron model-free control method has satisfying performance not only in normal case but also in other cases. Comparing with other reported results ([4], [5]), this control algorithm is very simple and model-free, that is to say that this control method does not request to model the controlled plant during the design of controller.

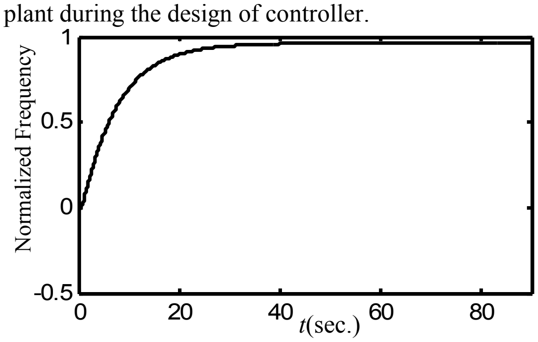

Fig.4. The unit step response of the hydroelectric generating unit under $a = 21.0$ mm

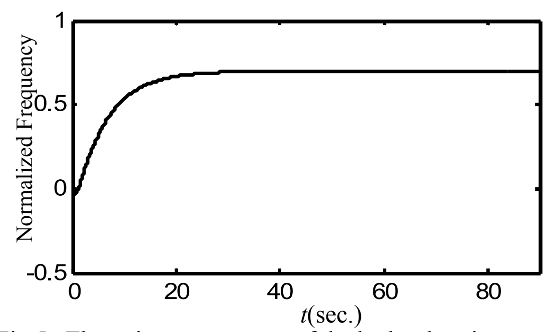

Fig.5. The unit step response of the hydroelectric generating unit under $\alpha = 25.0$ mm

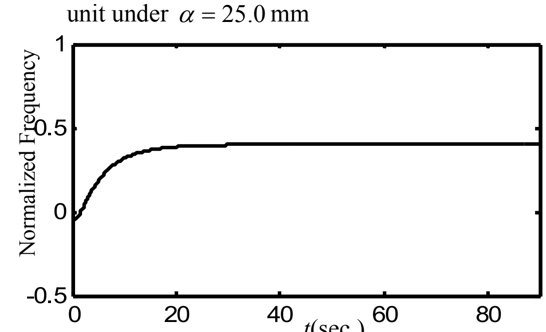

Fig.6. The unit step response of the hydroelectric generating unit under $\alpha = 31.0$ mm

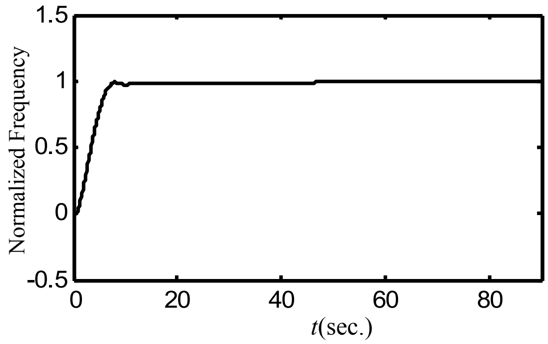

Fig.7. Tracking using the proposed controller when $a = 21.0$ mm

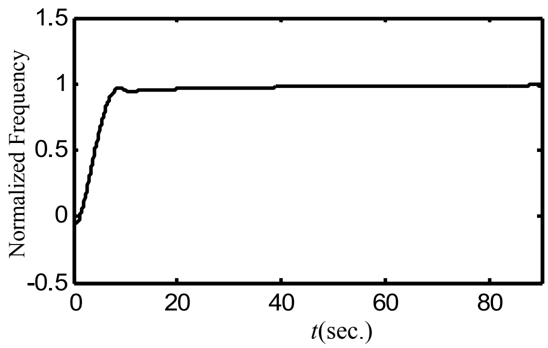

Fig.8. Tracking using the proposed controller when $a = 25.0$ mm

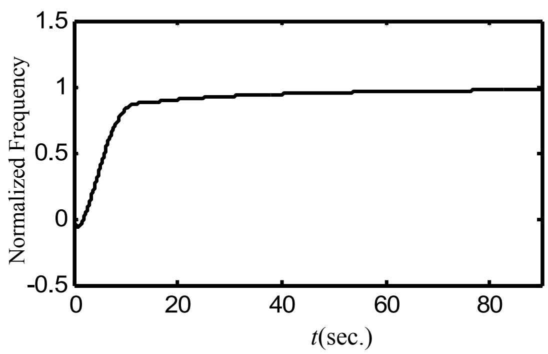

Fig.9. Tracking using the proposed controller when $a = 31.0$ mm

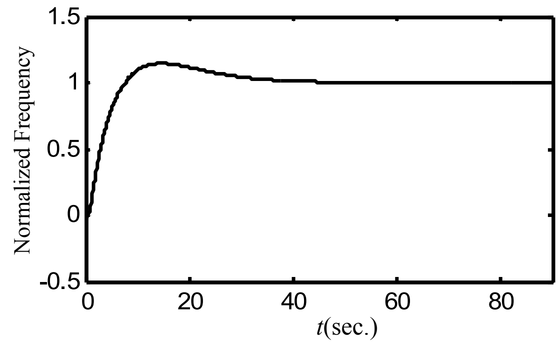

Fig.10. Tracking using the neuron of Eqs. (2) and (3) controller when $a = 21.0$ mm

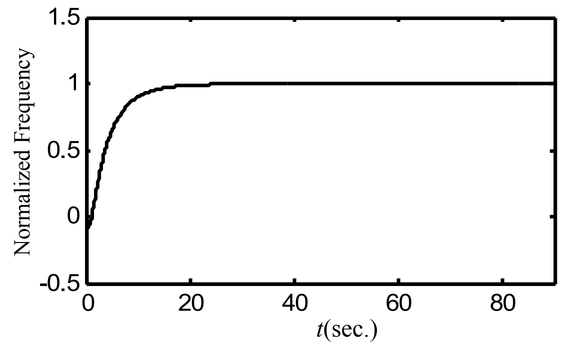

Fig.11. Tracking using the neuron of Eqs. (2) and (3) controller when $a = 25.0$ mm

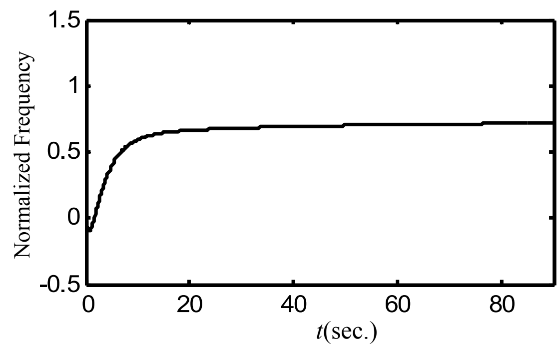

Fig.12. Tracking using the neuron of Eqs. (2) and (3) controller when $a = 31.0$ mm

IV. Conclusions

In this paper, a developed neuron model-free control method based on the immune feedback law is proposed, and simulation tests for a complex hydroelectric generating unit are performed. The results verified that the proposed approach is of effectiveness and has a quick response and good performance. One of the advantages of this method is model-free, that make the control system design procedure very simple for practical.

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