Research on speed regulation system of water turbine generator unit based on PID neural network

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Abstract. For the water turbine generator unit speed control system control error is large, long adjustment time, low control accuracy, poor stability and other problems, the PID neural network speed control strategy is proposed. First of all, the PID neural network (PIDNN) is used to design the speed control system of the turbine generator unit, and a complete model of the turbine generator unit speed control system is established. Secondly, using MATLAB for simulation, the step response of the water turbine generator unit speed control system is obtained. Finally, compared with the traditional PID controller, the PID neural network controller has obvious advantages in controlling error, adjusting time, over-tuning inhibition, etc., and has good stability.

1. Introduction

The speed control system of the turbine generator unit is an important control system to realize the rapid response load change of hydropower. The nonlinear system consists of hydraulic, mechanical and electrical parts, and its dynamic characteristics depend to a large extent on internal uncertainty and external disturbance [1]. The general study of the speed control system of the turbine generator unit assumes that the model parameters are constant, and the PID control is widely used because of its simplicity and practicality [2].

However, PID control is not suitable for complex nonlinear systems such as the speed of water turbine generator units, and it is difficult to deal with the uncertainty of model parameters [3]. In order to get better operating quality and system performance, intelligent algorithms such as genetic algorithm and particle group algorithm have been applied in the optimization of control structure and controller parameter selection, which makes the design of the turbine governor develop further, but the design method of the intelligent algorithm also puts forward higher requirements for the modeling accuracy of the turbine. Compared with the transfer function used in classical control theory, modern control theory uses state equation to describe the system and establish the state model of the water turbine generator unit speed control system, so that modern control methods such as nonlinear control[4-8], adaptive control[9-10], and robust control [11-12] can be used. The robust control is a kind of control method which requires low precision for system uncertainty and modeling in reference [11], a dual loop governor control system is designed by using the method of mixed sensitivity. In reference [12], the deficiencies in the application of reference [11] are pointed out and the PI control system is designed by using the \( \mu \) - synthesis method. However, when the controller acts on the system, the regulating time and the time required to restore stable operation after being disturbed are still long.
In this paper, based on the characteristics of PID neural network, such as simple structure and specification, fast response, small overshoot, no static difference, and control of the controlled object without measuring and identifying the internal structure and parameters of the controlled object [13], the PID neural network is applied to the speed control system of hydro generator unit, and the speed control system of hydro generator unit based on PID neural network is designed to get better control effect and system The stability of the system.

2. Speed governing system model of water turbine generator

2.1. The structure of the speed control system of the traditional water turbine generator unit

The water turbine generator unit consists of hydraulic system, water turbine, generator, servo system and governor. The water from the upstream of the reservoir flows into the volute through the penstock and drives the turbine and generator to rotate. Generally, the generator and the turbine are connected through the coupling, and the governor controls the opening of the guide vane of the turbine to adjust the speed. The typical block diagram of the speed control system is shown in Figure 1 [14].

![Figure 1. Structure diagram of speed control system of water turbine generator unit](image)

In Figure 1: $C(s)$ is the transfer function of system controller; $G_i(s)$ is the transfer function of servo system model; $G_t(s)$ is the transfer function of the turbine model; $G_g(s)$ is the transfer function of the generator model; $r$ is the given reference speed; Water gate opening deviation $\Delta G(s)$ as the intermediate output to improve performance; $\Delta \omega(s)$ is the output generator speed deviation; $R_{ref}$ is feedback; $d$ is the load change of power grid.

2.2. Hydraulic system model

In the speed control of the turbine generator unit, the head $H_t$ and water in the pressure pipe $V$ is two key variables, and there is a relationship between the two. The water hammer effect is the effect of pressure on the valve when the water flow in a smooth pipe change rapidly. Because of the elasticity of penstock and the compressibility of water, the pressure wave will propagate on the column, so the wave propagation time becomes very important. This paper discusses a single-tube single machine, the ratio of head increment and water flow increase at the inlet of the turbine is the ratio of the water flow increase rate [15]:

$$\frac{\Delta H_t(s)}{\Delta V(s)} = -\Omega_p - 0.5Z_p \tan h(T_e s)$$  \hspace{1cm} (1)

In this expression: $\Delta H_t$ is head increment; $\Omega_p$ is the friction coefficient of pressure pipe; $T_e$ is wave propagation time; $Z_p$ is surge shaft impedance for standardized pressure pipe.

2.3. Turbine model

The increment of water speed and mechanical power are:

$$\Delta V(s) = 0.5\Delta H_t(s) + \Delta G(s)$$  \hspace{1cm} (2)

$$\Delta P_m(s) = \Delta H_t(s) + \Delta G(s)$$  \hspace{1cm} (3)

In this expression: $\Delta V$ is water velocity increment; $\Delta P_m$ is mechanical power increment.

Combining expressions (1), (2) and (3), considering water hammer effect, head loss caused by
friction and the influence of inelastic pressure pipeline, turbine model $G_t$ is as follows:

$$G_t(s) = \frac{1 - \Omega_p - Z_p \tan h(T_p s)}{1 + 0.5\Omega_p + 0.5 \tan h(T_p s)}$$

(4)

2.4. Generator model

The generator model is as follows [16, 17, 18, 20]:

$$G_g(s) = \frac{\Delta \omega(s) / \Delta P_g(s)}{s} = \frac{1}{H + D}$$

(5)

In this expression: $H$ is the time coefficient of rotational inertia; $D$ is the damping coefficient of generator.

2.5. Servo system model

The servo system model is as follows [16, 17, 19, 20]:

$$G_s(s) = \frac{1}{1 + (T_p s + 1)(T_s s + 1)}$$

(6)

In this expression: $T_p$ is the time constant of servo system; $T_s$ is the time constant of servo motor.

3. The structure and algorithm of PID neural network

Because this paper only involves the single input and single output of the turbine speed control system, that is, the given reference speed input and generator speed deviation output, the PID neural network can be divided into a single-control neural network that controls the single variable system according to the number of control quantities of the accused system. PID Neural network can be divided into input layer, hidden layer and output layer, the neural networks of $n$ control quantities include $n$ parallel and identical subnetworks, each of which is independent of each other and connected with each other through network weights. The input layer of each subnetwork has two neurons that receive the given and actual values of the control quantity, respectively. The hidden layer of each sub-network is composed of proportional neurons, integral neurons and differential neurons, respectively corresponding to proportional control, integral control and differential control in PID controller. This paper only involves the single control quantity PID neural network (SPIDNN), as shown in figure 2 [13].

![Figure 2](image)

The input layer, the hidden layer and the output layer

In the figure: $X_1$ is the target value or the given value of the controlled quantity; $X_2$ is the current value or the actual value of the controlled quantity; $Y$ is the control law obtained by the calculation of the neural network; $\omega_i$ and $\omega_j$ are the network weight values. It can be seen from the figure that the single controlled quantity neural network is a three-layer forward neural network with the network structure of 2-3-1, and the hidden layer contains proportional element, integral element and differential element.

3.1. Forward algorithm of SPIDNN

3.1.1. Input layer
There are two neurons in the input layer of DNN, and when the control system is constituted, the given value $r(k)$ and the actual value $y(k)$ of the controlled quantity of the system can be input respectively. At any time $K$, its input:

$$net_1(k) = r(k)$$  \hspace{1cm} (7)

$$net_2(k) = y(k)$$  \hspace{1cm} (8)

The state of the neuron in the output layer is:

$$u_i(k) = net_i(k)$$  \hspace{1cm} (9)

The output of the input layer neuron is:

$$x_i(k) = \begin{cases} 
1 & u_j(k) > 1 \\
0 & -1 \leq u_j(k) \leq 1 \\
-1 & u_j(k) < -1 
\end{cases}$$  \hspace{1cm} (10)

In each of the above expressions $i = 1, 2$, $j = 1, 2, 3$.

### 3.1.2. The hidden layer

The hidden layer is the most important layer in the neural network. The hidden layer of DNN has three neurons, namely proportional element, integral element and differential element. The total value of their input is:

$$net_j'(k) = \sum_{i=1}^{3} \omega_{ij} x_i(k)$$  \hspace{1cm} (11)

The state of proportion element is:

$$u_{j}'(k) = net_j'(k)$$  \hspace{1cm} (12)

The state of the integration element is:

$$u_{j}''(k) = u_{j}(k) - net_j'(k)$$  \hspace{1cm} (13)

The state of the differentiator is zero:

$$u_{j}'''(k) = net_j'(k) - net_j'(k-1)$$  \hspace{1cm} (14)

The output of each neuron in the hidden layer is:

$$x_{j}'(k) = \begin{cases} 
1 & u_{j}'(k) > 1 \\
0 & -1 \leq u_{j}'(k) \leq 1 \\
-1 & u_{j}'(k) < -1 
\end{cases}$$  \hspace{1cm} (15)

In the formula: $j = 1, 2, 3$, $\omega_{ij}$ is the connection weight value of the input layer to the hidden layer, and superscript “ ’ ” is the variable marker of the hidden layer.

### 3.1.3. The output layers

The output layer structure of SPIDNN is relatively simple. It only includes one neuron to complete the summation output function of the network. Its total input is:

$$net''(k) = \sum_{j=1}^{3} \omega_{j} x_{j}'(k)$$  \hspace{1cm} (16)

In the formula: $x_{j}'(k)$ is the output value of each neuron in the hidden layer, $\omega_{j}$ is the connection weight value from the hidden layer to the output layer.

The state function of the neuron in the output layer is the same as that of the proportional element in the hidden layer, and the state is:

$$u''(k) = net''(k)$$  \hspace{1cm} (17)
The output function of the neuron in the output layer is the same as that of other neurons in the network, and the output \( x'(k) \) is:

\[
x'(k) = \begin{cases} 
1 & u'(k) > 1 \\
 u'(k) & -1 \leq u'(k) \leq 1 \\
-1 & u'(k) < -1
\end{cases}
\]  

(18)

The control law of the output of SPIDNN is equal to the output of the neuron in the output layer.

3.2. Error back propagation algorithm of SPIDNN

Based on the square mean of the deviation between the given value of the controlled quantity and the actual value (as shown below), the network connection weight value is modified. The entire SPIDNN takes a minimum of \( E \) as the training guideline and purpose.

\[
E = \frac{1}{l} \sum_{k=1}^{l} (r(k) - y(k))^2 = \frac{1}{l} \sum_{k=1}^{l} \hat{y}'(k)
\]  

(19)

In the formula: \( E \) is the mean value of deviation squared; \( l \) is the number of sampling points; \( r(k) \) is the given value of the controlled quantity; \( y(k) \) is the actual value of the controlled quantity.

The weight value of SPIDNN network connection is adjusted according to the gradient method. Let the learning step be \( \eta \), after \( n \) steps of training and learning, the iterative equation of the weight of each layer is as follows:

\[
\omega(n+1) = \omega(n) - \eta \frac{\partial E}{\partial \omega}
\]  

(20)

3.2.1. Hidden layer to output layer

SPIDNN’s network connection weight iteration formula from the hidden layer to the output layer is:

\[
\omega_j(k+1) = \omega_j(k) - \eta_j \frac{\partial E}{\partial \omega_j}
\]  

(21)

According to the forward algorithm, the following can be obtained:

\[
\frac{\partial E}{\partial \omega_j} = \frac{1}{l} \sum_{k=1}^{l} \delta'(k)x'_j(k)
\]  

(22)

In the above formula, \( \delta'(k) \) is:

\[
\delta'(k) = 2[r(k) - y(k)] \text{sgn}\left(\frac{y(k+1) - y(k)}{v(k) - v(k-1)}\right) x'_j(k)
\]  

(23)

3.2.2. Input layer to hidden layer

SPIDNN’s network connection weight iteration formula from the input layer to the hidden layer is:

\[
\omega_i(k+1) = \omega_i(k) - \eta_i \frac{\partial E}{\partial \omega_i}
\]  

(24)

According to the forward algorithm, the following can be obtained:

\[
\frac{\partial E}{\partial \omega_i} = \frac{1}{l} \sum_{k=1}^{l} \delta'_i(k)x_i(k)
\]  

(25)

In the above formula, \( \delta'_i(k) \) is:

\[
\delta'_i(k) = \delta(k) \text{sgn}\left(\frac{u'(k) - u'(k-1)}{net'_i(k) - net'_i(k-1)}\right)
\]  

(26)
3.3. The structure of hydraulic turbine generator system based on PID neural network

According to the structure of traditional water turbine generator unit speed regulation system and SPIDNN structure, the structure of water turbine generator unit speed regulation system based on PID neural network can be obtained, as shown in the following figure:

![Figure 3. Structure diagram of speed regulation system of water turbine generator unit based on PID neural network](image)

In the figure, \( r \) is the given reference speed, \( u \) is the control law calculated by PID neural network, \( \Delta G(s) \) is the gate opening deviation as the intermediate output to improve performance, and \( y \) is the actual value of the output generator speed.

4. The simulation analysis

MATLAB was used to carry out simulation experiments on the speed regulation system of the water turbine generator unit. The values of each parameter in the paper are: \( T_e = 0.35 \), \( T_w = 2.25 \), \( T_p = 0.0125 \), \( T_s = 0.275 \), \( H = 8.6 \), \( D = 0.5 \). It can be seen in section 2.3 for the structure of the turbine speed regulation system of the water turbine generator unit based on PID neural network, and literature for simulation parameters [20].

4.1. The simulation results of turbine speed regulation system based on PID neural network are analyzed

According to the selection principle of SPIDNN connection weight initial value [13], The initial values of the connection weight from the input layer to the hidden layer are \( \omega_{ij} = +1 \), \( \omega_{ij} = -1 \). The initial values of the connection weight from the hidden layer to the output layer are \( \omega_{i1} = K_p = 0.4 \), \( \omega_{i2} = K_i = 0.4 / 4.485 \), \( \omega_{i3} = K_d = 1.2 \).

Then, the sum of the input of the neuron in the output layer can be obtained as follows:

\[
\text{net}(k) = \sum_{i=1}^{k} \omega_{ij} x_i(k) = \omega_{i1} x_1(k) + \omega_{i2} x_2(k) + \omega_{i3} x_3(k) = K_p e(k) + K_i \sum_{i=0}^{k} e(i) + K_d[e(k) - e(k-1)]
\]  \( (27) \)

Finally, we can get the network output of SPIDNN when the connection weight takes the initial value as follows:

\[
v(k) = K_p e(k) + K_i \sum_{i=0}^{k} e(i) + K_d[e(k) - e(k-1)]
\]  \( (28) \)

Let the reference speed be \( 1 \text{ min}^{-1} \). Using the above parameters for simulation, the step response of the speed regulation system of a hydro-generator unit based on PID neural network can be obtained, as shown in figure 4. In the figure, red represents the actual generator output speed, and blue represents the given generator speed. It can be obtained from the figure that: when the PID neural network takes the initial value of connection weight, the actual generator output speed of the speed regulating system of the hydro-generator unit has a large deviation from the given generator speed. PID neural network through self-learning and weight adjustment, the water turbine generator unit speed regulation system can reach a stable state at 15s, and the whole process is very stable, no overshoot, no static error. What is shown in figure 5 is the square mean of the deviation between the actual generator output speed and the given generator speed of the speed regulating system of a hydro-generator unit. The square mean of
the deviation of the system is monotonically decreasing and reduces to 0 at 15s, indicating a good convergence performance of the system.

![Step response diagram of speed regulation system of hydraulic turbine generator unit based on PID neural network](image)

Figure 4. step response diagram of speed regulation system of hydraulic turbine generator unit based on PID neural network

![Deviation squared mean E](image)

Figure 5. deviation squared mean E

4.2. Compared with the traditional PID speed control system

This paper compares the speed regulation system of water turbine generator unit based on PID neural network with the traditional PID speed regulation control system. Among them, the transfer function of the controller in the traditional PID single-loop speed regulation control system is [21]:

$$K_{PID} = 0.4\left(1 + \frac{1}{4.485s} + 3s\right)$$  \hspace{1cm} (29)

The step response of the water turbine generator unit speed regulation system based on PID neural network is compared with the traditional PID speed regulation system, as shown in figure 6, where red represents the step response of the water turbine generator unit speed regulation system based on PID neural network, and blue represents the step response of the traditional PID speed regulation system. As can be seen from the figure, the speed regulation system of water turbine generator unit based on PID neural network has better stability than the traditional PID speed regulation system, and the control error is small, the control accuracy is high, and the regulation time is short. The traditional PID speed control system was able to reach a stable state around the time of 80s, with a large overshoot and a large number of oscillations.
5. Conclusion
In order to improve the performance of water turbine generator speed regulation system, a PID neural network control method is proposed. PID neural network is the traditional PID control law into the neural network, with the advantages of traditional PID control and neural network control. The structure is simple, standard, combined with the selection rules of the initial value of the weight of the connection of online self-learning and adjustment, can get better control effect. The simulation results show that compared with the traditional PID water turbine generator unit speed regulation system, the PID neural network based water turbine generator unit speed regulation system is superior in the time domain indexes such as rise time and adjustment time, and has good control effect and system stability.

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