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Hydraulic turbine system identification and predictive control based on GASA–BPNN

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Abstract: Based on the characteristics of nonlinearity, multi-case, and multi-disturbance, it is difficult to establish an accurate parameter model on the hydraulic turbine system which is limited by the degree of fitting between parametric model and actual model, and the design of control algorithm has a certain degree of limitation. Aiming at the modeling and control problems of hydraulic turbine system, this paper proposes hydraulic turbine system identification and predictive control based on genetic algorithm-simulate anneal and back propagation neural network (GASA–BPNN), and the output value predicted by GASA–BPNN model is fed back to the nonlinear optimizer to output the control quantity. The results show that the output speed of the traditional control system increases greatly and the speed of regulation is slow, while the speed of GASA–BPNN predictive control system increases little and the regulation speed is obviously faster than that of the traditional control system. Compared with the output response of the traditional control of the hydraulic turbine governing system, the neural network predictive controller used in this paper has better effect and stronger robustness, solves the problem of poor generalization ability and identification accuracy of the turbine system under variable conditions, and achieves better control effect.

Keywords: hydraulic turbine system; system identification; genetic algorithm; simulated annealing algorithm; predictive control

1. Introduction

The hydraulic turbine regulating system is the core part of the control components of the hydropower station. It is a time-varying system that is a complex non-linear system, and the system is interlocked with mechanical, electrical, and hydraulic power. The parameters of the turbine will change due to changes in the water head, load, speed, etc., that is, the parameters of different operating conditions will also change.

In the field of non-linear modeling of hydraulic turbine systems, the IEEE Association considered factors such as rigid water hammer in the early stage, and used simple models to compare the guide vane opening and water head [1]. According to the characteristic curve of the unit, the literature [2] approximated the function expression of the torque characteristic and the flow characteristic, and established a model by directly calculating the characteristic parameters of the turbine, which better solved the non-linear problem of the hydraulic turbine. Due to the variable working conditions of hydraulic turbine during operation, Chang and Ren [3] proposed an analysis model of hydraulic turbine based on internal characteristics according to the generalized basic equation of blade type hydraulic machinery, which is used to approximate the comprehensive characteristic curve and actual characteristic curve. The system identification method based on the system input and output data can approach any nonlinear model in theory, and combine with the system mechanism model to get a better turbine system model [4–8]. In terms of control algorithm design, PID (Proportional Integral Derivative) control and its corresponding optimization algorithm have always been the mainstream algorithm in the field of steam turbine control [9–11] according to the time-varying nonlinear characteristics of each link of turbine governing system. Intelligent control, neural network control, and predictive control have been extensively studied and applied in recent years [12–14], but most of them are based on the nonlinear characteristics of hydraulic turbines and cannot solve problems such as multiple operating conditions. All of the above problems are one of the solutions to the three problems of multi working conditions, nonlinearity, and time-varying in the operation process of hydraulic turbine, but they are not solved together.

According to the simulation and actual operation data of hydraulic turbine, this paper uses GASA–BPNN (genetic al-

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gorithm-simulate anneal and back propagation neural network) to optimize and realize high-precision identification, and designs the model predictive controller. At the same time, combined with the three problems of multi working conditions, nonlinearity, and time-varying, the control performance of hydraulic turbine system is optimized to a great extent.

2. System identification of hydraulic turbine model

2.1. Working principle of system identification

The schematic diagram of hydraulic turbine system identification based on Nonlinear Auto-Regressive Moving Average Model (NARMA) [15] is shown in Fig. 1.

In Fig.1, $y_m(k)$ is the predicted output value, $y(k)$ is the actual output value, $e(k)$ is the error between predicted value and actual value, $m_g(k)$ is the external disturbance, z^{-n_u} is the discrete guide vane opening signal, and z^{-n_y} is rotation speed output signal.

Fig.1 shows that hydraulic turbine regulation system is the approximate object of neural network. Those input signals of the whole identification system are discrete guide vane opening signal and rotation speed output signal. The output signals identified by the neural network are predicted value $y_m(k)$. Then take a sufficient number of training samples for training, and the weights and thresholds of the neural network are optimized by continuously reducing the value of $e(k)$.

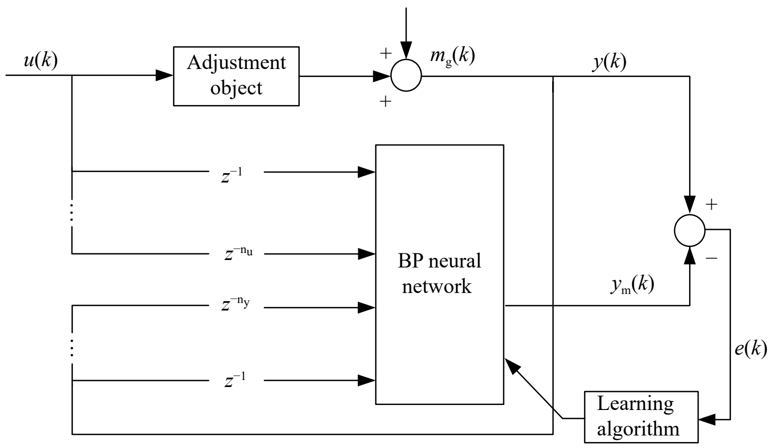

Fig. 1. Schematic diagram of hydraulic turbine system identification.

2.2. Improved GASA hybrid optimization algorithm

The traditional BP (back propagation) neural network is optimized by gradient descent method of continuous backward propagation. Although the approach of hydropower units can be achieved as a complex system, the working mode of hydropower units changes frequently with factors such as working conditions and disturbances. This arbitrary transformation reduces the generalization ability of network and the convergence speed is correspondingly slowed down. In view of shortcomings of BP neural network model in the process of approaching hydropower units, this paper proposes to improve on two aspects.

(1) BP neural network aims to optimize all weights and thresholds, and the model has poor stability and unsatisfactory convergence speed in the process of hydraulic turbine regulation system identification. Therefore, genetic algorithm is proposed to optimize and obtain the optimal weights and thresholds of neural network. The optimal weights and thresholds are assigned to neural network as initial weights and thresholds, which improves learning rate of BP neural network and improves stability of the identification process.

(2) Although using genetic algorithm to optimize neural network can improve convergence speed and stability, genetic algorithm itself has a phenomenon of "prematurity" and BP neural network is prone to fall into local optimal solution [16−17]. Therefore, the simulated annealing algorithm based on the Boltzmann probability distribution mechanism is introduced to optimize the neural network and obtain the global optimal solution to a higher probability so as to achieve a better approximation to the nonlinear system of hydropower units and achieve an ideal identification effect.

2.3. GASA−BPNN algorithm analysis

According to the specific situation of hydraulic turbine system identification, we selected three-layer neural network. Input nodes number is 6, hidden layer nodes number is 13, and output layer node number is 1. The objective function of neural network are the minimum mean square error function, convergence value is set as 1×10^{-5} and iteration number is set as 1000 times. Each individual of GASA algorithm population is a group of solutions of neural network weights and thresholds. In order to improve the competitiveness among individuals, the following fitness function is used:

$$f_i = \frac{\exp\left(\frac{\zeta_i}{T}\right)}{\sum_{i=1}^{M}\exp\left(\frac{\zeta_i}{T}\right)} \tag{1}$$

where $\zeta_i = 1/E(k)$, $E(k)$ is the error function between the predicted value and the actual value, T is the current temperature, M is the individual number of contemporary population, and f_i is the fitness function of individual i.

The improved selection probability (p) function based on sampling probability of simulated annealing algorithm is [18]:

$$p = \exp\left(\frac{(f_i - f_j)}{T_a}\right) \tag{2}$$

where T_a is the annealing temperature, f_i and f_j are the fitness functions of individual i and individual j.

The improved adaptive crossover probability (p_c) function based on sampling probability of simulated annealing algorithm is:

$$p_c = \begin{cases} k_1 - \dfrac{k_2(f_{avg} - f)}{f_{avg} - f_{min}}, & f < f_{avg} \\ k_1, & f \geqslant f_{avg} \end{cases} \tag{3}$$

where f_{min} is the fitness of the optimal individual in this generation, f_{avg} is the average fitness in each population generation, f is the smaller fitness value of two crossed individuals, $k_1 = 0.9$, $k_2 = 0.3$.

The improved adaptive variation probability (p_m) function based on sampling probability of simulated annealing algorithm is:

$$p_m = \begin{cases} k_1 - \dfrac{k_2(f_{avg} - f_{mi})}{f_{avg} - f_{min}}, & f_{mi} \leqslant f_{avg} \\ k_1, & f_{mi} > f_{avg} \end{cases} \tag{4}$$

where f_{mi} is fitness value of the mutant individual, $k_1 = 0.9$, $k_2 = 0.099$.

After the crossover operation of selection and mutation on population, SA (Simulate Anneal) operation is carried out on the population. The state disturbance mechanism of the new population generated in this paper is:

$$S' = S + \beta \tag{5}$$

where S is the initial solution of SA algorithm, S' is a new solution of SA algorithm flow, β is a random number for (−0.1,0.1).

3. System identification simulation based on GASA−BPNN

A simulation model of hydraulic turbine regulation system is adopted in this chapter. As shown in Fig. 2, training samples and test samples of two different working conditions are obtained through simulation experiments with no-load and load conditions.

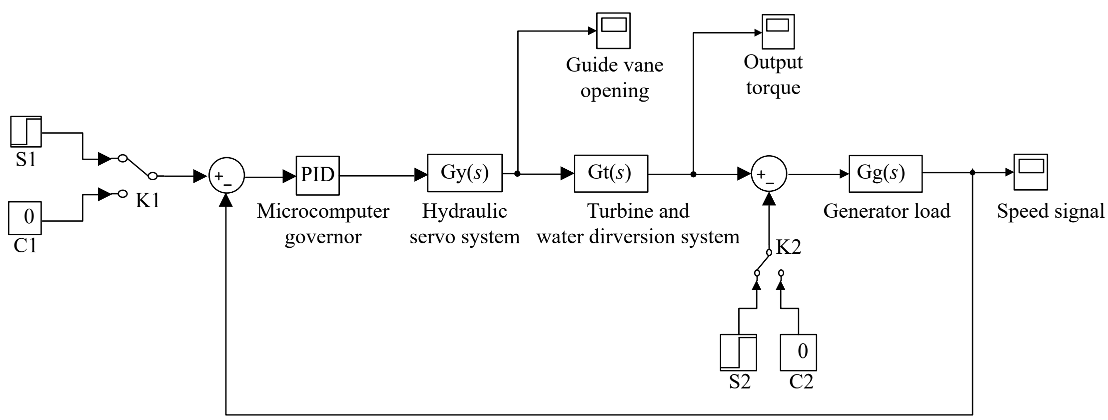

Fig. 2. Simulation model of hydraulic turbine regulation system.

In Fig. 2, S1 and S2 are step modules, K1 and K2 are manual switch modules, C1 and C2 are constant modules. Gy, Gt, and Gg are S-function modules.

3.1. No-load disturbance

Fig. 3 shows the GASA–BPNN identification effect curve of hydraulic turbine regulation system under no-load conditions. It can be seen that actual output curve of the speed and network identification output curve is basically overlapping, and identification effect of whole identification process is relatively stable. By reading identification error curve, it can be seen that identified error level at this time is 1×10^{-3}, maximum error is -5.859×10^{-3}, steady-state error is -7.867×10^{-4}, actual steady state value is 0.9998, and calculated accuracy at this time is 99.92%. Therefore, the GASA algorithm improves approximation accuracy of BP neural network and enables it to identify the hydraulic turbine regulation simulation system better, which reflects the feasibility of the algorithm.

3.2. Load disturbance

As shown in Fig. 4, the identification output of improved

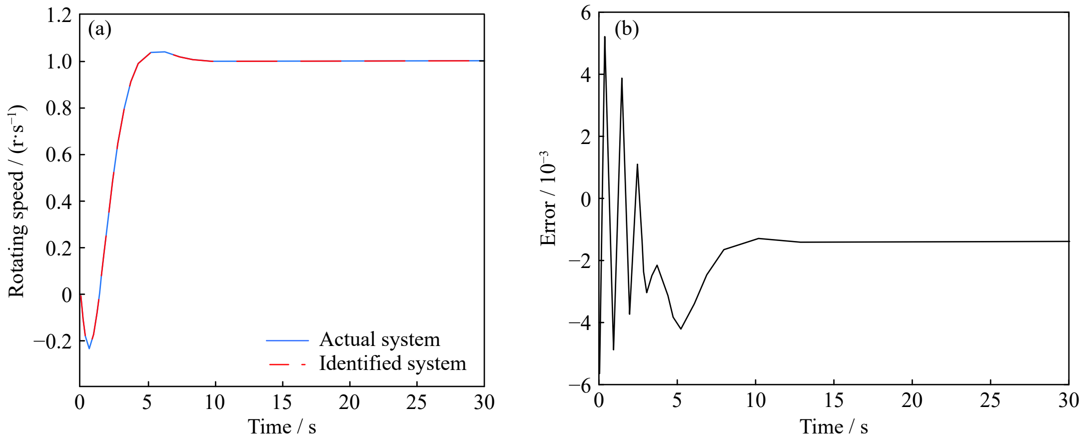

Fig. 3. **GASA−BPNN identification effect diagram (no-load condition): (a) system output comparison; (b) identification error.**

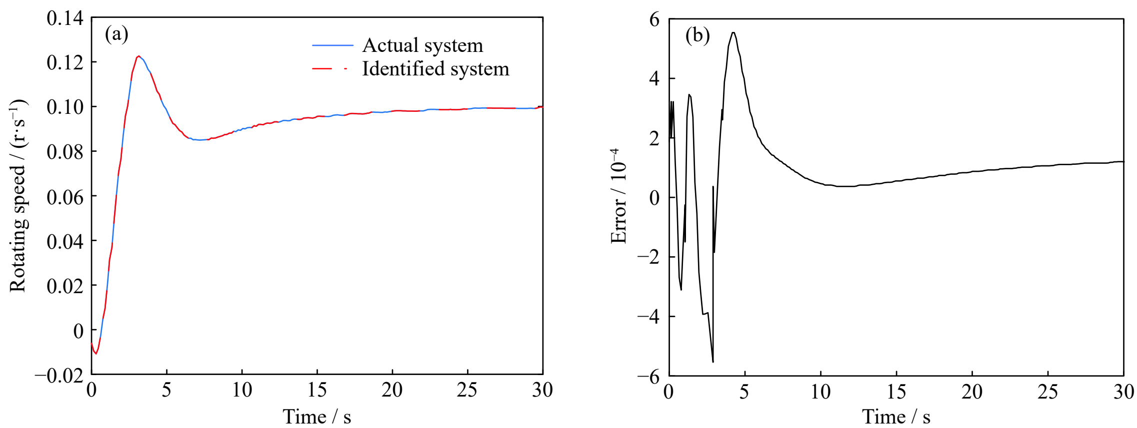

Fig. 4. **GASA–BPNN identification effect diagram (load condition): (a) system output comparison; (b) identification error.**

BP neural network model that based on GASA under load conditions roughly coincides with the actual speed output curve. It is consistent with the conclusions of the fitting graph given above and indicates that the identification accuracy is relatively high. The initial error of identification fluctuates to some extent. The maximum error is 5.535×10^{-4}, and corresponding actual value is 0.1096. When the system tends to a steady state, the steady-state error is 1.779×10^{-4}, and corresponding actual value is 0.0992. By calculation, the steady-state identification accuracy under this condition is 99.82%. Therefore, the identification error of improved neural network model under load conditions is also small, and the modified model preliminarily overcomes disadvantages of worse identification effect of neural network model when working conditions change.

3.3. Start-up process

Fig. 5 shows real time data curve of real start-up process of a hydropower station. It is mainly about turbine speed, vane opening degree, throw and other data within 64 s of the hydraulic turbine operation process. The data reading frequency is 100 Hz. By serializing rotational speed and vane opening data in the figure, the training samples for neural network training and the predictive samples of identification system can be obtained. The processed sample data is shown in Table 1. $u_c(k)$ is the guide vane openning, $y_c(k)$ is rotating speed.

Based on trained neural network, Fig. 6 shows the identification effect diagram and identification error curve of hydraulic turbine regulating system's real start-up process. As shown in the figure, identification output curve of improved BP neural network modelled based on GASA roughly coincides with actual rotation speed output curve, and the identification accuracy is relatively high. During identification process, the error fluctuates from 15 to 20 s, maximum error is 0.830, corresponding point is the 1796th point, and corresponding actual speed is 17.782. By calculation, the identification accuracy at this time is 95.32%. When the system tends to be in steady state, the steady-state error is 0.0502, and the corresponding actual value is 199.8. The steady-state identification accuracy under this condition can be obtained through calculation. Therefore, the identification error of im-

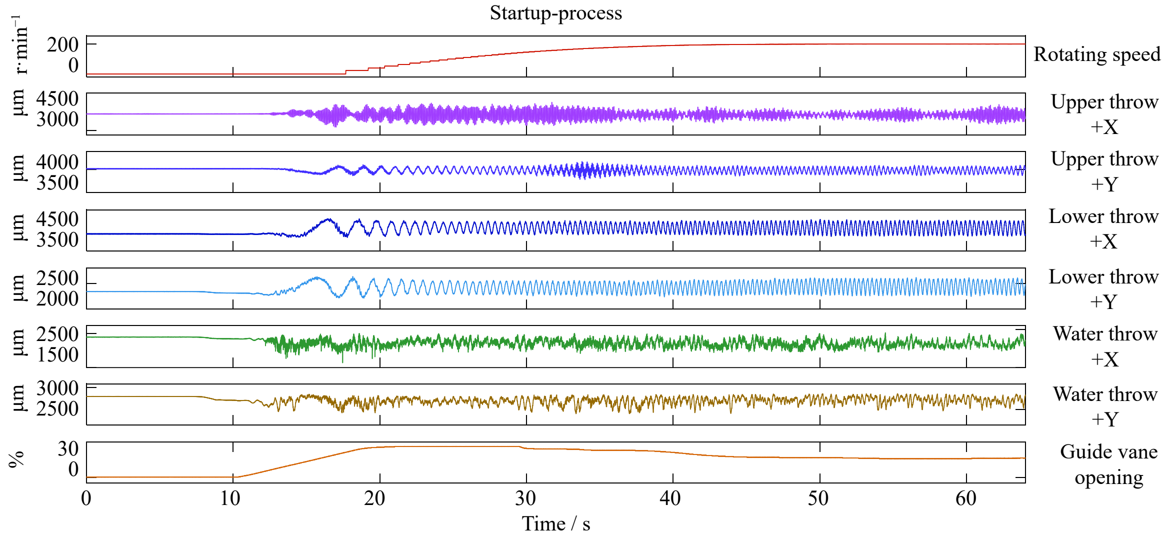

Fig. 5. Real time data curve of start-up process.

Table 1. Training sample data

Series	Sample 1	Sample 2	Sample 3	…	Sample 6398	Sample 6399	Sample 6400
$y_c\ (k-3)$	17.7206	17.7206	17.7206	…	199.9169	199.9169	199.9169
$y_c\ (k-2)$	17.7206	17.7206	17.7206	…	199.9169	199.9169	199.9169
$y_c\ (k-1)$	17.7206	17.7206	17.7206	…	199.9169	199.9169	199.9169
$u_c\ (k-3)$	0.2573	0.1966	0.1880	…	16.5128	16.4957	16.4697
$u_c\ (k-2)$	0.1966	0.1880	0.2400	…	16.4957	16.4697	16.4871
$u_c\ (k-1)$	0.1880	0.2400	0.2066	…	16.4697	16.4871	16.5391
$y_m(k)$	17.7206	17.7206	17.7206	…	199.9169	199.9169	199.9169

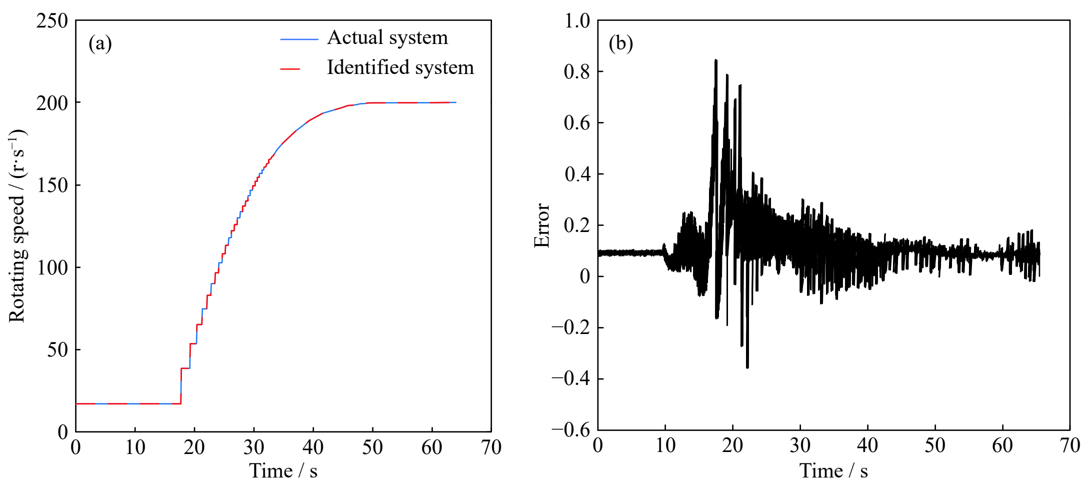

Fig. 6. GASA–BPNN identification effect diagram (start-up process): (a) system output comparison; (b) identification error.

proved neural network model in real start-up process of turbine regulation system is also very small, which verifies that the improved neural network not only has a good identification effect on the simulation system under ideal conditions, but also has a good effect on the real start-up process of turbine regulation system.

4. Model predictive control (MPC) method

4.1. Predictive control principle

Fig. 7 is the schematic diagram of hydraulic turbine system predictive control based on GASA-optimized BP neural network prediction model. As shown in the figure, $r(k)$ is a given reference value of rotating speed, $u(k)$ is the output value of predictive controller[19].

As shown in Fig. 7, the first step of predictive control process is the system identification of hydropower unit. The intelligent GASA algorithm is used to optimize BPNN model that approximated by the turbine regulation system of the controlled object under any working mode, until the identification value $y_m(k)$, which can approximately replace the dynamic response of the controlled object, is obtained. In the schematic diagram, the error function value $e(k)$ calculated by current time identification output value $y_m(k)$ and actual output value $y(k)$ of hydropower unit is as small as possible.

The predictive control model is obtained after identification of turbine regulation system. The model is used to predict guided vane opening control signal and speed output signal of the system in a short time domain in the future. Optimal guide vane opening control signal output values u are obtained by using nonlinear optimization controller. Control signal of guide vane opening output by the controller at each time is calculated online according to the reference value of given speeds signal and the predicted value of the GASA neural network speed signal. The performance index function given by nonlinear control module in the figure is as follows [20] :

$$J = \sum_{j=1}^{N_2} [y_r(k+j) - y_m(k+j)]^2 + \rho \sum_{j=1}^{N_u} [u(k+j-1) - u(k+j-2)]^2 \tag{6}$$

where J is used to obtain control quantity u. The optimization method is selected according to the actual needs, such as the gradient optimization method. j is jth moment, y_r is the reference setting response value; y_m is the predicted output response; ρ is the weighted coefficient; N_2 is the forecast duration; N_u is the control duration.

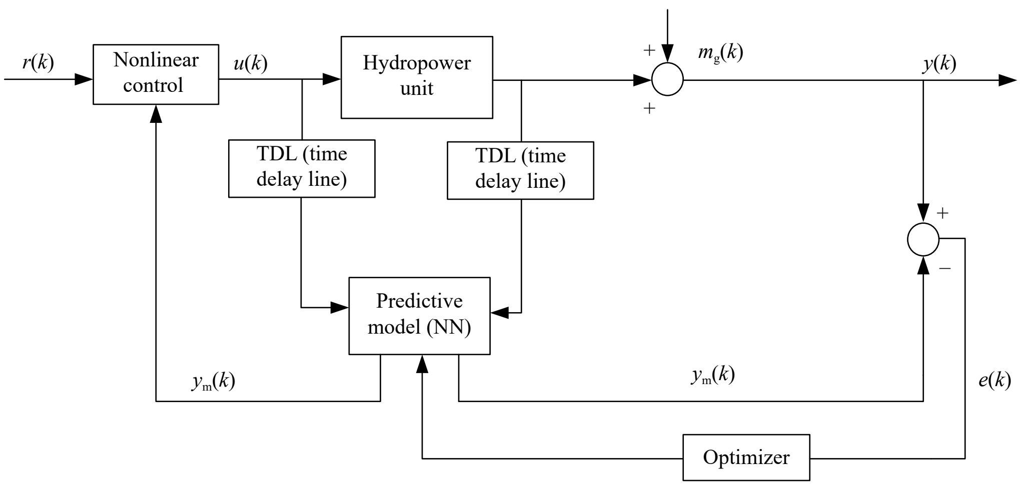

Fig. 7. Schematic diagram of hydraulic turbine system predictive control.

As shown in Fig. 7, there are many disturbances similar to $m_g(k)$ in the turbine regulation system. Due to the influence of unknown disturbances and mutative working conditions, its structural parameters will change, resulting in a poor prediction of the system-identification neural network model. Therefore, through the feedback link, the corresponding intelligent optimization algorithm is selected based on $e(k)$ and it constantly adjusts network model so as to correct predicted value. Then the "sliding window" optimization is carried out to obtain the control quantity which can make the system output closer to the given reference output value.

4.2. Model predictive control of hydraulic turbine

The trained neural network model optimized by GASA algorithm is used for prediction. 30 groups of test samples are selected in each working condition, and the acquisition method of test samples is given above. Figs. 8 and 9 are respectively the prediction effect diagram of simulation system under no-load disturbance and the prediction effect diagram under load disturbance.

According to the scatter diagram of error variation, the initial error value of system prediction is relatively large and slightly fluctuates, but it tends to be stable with the network learning. According to Fig. 9, it can be calculated that the maximum error value is 5.456×10^{-3}, corresponding accuracy is 99.27%, stable error value is 1.754×10^{-3}, and steady-state accuracy is 99.30%. The simulation results show that predicted value and true value of GASA–BPNN are almost the same under the conditions of no-load disturbance and load disturbance, and the prediction is relatively accurate.

In the two given working conditions, the traditional PID strategy and the GASA–BPNN model-based strategy are used to control the unit. The corresponding speed signals data and vane opening signal data under two different working

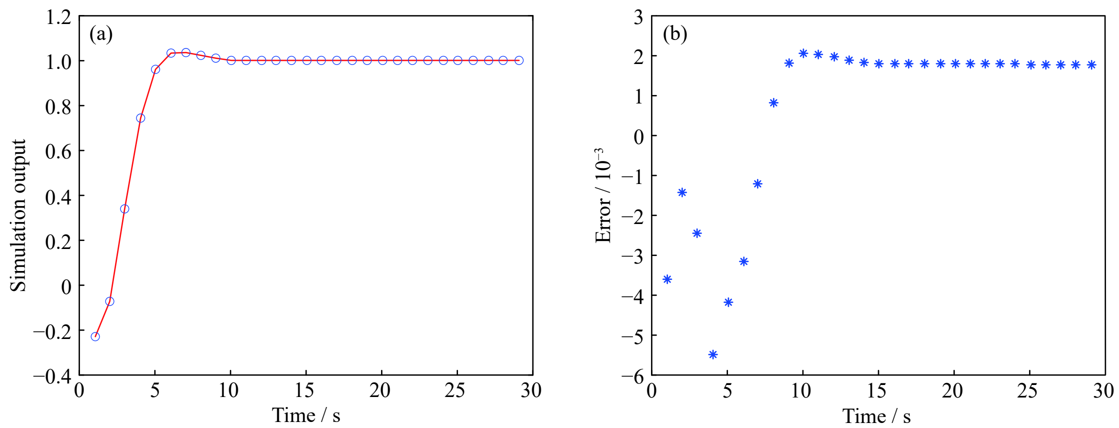

Fig. 8. Forecast effect diagram of no-load disturbance condition: (a) network output after training; (b) error scatter plot.

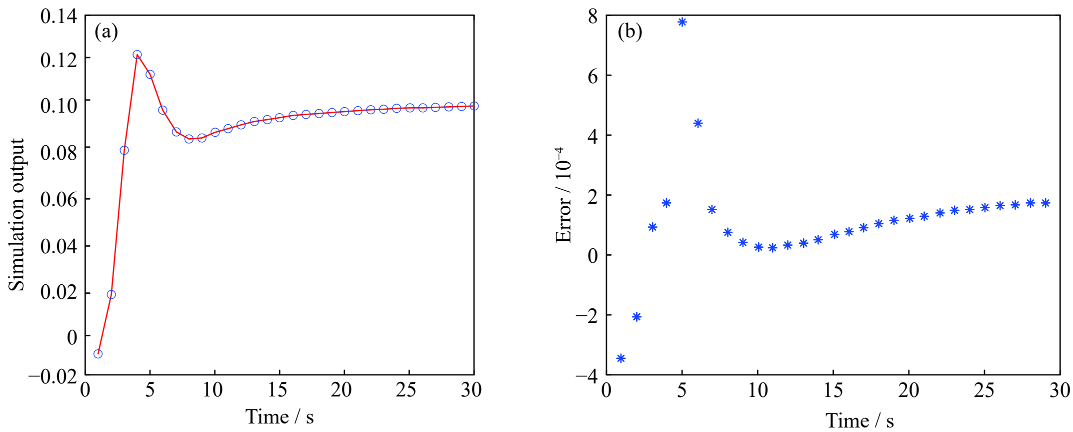

Fig. 9. Forecast effect diagram of load disturbance condition: (a) network output after training; (b) error scatter plot.

conditions of the turbine regulation system are obtained. The identified GASA–BPNN is used to predict the unit speed value, and fed back to the nonlinear optimization controller. At the same time, combined with the given speed reference, the optimal vane opening control amount of the corresponding time is obtained so as to realize the tracking of unit output value to reference value. Here, $N_2 = 7$, $N_u = 2$, $\rho = 0.05$.

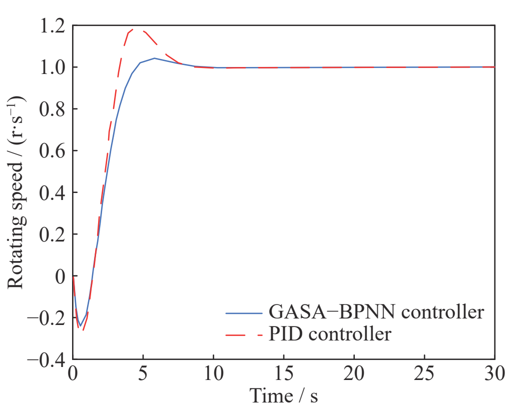

Fig. 10. GASA–BPNN control effect (no-load condition).

As shown in Fig. 10, the red dotted line is PID control effect curve, and the blue solid line is GASA–BPNN control effect curve. From the simulation diagram, the no-load condition adds 20% frequency disturbance at the third second moment, and PID-controlled turbine adjustment system shows obvious overshoot phenomenon. The overshoot is 19.8%, the rise time is 4.5 s, and there is a certain oscillation phenomenon. The stability of control effect based on GASA–BPNN is better, the overshoot of output response is 1.9%, the rise time is longer than PID control, which is 5.8 s. Adjustment time of the both is roughly the same.

As shown in the Fig. 11, the red dotted line is control effect graph under the load condition of PID controller, and the blue solid line is the control effect curve of GASA−BPNN. Simulation results show that, under load condition, the output speed of turbine regulation system controlled by traditional PID controller increases greatly, and the adjustment speed is slow. The predictive control of GASA−BPNN has a small increase in rotating speed when the load is dropped, and the adjustment time is obviously less than adjustment time of PID control, with better robustness.

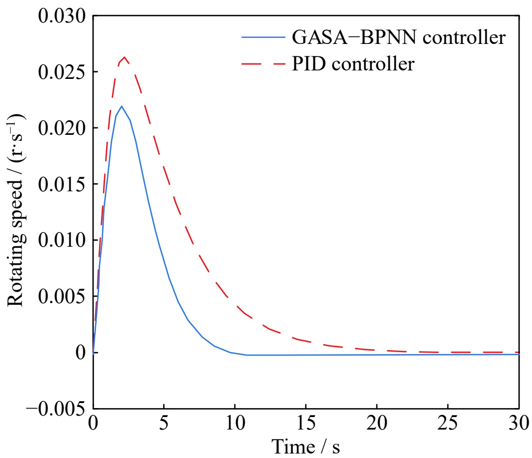

Fig. 11. GASA–BPNN control effect (load condition).

5. Conclusion

Based on the research of domestic and foreign scholars in the field of hydraulic turbine, this paper makes improvement on the identification and control strategy of hydraulic turbine system. The main work and conclusions are as follows.

Based on the general identification effect of traditional BP neural network and the instability of identification system effect when the working condition changes, this paper proposes an improved simulated annealing genetic hybrid intelligent algorithm to optimize BP neural network. The execution efficiency of simulated annealing algorithm is increasd, and the premature phenomenon of genetic algorithm is improved. At the same time, SA has the advantage of jumping out of extreme value, which will make BP neural network have better global approximation ability, and to some extent, it can overcome the phenomenon of unstable identification caused by mutative working conditions. The simulation results show that the identification accuracy and prediction accuracy of neural network identification model of hydraulic turbine regulating system are improved. By training GASA−BPNN, the predicted value of model is close to real value, and the corresponding predictive control is realized. The simulation results verify that GASA−BPNN largely optimizes the control performance of hydraulic turbine system.

Acknowledgements

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