Study on the Annual Runoff Forecast Model of the Main Stream of Nanxi River Based on PSO-ANFIS

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Abstract

In 2021, Wenzhou adopted measures to restrict the use of electricity, and the shortage of electricity became an important factor affecting the production and life of Wenzhou. Nanxi River is one of the main rivers in Wenzhou City, and its water resources are very rich. According to the statistics of the water conservancy planning of the Nanxi River basin, there are 96 hydropower stations in the Nanxi River basin, with a total installed capacity of 152100 kW, accounting for 57% of the installed capacity. The development and utilization of the Nanxi River water resources can alleviate the power shortage in Wenzhou power grid to a certain extent. The development and utilization of hydropower are closely related to the runoff of the basin. The river runoff is mainly determined by rainfall, underlying surface and upstream inflow. River runoff is affected by many factors in the process of formation, so it is difficult to improve its prediction accuracy. In order to improve the prediction accuracy of the runoff of the main stream of the Nanxi River, this paper introduces the runoff prediction model of particle swarm

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optimization adaptive fuzzy inference system (PSO-ANFIS). ANFIS model has the advantages of applying fuzzy rules and the nonlinear approximation ability of neural network, but the antecedent parameters of ANFIS model are prone to fall into local optimization. In order to improve the generalization ability of the antecedent parameters of ANFIS model, the PSO algorithm of global optimization is introduced to optimize the antecedent parameters of ANFIS. Through the application of the example, it is found that the decision coefficient of PSO-ANFIS model in the simulation stage is 0.987, and the decision coefficient in the prediction stage is 0.856. This model can be applied in the annual runoff forecast. Through comparison with ANFIS model, it is found that PSO-ANFIS model has better prediction effect.

Keywords: Nanxi river, hydropower, PSO-ANFIS, runoff prediction, prediction accuracy.

1 Introduction

In 2021, the power supply in Wenzhou was cut off, and the power shortage affected the production and life of Wenzhou. Nanxi River is the largest tributary of Oujiang River, which flows into the sea alone in Wenzhou. The current development of hydraulic resources of Nanxi River is about 60%. The development of hydraulic resources of Nanxi River can further alleviate the problem of power shortage in Wenzhou. The development of hydraulic resources is closely related to the amount of runoff. The development of hydraulic resources is closely related to the amount of runoff. Accurate runoff forecast can provide important data support for the development and utilization of hydraulic resources. At present, the research on runoff prediction at home and abroad can be roughly divided into two categories: deterministic model and uncertain model. Deterministic model is mainly mechanism research. It analyzes the causes of runoff Generally, the mathematical and physical model of runoff generation process is established. The advantage of this model is that it has certain physical concepts, including Xin'anjiang model. Non deterministic models generally do not have physical concepts. They approximate the hydrological law by establishing a black box model of input and output. The non deterministic model is flexible in modeling and application, so it is widely used in the near future.

However, runoff prediction is a problem involving many factors. In the process of runoff formation, it is difficult to improve the prediction accuracy due to the influence of meteorological, geological, geomorphic and other factors. The current method is to introduce computer technology and use the big data processing ability of the computer and the advantages of various intelligent algorithms. Adaptive neuro fuzzy inference system (ANFI) was proposed in the 1990s. It has many advantages, such as self-adaptive, self-learning and strong linear approximation. Particle Swarm Optimization (PSO) has the advantage of global optimization. Applying it to ANFIS model can improve the convergence speed of the model and make the prediction result of the model better. Therefore, this paper uses PSO to optimize the parameters of ANFIS and takes the main stream of Nanxi River as an example to better predict the runoff of Nanxi River and provide data reference for the development of water energy resources in Nanxi River.

2 Research Progress of Runoff Prediction

In 1981, Takens, Packard, farmer and others [1, 2] proposed a delay method for reconstructing the phase space of dynamic orbit. In 1993, ML Zhu et al. [3] studied the application of BP network in flood forecasting and pointed out that the performance of BP network depends on the representativeness of training samples. In 1994, N. Karuanithi et al. [4] Ann is applied to predict the measured daily discharge data of the river channel, and the effect is good. In 1994, Wang Genxu [5] applied the grey two-way difference model to the long-term runoff prediction of hydropower stations. In 1999, Shuchang et al. [6] used ANN to model and analyze the rainfall runoff process. In 1997, Roy and Govil [7] introduced a RBF neural network method. In 1996, Zhong Guifang [8] tried to apply the grey variable basis model to the Long-term Hydrological Prediction of the reservoir. In 1997, Chen Shouyu [9] proposed a medium and long-term hydrological prediction method considering the weight of prediction factors. In 2003, Sivakumar et al. [10] established a second-order local prediction model for the monthly runoff prediction of ariguari basin in Brazil, and the results verified the feasibility of the model. In 2002, R.K. Agrawal et al. [11] proposed a nonlinear dynamic prediction model. In 2002, Sivakumar et al. [12] predicted the daily runoff series of chaophre basin in Thailand by using the local method based on phase space reconstruction and the global method based on ANN respectively. When the prediction period is 1 to 7 days, the prediction results of the two models are ideal, and the local method is superior to the ANN method. In 2002, Liong et al. [13, 14] first introduced SVM into hydrological forecasting. In 2000, S. Bordegnon et al. [15] analyzed the chaotic characteristics of the daily average flow time series of Adige River in Italy from 1955 to 1981, and predicted 850 data with the local linearized nonlinear model in the neighborhood and the step size of 1,2,...,15 by using the first-order polynomial fitting. Compared with the random AR model, the prediction of chaotic time series is obviously better. In addition, the two-dimensional time series of rainfall and flow are adopted, and the prediction effect is significantly improved. In 2009, Zhang Ming [16] et al. Introduced Bayesian probabilistic Hydrological Prediction Theory and medium and long-term runoff prediction. In 2012, Zhao Tongtiegang [17] introduced random forest model to predict runoff in dry season. In 2021, Reddy Beeram Satya Narayana [18] and others applied the artificial intelligence model Eann to runoff prediction. In 2021, Yuan Xiaohui [19] and others applied the hybrid clustering model based on WOA interval mapping model to runoff prediction. In 2021, Muhammad Sibtain [20] applied the model based on variational modal decomposition and artificial neural network to runoff prediction.

3 Runoff Prediction Model

At present, there are many computer data models for runoff prediction at home and abroad, most of which are improved models based on BP network and regression model. Most of these models have problems such as slow calculation speed, over reliance on past samples, inconsistent training ability and simulation prediction ability, etc. ANFIS model was proposed by JYH Shing Roger JA in 1993. This algorithm solves the shortcomings of artificial neural network to a certain extent. Since it was proposed, it has been widely used in [21], classification [22, 23], prediction [24], etc. In order to improve the calculation speed and accuracy of the model, some scholars have proposed to use the global optimization ability of PSO to optimize the structural parameters of ANFIS. Through experiments, this method can improve the calculation accuracy of the model by about 15% [25]. Due to the influence of many factors, the improvement of prediction accuracy of river runoff has always been a difficult problem for the hydrological community. This time, PSO-ANFIS model is introduced to predict the main stream of Nanxi River, so as to obtain more accurate runoff prediction values.

3.1 Adaptive Neuro Fuzzy Inference System

The adaptive neuro fuzzy inference system (ANFIS) model proposed by J.S.R. Jang realizes fuzzy control with the help of neural network principle, including three basic processes: fuzziness, fuzzy reasoning and anti fuzziness. The model approximates a nonlinear function by several linear functions. This process is simple, fast and effective. ANFIS model has the advantages of self-adaptive and self-learning, which makes it widely used in the construction and solution of nonlinear models.

Establish a model with multiple inputs and one output, so that each component of the input parameter s $= [s_1, s_2, \ldots, s_w]^T$ is a fuzzy language variable. Set:

$$T(s_x) = \{A_x^1, A_x^2, \ldots, A_x^y\},\ x = 1, 2, \ldots, w \tag{1}$$

Where $A_x^y(y = 1, 2, \ldots, w_l)$ is the y language variable of s_y, which is a fuzzy set defined on U_x. The corresponding membership function is $\mu_{A_x^y}(s_x)$ $(x = 1, 2, \ldots, w; y = 1, 2, \ldots, l_x)$.

The linear combination of input variables is the fuzzy rule of the model, that is, R_y. If s_1 is A_1^y and s_2 is A_2^y and x_w is A_w^y, then:

$$z_y = p_{y0} + p_{y1}s_1 + \cdots + p_{yw}s_w \tag{2}$$

The fitness of input s:

$$\alpha_j = \mu_{A_1^y}(s_1)\mu_{A_2^y}(s_2)\ldots\mu_{A_w^y}(s_w) \tag{3}$$

It is assumed that the input variable adopts the fuzzification method of single point fuzzy set. Output z is the weighted average of z_x, namely, that is:

$$z = \sum_{y=1}^{l} \alpha_y z_y \Bigg/ \sum_{y=1}^{l} \alpha_y = \sum_{y=1}^{l} \overline{\alpha}_y z_y \tag{4}$$

Where $\overline{\alpha}_y = \alpha_y / \sum_{y=1}^{l} \alpha_y$, it is a fuzzy neural network structure, including two parts: pre component network and post component network.

1. Precursor network

The antecedent network consists of four parts:

(1) Input section. The number of nodes $W_1 = w$ of this section, each node of the input section corresponds to the component s_x of the input parameter, and transmits the input parameter $s = [s_1, s_2, \ldots, s_w]^T$ to the second section.

(2) Blur section. Each node represents a language variable value. He fuzzifies each input variable and outputs the corresponding membership function μ_x^y:

$$\mu_x^y = \mu_{A_x^y}(s_x) \tag{5}$$

Where, $x = 1, 2, \ldots, w$, $y = 1, 2, \ldots, l_x$. w is the dimension of the input variable and l_y is the fuzzy partition number of s_x. Membership function is usually Gaussian function, then:

$$\mu_x^y = e^{-\frac{(s_x - c_{xy})^2}{\sigma_{xy}^2}} \tag{6}$$

Where σ_{xy} and c_{xy} represent the width and center of the membership function respectively. The sum of nodes in this section is $N_2 = \sum_{x=1}^{w} l_x$.

(3) Regular release strength section. This section calculates the corresponding usage degree according to the fuzzy rules of the front part. Namely:

$$\alpha_y = \mu_1^{x_1} \mu_2^{x_2} \ldots \mu_l^{x_l} \tag{7}$$

Where $x_1 \in \{1, 2, \ldots, l_1\}$, $x_2 \in \{1, 2, \ldots, l_2\}, \ldots, x_n \in \{1, 2, \ldots, l_w\}$, $y = 1, 2, \ldots, l$, $l = \prod_{x=1}^{w} l$ the number of nodes in this section $w_3 = l$.

(4) Normalization section. It can normalize the usage of each rule. Its node $W_4 = W_3 = l$, output is;

$$\overline{\alpha}_x = \alpha_y \Big/ \sum_{y=1}^{l} \alpha_y \tag{8}$$

Where: $y = 1, 2, \ldots, l$.

2. Aftermarket network

The latter network has three sections:

(1) Input section, which is used to transfer thevalue enteredto the next section.
(2) The second section is to calculate the subsequent parts of the rules corresponding to l nodes, namely:

$$z_y = p_{y0} + p_{y1}s_1 + \cdots + p_{yw}s_w \tag{9}$$

Where p_{j0} is the constant term of the latter part.
(3) Output section, i.e.:

$$z = \sum_{y=1}^{l} \overline{\alpha}_y z_y \tag{10}$$

3.2 Particle Swarm Optimization

Particle Swarm Optimization (PSO) is an evolutionary algorithm for global optimization. He makes evolutionary calculations by adjusting the speed and position of particles. Each instance particle represents a candidate value. His calculation process is to first set the initial example speed, then let the particles search forward, and adjust the particle speed in the process. In addition, the L-th particle is $X_l = (X_{l1}, X_{l2}, \ldots X_{ln})$, which can be substituted into the fitness function to calculate the fitness value of the particle at the position. The size of the value represents the degree of the position. The optimal solution found by the particle is recorded as $P_l = (P_{l1}, P_{l2}, \ldots P_{ln})$, which is called the individual extreme point pbest; The best position found by the group is recorded as $P_g = (P_{g1}, P_{g2}, \ldots P_{gn})$, which is called the global extreme point gbest. The velocity update equation and position of any particle I in its d-dimensional space ($1 \leq \mathrm{D} \leq \mathrm{d}$) are as follows:

$$\begin{aligned} V_{ld}(m+1) = a \times V_{ld}(m) + c_1 \times rand() \times (P_{ld}(m) - X_{ld}(m)) \\ + c_2 \times rand() \times (P_{gd}(m) - X_{ld}(m)) \end{aligned} \tag{11}$$

$$X_{ld}(m+1) = X_{ld}(m) + V_{ld}(m+1) \tag{12}$$

Where: c_1 and c_2 are acceleration factors, a is the inertia weight coefficient, X_{ld} is the position of particle l in D-dimensional space, $rand()$ is the random number within the range [0,1], V_{ld} is the velocity of particle l in D-dimensional space, $V_{ld} \in [-V_{l\max}, V_{l\max}]$ and P_{ld} are individual extreme points, and P_{gd} is global extreme points. In order to make the house particles exceed the set variable range in the process of flying, the maximum flying speed $V_{\max}$ is generally set according to the variable range of the problem to be solved. If the current speed is $V > V_{\max}$ or $V < -V_{\max}$, take $V = V_{\max}$ or $V = -V_{\max}$.

3.3 PSO-ANFIS Model

PSO-ANFIS model uses the global optimization ability of PSO to optimize the network structure parameters of ANFIS, so as to improve the convergence speed of ANFIS parameter identification. This method can improve the accuracy and calculation speed of runoff prediction model. Its calculation process is as follows: firstly, determine the scale of PSO, replace the pre component parameters of ANFIS with initialized particles, then estimate the post component parameters from the calculated pre component parameters, calculate the model structure error at this time, take the

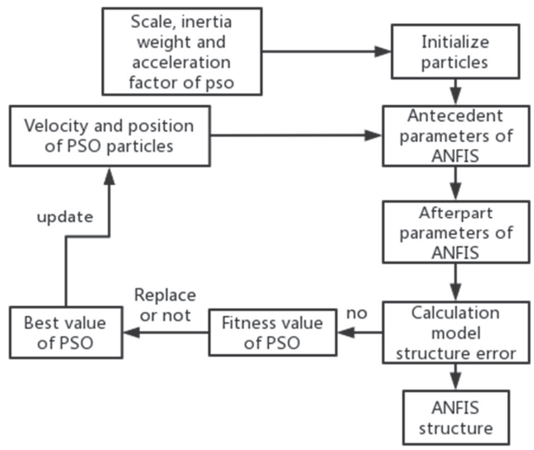

Figure 1 PSO-ANFIS calculation process diagram.

error as the fitness value of PSO, compare the current fitness value with the best value, and judge whether to replace the best value. Update the speed and position of PSO particles. Loop iteration until the optimal ANFIS parameters are found.

3.4 Model Evaluation Criteria

In order to verify the results of the model, this paper uses the average absolute value percentage error (M), root mean square error (R), average absolute pair error (M') and determination coefficient (R^2) to evaluate the simulation and prediction results of the model. The calculation formula is as follows:

$$
\begin{aligned}
M &= \frac{1}{N}\sum_{i=1}^{n}\left|\frac{y_i-\widehat{y}_i}{y_i}\right| \times 100\% \\
R &= \sqrt{\frac{1}{N}\sum_{i=1}^{n}(y_i-\widehat{y}_i)^2 \times 100\%} \\
M' &= \frac{1}{N}\sum_{i=1}^{n}|y_i-\widehat{y}_i| \times 100\% \\
R^2 &= 1-\frac{\frac{1}{N}\sum_{i=1}^{n}(y_i-\widehat{y}_i)^2}{\frac{1}{N}\sum_{i=1}^{n}(y_i-\overline{y})^2}
\end{aligned}
\tag{13}
$$

4 Example Application

4.1 Overview of Climate in Wenzhou

Wenzhou has a monsoon climate. The seasonal distribution of precipitation is uneven, and the change of precipitation is bimodal. There are two rainy and dry seasons in a year. The first rainy season is from March to June, the second rainy season is from mid August to the end of September, and there are two relatively dry seasons from July to mid August and from October to February next year. The interannual precipitation is unbalanced. The wet and dry years occur alternately, and the ratio of wet to dry is large. For example, at Wenzhou station, the annual average precipitation is 1843.3 mm, the maximum year is 2919.8 mm (1911), the minimum year is 1103.0 mm (1979), and the ratio of wet to dry is 2.65. There are great regional differences in precipitation. Generally, the precipitation is small on islands, second in order, and large in mountainous areas.

Wenzhou has four distinct seasons, with more light and abundant rainfall. According to the observation data of Wenzhou station, the monthly average minimum temperature is 4.6°C (January), the monthly average maximum temperature is 32.1°C (July), the multi-year average temperature is 17.9°C, and the average relative humidity is 81%. The annual average maximum wind speed is 14.8 m/s, the average wind speed is 2.0 m/s, and the corresponding wind direction is ene.

4.2 Runoff Forecast

The annual runoff from 1959 to 2015 is used as the simulation sequence, and the annual runoff from 2016 to 2019 is used as the prediction sequence. Particle swarm optimization is used to optimize the antecedent parameters of ANFIS model. By observing the error change process, the number of particles is set to 100, the inertia weight is 0.5, the maximum speed is set to 2, and the number of iterations is set to 500. The membership function of ANFIS model is set as Gaussian function, and the number of clusters of the membership function is set as 50. The results of simulation phase and prediction phase are shown in Figures 2–4.

From the result chart, we can see that the PSO-ANFIS model can not only simulate the runoff series well, but also predict the annual runoff well. But in general, the error result in the simulation stage is smaller than that in the prediction stage. The accurate prediction of annual runoff can provide better reference for the utilization of water resources and the planning of hydropower projects in the Nanxi River basin.

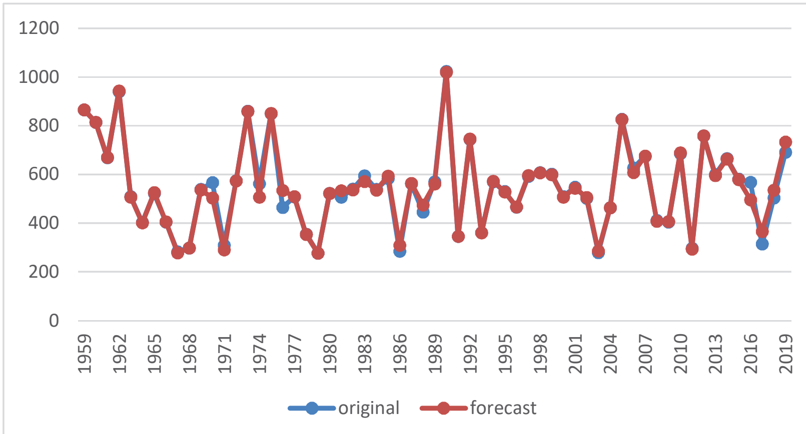

Figure 2 Comparison of simulation results.

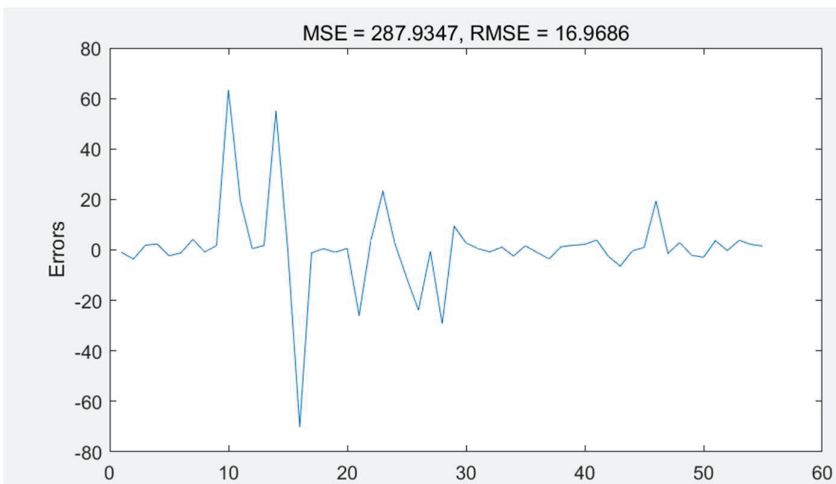

Figure 3 Error distribution diagram of PSO-ANFIS model in simulation stage.

5 Discuss

In order to verify the simulation and prediction effects of the model, the calculation results of ANFIS model are selected for comparison. For the function of ANFIS model, select Gaussian function as the membership function, and set the number of clusters of the membership function as 50. The number of iterations is set to 500. The simulation and prediction results are shown in Figures 5–6.

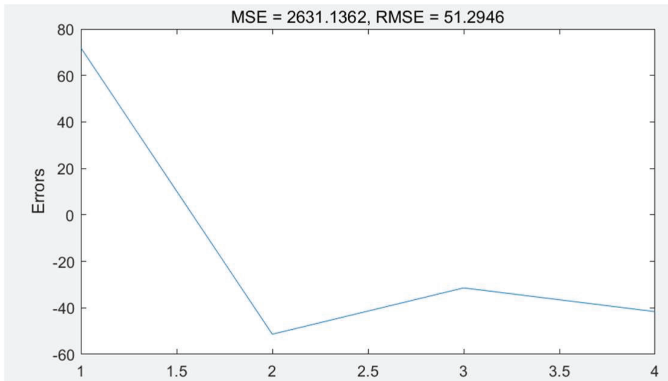

Figure 4 Error distribution of PSO-ANFIS model in prediction stage.

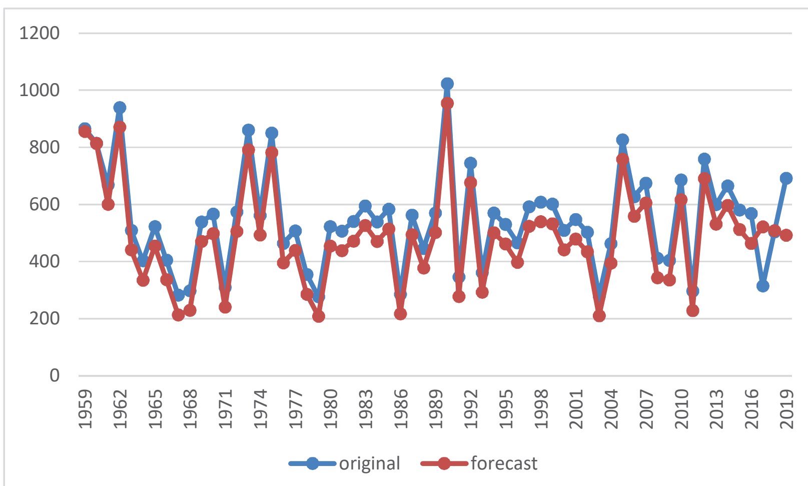

Figure 5 Comparison of simulation and prediction results of ANFIS model.

It can be seen from the result chart that the ANFIS model can get good simulation results, but its prediction results are poor. The calculation results of the PSO-ANFIS model and the ANFIS model are evaluated using the percentage error of the average absolute value, the root mean square error, the average absolute pair error and the determination coefficient. The evaluation results are shown in Table 1.

It can be seen from Table 1 that the decision coefficient of the PSO-ANFIS model simulation stage is 0.987, and the decision coefficient of the

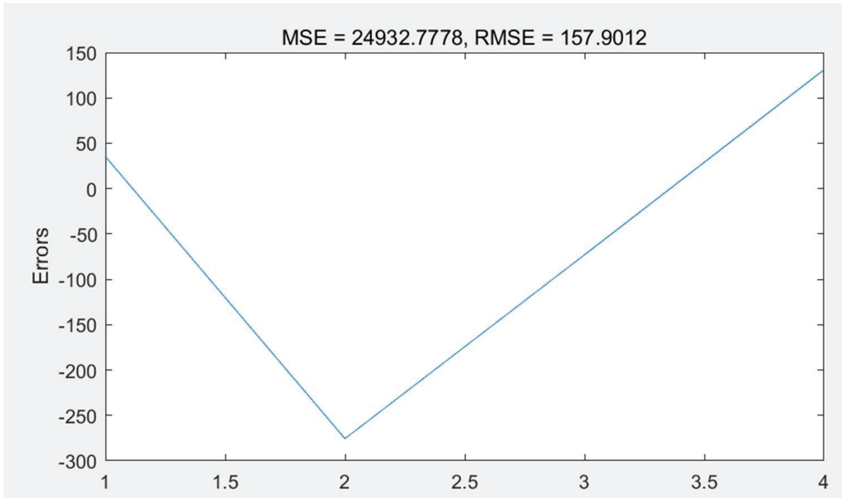

Figure 6 Error distribution diagram of ANFIS model in prediction stage.

Table 1 Result evaluation of PSO-ANFIS model and ANFIS model

Model	Stage	M	R	M′	R^2
PSO-ANFIS	Simulation	0.017	7.953	16.969	0.987
	Forecast	0.103	49.070	51.295	0.856
ANFIS	Simulation	0.140	68.730	68.548	0.847
	Forecast	0.285	128.766	152.935	−26.961

ANFIS model simulation stage is 0.847. Both models can get good simulation results. The decision coefficient of the PSO-ANFIS model in the simulation stage is 0.856, and the decision coefficient of the ANFIS model in the simulation stage is −26.961. The PSO-ANFIS model has obvious prediction advantages. Since the antecedent parameters of ANFIS model are easy to fall into local optimization during the calculation process, the PSO algorithm of global optimization can be used to optimize its antecedent parameters, and better prediction results can be obtained. The comparison results of the predicted values and the original values of the two models are shown in Table 2.

It can be seen that the two models have good results for the first prediction value, but with the increase of the number of predictions, the PSO-ANFIS model can still get better prediction results, but the prediction results of ANFIS model gradually deviate from the original trend.

Table 2 Comparison between predicted value and original value

Number of Forecasts	Original Sequence	PSO-ANFIS	ANFIS
1	567.80	495.92	463.88
2	314.55	365.90	521.64
3	503.90	535.31	508.33
4	691.60	733.24	491.97

6 Conclusion

The development of Nanxi River water resources can alleviate the power shortage in Wenzhou. The development of hydraulic resources is closely related to the runoff of the river basin. Due to the impact of human activities, underlying surface and other factors, the accuracy of runoff prediction has been difficult to achieve the expected effect. In recent years, runoff prediction models can be divided into deterministic models and non-deterministic models. Because of the advantages of convenient application and fast modeling, the uncertain model is more and more widely used in runoff prediction. In this paper, the adaptive fuzzy neural network and PSO are combined to predict the runoff of the main stream of the Nanxi River, using the advantages of adaptive fuzzy neural network, self-learning, strong nonlinear approximation and the strong search ability of PSO, so as to improve the accuracy of runoff prediction. The main conclusions are as follows:

(1) Because of the characteristic that the antecedent parameters of the individual ANFIS model are easy to fall into the local minimum, its decision coefficient in the simulation stage is 0.847, which can meet the requirements of the simulation stage, but the decision coefficient in the prediction stage is only -26.961, which cannot meet the requirements of the prediction.

(2) PSO-ANFIS model uses the global optimization advantages of PSO algorithm to optimize the antecedent parameters of ANFIS model. It can more globally optimize the best parameters for annual runoff simulation and prediction. The decision coefficient of PSO-ANFIS model in the simulation stage is 0.987, and the decision coefficient in the prediction stage is 0.856, which can meet the requirements of model calculation.

(3) The first prediction value of PSO-ANFIS model and ANFIS model can meet the requirements of the model, but with the increase of prediction length, the prediction result of PSO-ANFIS model can meet the trend of annual runoff development, and the result of ANFIS model deviates from the trend of original runoff series.

(4) PSO-ANFIS model can be used in the annual runoff forecast. Accurate annual runoff forecast is the basis of water resources utilization and hydropower resources development in the basin. PSO-ANFIS model can provide a new reference for the field of annual runoff forecast.

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Biographies

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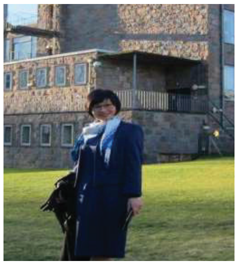

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