Proceedings of the 2nd International Conference on Environmental Geoscience and Earth Ecology
DOI: 10.54254/2753-8818/37/20240160

Research on a global periodic climate prediction method based on improved BP neural network

Yan Lu

College of History Culture and Tourism, Liaocheng University, Liaocheng, 252000, Shandong, China
China-Pacific Island Countries Climate Action Cooperation Center, Liaocheng University, Liaocheng, 252000, Shandong, China
Shandong Society for Environmental Sciences, Jinan, 250014, Shandong, China

luyan_edu@163.com

Abstract. Climate prediction has a wide social demand, but due to the complexity of climate system formation and the uniqueness of China's terrain, accurate prediction is extremely complex and difficult. Therefore, this article proposes a global periodic climate prediction method based on an improved BP neural network. Firstly, based on historical meteorological data, establish a climate model and summarize and analyze the characteristics of the patterns; Then, based on the BP neural network, considering the relationship between adjacent days, rolling sampling of historical data is carried out according to seasonal and meteorological factors in the sampling interval, establishing a multi-state transition probability matrix, and constructing an annual time series forecasting model; Finally, taking precipitation prediction as an example, an example was used to simulate the annual precipitation situation. The calculation results have verified the effectiveness of the proposed method, indicating that it can simulate climate conditions well and provide guidance for climate governance and engineering construction.

Keywords: Climate prediction, Improve neural networks, Precipitation, Time series simulation.

1. Introduction

Climate resources are an important resource for human survival, and the rational utilization of precipitation resources is related to the future survival and development of humanity. Climate forecasting plays an important reference role in the planning and utilization of future water resources. Therefore, improving the accuracy of climate forecasting and extending the foresight period of climate forecasting are important directions for current precipitation forecasting research. It is of great significance in flood disaster warning, hydropower construction, and efficient utilization of basin resources [1].

Currently, big data has become an important national strategic resource. The 14th Five Year Plan proposes to implement the national big data strategy, promote open sharing of data resources, unleash technological, institutional, and innovation dividends, and promote economic transformation and upgrading [2-3]. The Guiding Opinions on Promoting the Development of Big Data in Climate Resources issued by the Ministry of Climate Resources in 2018 proposed to accelerate data integration, sharing, and orderly opening, promote the deep integration of climate conservancy business and information technology, deepen the innovative application of big data in climate conservancy work, and promote the modernization of climate governance system and governance capacity. With the development of technology and technological progress, there are more and more means to record and monitor climate situation information. Insufficient climate situation information is gradually no longer the main reason hindering the development of climate related research. Currently, how to utilize the existing massive data to provide decision-making for future climate resource planning and utilization is a hot topic [4-6].

There are many studies on the current status of climate forecasting. Reference [7] improved the soil model in the Yangtze River Basin using a long-term memory network model and proposed a climate evaluation model (SWAT) over a long time scale. There has been a more significant improvement in traffic prediction compared to previous methods. The article conducts non-linear fitting on historical data of the Yangtze River, demonstrating strong learning ability for complex climate situations. Reference [8] proposed a method for predicting urban climate based on deep neural networks. On the basis of traditional LSTM networks, the introduction of short-term memory modules improves the stability of the model. Model cities with abundant climate resources such as Shenzhen. Using groundwater data as the research object, six precipitation models were constructed for different scenarios. The proposed long short-term memory network method has better fitting and stability. Reference [9] proposed a climate quality parameter prediction method based on long-term time series data. The need for a large amount of data for learning and calculation has to some extent overcome the problem of gradient explosion caused by the probability of traditional methods. Reference [10] transformed the approach and applied a neural network-based climate prediction method to watershed pollutant sorting. Converting flow rate prediction into load simulation prediction yields better results than other models. It can be used to predict the dissolved organic matter and various pollutants in precipitation.

2. Climate precipitation model

The WetSpa precipitation model used in this article. This model considers physical processes such as precipitation, evapotranspiration, surface runoff, and groundwater runoff. Therefore, multi-layer results are used to represent the water and energy balance of each unit. The framework is shown in Figure 1. The model needs to collect decision data on vegetation canopy, surface layer, soil layer, and groundwater aquifer.

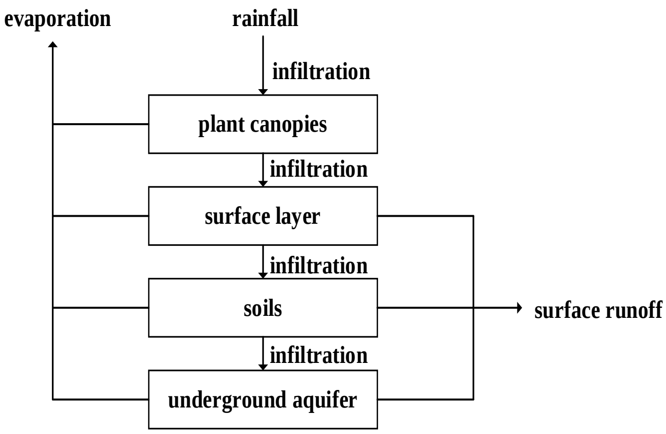

Figure 1. Probability density curve of light intensity.

The data required to construct a SWAT model for the middle and upper reaches of the Jinsha River basin is shown in Table 1.

Table 1. Formatting sections, subsections and subsubsections.

Type	Density / (g·cm-3)	Length / mm
Global parameters	Soil flow shape index(ki_sub)	0.5-2
	Groundwater Shape Index(kg_tot)	0.001-0.005
	Snowmelt temperature(T0)	0.1-0.9
	Temperature degree daily coefficient(k_rain)	0.0001-0.001
	Snowfall daily coefficient(k_snow)	0.1-2
	Maximum rainfall intensity(p_max)	100-500
Flow correction parameters	Slope correction factor(UnitSlopeM)	0.3-10
	Correction coefficient for soil saturated hydraulic conductivity(ConductM)	0.5-15
	Correction coefficient for maximum leaf area index(Lai MaxM)	0.5-1.5
	Correction coefficient for maximum canopy interception capacity(ItcmaxM)	0.3-5
	Correction coefficient for impermeable area ratio(Imp_M)	0-2
	Evaporation correction coefficient(petm)	0.5-1
	Correction coefficient for soil porosity(PorosityM)	0.05-0.9
Confluence correction parameters	Correction coefficient for the slope of the main river channel in the sub basin(CH_S2)	0.3-10
	Correction coefficient for the length of the main river channel in the sub basin(CH_L2)	0.5-2
	Correction coefficient for Manning roughness coefficient of the main river channel in the sub basin(CH_N2)	0.3-3
	Correction coefficient for the bottom plate hydraulic conductivity of the main river bed in the sub basin(CH_K2)	0.3-3

The overview of the climate precipitation of the middle and upper reaches of the Jinsha River basin is shown in Figure 2.

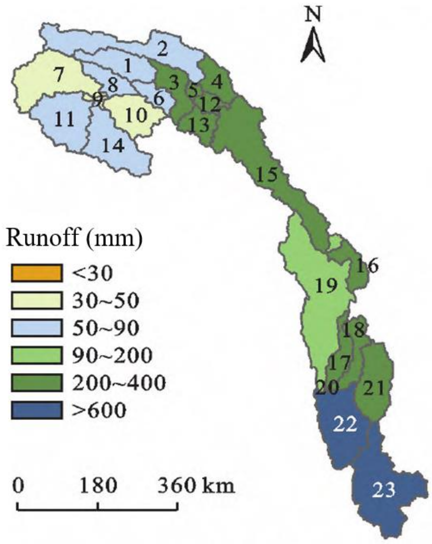

Figure 2. Overview of the climate precipitation of the middle and upper reaches of the Jinsha River Basin.

Climate precipitation is influenced by various factors, such as the length of day and night caused by the Earth’s revolution, the annual variation of noon solar altitude, and the changes in solar altitude and azimuth caused by seasonal changes, all of which can affect the actual intensity of light. Therefore, over time, climate precipitation not only exhibits randomness and volatility, but also has certain regularity. Figure 3 shows the time series of climate precipitation deviation for 8760 hours.

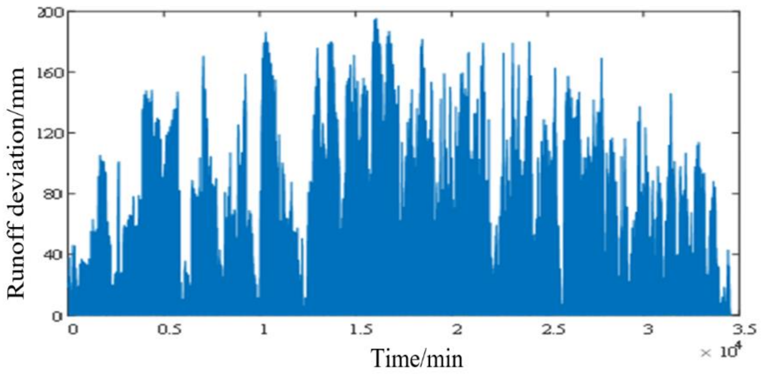

Figure 3. 8760h climate precipitation deviation curve.

The randomness of weather on climate precipitation is mainly influenced by the absorption, reflection, and scattering of solar radiation by different weather clouds. For example, on sunny days, the weakening effect of cloud cover on solar radiation is relatively small, and the climate precipitation value is large and stable, while on cloudy and heavy rain weather, the opposite is true. Therefore, weather changes can affect the intensity of light radiation, thereby affecting the randomness of climate precipitation. Secondly, seasonal changes affect the regularity of climate precipitation. Generally speaking, summer has long and intense sunlight, followed by spring and autumn, and winter comes at the end.

3. Improved BP neural network prediction method

BP neural network is an intelligent sample training method mainly used for optimizing and predicting nonlinear variables, similar to the biological neural response method. When dealing with prediction problems, it does not have high requirements for the original input parameters and has strong data processing capabilities [11]. It mainly calculates the output layer function and inverse error function values of the training samples continuously, and compares and analyzes them with the original parameter requirements until the relevant requirements are met. The sample training is stopped and the optimal output result is output.

The revised mathematical calculation expression is as follows:

$$v_{id}^{(k+1)} = wv_{id}^{(k)} + c_1 r_1 (p_{id}^{(k)} - x_{id}^{(k)}) + c_2 r_2 (g_d^{(k)} - x_{id}^{(k)}) \tag{1}$$

$$x_{id}^{(k+1)} = x_{id}^{(k)} + v_{id}^{(k+1)} \tag{2}$$

w is the inertia weight; v is the velocity of the particle; x is the position of the current particle; c_1 and c_2 is the acceleration factor; r_1 and r_2 is the random numbers between B (0,1); $p_{id}^{(k)}$ is the d-th dimensional component of the optimal position vector for the i-th particle at time k; $g_d^{(k)}$ is the d-th dimensional component in the optimal position vector of the population at time k.

The performance improvement of neural network algorithms mainly comes from two aspects. On the one hand, it improves the rationality of the input data of the model, and on the other hand, it improves the model itself, thereby reducing the limitations of algorithm optimization and improving the optimization ability of the algorithm to handle high-dimensional complex data. This article adopts the momentum gradient method with variable step size to improve the learning factor of neural networks, reduce the oscillation of algorithm optimization, and improve the reliability of network training samples. The calculation expression for adjusting the learning factor of neural networks based on variable step size is as follows:

$$lr(t)=\begin{cases}0.7lr(t-1), E(t-1)>E(t-2)\\ 1.05lr(t-1), E(t-1)\le E(t-2)\end{cases} \tag{3}$$

On this basis, the momentum term influence factor of the reverse error calculation bias in the neural network training samples is taken into account.
The flowchart is shown in Figure 4.

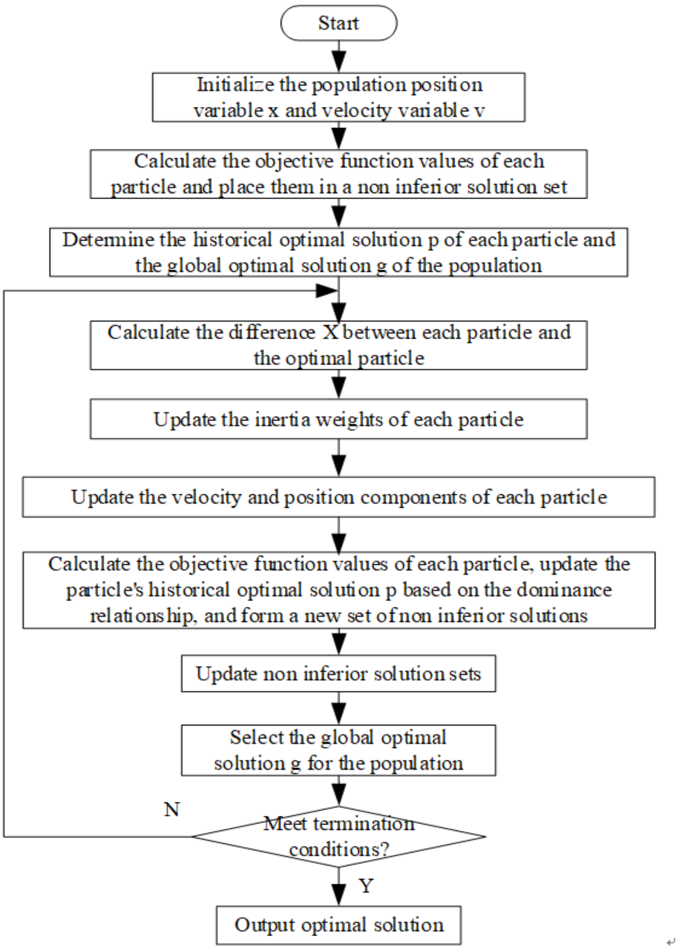

Figure 4. Improved BP neural network method flowchart.

4. Simulation analysis

This example uses the Jinsha River climate precipitation data throughout the year for simulation verification. The time interval for historical data is 15 minutes.

This article focuses on the 10 main weather types classified by the National Meteorological Administration of China. The schematic diagram of 10 typical daily output curves for different weather conditions is shown in Figure 5.

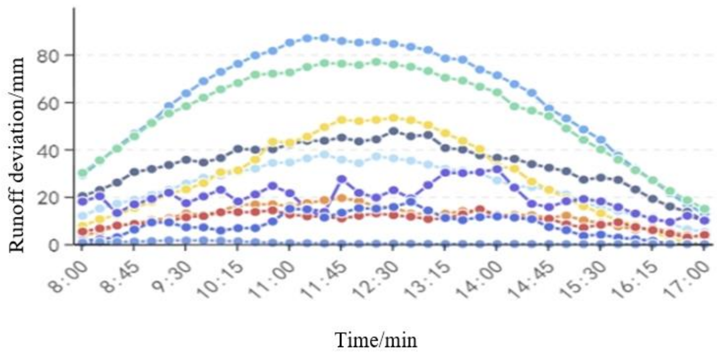

Figure 5. Climate diagram of ten weather types.

Using improved BP neural network simulation method to generate annual climate precipitation series. Obtain its simulated hydrological runoff sequence throughout the day and compare it with the historical output sequence. The January data is shown in Figure 6.

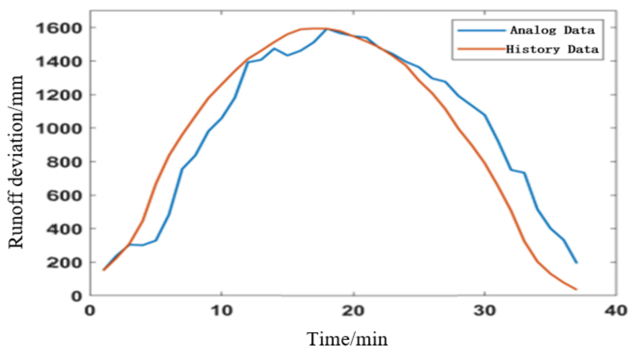

Figure 6. Jan time series model climate precipitation sequence.

Due to certain differences between the simulated weather conditions and climate precipitation reality, there is a certain error in the average climate precipitation generated by the simulation compared to the historical sequence, but the overall trend of change is consistent. The entire probability matrix is consistent with the actual situation.

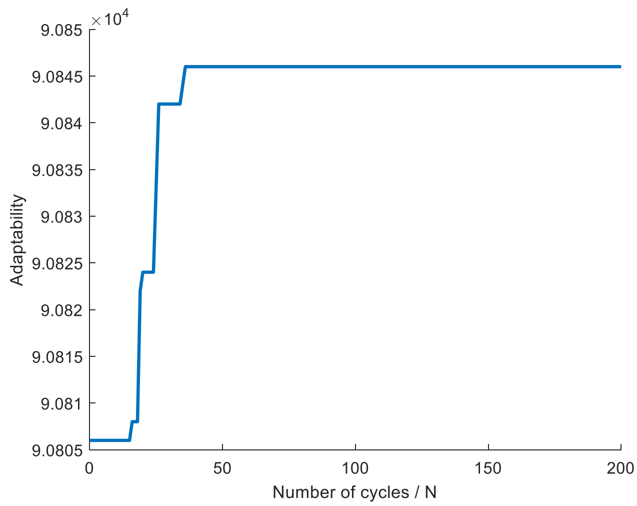

Figure 7. Improved BP neural network method flowchart.

Calculate based on measurement data. The convergence curve is shown in Figure 7.

From Figure 7, it can be seen that the established prediction model has high accuracy and reliability in predicting the degree of concrete salt frost damage. From the graph, it can be seen that the simulation curve adopts the particle swarm optimization algorithm. Its fitting effect is very close to the actual working conditions. Under more than ten actual testing conditions. The overall trend is consistent with the pattern summarized in the experiment. Meanwhile, in terms of convergence, it can converge quickly. There was no disagreement. In terms of the number of iterations, it also maintains overall controllability. The simulation time is very fast. Provide guidance for practical engineering applications.

5. Conclusions

This article proposes a global periodic climate prediction method based on improved BP neural network. Eliminated the problem of decreased model accuracy caused by fragmentation in adjacent months. The calculation results show that the improved time series production simulation method is more in line with historical data in terms of maximum climate precipitation, with small errors, proving that the improved method is effective and feasible, consistent with the actual output change trend.

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