World Scientific Research Journal Volume 9 Issue 4, 2023
ISSN: 2472-3703 DOI: 10.6911/WSRJ.202304_9(4).0020

Triple La Niña Event Prediction and Loss Evaluation Strategies Based on LOGISTIC and TOPSIS Models

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Abstract

In the past three years, the triple La Nina phenomenon has brought abnormal weather around the world. High temperature, heavy rainfall and drought disasters have caused certain scale of economic losses and casualties in many regional cities. Therefore, it is of great practical significance to establish an effective prediction and loss assessment model for triple La Nina, so as to scientifically prevent and cope with it. In this paper, the ARIMA differential autoregressive model and Logistic regression model are used to predict the impact of triple La Nina. The AHP model and TOPSIS model are used to evaluate the regional losses caused by La Nina. At the same time, the comprehensive neural network model is calibrated and improved to realize the overall prediction and loss assessment of La Nina phenomenon.

Keywords

Triple La Niña; Logistic; Neural network; AHP; TOPSIS; ARIMA.

1. INTRODUCTION

1.1. Background

From July to August 2022, many cities in the south of China experienced many days of hot weather, while in some parts of the north there were also large-scale heavy precipitation. In addition, many European countries have also experienced historically rare drought disasters. Whether it is high temperature weather in the south, heavy precipitation in the north, and dry weather in Europe, it is unprecedented for decades, and even the highest temperature, heavy precipitation and drought disasters have been recorded since meteorological data. The high temperature weather has caused economic losses and casualties to a certain scale in many cities in the south and European countries. Similarly, the heavy rainfall has caused a significant reduction in agricultural production or even no harvest in some areas of the north. The meteorological department attributed this high temperature phenomenon and heavy precipitation event to the Triple La Niña event.

2. PROBLEM ANALYSIS

2.1. Data analysis

We mainly searched relevant data on the international meteorological data platform. For the data, we first processed the outliers, and then carried out numerical and forward processing to facilitate the use of subsequent evaluation models.

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3. SYMBOL AND ASSUMPTIONS

3.1. Symbol Description

Symbol Definition	Symbol Description
S_i	TOPSIS score of the ith series
w_{ij}^l	Neuron connection weight
b_j^l	Bias of neuron
α	Learning rate

3.2. Fundamental assumptions

Assumption 1: It is assumed that the climate in different regions does not affect each other.

Assumption 2: It is assumed that the influence of climate in the target region depends only on La Niña.

Assumption 3: It is assumed that extreme data and abnormal data can be eliminated directly.

Assumption 4: It is assumed tha the data noise is normally distributed.

4. MODEL

4.1. Triple La Nina events possibility prediction model based on Logistic regression model

In order to predict the possibility of Triple La Nina events, we can use BP neural network to realize the prediction, and use the Logistic activation function to map the output to the interval of 0-1 to complete the output of quantitative possibility probability.

Based on the statistical analysis of the major countries and regions involved in Triple La Nina events, we can take the known data as the training set and predict the possibility of Triple La Nina events through the Logistic regression model in the dynamic neural network. That is, the time series data of Triple La Nina events corresponding to m regions are respectively denoted as $x_1 - x_m$. Here x is a key-value pair, expressed as x_i=(u_i, w_i), u_i is the ith region, where w_i is the ith region Triple La Nina events occurrence time series, output l forecast data, respectively denoting as $o_1 - o_l$, o_i=(u_i, w_i), as shown in Figure 1 below.

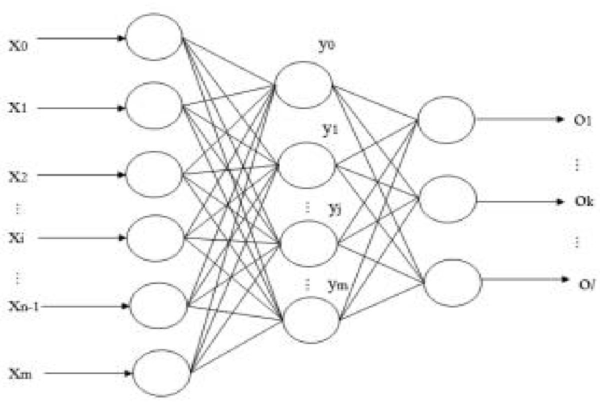

Figure 1. Dynamic BP neural network

The neural network model can be further realized through the following steps, input layer 1×m vector:

$$X = (x_1, x_2, \dots, x_i, \dots, x_m);$$

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Layer l (l=1,2,3... n) hidden layer vector:

$$H^l = \left(h_1^l, h_2^l, \dots, h_j^l, \dots, h_{s_l}^l\right)(l = 2,3, \dots, L-1, j = 1,2, \dots, s_l)$$

Output layer output vector:

$$O = (o_1, o_2, \dots, o_i, \dots, o_l);$$

Let w_{ij}^l be the connection weight between the ith neuron of the L-1 layer and the JTH neuron of the l layer, b_j^l be the bias of the JTH neuron of the l layer, and net_j^l be the input of the JTH neuron of the l layer, $f(\cdot)$ is the activation function, Select the activation function as sigmoid function, i.e

$$f(\cdot) = \frac{1}{1+e^x}$$

Thus:

$$h_j^l = f\left(\mathrm{net}_j^l\right) = \frac{1}{1+e^{\mathrm{net}_j^l}}$$

$$net_j^l = \sum_{j=1}^{s_{l-1}} w_{ij}^l + b_j^l$$

Define the error function:

$$E = \frac{1}{m}\sum_{i=1}^{m} E(i)$$

Where $E(i)$ is the training error of a single sample:

$$E(i) = \frac{1}{2}\sum_{k=1}^{2} (d_k(i) - y_k(i))^2$$

So the global error function:

$$E = \frac{1}{2 \times m}\sum_{i=1}^{m}\sum_{k=1}^{2} (d_k(i) - y_k(i))^2$$

Finally, parameters are solved by gradient descent, and the best binary effect can be obtained by constantly optimizing the solving process by adjusting hyperparameters. The weight and bias process is updated as follows, where α is the learning rate and $\alpha \in (0,1)$:

$$w_{ij}^l = w_{ij}^l - \alpha \frac{\partial E}{\partial w_{ij}^l}$$

$$b_j^l = b_j^l - \alpha \frac{\partial E}{\partial b_j^l}$$

The network structure is set in MATLAB as shown in Figure 2, and the prediction results are shown in Figure 2.

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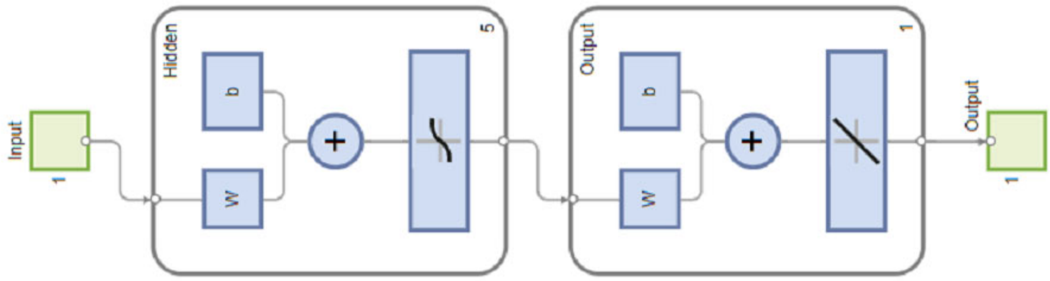

Figure 2. Grid diagram of neural network

For output time series data, we can further use the Logistic mapping, only consider a transformation, assuming that the relationship between y_i' and x_i is as follows: $y_i' = \alpha + \sum_{i=1}^{m} \beta_i x_i + \varepsilon = w^T X + \varepsilon$

By substituting the linear expression into the conditional probability of Triple La Nina events, we can obtain:

$$
\begin{aligned}
P(y_i = 0|x_m) &= P[(\alpha + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_m x_m + \varepsilon) < T] \\
&= P[\varepsilon < (-\alpha - \sum \beta_m x_m)] \\
&= P[\varepsilon \geq (\alpha + \sum \beta_m x_m)] \\
&= 1 - F[\alpha + \sum \beta_m x_m]
\end{aligned}
$$

The conditional probability of Triple La Nina events can be obtained by the Logistic model as follows:

$$P(y_i = 0|x_i) = 1 - \frac{1}{1+e^{-(\alpha+\sum\beta_m x_m)}} = \frac{1}{e^{(\alpha+\sum\beta_m x_m)}+1}$$

According to the above equation, the occurrence probability of Triple La Nina events is as follows:

$$P(y_i) = p^{y_i}(1-p_i)^{1-y_i} \quad (i = 1,2,\cdots,n)$$

Thus, the Logistic regression model is completed to establish the possibility prediction model of Triple La Nina events. Select one of the regions, and the possibility prediction of Triple La Nina events is shown in Figure 3 below.

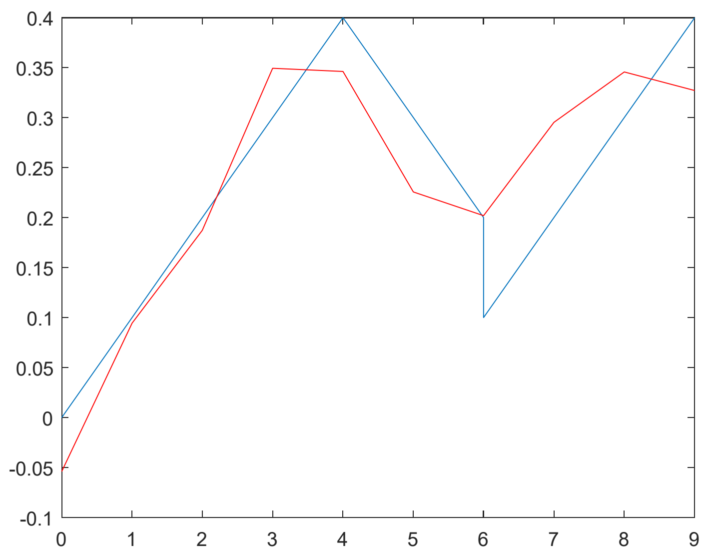

Figure 3. Logistic model prediction results

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For this model, its training state and regression are shown in Figure 4 below. The overall training state is good. Optimization can be realized through gradient descent and BP, and finally the possibility of Triple La Nina events can be obtained by Logistic model mapping.

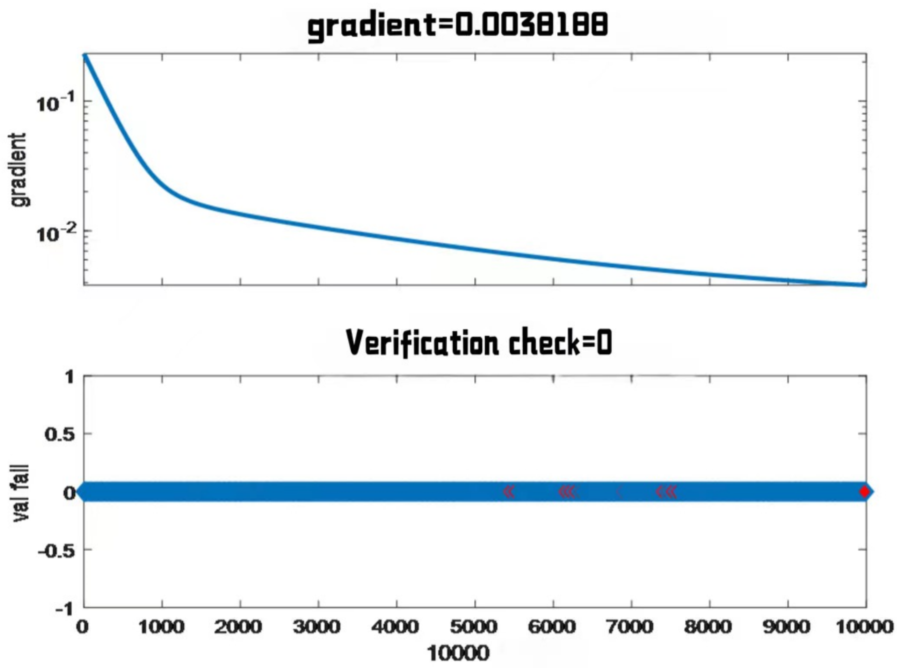

Figure 4. Training state

5. TEST THE MODELS

The performance and error of our test model are shown in Figure 5 below. It can be seen that the model has good performance, the error is within the allowed range, and has good robustness.

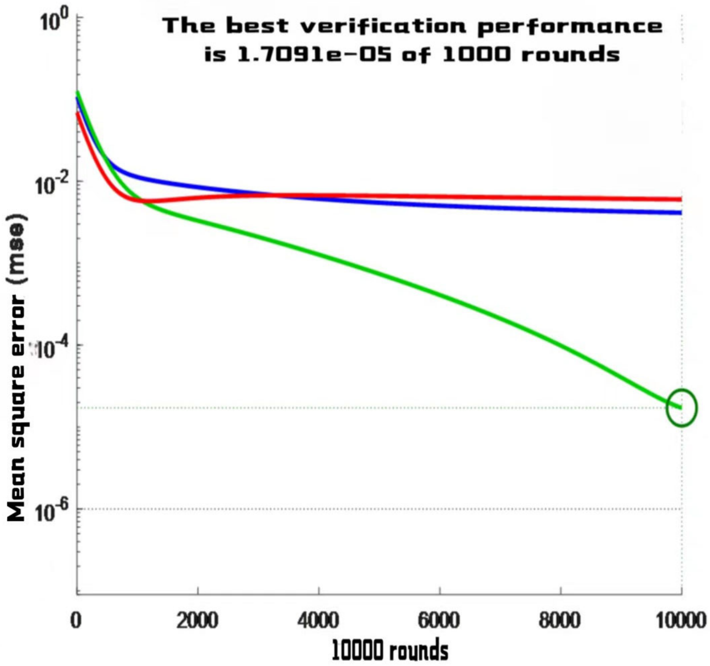

Figure 5. Model performance

ISSN: 2472-3703 DOI: 10.6911/WSRJ.202304_9(4).0020

6. SENSITIVITY ANALYSIS

When we input noise data to the model, the model receives small disturbance, indicating that the model has good anti-interference ability, which is mainly due to the strong robustness obtained by the model, especially the neural network model pre-training.

At the same time, when we analyze different situations, we can see that the model can carry out transformation and mutation well under different situations and has good adaptability to different regions, which is mainly due to the universality of TOPSIS and the stability of ARIMA prediction, so the model has a good sensitivity effect.

7. CONCLUSION

In this paper, loss assessment and prediction were mainly carried out based on Logistic and TOPSIS, and other regression methods including ARIMA were integrated. Through data analysis and modeling, it was finally found that La Nina has the characteristics of wide distribution and great influence, but through active intervention and preparation adjustment, losses can be reduced to a minimum.

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