Prediction and suggestion of weather in Chengdu based on grey neural network combination model

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ABSTRACT

In this paper, a combined model based on grey neural network is proposed to predict the future meteorological data of Chengdu, and the impact of the forecast results on the decision making of agriculture, tourism and energy industry is discussed. First, we use the grey neural network method to predict the future meteorological data by using a small amount of known meteorological data. Second, we build combinatorial models that combine grey neural networks with other forecasting methods to improve forecast accuracy and stability. Finally, we discuss the impact of the forecast results on decision -making in agriculture, tourism and energy industries, and make corresponding recommendations. The results show that the combined model based on grey neural network can effectively predict the future meteorological data of Chengdu, and provide a valuable reference for the decision making of related industries.

Keywords: Grey Neural Network; Combinatorial Model; Agriculture; Tourism; Energy

1 INTRODUCTION

With the continuous intensification of global warming and climate change, the uncertainty and variability of weather conditions have become increasingly large.

In recent years, China has attached great importance to digital meteorological services, and meteorological data are used to detect and forecast the weather. In agriculture, different crops have different adaptability to weather conditions, and different agricultural production measures need to be adopted [1]. Moreover, extreme meteorological events such as drought and heavy rainfall will cause irreversible losses to agricultural production. In terms of energy, the site selection, development and utilization of new energy and other power resources require accurate and timely meteorological analysis and prediction, so as to improve the efficiency and reliability of new energy use; In terms of tourism, weather affects the choice of tourist destinations [2]. The operation of the tourism market and the behavior of consumers, the importance of more accurate weather prediction and analysis of local climatic conditions can provide consumers with better services and experiences, and promote the sustainable development of tourism.

2 LITERATURE REVIEW

2.1 Research methods of meteorological prediction in Chengdu

Weather prediction is an important basis for many fields such as urban planning, environmental protection, agricultural production and energy utilization, and plays an important role in the development of Chengdu. This study aims to use the combination model of neural network model and gray model to forecast the meteorological data of Chengdu (including precipitation, temperature, humidity, etc.). However, the complexity and uncertainty of the meteorological system bring challenges to the meteorological prediction. Grey model and neural network model are two widely used forecasting models with different advantages and scope of application [3]. Grey models are good for situations where the amount of data is small and the sequence is short, while neural network models are good for dealing with complex, nonlinear relationships. For this reason, combining the two models can better meet the challenges of weather forecasting.

2.2 How can agriculture, energy and tourism be helped to make decisions

After predicting the weather in Chengdu through neural network models and grey models, farmers can more accurately understand future climate change and adjust agricultural plans based on the predicted weather data. Based on forecasted weather conditions, energy companies can more accurately estimate future power demand and adjust power generation plans accordingly. The forecasted meteorological data can help the tourism industry make better decisions.

3 RESEARCH DESIGN

3.1 Data source

The data sources of Chengdu meteorological data are mainly from Chengdu Meteorological Bureau, China Meteorological Administration, Sichuan Meteorological Bureau and the global meteorological monitoring network.

3.2Data processing

It can be seen from the data that precipitation and average temperature show a strong cyclical fluctuation, and the period is about 6 months and 8 months, respectively. The change of sunshine duration is more complex and changeable, with the maximum sunshine duration of about 230h and the minimum sunshine duration of about 10h. For Chengdu, the average temperature from April to June is the highest, and the precipitation is also more in this period, while the average temperature from November to February is the lowest, and the precipitation is also less.

Regression analysis was conducted on precipitation and average temperature to explore whether there is a linear relationship between precipitation and average temperature. SPSS was used for regression analysis, and the ANOVA chart was obtained:

It can be seen from the figure that $p \leq 0.05$, so it can be considered that there is a significant linear relationship between these two variables, but the accuracy of their linear relationship needs further investigation.

From $p \leq 0.05$ in the coefficient table, it can be obtained that the average temperature of the independent variable has a significant influence on the dependent variable precipitation, which means that the average temperature is considered to be a cause variable of precipitation change, and the regression coefficient is 9.031, which has a positive influence. The higher the average temperature, the more precipitation. Although the linear relationship is obtained, further diagnosis is needed for its reliability [4].

The standardized residuals of regression roughly conform to the normal distribution, so it can be considered that the residuals have strong normality. n the normal P-P plot of the normalized residual of the regression, the scatter also basically falls on the diagonal, so it can be considered that the residual is a normal distribution.

4 ANALYSIS AND ESTABLISHMENT OF THE MODEL

4.1Neural network prediction

Algorithm:

Initialize the connection weightbetween interlayer nodes i and j and the threshold of node $\theta_j$with random numbers j.

Add the trained processing samples $\{X_{PL}\}$ and $\{Y_{PK}\}$.

Calculate the output of nodes in each layer (for the PTH sample) $\delta_{pk} = O_{pk}(y_{pk} - O_{pk})(1 - O_{pk})$, where I pi is both the output of node i and node j.

Calculate error signals of nodes at each layer. Output layer:

$\delta_{pk} = O_{pk}(y_{pk} - O_{pk})(1 - O_{pk})$; Implicit layer: $O_{pk} = O_{pi}(1 - O_{pi}) \sum_i \delta_{pi} W_{ij}$

Backpropagation. $E_p = (\sum_m \sum_k)(O_{pk} - Y_{pk})^2/2$

Calculate error

The following is the flow chart of neural network analysis using SPSS software: It can be seen that 71.4% of the sample was used for training and 28.1% for testing.

As can be seen from the figure, there is a linear relationship between the date and the hidden layer, and the number of hidden layers is 4, which corresponds to the nonlinear relationship of precipitation amount, sunshine hours and average temperature.

According to the model summary table, the average population relative error of training is 0.357, and the average population relative error of testing is 0.387, indicating that the model has good prediction accuracy. The following figure shows the scatterplot of neural network prediction:

4.2Grey prediction model GM(1,1)

Grey theory holds that all random variables are grey quantities and grey processes that change within a certain range and over a certain period of time. Instead of looking for statistical laws and probability distributions in data processing, the original data is processed into regular time series data, and then mathematical models are established. Before establishing the grey prediction model GM(1,1), the time series is tested by level ratio. If it passes the level ratio test, the series is suitable for building the grey model; if it fails to pass the level ratio test, the series can be "flat shift" to make the new series meet the level ratio test.

SPSS was used to conduct a level ratio test on the obtained data, and some results were as follows.

Table 1: grade ratio test results

Index entry	Original value	Tier ratio	Translation-transformed sequence values	Level ratio after translation conversion
1990-01-01	49.9	-	5025.9	-
1990-11-01	70.5	0.708	5046.5	0.996
1991-01-01	37.7	1.87	5013.7	1.007
1991-11-01	51	0.739	5027	0.997
1992-01-01	25.2	2.024	5001.2	1.005
1992-11-01	120	0.21	5096	0.981

The test analysis of the level ratio shows that all the level ratios of the translated sequence are within the interval (0.971, 1.03), indicating that the translated sequence is suitable for constructing the gray prediction model. SPSS was used to construct the grey prediction model.

4.3 Combined model

4.3.1 Model combination

grey model and neural network model can be combined to form paralle l prediction model (PPM) and series prediction model (SPM). In this paper, parallel prediction model (PPM) is used to predict the combined model.

The model prediction accuracy sequence is defined first, so that:

$$pr(k) = 1 - \left|\frac{x_{(0)}(k) - \hat{x}_{(0)}(k)}{x_{(0)}(k)}\right|, k = 1,2,3\ldots, n \tag{1}$$

Calculate the mean and mean square error of the prediction accuracy sequence:

$$\begin{cases} Arm = \dfrac{1}{n}\sum_{k=1}^{n} pr(k) \\ Std = \sqrt{\dfrac{1}{n}\sum_{k=1}^{n} (pr(k) - Arm)^2} \end{cases} \tag{2}$$

The parallel weighting coefficients of the combined grey neural network model were defined as and δ_i, respectively2 , and calculated as follows:

$$\delta_i = \frac{Arm_i \times (1 - Std_i)}{\sum_{j=1}^{2} Arm_j \times (1 - Std_j)}, i = 1,2 \tag{3}$$

According to the defined prediction precision sequence of the model, the prediction results can be obtained as follows:

$$x_{(0)}{}'(k) = \delta_1 \times x_{(01)}{}'(k) + \delta_2 \times x_{(02)}{}'(k) \tag{4}$$

Where $x'_{(01)}(k)$ and $x'_{(02)}(k)$ are the predicted calculated values of the grey model and the neural network model, respectively.

According to the following process, the final predicted value can be obtained by using SPSS software for processing and analysis: Use the gray model to get the initial predicted value; Construct a neural network prediction model; Bring the resulting prediction data into the neural network model; Adjust the parameters and train them; Get the final predicted value

5 CONCLUSION

5.1 Agricultural decision making

In the face of agricultural meteorological disasters, we should not only do a good job of prevention and early warning before the occurrence of agricultural meteorological disasters, but also do a good job of relief after the occurrence of agricultural meteorological disasters. After the occurrence of agri-meteorological disasters, it is necessary to carry out the work of rescuing crops in time, and minimize the economic losses caused by agro-meteorological disasters as much as possible [4]. At the same time, relevant agricultural technical means should be taken to deal with the damaged crops, so as to restore the agricultural products to normal state as far as possible.

5.2 Energy decision——making

In recent years, Chengdu's energy industry has developed rapidly. Around 2020, oil and gas production and processing have continued to increase, oil and gas production enterprises continue to increase production load, and strengthen oil and gas supply. The annual crude oil output was 195 million tons, an increase of 1.6% over the previous year, and the growth rate was 0.8 percentage points higher than that of the previous year [5-10]. Natural gas production was 188.8 billion cubic meters, an increase of 9.8% over the previous year.

Electricity production grew steadily. The power generation in the year was 7.4 trillion KWH, up 2.7 percent from the previous year. By type, thermal power generation grew by 1.2 percent; Hydropower, nuclear power, wind power and solar power maintained rapid growth, up 5.3 percent, 5.1 percent, 10.5 percent and 8.5 percent, respectively.

5.2.1 Impact on the energy industry of Chengdu

(1) Power industry.
(2) The gas industry.
(3) The coal industry.
(4) Water resources.

5.2.2 Recommendations for energy businesses

(1) Do a good job of energy reserve and allocation in advance.
(2) Strengthen energy transport and storage facilities.
(3) Develop new energy resources.

(4) Strengthen cooperation with the government and relevant enterprises.

(5) Strengthen monitoring and analysis of the energy market.

5.3 Tourism decision-making

Provide diversified tourism activities.

Strengthen tourism facilities and services.

Provide weather information and advice.

Promote food culture.

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