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Research on Temperature Prediction based on BP Neural Network Approach

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Abstract

Weather changes have an important impact on human production and life as well as socio-economic activities. In recent years, people have also gradually paid attention to the study of weather, especially the study of temperature, and it is of great practical significance to find an accurate temperature prediction model. At the same time, the use of machine learning methods to construct a temperature model can predict temperature changes more accurately and quickly, and provide a more reliable basis for weather forecasting. Therefore, in response to the unsatisfactory accuracy of temperature prediction by traditional prediction models, this paper uses the time series of daily average temperature of Hangzhou City, China, from 2013 to 2022 as the sample data, and combines the traditional ARMA model with the BP neural network model, which enables the BP neural network model to better fit and predict the temperature changes. The study shows that the prediction accuracy of the BP neural network model is significantly improved compared with the ARMA model.

Keywords

Temperature Model; BP Neural Network; ARMA Model; Machine Learning.

1. Introduction

Since the beginning of the twenty-first century, addressing global climate change has become the most serious challenge facing humankind in achieving global sustainable development. Especially in recent years, the intensification of the greenhouse effect, global warming and frequent meteorological disasters have caused great losses to people's lives and property, production and operation as well as economic development. For a traditional agricultural country like China, the annual losses caused by meteorological disasters are even more numerous. 2020, China's Jianghuai Basin experienced an extremely heavy precipitation (also known as the 'Super Violent Plum') in the summer of 2020, which caused serious economic losses in China. 2021, the daily rainfall in Henan and Shanxi exceeded the historical extreme, and the daily rainfall in Henan and Shanxi exceeded the historical extreme, and the daily rainfall in Shanxi exceeded the historical extreme. In July 2021, daily rainfall in Henan, Shanxi and other places exceeded historical extremes, and many places were hit by super-heavy rainfall, causing great harm. With the gradual emphasis on weather risks, the state has also introduced a series of policies: on 28 April 2022, the Outline for High-Quality Development of Meteorology (20222035) (hereinafter referred to as the Outline) issued by the State Council of China pointed out that it is necessary to strengthen the basic capacity of meteorology, to build the first line of defence for meteorological disaster prevention and mitigation, to raise the level of high-quality development of meteorological services for the economy, and to work hard to build a leading science and technology, The Outline states that by 2035, major breakthroughs will have been achieved in key scientific and technological fields of meteorology, and meteorology will be deeply integrated with various fields of the national economy.

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The construction of temperature models occupies a crucial position in weather forecasting. With the gradual increase of meteorological data and the improvement of computing power, traditional prediction methods are gradually difficult to meet the demand for accurate prediction. Therefore, the use of advanced machine learning techniques to construct temperature prediction models has become an important trend in current research. Machine learning methods have shown significant advantages in dealing with temperature change prediction by virtue of their powerful data processing and modelling capabilities. For example, the Extreme Learning Machine (ELM) approach adopted by Yang (2021)[1] demonstrated its efficiency and accuracy in processing meteorological data, providing a more reliable basis for weather forecasting. In recent years, continuous advances in machine learning techniques and algorithms have led to significant breakthroughs in this field of research [2]. Common machine learning algorithms such as linear regression [3], support vector machine (SVM) [4], and neural network [5] each have their unique advantages in temperature prediction. Linear regression can effectively deal with linear trends by establishing a linear relationship between temperature and time and other factors; support vector machines perform classification and regression by constructing an optimal hyperplane in a high-dimensional feature space, which is suitable for dealing with complex pattern recognition tasks; and neural networks, especially deep learning networks, are able to capture complex nonlinear relationships in the data through their multilayered structure, which can improve the accuracy of the prediction [6].

In this paper, we will focus on how to use BP (backpropagation) neural network, a classical deep learning algorithm, to construct a temperature prediction model.BP neural network can effectively deal with complex nonlinear relationships with its multilayered network structure and the training mechanism of backpropagation.The basic principles of BP neural network include forward propagation, error computation and backpropagation, and iteratively updating the weights of the network to finally optimise the prediction performance of the model. predictive performance of the model. We will introduce the network structure design, activation function selection, training algorithm of BP neural network and its application method in real temperature prediction, and verify its prediction ability through empirical cases [7].

In temperature forecasting, in addition to machine learning methods, traditional time series models, such as ARMA (Autoregressive Moving Average Model) and ARIMA (Autoregressive Integral Sliding Average Model), are still of significant application value.ARMA model is particularly good at dealing with the seasonal and trend components in time series, e.g., Hou (2019)[8] and Wang (2021)[9] Excellent forecasting results have been achieved through the use of the ARIMA model, which is able to effectively capture temporal correlation and trend changes in the data by modelling autoregressive and moving averages on time series data [10]. Therefore, this paper plans to combine the ARMA model with BP neural network in order to combine the advantages of both to construct a more accurate temperature prediction model. Specifically, the ARMA model will be used to capture linear trends and seasonal variations in time series, while the BP neural network will be used to deal with nonlinear and complex data patterns. We will model and forecast the temperature time series data of HCM City and analyse the prediction results of this combined model in comparison to the results of using the ARMA model alone.With this approach, we hope to achieve a more accurate prediction of temperature changes and to test the effectiveness of combining the ARMA model with a BP neural network. In this paper, we will discuss in detail the steps of data preprocessing, feature selection, model training, and evaluation of prediction results, and demonstrate the application effect of this combined model in temperature prediction through real cases.

To conclude, this study will not only explore the application of BP neural network in temperature prediction, but also explore ways to improve the prediction accuracy by combining with ARMA model. We expect that this combined approach will provide a more

ISSN: 2710-0723

accurate and reliable forecasting tool for weather forecasting and promote the further development of meteorological forecasting technology. Data Sources and Statistical Analyses

1.1. Data Sources and Processing

The data in this paper were obtained from the global summary of the day database of the National Oceanic Atmosphere Administration (NOAA) (port provided in Yang (2021) [1]. The 10-year average daily temperatures of Hangzhou City, China (the meteorological station is Xiaoshan International Airport in Hangzhou), from 2013 to 2022, were selected as the study object. International Airport, Hangzhou, China) from 2013 to 2022, and the 10-year average daily temperatures were selected as the study object. In order to facilitate the analysis of the study, the data of 29 February in the leap years (2016 and 2020) were excluded, and a total of 3,650 daily average temperature data were available. Of these, the temperature data for the first nine years (3,285 in total) were used to construct or train the model, and the data for 2022 (365 in total) were used for the comparative study with the model prediction results. The temperatures in the raw data were recorded in Fahrenheit, and to facilitate the harmonisation with the temperatures in the following section, all the temperature data were converted into degrees Celsius according to the conversion formula: degrees Celsius = (Fahrenheit - 32°F)/1.8. Some of the processed data are shown in Table 1.

Table 1. Three Scheme comparing

NUMBER	DATE	CITY	TEMP(℉)	CH.TEMP(℃)
1	1-Jan-13	HangZhou	39.4	4.1
2	2-Jan-13	HangZhou	37.0	2.8
3	3-Jan-13	HangZhou	28.6	-1.9
4	4-Jan-13	HangZhou	30.1	-1.1
5	5-Jan-13	HangZhou	33.1	0.6
6	6-Jan-13	HangZhou	33.3	0.7
7	7-Jan-13	HangZhou	34.6	1.4
8	8-Jan-13	HangZhou	38.4	3.6
9	9-Jan-13	HangZhou	38.7	3.7
10	10-Jan-13	HangZhou	35.9	2.2
11	11-Jan-13	HangZhou	38.8	3.8
12	12-Jan-13	HangZhou	42.0	5.6
13	13-Jan-13	HangZhou	41.5	5.3
14	14-Jan-13	HangZhou	40.9	4.9
15	15-Jan-13	HangZhou	42.2	5.7
16	16-Jan-13	HangZhou	39.2	4.0
17	17-Jan-13	HangZhou	34.8	1.6
18	18-Jan-13	HangZhou	33.7	0.9
19	19-Jan-13	HangZhou	41.2	5.1
20	20-Jan-13	HangZhou	51.3	10.7

1.2. Statistical Analysis of Data

Descriptive statistics were performed on the processed average daily temperature data of HangZhou City from 2013 to 2021, and the results obtained are shown in Table 2.

As can be seen from Table 2, the temperature in HCM City is between 10.8°C and 25.6°C most of the time, with a mean value of 18.33°C. Overall, as HCM City is in the subtropical monsoon zone, the temperature is generally high during the year. In order to observe the changes of the average daily temperature in Hangzhou more obviously, a time series plot was constructed for the data from 2013-2021, as shown in Figure 1.

Table 2. Table of descriptive statistics

Statistic	count	mean	std	min	25%	median	75%	max
statistical value	3285.00	18.33	8.78	5.30	10.80	19.10	25.60	35.40

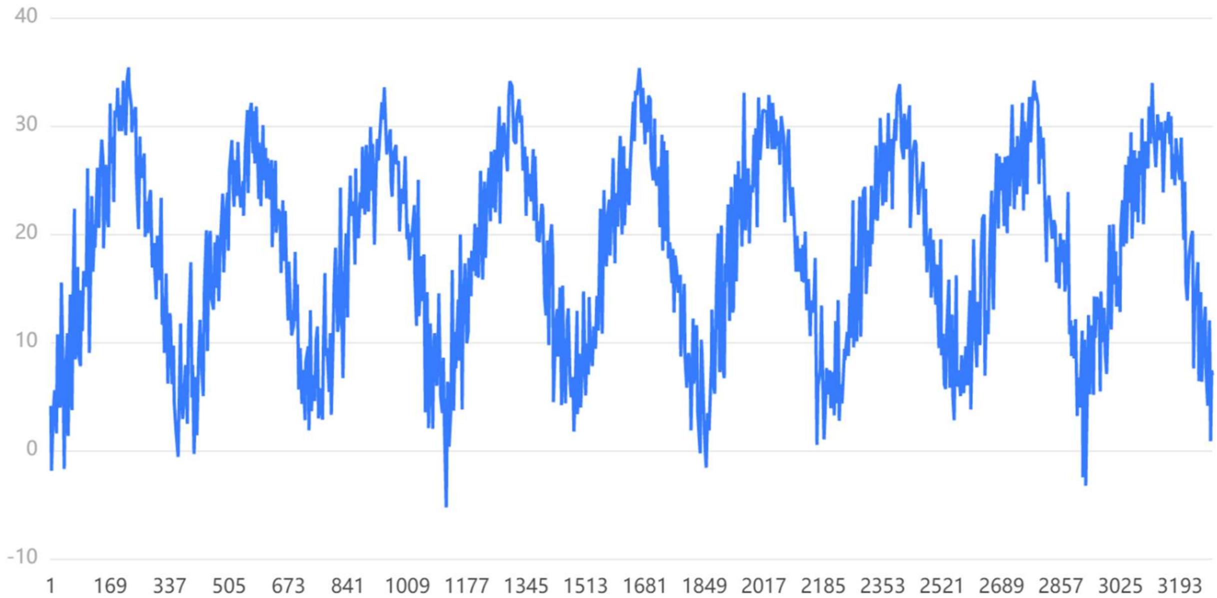

Figure 1. Time series graph of daily average temperature in Hangzhou

From Figure 1, it can be intuitively seen that the daily average time series of Hangzhou has obvious cyclical and seasonal fluctuations, and the series is a non-stationary series. In order to judge the smoothness of the series more accurately, the ADF test was carried out, and the test results are shown in Table 3.

Table 3. ADF test table for the original series

ADF Inspection Form							
Variable	Difference in order	t	P	AIC	threshold value		
					1%	5%	10%
CH.TEMP	0	-3.5	0.08***	14794.698	-3.432	-2.862	-2.567

Based on the results of the ADF test, it can be seen that the p-value is >0.05, so the original hypothesis that the series is not smooth cannot be rejected, and therefore it can be determined that the original time series is a non-stationary series.

2. Model Construction and Theoretical Basis

2.1. The Model Building Process

This paper focuses on using the analysis and forecasting functions of BP neural networks and ARMA time series models to compare the forecasting results of the two methods. Since the

ISSN: 2710-0723

ARMA model has good performance in dealing with seasonal fluctuations and autocorrelation characteristics of time series data, but poor performance in dealing with data extremes, and the BP neural network is more accurate in temperature prediction, this paper tries to combine the two for temperature prediction. The construction of the BP neural network model includes the following four steps.

1) Develop an autoregressive model for time series data;

2) Determine the effect of lag order on the data based on the results of the model;

3) Determine the number of input layers according to the degree of influence of different lag orders on the data;

4) Set appropriate parameters for the BP neural network and carry out training, and finally make predictions of the data according to the training model.

2.2. Theoretical Basis of Model

2.2.1. ARMA Model

The ARMA model (Autoregressive Moving Average Model), a common model in time series analysis, is composed of two parts, the autoregressive model (AR) and the moving average model (MA), where the autoregressive model is used to describe the autocorrelation of the series, and the moving average model is used to describe the lagged error of the series.The ARMA model can be used for forecasting and modelling of time series. It is characterised by using the historical data of the time series itself to predict future values, and is therefore often used in forecasting exercises in finance, economics, weather, etc. For the time series $\{x_t\}$,the basic structure of ARMA(p,q) is shown in equation (1).

$$\begin{cases} x_t = \phi_0 + \phi_1 x_{t-1} + \ldots\ldots + \phi_p x_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \ldots\ldots - \theta_q \varepsilon_{t-q} \\ \phi_p \neq 0; \quad \theta_q \neq 0 \\ E(\varepsilon_t) = 0, Var(\varepsilon_t) = \sigma_\varepsilon^2, E(\varepsilon_t \varepsilon_s) = 0, s \neq t \\ E(x_s \varepsilon_t) = 0, \forall s < t \end{cases}, \tag{1}$$

where $\{\varepsilon_t\}$ is the white noise sequence and ϕ_p; θ_q is the model coefficient.

2.2.2. BP Neural Network Model

BP neural network model, full name Backpropagation Neural Network Model, is a commonly used artificial neural network model. It consists of an input layer, a hidden layer and an output layer, where the number of neurons in the hidden layer can be determined according to the actual problem.The algorithm of the BP neural network model is based on the gradient descent method, which is trained using the error backpropagation algorithm, so that the neural network can automatically learn the underlying data patterns.

The idea of the implementation of the BP neural network model is: first, the sample data is input into the input layer, then processed through the implicit layer, and finally the output layer gets the prediction result of the model. In the training process, the data is needed to iteratively update the network weights, so that the error between the output results of the network and the real results is constantly reduced. Specifically, the process of BP neural network model training is:

1) Forward propagation: Input the samples into the neural network, and realise the transmission of signals layer by layer by matrix operation, from the input layer to the implied layer, and then to the output layer, to get the prediction result of the model;

ISSN: 2710-0723

2) Calculate the error: Compare the prediction result of the model with the actual output result, and calculate the error, which is used to measure the fitting degree of the model;

3) Error back-propagation: Starting from the output layer, the error is back-propagated back to the input layer layer layer by layer, and according to the size of the error, the weights and thresholds between each neuron are adjusted, so that the error is gradually reduced;

4) Update the weights: Through the gradient descent method, derive the error function, calculate the gradient of the weights and thresholds between each neuron, and then substitute it into the process of error backpropagation to get the new weights and thresholds. Repeat the above steps until the error reaches an acceptable range or a set number of iterations.

The topology of the BP neural network is shown in Figure 2.

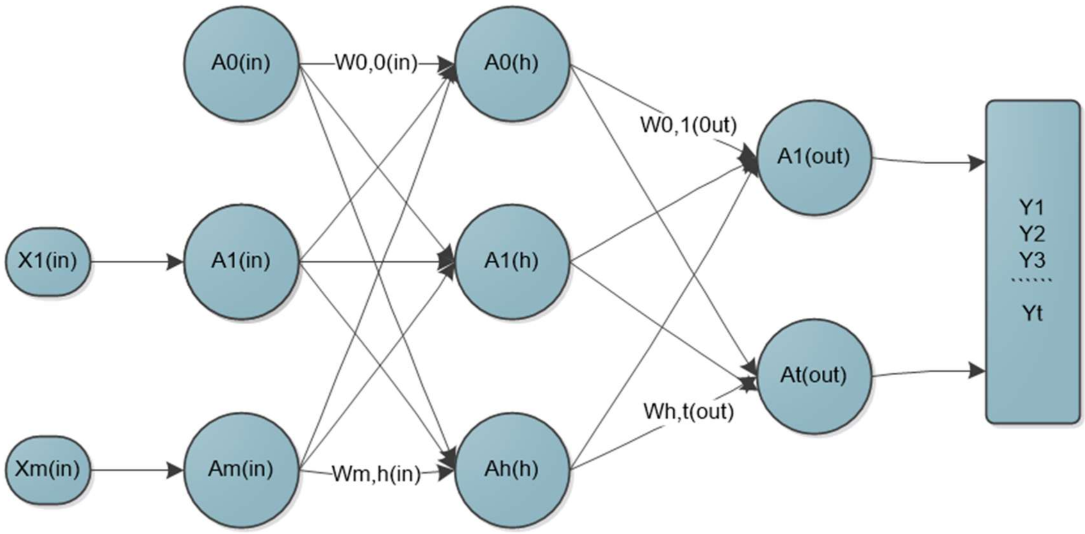

Figure 2. BP neural network topology diagram

In Figure 2, where: Xi(in)=Ai(in) denotes the ith net input unit; Wm, h(in): the weight between the mth unit of the input layer and the hth unit of the implied layer; Wh ,t(out): the weight between the hth unit of the implied layer and the tth unit of the output layer; and Ai(h) denotes the ith hidden unit of the implied layer. If Zi(h) is used to denote the ith net input unit of the hidden layer, then,

$$Ai(h)= g(Zi(h))$$

$g(x)$ is the activation function, in this paper the sigmoid function is selected. sigmoid function has the property of strict monotonicity, can regulate the relationship between linear and nonlinear, and can satisfy the general approximation ability of single hidden layer neural network, so the function is selected as the activation function of the BP neural network. sigmoid function expression is shown in Equation (2):

$$\text{sig} = \frac{1}{1 + e^{-x}} \tag{2}$$

ISSN: 2710-0723

3. Temperature Forecasts

3.1. ARMA Forecasting Model

As can be seen from Table 3, the original HCM City daily mean temperature time series from 2013-2021 is non-stationary, and the first-order difference is applied to the original time series and the ADF test is performed, and the results obtained are shown in Figure 3 and Table 4.

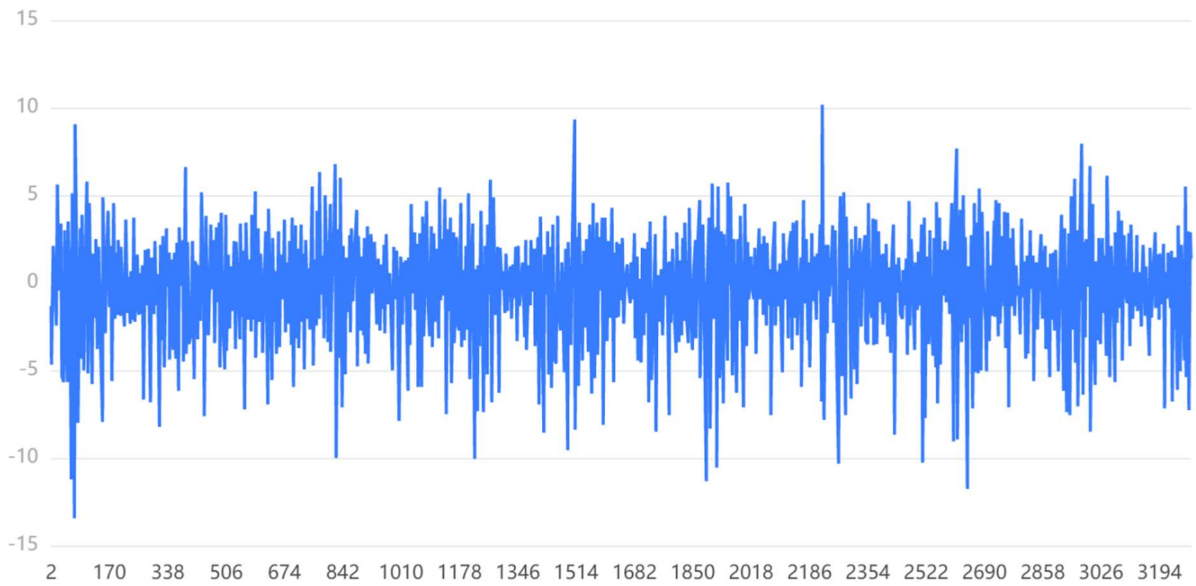

Figure 3. Time series plot after first order differencing

Table 4. ADF test for first order difference series

ADF Inspection Form							
Variable	Difference in order	t	P	AIC	threshold value		
					1%	5%	10%
CH.TEMP	1	-9.488	0.000***	14782.474	-3.432	-2.862	-2.567

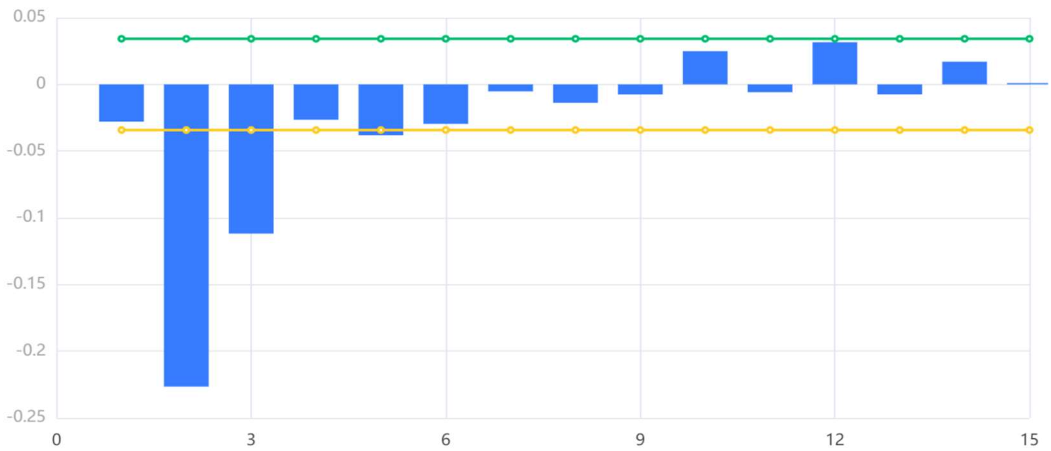

Figure 4. Autocorrelation diagram (ACF) for first-order difference data

As can be seen in Figure 3, the time series after first order differencing fluctuates above and below the value of 0, and there is no longer any obvious seasonality or trend, as can be seen through Table 4, P<<0.05, so the original hypothesis is rejected, and the time series after first order differencing is a smooth series. The autocorrelation plot is done for the processed time series and is shown in Figure 4.

According to the ending of the autocorrelation coefficient and the results of the automatic order fixing, it can be seen that the processed time series data are suitable for AR (3) model, that is to say, it shows that there is an obvious correlation between the time series data after the first-order differencing and the data lagged by the third order, and the estimation of the parameters in the AR (3) model is carried out, and the results obtained are shown in Table 5.

Table 5. ARMA model parameter table

Table of model parameters						
	ratio	std	t	P>|t|	0.025	0.975
constant	0.001	0.014	0.086	0.931	-0.027	0.03
ar.L1.CH.TE(1)	0.433	0.033	13.182	0	0.369	0.498
ar.L2.CH.TE(1)	-0.557	0.033	-16.92	0	-0.622	-0.492
ar.L3.CH.TE(1)	-0.243	0.022	-11.302	0	-0.285	-0.201

3.2. BP Neural Network Forecasting Model

The construction of the prediction model for the BP neural network was carried out on the basis of the ARMA model described above. Since the lag order of the autoregressive model was determined to be 3rd order in Section 4.1, this was used as the basis to determine the input layer of the neural network. Therefore, in this paper, the daily average temperature data of Hangzhou on day t-1, t-2 and t-3 are used as the input layer; the temperature data on day t are used as the output layer, and an empirical formula is used for the setting of the hidden layer: the number of hidden layers = the number of input layers * 2 + 1, and the learning rate and the learning accuracy are set to be 0.01 and 0.0036, respectively.The specific parameter settings of the code of the BP neural network model are shown in Table 6.

Table 6. Parameterisation of the BP neural network

Number of input nodes	Number of output nodes	Hidden layer	Learning rate	accuracy
3	1	7	0.01	0.0036

3.3. Model Forecasting and Error Analysis

3.3.1. ARMA Model Forecasting Result

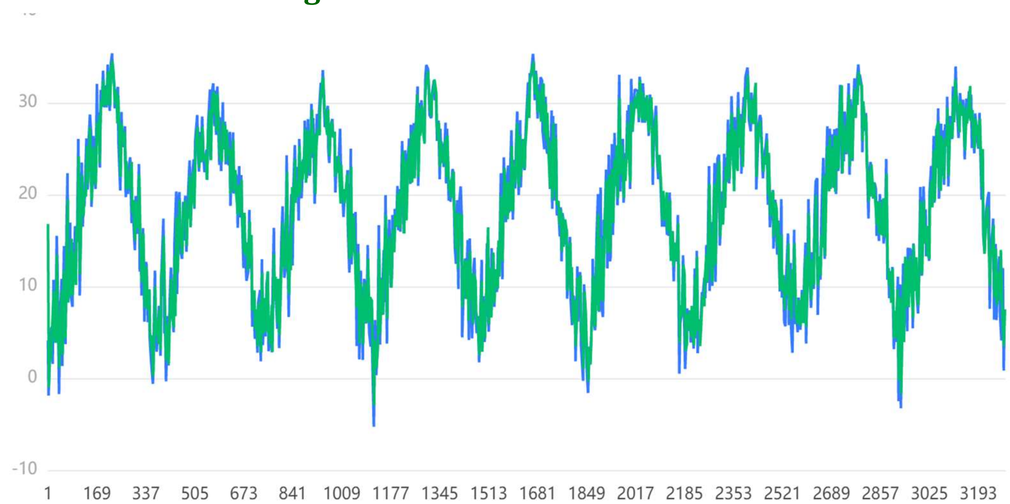

Figure 5. ARMA model fit plot

ISSN: 2710-0723

The first nine years of data were fitted according to the constructed ARMA model, and the results and fit are shown in Figure 5 and Table 7.

Table 7. ARMA model test table

Item	Symbol	Value
	Df Residuals	3279
Sample size	N	3285
Q-Statistic	Q6(P)	0.022(0.882)
Information criterion	AIC	14940.347
	BIC	14983.027
Goodness of fit	R^2	0.928

Table 7 shows clearly and intuitively that the goodness of fit of the ARMA model to the time series of daily mean temperature between 2013-2021 is at 0.928, and the model's fitting performance is better, and the model can be used to predict the data of daily mean temperature in 2022, and the comparison of the predicted value and the real value is shown in Figure 6.

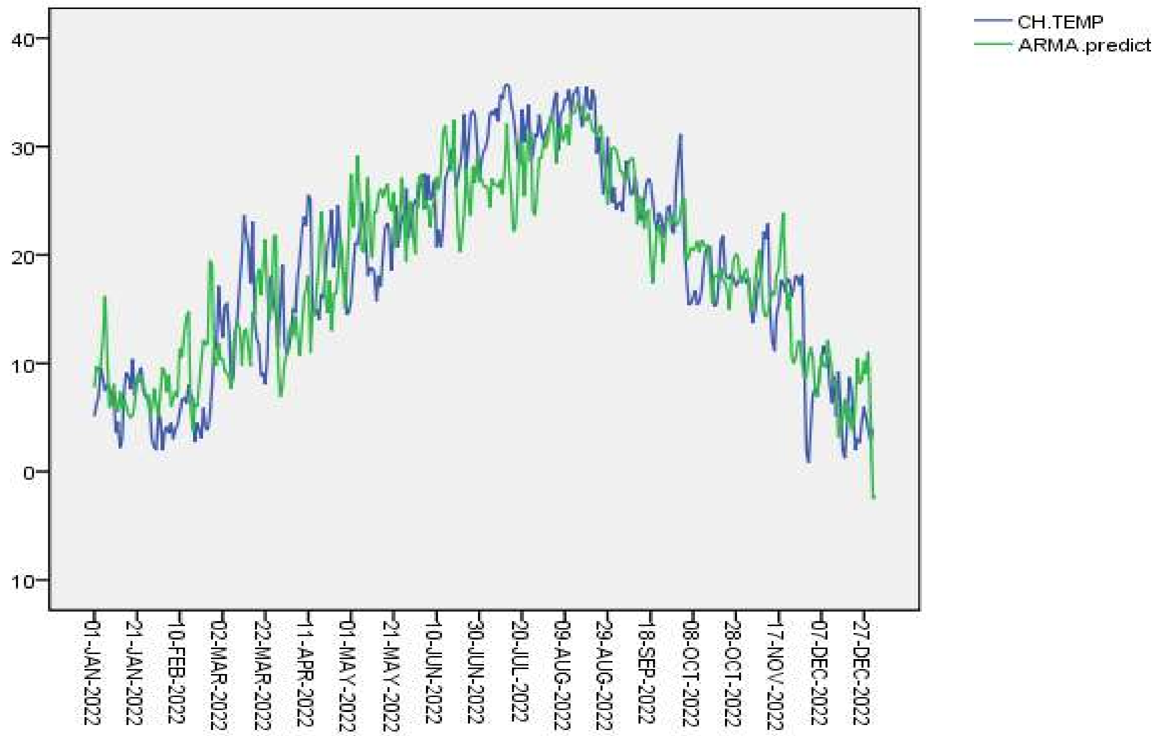

Figure 6. ARMA model prediction chart

In Figure 6, the blue line represents the real data of the average daily temperature in HCM City in 2022, and the green line represents the predicted temperature data using the ARMA model. As can be seen from Figure 6, the average daily temperature curve predicted by the ARMA model is slightly lower than the real temperature data curve in general, and it can be clearly observed that the ARMA model is less effective in predicting temperature extremes, with a larger deviation from the real temperature.

3.3.2. BP Neural Network Forecasting Result

According to the BP neural network model constructed above, the model was first trained using the average daily temperature data of Hangzhou from 2013-2021, with a ratio of 9:1 between

ISSN: 2710-0723

the training set and the test set, and the data were normalised, and the model was stopped when the loss function of the training set was smaller than the set learning accuracy.

The fitting effect of the BP neural network model on the training set and the test set is shown in Figure 7 (training set) and Figure 8 (test set), respectively, and it can be seen that, after 266 times of training, the BP neural network model's fitting of the temperature data is better on both the training set and the test set. The model can be used to predict the average daily temperature data of Hangzhou in 2022.

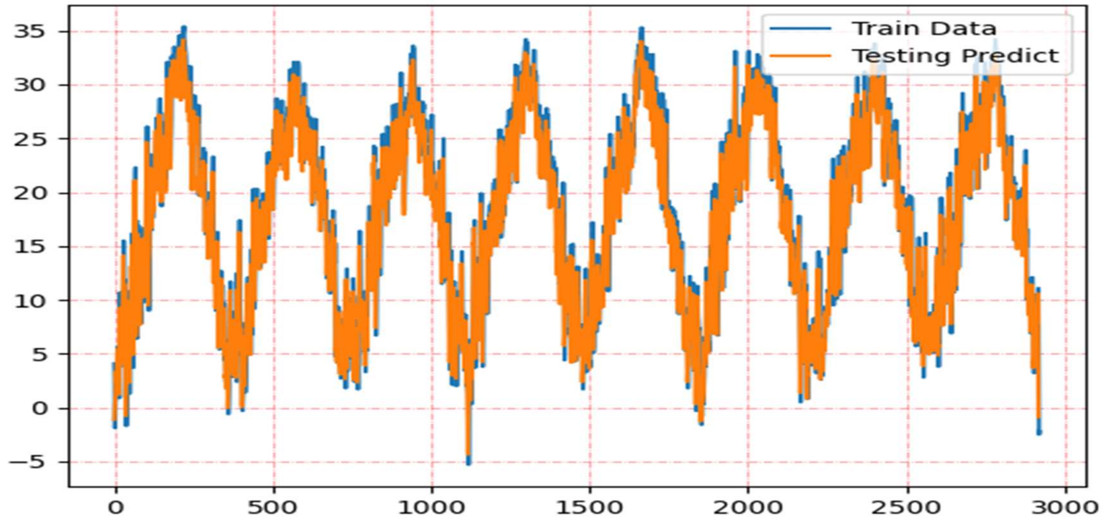

Figure 7. Training set fitting effect graph

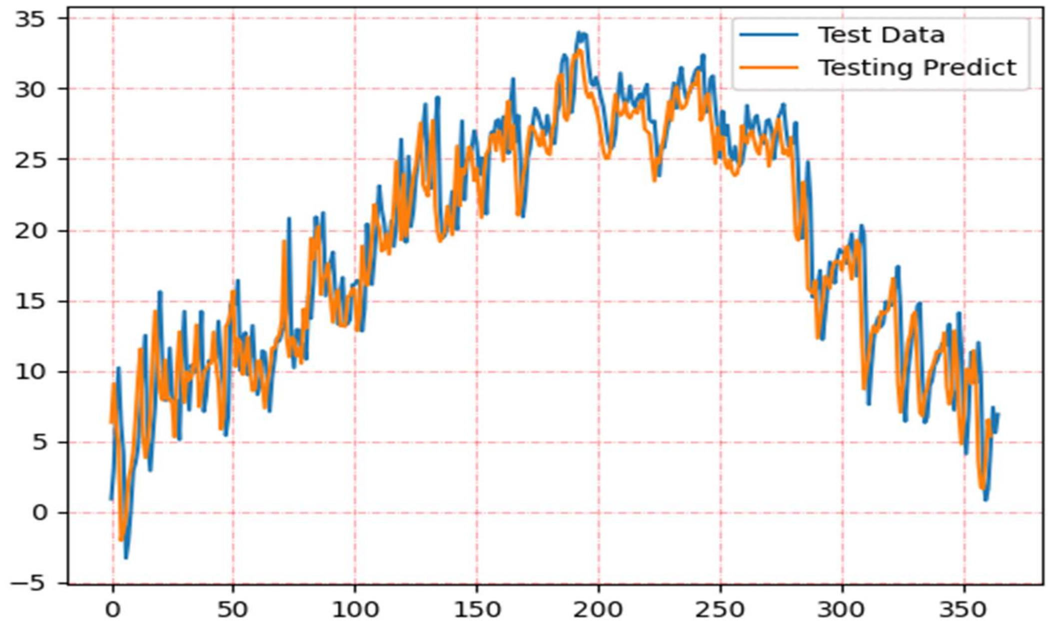

Figure 8. Testing set fitting effect graph

According to the model of BP neural network that has been trained, the average daily temperature of Hangzhou in 2022 is predicted, and the prediction results are shown in Figure 9.

ISSN: 2710-0723

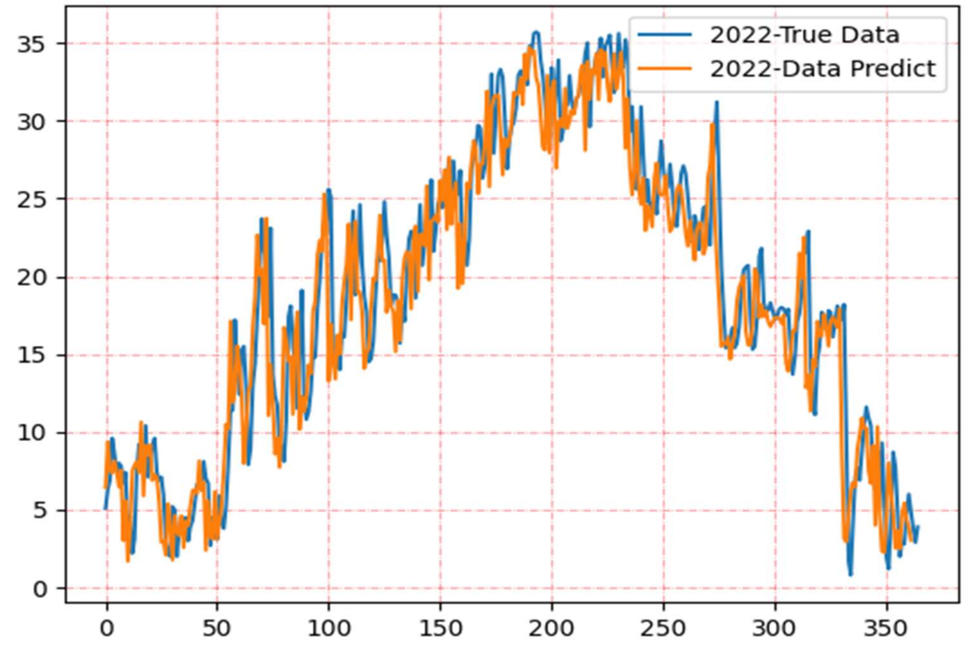

Figure 9. BP neural network model prediction graph

In Figure 9, the blue line represents the real value of the average daily temperature in Hangzhou in 2022, and the yellow line represents the predicted value using the BP neural network. Intuitively, the curve of the average daily temperature predicted by the BP neural network model is basically the same as the curve of the real temperature, and the model is also more accurate on the prediction of the temperature extremes.

3.3.3. Error Analysis and Comparison

As can be seen from Sections 4.3.1 and 4.3.2, the accuracy of the ARMA model and the BP neural network model for temperature prediction is different. In order to be able to better quantitatively compare the prediction accuracies between the two models, this paper adopts three measure formulas of Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) for the comparison and evaluation, and the specific formulas of the three measures are as follows:

$$MAE = \frac{1}{N}\sum_{i=1}^{N} | Y_i - Y_i^{'} | \tag{3}$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N} (Y_i - Y_i^{'})^2 \tag{4}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (Y_i - Y_i^{'})^2} \tag{5}$$

In the above equation (3-5), N denotes the length of the dataset, Y_i denotes the predicted value using the model and $Y_i^{'}$ denotes the true value of the data, the prediction error values of the ARMA model and the BP neural network are shown in Table 8.

ISSN: 2710-0723

Table 8. Model prediction error table

Model Error	MAE	MSE	RMSE
ARMA model	3.809	22.677	4.7620
BP Neural Network model	2.3878	10.1315	3.1830

As can be seen from Table 8, the predictions of the BP neural network model have smaller values than the predictions of the ARMA model in the three measures of MAE, MSE, and RMSE, so it can be more accurately judged that for the prediction of the average daily air temperature in Hangzhou, the BP neural network model has a better prediction effect than the ARMA model.

4. Conclusion

In this paper, we propose an improved temperature prediction method based on the time series data of daily mean temperature in Hangzhou. Specifically, we combine an autoregressive sliding average (ARMA) model with a back-propagation (BP) neural network model to construct a hybrid model capable of accurately predicting changes and trends in daily mean temperature. By comparing the prediction results of the ARMA model with the BP neural network model on the 2022 temperature data, we found that the ARMA model, while able to capture the general trend of temperature change, does not perform well in predicting temperature extremes and regions with frequent temperature changes.The ARMA model responds more slowly to these extreme fluctuations, resulting in predictions that are less accurate in these specific cases lower in these specific cases.

In contrast, the BP neural network model shows significant advantages in temperature prediction accuracy, as the BP neural network is able to learn complex nonlinear relationships, which leads to a significant improvement in the accuracy of temperature prediction. Especially in capturing the extreme points of temperature and dealing with the frequent fluctuation part, the BP neural network shows its strong adaptive ability and higher prediction accuracy.

According to the analysed results, all three prediction error values of the BP neural network model were significantly reduced, proving the effectiveness of the model in improving the prediction accuracy. Therefore, the BP neural network model performs well in the prediction of temperature in Hangzhou, which not only can better deal with the complex patterns in the temperature data, but also accurately reflects the trend of temperature change. Meanwhile, the successful application of this model provides a valuable reference and lesson for temperature prediction in other cities, especially in cities with similar climatic and data characteristics, which may achieve the same excellent results. With this approach, we can provide a more accurate tool for urban temperature prediction, which in turn can support related climate research and decision-making.

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