Comparative global temperature prediction based on arima and bp neural networks

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Abstract. This paper focuses on the issue of global warming. Due to a large amount of alarming temperature reporting data in the past, with some countries hitting new temperature highs again and many countries declaring emergencies, this has raised concerns about future temperatures. Therefore, this paper predicts the future temperature changes based on historical data, and observes the future temperature trends in 2050 and 2100 as an example, focusing on comparing which one is more accurate in global temperature prediction, the ARIMA model or the BP neural network model. The data was first processed and then an ARIMA model was built using MATLAB and a BP neural network model was built using SPSS. These two models were used to describe the past and predict the future global temperature levels, and line graphs were plotted using SPSS. The two models predict that the temperature in 2050 will be 10.16 °C and 11 °C respectively, the temperature in 2100 will be 10.87 °C and 13 °C differently, and the time for the temperature to reach 20 °C will be 2202 and 2350 separately. Finally, the model was tested by regression analysis of the two models, and the goodness of fit of Arima model and BP neural network was calculated to be 0.726 and 0.84668 respectively, BP neural model is better.

Keywords: Data visualization, ARIMA model, BP neural network model, global warming.

1. Introduction

As a result of the continuous accumulation of greenhouse effect, the Earth's atmospheric system emissions of energy absorption and consumption imbalance, the Earth's energy accumulation.[1] The atmospheric system, rising temperatures, global warming, new high temperature records in many areas, many countries declared a state of emergency.[2] However, in previous studies, there have been used ARIMA model and BP neural network model, but there is no comparison of the performance and applicability of the two in global temperature prediction. Therefore, this paper not only adopts ARIAM model and BP neural network model for global temperature prediction, but also compares the two models. It is convenient for people to choose a high-precision temperature prediction model to better meet the challenge of climate change. In this paper, the two models are built in the 2022_APMCM_C_Data.csv dataset respectively, and it should be noted that when selecting cities, care should be taken to select places with more complete temperature data.[3] By comparing the prediction performance of the two methods, this paper aims to determine which method is more suitable to cope with the complexity of global temperature change, to improve the accuracy of temperature prediction, to provide better information for the whole society, and to promote sustainable development.[4]

2. Model building

2.1. The basic fundamental of ARIMA model

The historical global temperature levels are shown in Fig.1, and it was found that the amplitude of fluctuations in these data is more stable and the amount of data is larger, so the first model the paper chooses is an ARIMA model.[5]

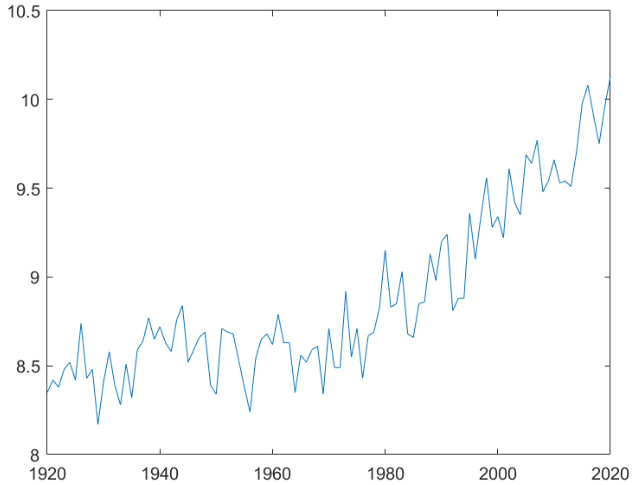

Fig. 1 Line chart of global average temperature data from 1920-2020

Differencing is the core step of the ARIMA model, eliminating the local trendiness and converting the non-stationary event series into a stationary time series.[6]

Noting ∇ as the difference operator, then there is that

$$\nabla^2 y_t = \nabla(y_t - y_{t-1}) = y_t - 2y_{t-1} + y_{t-2} \tag{1}$$

For the delay operator B , we have that

$$y_{t-p} = B^p y_t, \forall p \geq 1 \tag{2}$$

It can therefore be concluded that

$$\nabla^k = (1 - B)^k \tag{3}$$

With a sub-nonsmooth time series of order y_t, then $\nabla^k y_t$ is a smooth time series, then it can be set as an ARMA(p,q) model, that is

$$\lambda(\mathrm{B})(\nabla^d y_t) = \theta(\mathrm{B})\varepsilon_t \tag{4}$$

Among them,

$$\begin{cases} \lambda(\mathrm{B}) = 1 - \lambda_1 - \lambda_2 B^2 - \cdots - \lambda_p B^p \\ \theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_p B^p \end{cases} \tag{5}$$

They are the autoregressive coefficient polynomial and the sliding average coefficient polynomial, respectively.

ε_t is a zero-mean white noise series. The proposed model can be called the autoregressive summation sliding average model, denoted as ARIMA(p,d,q), p is the number of autoregressive terms; q is the number of sliding average terms, and d is the number of differences (orders) made to make it a smooth series.

The first model was built with Matlab software to build a time series (ARIMA) model, first importing the processed and more accurate data, which formed a numerical matrix for subsequent use. Then, to avoid the influence of trend and periodicity, the data were differenced and tested for smoothness until a smooth series was obtained, which could be analyzed by ARMA. (The number of differences is the order of the model ARIMA, too many differences will cause a large loss of information and too few differences will not extract enough information about the non-smooth deterministic information of the time series information) Next, the article constructed the ARIMA model and used the BIC criterion for model ordering(traversing the parameters of R and M and choosing the simpler model with the smallest aic and bic). [7]

$$\begin{cases} AIC = 2k - 2\ln L \\ BIC = k \ln n - 2\ln L \end{cases} \tag{6}$$

Where, AIC is the deficit pool information criterion, BIC is the Bayesian information criterion, k is the number of model parameters, n is the number of samples, and L is the likelihood function

try to make the value of k as small as possible under the condition of guaranteeing the accuracy of the model.

2.2. The basic fundamental of BP neural network

The basic idea is that the learning process consists of two processes: forward propagation of the signal and backward propagation of the error. In forward propagation, the input samples are passed in from the input layer, processed by each hidden layer layer by layer, and then passed to the output layer. If the actual output of the output layer does not match the desired output, it is transferred to the reverse transmission stage of the error. The error back propagation is to back propagate the output error in some form through the hidden layer to the input layer layer by layer, and to apportion the error to all units in each layer, so as to obtain the error signal of each unit in each layer, which is used as the basis for correcting the weight of each unit. The adjustment of the signal forward propagation and the error back propagation of the weights of each layer is iterative until the error of the network output is reduced to an acceptable level or proceeds to a predetermined number of learning times, as shown in the structure diagram in Fig.2.[8]

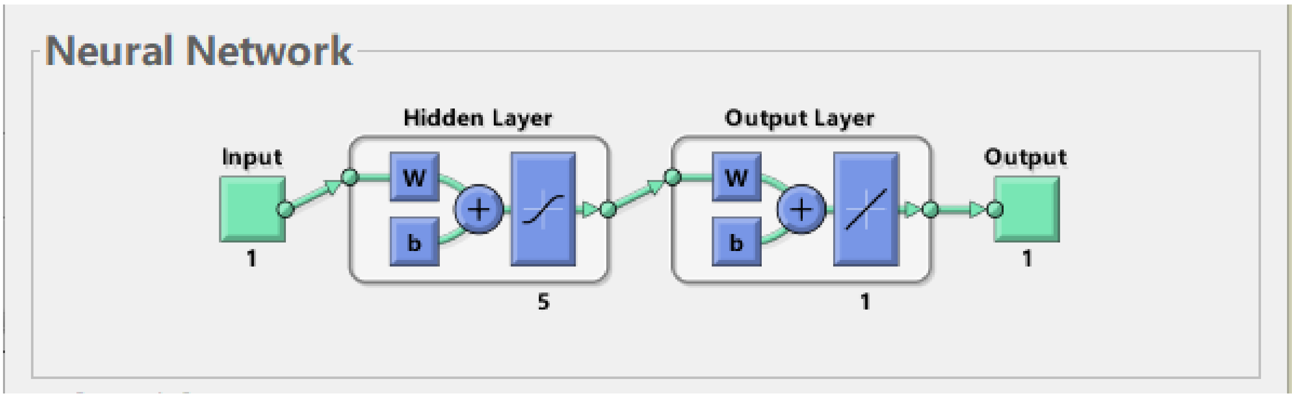

Fig. 2 BP neural network structure diagram

Next, the BP neural network is established.

From the schematic diagram X, the measured temperature corresponding to the year is taken as the input parameter variable $X = (x_1 x_2, x_3, \dots x_i)^T$,and the output variable of the hidden layer is set as one, which is expressed by $Y = y_i^T (i = 1 \dots\dots.7)$, the output vector (mean temperature) of the output layer is represented by the Vector Group H, and the expected output is the constant vector group D. [9]According to the principle of BP neural network, the following equations can be obtained.

For the output layer, there are:

$$\begin{cases} h_k = f(net_k) & k = 1,2, \dots 120 \\ net_k = \sum_{j=1}^{m} v_{jk} y_j & k = 1,2, \dots ,120 \end{cases} \tag{7}$$

For the hidden layers, there are:

$$\begin{cases} y_j = f(net_j) & j = 1,2, \dots m \\ net_j = \sum_{i=1}^{m6} w_{ij} x_i & j = 1,2, \dots , m \end{cases} \tag{8}$$

Among them,$f(x) = \frac{1}{1+e^{-x}}$

Finally, the BP neural network is solved.

(1) The data are first normalized and normalized to 0~1.1

(2) The network is initialized. The network will assign random numbers to the weight matrices W and V by itself, set the sample pattern counter P and training count q to 1, error E to 0, learning rate η = 0.1, and the accuracy E_{min} achieved by the network after training is taken as 0.01.

(3) The training sample pairs are input and the output of each layer is calculated. The current samples are used to assign values to the vector arrays X and D, and to calculate each component of Y and H; the training process is shown in Figure 2.

(4) The network output error is calculated. There are 6 pairs of training samples, the network has error for the ith sample, and the total output error (root mean square error) is: $RMSE = \sqrt{\sum_{k=1}^{120}\left(d_k^p - h_k^p\right)^2 /120q}$

(5) Adjust the weights of each layer. The amount of weight adjustment is:

$$\begin{cases} \triangle w_{jk} = -\eta \dfrac{\partial E}{\partial w_{jk}} & j = 1,2 \ldots .4; k = 1,2, \ldots m \\ \triangle v_{jk} = -\eta \dfrac{\partial E}{\partial v_{jk}} & j = 1,2 \ldots . m; k = 1,2,3 \end{cases} \tag{9}$$

(6) Check if one rotation is completed for all samples. If P<4, counters p and q are both added by 1 and step2 is returned, otherwise proceed to the next step.

(7) Check whether the total network error meets the accuracy requirement. If $E_{RME}<E_{MIN}$, training is finished, otherwise E is set to 0 and P is set to 1, and return to step2.[10]

2.3. Model evaluation and test

2.3.1 Evaluation and testing of ARIMA models

For the ARIMA model, this article uses the historical data to build a good model and calculates the theoretical value of the past global average temperature level M_i, and uses SPSS to analyze the fit of the actual value m_i and the theoretical value M_i of the past global average temperature level, and the fit is shown in Fig.3,and the relevant data of its model fit are shown in Table.1.

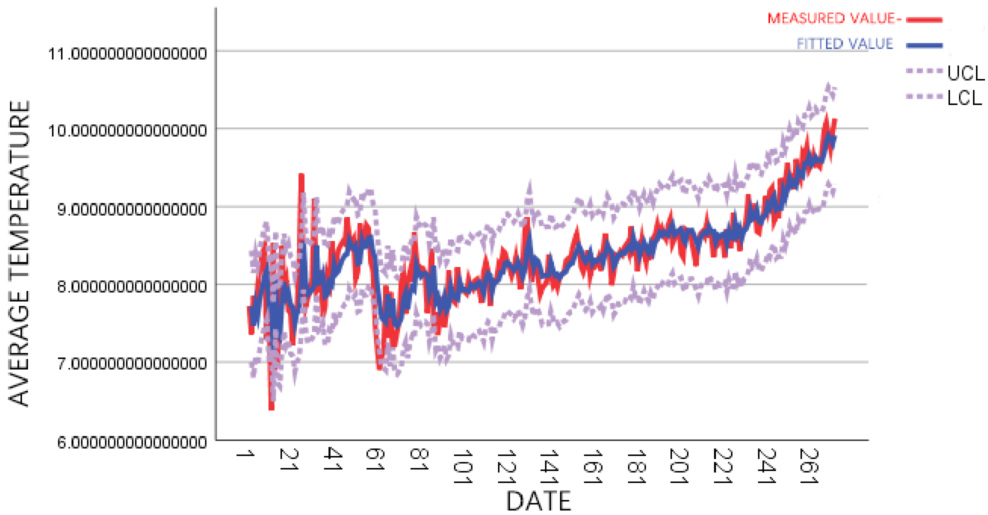

Fig. 3 Fitting line graph of ARIMA model

Table 1. Model Fitted Data Graph

Fitting statistics	**Average**	**minimum**	**Maximum**	**Percentile**						
				5	10	25	50	75	90	95
Stable R^2	0.234	0.234	0.234	0.234	0.234	0.234	0.234	0.234	0.234	0.23
R^2	0.726	0.726	0.726	0.726	0.726	0.726	0.726	0.726	0.726	0.72
RMSE	0.318	0.318	0.318	0.318	0.318	0.318	0.318	0.318	0.318	0.31
MAPE	2.611	2.611	2.611	2.611	2.61	2.61	2.61	2.61	2.61	2.61
MaxAPE	21.828	21.82	21.828	21.82	21.82	21.828	21.82	21.82	21.828	21.8
MAE	0.212	0.212	0.212	0.212	0.212	0.212	0.212	0.212	0.212	0.21
MaxAE	1.447	1.447	1.447	1.447	1.447	1.447	1.447	1.447	1.447	1.44
Normalization	-2.211	-2.211	-2.211	-2.21	-2.21	-2.211	-2.211	-2.21	-2.211	-2.21

From the data in Table.1, it can be seen that the goodness of fit of the ARIMA model is R2=0.726<0.8, so the fit of the model is poor, and the accuracy of the predicted values of the model can be introduced to be poor.

In the above process, the goodness-of-fit is calculated as:

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} \tag{10}$$

Among them,

$$\begin{cases} \bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i \\ SS_{tot} = \sum_{i=1}^{n}(y_i - \bar{y})^2 \\ SS_{res} = \sum_{i=1}^{n}(y_i - f_i)^2 \end{cases} \tag{11}$$

y_i is the simulated value, $\bar{y}$ is the mean of the simulation, f_i is the predicted value,, and the smaller the random error SS_{res}, the larger the R^2 and the closer to 1, the better the fit.

2.3.2 Evaluation and testing of BP neural network models

For the BP neural network model, the model was evaluated in the same way as described above. A regression analysis was performed based on the actual temperature level values collected and the theoretical values calculated through the model, using the goodness-of-fit formula, and $R^2 = 0.84668$ was calculated through Dev-C++, while a correlation analysis was performed on the model, and a line graph was plotted using SPSS, as follws.

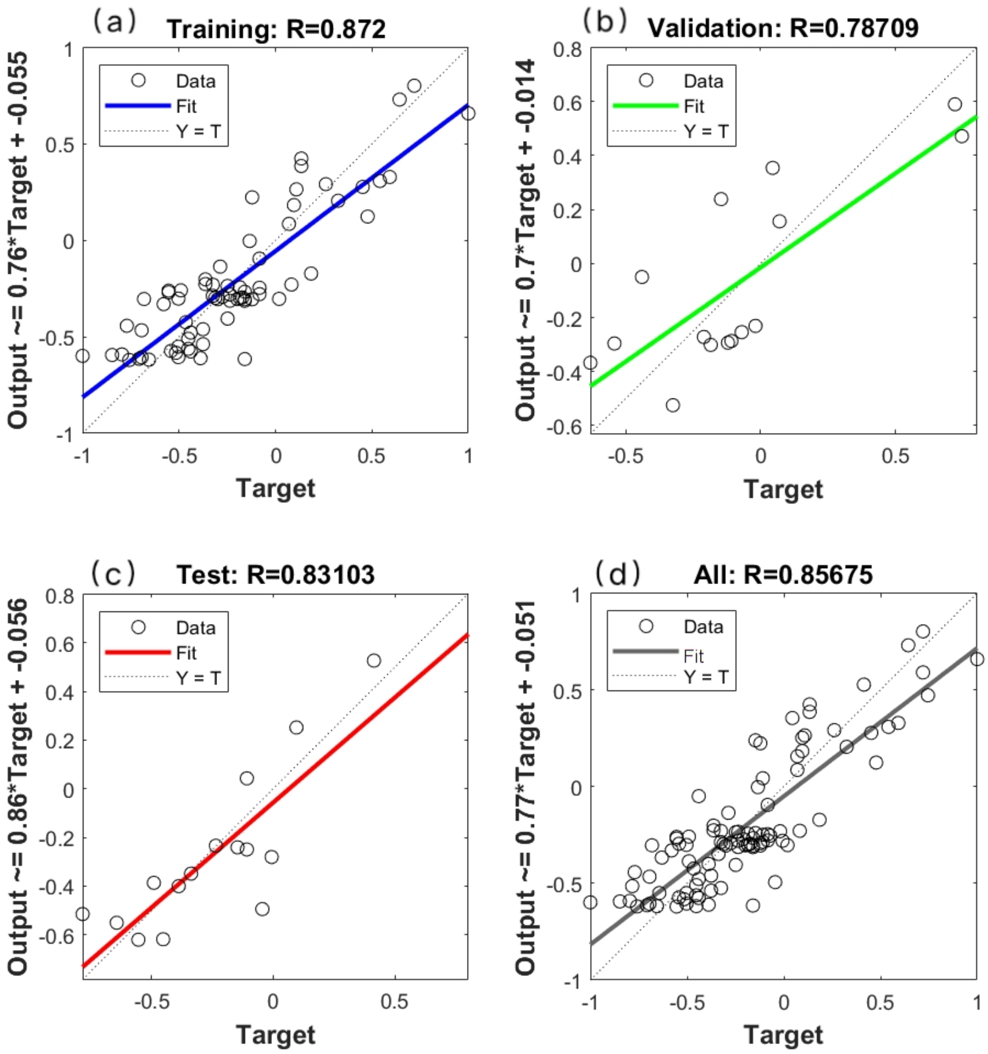

Fig. 4 Correlation coefficient line graph

3. Model results

3.1. The establishment of ARIMA model

Finally, this paper made the prediction according to the established model, and imported the prediction data into SPSS Pro to draw the line chart of the prediction result, which is shown in Fig. 5. The model predicts a global temperature of 11.49 ° C in 2050 and 14.26 ° C in 2100.

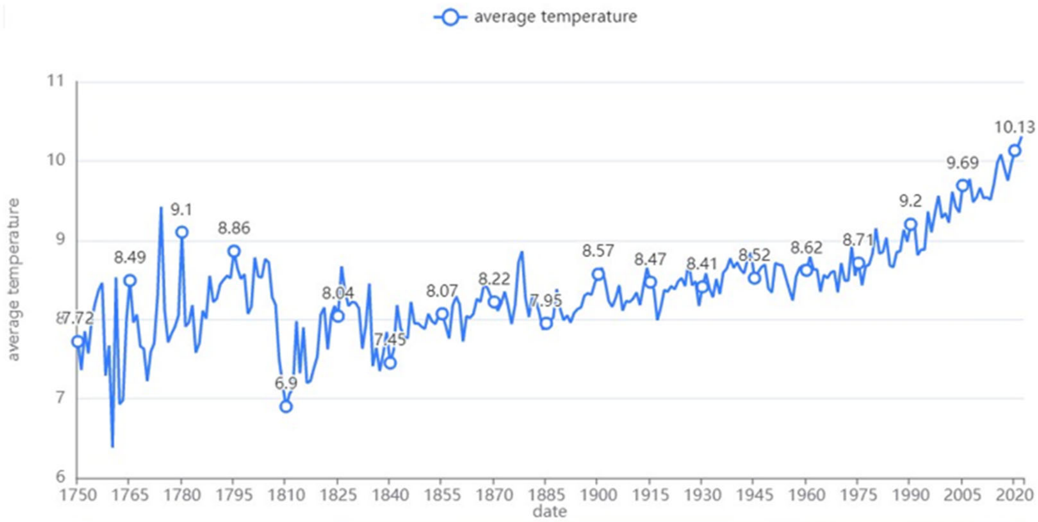

Fig. 5 ARIMA model of the results of the forecast line chart

3.2. The establishment of BP neural network model

Considering that the impact of human activities on the Earth's environment in the pre-industrial revolution was not significant,[1] this article choses the data after the second industrial revolution to the present - the global average annual temperature data from 1920 to 2020, as shown in Fig. 1. Based on the above established mathematical models of input and output layers , MATLAB was applied to solve it. The predicted data were imported into SPSS to draw a line graph as in Fig. 6

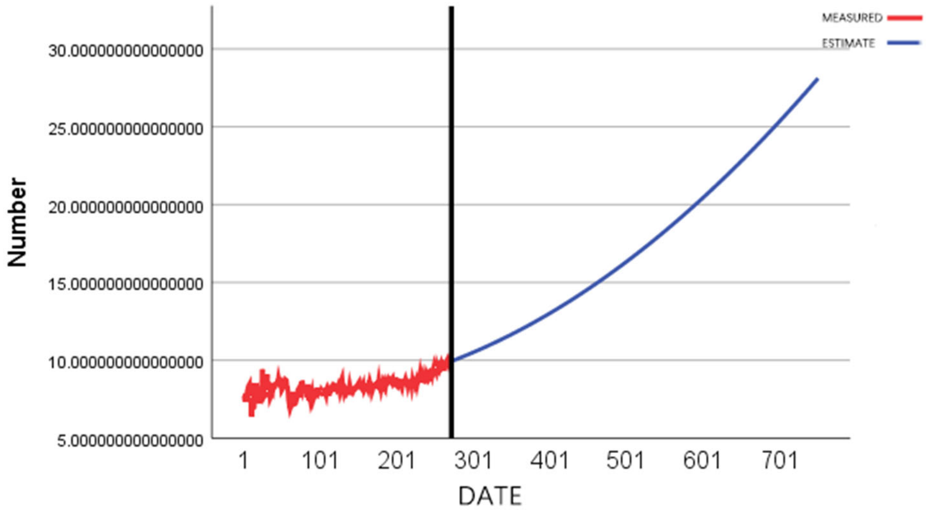

Fig. 6 BP neural network model of the results of the forecast line chart

3.3. Model comparison and conclusion

From the above analysis, the goodness of fit of Arima model is 0.726, and the goodness of fit of BP neural network is 0.84668. Therefore, the goodness of fit of BP neural network is higher and its prediction value is more accurate.

4. Conclusions

According to the two models established, we can describe the past global temperature level and can predict the future global temperature level based on the historical global temperature level.

According to the prediction results of ARIMA model, the global temperature in 2050 is 10.16℃, and the global temperature in 2100 is 10.87℃, and the temperature at the observation points cannot reach 20℃, but the average temperature at the observation points can reach 20℃ in 2202.

According to the prediction results of BP neural network model, the global temperature is 11℃ in 2050 and 13℃ in 2100, and the temperature at the observation point can not reach 20℃, and the average temperature at the observation point can reach 20℃ in 2350.

Finally, the two models are evaluated and tested, and it is concluded that the BP neural network model performs better in global temperature prediction and can provide more accurate information for scientists, policy makers, and the society at large to address the challenges posed by climate change and to promote the development of sustainable development and climate adaptation measures.

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