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Short-term prediction of BP neural network based on difference method

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Abstract—**Aiming at the problem of short-term time series forecasting, a neural network based on the difference method(DMBP) is proposed.And then using sunspot data and Mackey-Glass chaotic time series data to test the performance of DMBP.In the experiment,DMBP,BP neural network algorithms, support vector regression machine (SVR),and autoregressive integrated moving average model (ARIMA) are compared in two cases with a prediction length of 2, 5. Experiment resaults show that the prediction accuracy of the DMBP algorithm is significantly improved compared to the BP neural network, and it is far better than SVR. It is equivalent to the ARIMA algorithm in short-term prediction, but the DMBP modeling process is simpler than ARIMA.**

Keywords-differencemethods;BP neural net;time series prediction

I. INTRODUCTION

Time series data is a set of data indexed in the time dimension,used to describe changes of the object in a period.Usually, it means that the data is taken at equal time intervals.BP neural network has good nonlinear fitting ability so that it can fit any complex nonlinear relationships.Its learning rules are simple, which are convenient for computer to achieve.If the data in the past time is used for the input data of neural network, and the data at a later time is used as the output data, the neural network can be used for time series predict.

Paper [1] proposes a kind of combined model based on interactive information and BP network, and applies it to residential electricity load forecasting.Paper [2] establishes the ARIMA-RBF prediction model in order to improve the performance of the model and the results show that the prediction accuracy was improved.Paper [3] and Paper [4] use the LDHA and PSO algorithms to improve the performance of the BP neural network, and then make timing predictions to achieve good prediction results. Paper[5]-[12] uses bp net to different scenes, and achieved good results.But for a set of time series data,if the historical data is directly used as training data,it only can show the different influence of the data at different consecutive times, and can’t fully use its changing trend to predict.This makes the BP network have errors in the prediction.The difference method can reflect the change trend of a set of data: the absolute value of the first-order difference can reflect the change degree of the original data,and the positive and negative of the first-order difference can reflect the change trend of the data.In this paper, the difference method is introduced into the BP neural network, and proposeing a BP neural network prediction model based on the difference method for the prediction of time series data.

II. THEORETICAL MODEL

A. Difference Method BP Neural Network

The neural network model based on difference method (DMBP) is improved on the basis of the traditional BP neural network,and its structure is shown in Figure 1.The original hidden layer is changed to a training layer in DMBP, which consists of two sub-hidden layers (as shown in Figure 2), and there is no connection between the two sub-hidden layers.A difference layer is added before the training layer, which is used to calculate the first-order difference of the input data.We can get two sets of vector from the difference layer.Then the two sets of output vectors are input into the training layer to get another two sets of vectors called the trend vector and the degree vector.The trend vector and the forecast are used to predict the final resault. The specific process is described in the algorithm steps.

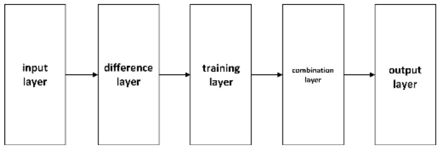

Figure 1. Differential neural network structure diagram

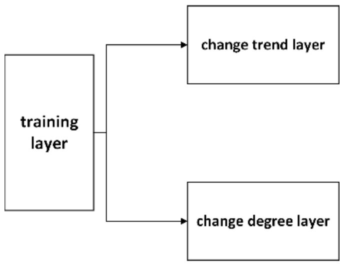

Figure 2. Training layer structure

The algorithm steps are as follows:

Supposing $X=\{x_m|1\leq m\leq n\}$ is a set of time series data,which of length is n.Supposing the training step is k(putting k values into the network at a time),and $X_i=\{x_{ij}|1\leq j\leq k,1\leq i\leq \frac{n}{k}\}$ is the i-th batch of training data.

Step 1.Calculate the first-order forward differ-ence of t he input data to get the first-order difference value (T) and the first-order differe-nce absolute value(D) of the input data.

$$T=\{x_{ij+1}-x_{ij}|1\leq j<k,1\leq i\leq \frac{n}{k}\} \quad (1)$$

$$D=\{|x_{ij+1}-x_{ij}||1\leq j<k,1\leq i\leq \frac{n}{k}\} \quad (2)$$

Step 2.Get the prediction reference value(the last data of the input data)

$$x_{steam}=x_{ik} \quad (3)$$

Step 3.Put D and T into two sub-hidden layers of the training layer respectively to get the trend vector(TO) and the degree vector(DO).(TO is activated by tanh activation function(formula 6))

$$DO=dnet(D) \quad (4)$$

$$TO=tnet(T) \quad (5)$$

$$f(x)=\frac{e^{x}-e^{-x}}{e^{x}+e^{-x}} \quad (6)$$

Step 4.Combine the output results DO, TO and the predicted reference value xsteam to get the predicted value.

$$Y_{pred}=x_{steam}+TO*DO \quad (7)$$

Step 5.Compare with expected output value, use gradient descent method for error back propagation training.

III. EXPERIMENT AND ANALYSIS

A. Simulation experiment

The 1749-2019 average monthly total number of sunspots and Mackey-Glass chaotic time series data are used as test data. Each data set uses the first 70% as training data and the last 30% as test data.Then the mean absolute error ,the root mean square error,and the mean absolute percentage error are used for evaluation indicators.

The root mean square error:

$$\sqrt{\frac{\sum_{i=1}^{m}(h_i-y_i)2}{m}} \quad (8)$$

The mean absolute error:

$$\frac{1}{m}\sum_{i=1}^{m}|h_i-y_i| \quad (9)$$

The mean absolute percentage error:

$$\sum_{i=1}^{m}\left|\frac{h_i-y_i}{y_i}\right|*\frac{100}{m} \quad (10)$$

The experiment compares the first-order differential neural network with BP neural network, SVR and ARIMA.The experimental setting prediction length are 2 and 5 respectively. When the prediction length is 2,the input length of BP and DMBP is 5; when the prediction length is 5, the training length of BP and DMBP is 10. It is found through experiments that when the SVR is trained with input length of 10 and 20, the prediction result is poor: In the sunspot dataset, when the training length is 10 and the prediction length is 5, the three indicators are: 137.725, 122.029, 1177.587; When the training length is 20 and the prediction length is 5, the three indicators are: 110.402, 96.603, 978.385. However, the three indicators of the overall modeling SVR are small (the specific values are shown in TableⅠ), so, for the two sets of test data, the SVR uses the overall data modeling.

B. results and analysis

TableⅠand TableⅡare the experimental results of the two sets of data above.The data in the table is the average of 10 experiments.As the tableⅡshows the results of DMBP in RMSE, MAE and MAPE are better than BP and SVR.It explains that DMBP makes better use of data fluctuations.And as the tableⅡshows the results of DMBP in the three indicators of RMSE, MAE and MAPE are far better than those of BP and SVR.Since Mackey-Glass chaotic time series data is mostly distributed between 0 and 1.32, the value is small and the fluctuation value is small, which causes a large error between the BP network and the SVR, but DMBP overcomes the small fluctuation value well.

TABLE I. 1749-2019 monthly average total sunspot number experimental results

algorithm		2	5
BP	RMSE	33.360	42.371
	MAPE	33.360	42.371
	MAE	153.998	143.798
SVR	RMSE	77.229	77.229
	MAPE	61.552	61.552
	MAE	425.380	425.380
DMBP	RMSE	31.876	41.449
	MAPE	31.876	41.449
	MAE	67.021	85.858

TABLE II. Mackey-Glass chaotic time series experiment results

algorithm		2	5
BP	RMSE	0.291	0.294
	MAPE	0.291	0.294
	MAE	24.988	26.584
SVR	RMSE	0.230	0.246
	MAPE	0.198	0.196
	MAE	24.796	27.398
DMBP	RMSE	0.064	0.120
	MAPE	0.064	0.120
	MAE	5.762	10.020

In order to further compare the property of DMBP,we compare DMBP and ARIMA algorithm. Because the ARIMA modeling error is larger when the training length is short, the training length is 20 to model ARIMA.The it compared with the DMBP with a training length of 20, the predicted length is 2, 5 respectively. TablesⅢandⅣare the experimental results of ARIMA and DMBP. It can be seen that the difference between the two algorithms in predicting the overall prediction results is small, but DMBP performs better than ARIMA on the MAE indicator. Moreover, the ARIMA modeling process is complicated. You need to determine the difference order d, and then determine q and p. The DMBP can directly input the data to predict it. The modeling process is relatively simple compared to ARIMA.

TABLE III. 1749-2019 monthly average total sunspot number experimental results

algorithm		2	5
ARIMA	RMSE	31.150	38.283
	MAPE	23.399	29.462
	MAE	89.924	116.941
DMBP	RMSE	32.290	37.470
	MAPE	32.290	37.470
	MAE	68.114	106.985

TABLE IV. Mackey-Glass chaotic time series experiment results

algorithm		2	5
ARIMA	RMSE	0.05	0.109
	MAPE	0.04	0.083
	MAE	5.173	10.012
DMBP	RMSE	0.041	0.126
	MAPE	0.041	0.126
	MAE	4.00	10.553

Figures 3 and 4 are predicted trend graphs. It can be seen from the figure that DMBP's forecast is more accurate when the data shows an upward or downward trend. But its prediction effect at the inflection point is not good and needs to be improved.

IV. CONCLUSION

The difference method can effectively reflect the changing trend of data. In this paper, the first-order difference is introduced into the BP network, and a BP network algorithm (DMBP) based on the difference method is proposed. Then use the actual data for simulation experiments.Experimental results show that the accuracy of DMBP in short-term time series prediction is greatly improved compared with BP network, and is superior to SVR algorithm, which is equivalent to ARIMA algorithm, but compared with DMBP, ARIMA modeling process is slightly more complicated. The error of the DMBP algorithm at the inflection point is large and needs to be improved.

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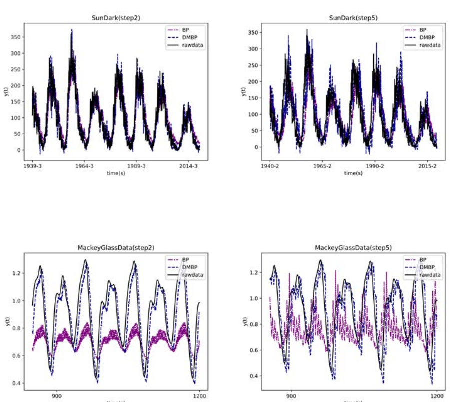

Figure 3. DMBP and BP forecast trends

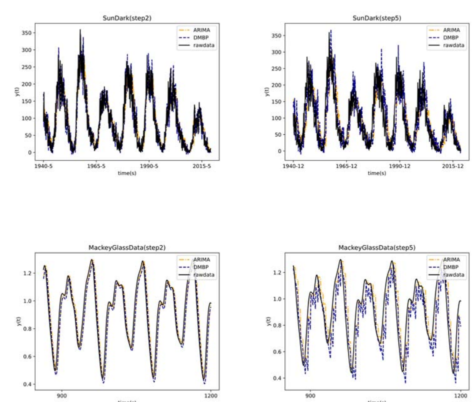

Figure 4. DMBP and ARIMA forecast trends