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Article

Research on deep neural network-driven macroeconomic forecasting in the context of economic transformation

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Abstract: Accurate prediction of macroeconomic development trends has a significant role in decision-making and preventive signaling for regional governments, industries and even residents. Based on the characteristics of macroeconomic development, this paper identifies five dimensions as the initial variables of the study: the number of employed population, fixed asset investment, financial expenditure, national bank loans, and scientific, educational and cultural inputs. Considering the volatility, correlation and systematic characteristics of the macroeconomic system as a whole, this paper introduces the neural network method as a forecasting tool for its development trend, and puts forward the time series forecasting and regression forecasting method based on neural network. And the linear mapping method is used to map the actual values and forecast values to the (0,1) interval. Region W is selected as the research sample, and the macroeconomic development forecasting model is constructed by setting assessment variables based on its macroeconomic performance during a total of ten years from 2006 to 2015. The proposed model shows significant macroeconomic forecasting performance compared to traditional statistical forecasting methods, with its root mean square error and average absolute error remaining below 0.001.

Keywords: macroeconomic forecasting; neural network method; linear mapping; time series forecasting; regression forecasting

1. Introduction

With the continuous progress of information technology, the volume of data shows an explosive growth trend, which widely covers all fields of economic activities and provides rich materials for macroeconomic analysis [1]. Macroeconomic forecasting has become an important branch of macroeconomic analysis. Macroeconomic forecasting is an important analytical method of using scientific and effective methods to qualitatively and quantitatively analyze the current situation of economic activities through statistical survey data and macroeconomic information as well as historical laws, to thoroughly understand the economic laws, and to effectively predict the development trend of future economic phenomena [2-3]. In the development of the national economy, macroeconomic forecasting has become an important basis for government leaders and economic managers to formulate policies, make macroeconomic development plans, respond to macroeconomic emergencies and provide effective measures, and it is also important for the guidance of monetary policy and fiscal policy [4-5].

The arrival of the intelligent era has brought unprecedented opportunities for macroeconomic forecasting, for example, through comprehensive information capture can reveal the subtle changes and trends in the economy, the use of data mining, machine learning algorithms and deep learning networks can discover complex associations and patterns, and then construct a forecasting model more in line with the complexity of the real economy [6-8]. However, this process faces many challenges, including inconsistency in data quality, dimensionality catastrophe due to high dimensionality characteristics, high complexity in model training, and high demand for model adaptability due to rapid changes in economic structures and relationships [9-10].

With the progress and innovation of science and technology, various forecasting methods have emerged in the macroeconomic field in recent years, and have made extraordinary academic achievements. Macroeconomic indicators of the relevant data are often a period of time series, with the passage of time constantly changing values, that is, the same statistical indicators of the value of the time order of its occurrence of the series, the study of more indicators, including stocks, crude oil and other consumption structure [11-12]. Literature [13] collected macroeconomic datasets from a number of developed economies and used four multivariate forecasting models to predict the macroeconomic changes in each economy from the next quarter to two years, and the study pointed out that the factor-enhanced model is more suitable for dealing with the problem of the existence of a large number of predictors in forecasting. Literature [14] compared the prediction accuracy of BP neural network and deep learning fuzzy algorithm on stock market prices, and it was found that BP neural network has better prediction effect and the best prediction effect when the prediction range is between 15 days, and its prediction value is within 10% of the true value. Literature [15] uses the ensemble empirical modal decomposition and support vector regression model to construct a prediction model to predict the Chinese consumer price index, which provides a powerful reference for China's macroeconomic development decisions. Literature [16] used principal components and other shrinkage techniques such as Bayesian model averaging and various bagging, boosting, least angle regression, and correlation methods to predict the trends of 11 key macroeconomic indicators under different scenarios. Literature [17] integrated neural network and Bayesian learning algorithms to forecast the monthly clearance export value of South Korea and the daily exchange rate of the won against the US dollar, and the forecasting results showed that the methods used were superior to the traditional macroeconomic forecasting models, and the models were able to efficiently extract the time-series features of the relevant data, which significantly reduced the forecasting requirements on the amount of data. Literature [18] improved the BP neural network through the ant colony algorithm and applied the improved model to the price prediction of stocks, gold, exchanges and inflation, etc., and the results confirmed the accuracy of the improved model in macroeconomic prediction. Literature [19] based on BP neural network and genetic algorithm to build GRA-GABP combination, the prediction model comprehensively consider the macroeconomy, market demand, railroad supply and other factors on the railroad freight volume prediction, the prediction results to meet the demand of different passengers for exchange.

Deep neural network is a machine learning model for learning hierarchical feature representation of data by multilayer nonlinear transformations, and its basic structure consists of an input layer, a hidden layer, and an output layer [20]. Each layer consists of multiple computational units (neurons), and these units establish associative relationships with each other through learnable connection weights, which are used by the input layer to obtain the original input information, the hidden layer for feature extraction, and the output layer to produce the final results [21-22]. In recent years, the rapid advancement of artificial intelligence technology has brought deep neural network-based models into the limelight in prediction research [23]. Literature [24] constructed a deep neural network to achieve high precision prediction of macroeconomic indicators with a small amount of data, and the study used four different neural network architectures to predict the unemployment rate, and the prediction performance shown is better than the traditional model. Literature [25] used a deep neural network structure called EcoForecast1 to make predictions based on China's actual macroeconomic data from 1992 to 2022, and in the test experiments, the prediction accuracy of EcoForecast1 was 3.94 times higher than that of the traditional method, and the prediction error was reduced by 2.51 times, which made the short-term macroeconomic prediction much more interpretable than that of the general method. The interpretability of short-term macroeconomic forecasts is much better than that of general methods. Literature [26] used three neural network structures, deep neural network, long and short-term memory neural network, and the combination of convolutional and long and short-term memory neural network, to forecast the U.S. crude oil price. Although the deep neural network did not achieve the best forecasting performance, its forecasting results are sufficient to help policy makers improve macroeconomic policies to provide better macroeconomic assessment. Literature [27] selected four factors as data inputs, namely energy price, climate environment, carbon market price and macroeconomy, and analyzed the influencing factors of carbon trading price based on deep neural network, and in order to highlight the superiority of the model and compare the prediction effect of several linear regression models, the method used has better prediction performance. Literature [28] proposed a deep neural network structure based on the hybrid of convolutional neural network and long and short-term memory neural network, by integrating six heterogeneous sources of stock-related information, the use of the hybrid model to achieve an accurate prediction of the stock market, in which the accuracy of the prediction is 98.31%, the specificity is 0.9975, and the F-value is 0.9672. Literature [29] also used a convolutional neural network that integrates the long and short-term memory network to analyze the factors affecting the carbon trading price. memory network of convolutional neural network to predict the new energy consumption structure, utilizing China's new energy consumption data from 1965-2018, the model used showed strong prediction fit, while predicting that the proportion of clean energy consumption will continue to increase after ten years.

In this paper, the theoretical basis, content and preprocessing method of macroeconomic forecasting indicators are firstly described in detail. Then, it explains the application of neural network method in univariate time series forecasting, focusing on the problem of interval mapping between the input and output values of the forecasting indicators. Then, based on the proposed research variable indicators, descriptive statistics of the macroeconomic development performance of W region during the period of 2006-2015 is formed to form the research sample data set. The reliability of the proposed algorithm is assessed by comparing the predicted values and prediction errors of similar modeling algorithms for the study sample. Then, the main influencing factors of macroeconomic development are screened, and the evaluation scale is designed and tested for its reliability and validity. Finally, the principal components of macroeconomic development are identified and used as predictor variables to construct a macroeconomic development prediction model and test its prediction results.

2. Macroeconomic development indicator selection and data processing

Macroeconomic forecasting is that people, under the guidance of certain economic theories, choose appropriate models, use their own macroeconomic information, and make reasonable macroeconomic pointers for the future according to the laws of economic operation.

Macroeconomic prediction includes the prediction of industrial structure and economic growth, while economic growth is the most concerned indicator, which mainly depends on the accurate prediction of GDP.

Macroeconomics has more obvious volatility, correlation and systematicity, and has certain randomness, ambiguity, sudden change and alteration, and any economic event is in a complex economic system, and will be disturbed by various uncertain factors. Macroeconomic forecasting methods generated under the guidance of different economic theories, for different problems, often need to use different methods to complement each other. However, each method faces a problem of indicator selection.

2.1. Rationale for the selection of indicators

Any economic model used for forecasting needs a certain theoretical foundation as support, without the economic theory foundation of the economic model can only be a castle in the air, GDP forecasting model must also be based on a certain macroeconomic theory, in this paper, the artificial neural network forecasting model of the input variable selection basis comes from the production function.

(1) Cobb-Douglas production function

The basic form of the Cobb-Douglas production function is shown in equation (1):

$$Y = AK^{\alpha}L^{\beta} \tag{1}$$

Where: Y is the amount of output, K is the amount of capital input, L is the amount of labor input, A is a certain state or level of technology, and α and β are parameters.

(2) Improved production function

The use of a certain time series of statistics, specific estimates of the contribution of technological progress, that is, in the time series of output increment after deducting the incremental capital factor inputs and incremental labor factor inputs to the output growth of their respective contributions, the “remaining” for the contribution of technological progress to the growth of output, that is, the improved production function, the basic form of equation (2): the basic form of the production function. The basic form of the function is equation (2):

$$Y = A + \alpha K + \beta L \tag{2}$$

Where: Y is the growth rate of output; K is the growth rate of capital input; L is the growth rate of labor input; A is the rate of technological progress; α , β are the parameters, which represent the output elasticity of capital and the output elasticity of labor, respectively.

(3) General form of production function

As can be seen from the previous analysis, the production function can be highly abstracted by the variety of complex production techniques used by people in a variety of production models simplified to be determined by the two elements of capital and labor. Production function in the form of formula (3):

$$Q = f(L, K) \tag{3}$$

where Q is output, L is labor, and K is capital It can be seen that there is always some kind of linear or nonlinear relationship between output and capital and labor.

2.2. Selection of indicators

Based on the model developed in the previous section, this paper identifies the five indicator dimensions that have the most impact on the macroeconomy as (E1) the number of people in employment, (E2) investment in fixed assets, (E3) fiscal expenditures, (E4) national bank loans, and (E5) science, education, and cultural inputs, as the initial variables of the study. Accordingly, the raw data of the statistical study sample from 2006 to 2015 are shown in Table 1, where the unit used for GDP is billion dollars.

Table 1. The original data from 2005 to 2015.

	GDP	E1	E2	E3	E4	E5
2006	6968.53	4785.77	3615.87	1760.19	4462.26	101.61
2007	7753.7	4875.86	3953.01	1835.79	4796.99	110.49
2008	8550.07	4936.46	3971.29	1917.22	6374.73	113.84
2009	9151.68	5018.43	4286.52	2087.17	7160.56	129.86
2010	9898.87	5030.88	4486.75	2200.46	8266.58	141.53
2011	10896.79	5223.88	4722.42	2304.42	8815.27	166.62
2012	11882.27	5293.19	5095.37	2555.89	9564.08	202.84
2013	12970.2	5368.93	5391.23	2755.64	10667.56	258.09
2014	14860.43	5630.49	6494.04	2930.19	12250.65	291.42
2015	17274.02	5916.55	7599.91	3087.51	12525.66	314.64

The five indicators were preprocessed and used as input variables for the neural network.

2.3. Pre-processing of input indicators

The neural network consists of the input samples and the initial weights connected to the first hidden layer for the inner product operation to obtain the total input of the neurons in the first hidden layer, the output is obtained by the action of the nonlinear excitation function, and this output is then used as the input of the next layer, and the calculation is carried out in turn until the output layer obtains the output of the network. However, if the total input of the neuron is too far away from the threshold value, due to the saturated nonlinear characteristic of the excitation function of each neuron, it will make the output of the neuron fall in the saturated region, so that the actual output of the network will be either the maximum value of the excitation function or the minimum value of the excitation function, which will make the derivative value of the output will be very small (tend to zero). This will result in a small modification of the weights, which not only makes learning slow, but also makes it difficult for the network to converge. At the same time, there is a risk that the small value information will be overwhelmed by the large value information. Therefore, before the neural network prediction, in order to avoid network paralysis caused by the original data is too large, the original data should be normalized, and for the prediction value, due to the large variation, it is also not suitable to be directly used as the output of the neural network.

For the unipolar Sigmoid function, the output varies between 0 and 1 and reaches (0,1) only when the input is $(-\infty,+\infty)$, which is generally mentioned as normalizing the input to (0,1). In this paper, equation (4) is used as the excitation function, which is characterized by a value domain of (-1,1).

$$f(x)=\frac{2}{1+\exp(-ax)}-1 \tag{4}$$

The sample data were normalized as in equation (5):

$$Y=(x-\min)/(\max-\min) \tag{5}$$

Where max and min are the maximum and minimum values in the sample data respectively, x is the original sample data and Y is the transformed value. This not only avoids the input data falling into the saturation region, but also maintains the original characteristics of the data. When the neural network processing is finished, then do the inverse normalization operation. For the network output, the following formula is used for the output data to make the output data within the same region as the original data, and the inverse normalization is as in equation (6):

$$Y=x*(\max-\min)+\min \tag{6}$$

Obviously, this is the inverse process of normalizing the raw data.

3. Research methodology for macroeconomic development forecasting

3.1. Neural Network Approach

3.1.1. Neural networks for univariate time series forecasting

Let a univariate time series $X_1, X_2, \ldots, X_m$ be predicted for it, which can be described as equation (7):

$$X_{m+1} = F\left(X_1, X_2, \Lambda, X_m\right) \tag{7}$$

A neural network is used to fit this functional relationship $\mathrm{F}(\cdot)$ and use it to derive future values. The prediction model is shown in Fig. 1, with a single-step prediction network with one number of outputs, which can compute the predicted values one step at a time. The main advantage of the model is that it can fit or reconstruct an arbitrary nonlinear continuous function $\mathrm{F}(\cdot)$, and this model is very flexible.

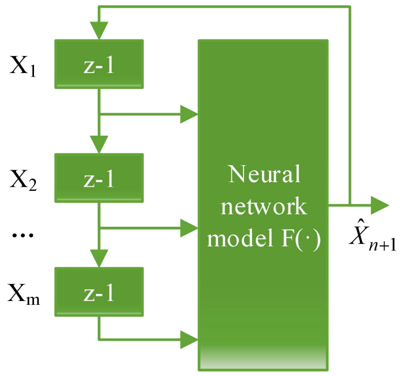

Figure 1. Time Sequence Framework of Neural Network Application.

3.1.2. Regression prediction methods for neural networks

Regression prediction refers to the existence of some causal functional relationship between the dependent variable Y and multiple independent variables $X_1, X_2, \ldots, X_k$ as in Eq. (8):

$$Y = F\left(X_1, X_2, \ldots, X_k\right) \tag{8}$$

A BP network is utilized to fit this functional relationship and use it as a predictive model for the future value of the dependent variable. Regression prediction with neural networks can perform not only linear but also nonlinear regression, which is significantly superior to traditional regression prediction methods.

The regression model is built based on the causal relationship between pointers. For example, the budget annual revenue will be affected by the three industries GDP income, annual total consumer goods, annual tax revenue, annual foreign trade exports, the natural growth rate of the population and other factors, so the model is established as equation (9):

$$CZSR = F_{CZSR}\left(GDP_{-1}, GDP_{-2}, GDP_{-3}, XFZE, SS, WMCK, RKZZ\right) \tag{9}$$

Where:, *CZSR*: Fiscal Revenue, GDP_{-1} : Primary Sector GDP, GDP_{-2} : Secondary Sector GDP, GDP_{-3} : Tertiary Sector GDP, *XFZE*: Total Consumer Goods, SS: Tax Revenue, *WMCK*: Foreign Trade Exports, *RKZZ*: Population Growth Rate.

3.1.3. Combined prediction methods for neural networks

A linear combination of forecasts obtained by multiple forecasting methods results in a much smaller overall error than the results obtained by any one of the methods. Better prediction results will be obtained with nonlinear combinatorial prediction. Combined prediction using artificial neural networks is a major breakthrough in the research of nonlinear combined prediction in recent years.

The basic idea of artificial neural network prediction is to first use the information to train the network, and then use the algorithm of artificial neural network to build the mathematical model and make predictions. Neural network used in macroeconomic forecasting, solved the problem of the image of nonlinear relationship in macroeconomic system, opened up a new effective way for economic forecasting analysis.

3.2. Questions about mapping intervals

Due to the requirements of the BP network itself, the inputs and outputs all use numbers in the (0,1) interval, which presents a problem of mapping the actual and predicted values to the (0,1) interval.

In order to be reasonable and simple, this paper uses linear mapping as follows:

(1) For the indicators to be predicted, the values of its inputs and outputs use the same mapping as in equation (10):

$$a_f = \left(a_t - \min\right) / (\max - \min) \tag{10}$$

Where a_f denotes the input and output values of the network $\left(a_f \in (0,1)\right)$. a_t denotes the actual value. max, min denote the upper and lower limits of the metric, respectively.

At this point, it is important to make the input values all map onto the (0, 0.5] interval to ensure that the growth of the output values after transforming them to actual values is objective and to avoid human interference.

(2) For other inputs

Use formula (10) to map the actual value to the (0, 1) interval.

It should be noted that the program does not calculate the upper and lower limits of each input at the beginning, it must be placed in the data file, and the program will automatically calculate the upper and lower limits of each indicator when predicting the next year after the program begins.

4. Construction and testing of macroeconomic development forecasting models

In this chapter, Region W is selected as a research sample to comb the region's index performance of five macroeconomic development indicators in 2006-2015 as a research and analysis dataset. The predictive effect of the proposed model is examined in the form of comparison with similar modeling algorithms. Then, based on the proposed variable indicators, the main factors affecting macroeconomic development are screened to form an evaluation scale, and after determining its reliability and validity, the BP neural network model is constructed and its predictive performance is tested.

4.1. Preparation of the study

4.1.1. Descriptive statistics of the sample

The descriptive statistics of the five indicators of the macroeconomy and the major industries (industry, services, agriculture, forestry, fisheries and construction) in Region W are shown in Table 2, with the service sector (E1) having the highest number of employees (mean index of 59.04), the industry (E2) having the highest investment in fixed assets, (E3) financial expenditures, and (E5) science, education, culture and literature (mean indices of 60.73, 60.59 and 59.05), and the construction sector having the highest number of state bank loans (E4) (mean index of 57.57). 59.05), and the construction sector received the most (E4) state bank loans (mean index of 57.57).

Table 2. The descriptive statistics of variables for macroeconomy and main industries.

Predicted object	Statistical variable	E1	E2	E3	E4	E5
Macro economy	Mean	39.11	55.25	46.4	25.98	52.95
	Median	33.07	53.36	42.18	19.29	54.77
	Maximum	62.32	91.43	70.33	75.55	95.09
	Minimum	5.68	5.29	7.43	23.26	15.6
	Standard deviation	17.31	1.41	16.11	13.21	9.26
	K	20.13	22.78	28.73	29.2	21.05
	Skew	-0.15	1.14	0.34	1.52	1.59
Industrial	Mean	51.7	60.73	60.59	31.5	59.05
	Median	57.63	56.29	56.24	32.85	34.03
	Maximum	72.4	85.82	87.05	64.56	74.32
	Minimum	24.09	10.59	8.77	8.27	11.29

	Standard deviation	7.42	5.71	15.5	13.97	4.19
	K	20.93	16.61	23.8	18.36	24.55
	Skew	-1.24	1.12	-1.15	2.42	1.62
Service industry	Mean	59.04	36.06	22.44	37.01	28.71
	Median	52.02	36.03	15.52	36.00	19.01
	Maximum	85.26	88.11	89.38	87.86	70.26
	Minimum	21.09	19.28	31.24	44.58	7.47
	Standard deviation	13.79	13.95	8.77	16.31	11.71
	K	14.97	12.7	9.71	19.13	24.92
	Skew	2.65	0.07	-1.1	2.17	1.95
Agriculture, forestry, animal husbandry and fishery	Mean	48.23	55.29	20.08	46.7	24.39
	Median	47.94	55.29	24.08	44.49	23.35
	Maximum	88.09	80.41	71.83	87.08	78.96
	Minimum	16.63	23.64	8.6	16.44	4.73
	Standard deviation	0.87	6.14	13.57	15.8	19.52
	K	21.1	14.99	11.16	5.37	5.58
	Skew	-0.91	2.81	-1.4	1.37	2.65
Construction	Mean	35.18	39.36	35.54	57.57	46.55
	Median	36.57	35.25	30.05	56.46	42.9
	Maximum	92.86	83.24	80.89	93.59	87.74
	Minimum	17.83	17.91	10.09	10.47	19.26
	Standard deviation	9.17	17.23	2.13	5.85	18.01
	K	8.23	3.24	12.98	8.53	16.8
	Skew	0.45	2.77	1.24	-0.96	-1.4

4.1.2. Analysis of the predictive effectiveness of the algorithm

The (M2) two-stage algorithm and (M3) three-stage algorithm are selected as the control, and the GDP development of W region based on 2006-2010 is the experimental object. The comparison of the predicted and actual values of 2011-2015 GDP by combing (M1) this paper's algorithm and other two modeling algorithms is shown in Fig. 2, and the performance of the error rate between the model's predicted value and the actual value is shown in Fig. 3. Overall the predicted value of the GDP development of W region in 2011-2015 by (M1) this paper's modeling algorithm and its trend of the actual value is the most close to the trend direction, and the error rate of the prediction is controlled within 0.36. (M2) The prediction ability of the two-stage algorithm is the worst among the three model algorithms, with the largest deviation, and the error rate between the predicted value and the actual value is as high as 76.01%. The (M3) three-stage algorithm prediction performance is slightly better than the (M2) two-stage algorithm, but the highest error rate still reaches 57.81%.

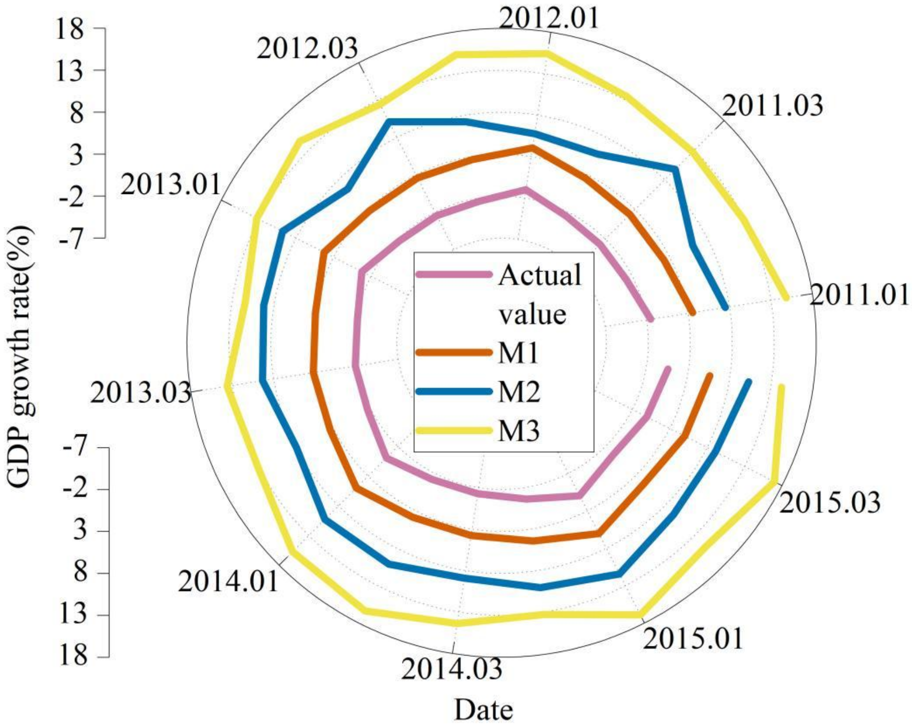

Figure 2. The predicted and actual values of GDP growth rates (2011-2015).

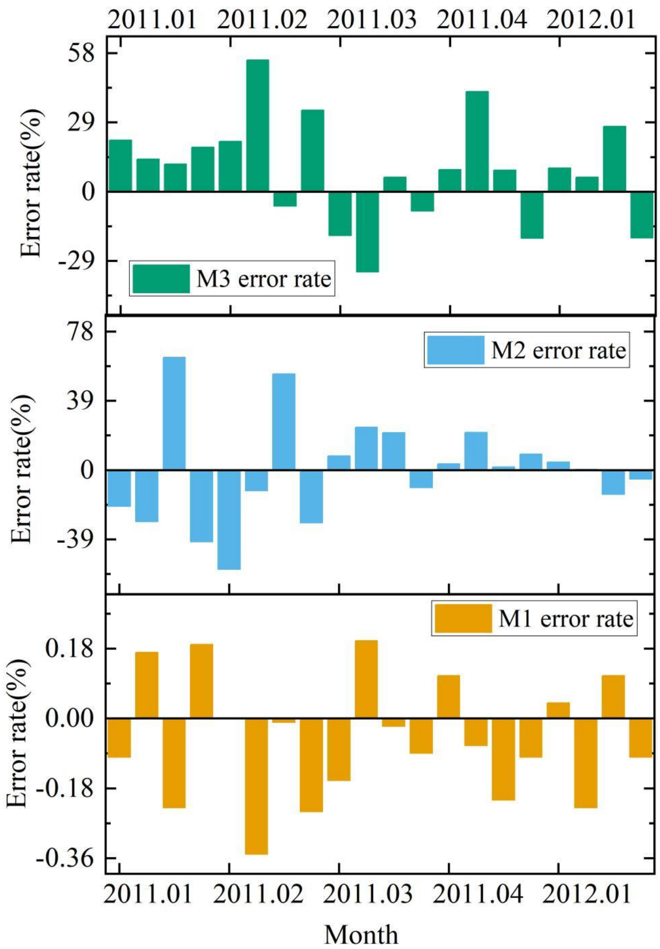

Figure 3. Model error rate performance.

4.2. Macroeconomic development forecasting models

4.2.1. Reliability and validity analysis of data

The main factors influencing macroeconomic development were selected from the five dimensions of (E1) number of employed population, (E2) investment in fixed assets, (E3) fiscal expenditure, (E4) national bank loans and (E5) investment in science, education and culture to form the scale of evaluation. The factor variables under different dimensions are as follows:

(1) (E1) Number of employed population: (E11) Structure of industry development, (E12) Prospects of industry development, and (E13) Thresholds of industry entry.

(2) (E2) Fixed Asset Investment. (E21) Marginal productivity of capital, (E22) Real interest rate, (E23) Tax policy, and (E24) Expected returns.

(3) (E3) Fiscal spending. (E31) political factors, (E32) tax policy, and (E33) the economic development cycle.

(4) (E4) National bank loans. (E41) Monetary policy, (E42) Financial regulatory policy, (E43) Bank operating objectives, and (E44) Bank capital adequacy.

(5) (E5) Science, education, and cultural inputs. (E51) industry characteristics and (E52) industry environment.

Doing reliability analysis on the data of the five initial variables of the study combed is shown in Table 3, and its five dimensional variables reliability validity number are > 0.800, the data reliability is good, and further expand the factor analysis.

Table 3. The reliability of each dimension and total amount.

	Reliability coefficient
E1	0.887
E2	0.841
E3	0.852
E4	0.896
E5	0.830
Total quantity table	0.906

The factor analysis of the five dimensions of (E1) the number of employed population, (E2) fixed asset investment, (E3) financial expenditure, (E4) national bank loans, and (E5) science, education and culture inputs is shown in Table 4, based on which the five dimensional factors are able to explain 68.94% of the content of the measurement. On the whole, the public factor structure of the scale is clear and has reliable reliability and validity.

Table 4. The main influencing factors of macroeconomic development.

Common factor	Project	Factor loading
E1	E11	0.6973
	E12	0.8296
	E13	0.6141
E2	E21	0.9759
	E22	0.7068
	E23	0.6244
	E24	0.7869
E3	E31	0.9905
	E32	0.8861
	E33	0.8241
E4	E41	0.6467
	E42	0.6465
	E43	0.8401
	E44	0.8417
E5	E51	0.8667
	E52	0.6909

4.2.2. Testing of model predictions

From the analysis in the previous section, it can be seen that (E1) the number of employed population, (E2) fixed asset investment, (E3) fiscal expenditure, (E4) national bank loans, and (E5) science, education, and culture inputs, totaling five factor variables, are the principal components of macroeconomic development. The BP neural network model for macroeconomic development prediction is constructed by using them as predictor variables. Using the principal component analysis (PCA) model and the logistic regression model, which are widely used in economic forecasting, the comparison of the root mean square error and the comparison of the average absolute error of the three models in the forecasting of the economic development of Region W from 2011 to 2015 are shown in Table 5 and Table 6, respectively. Regardless of the root mean square error or the average absolute error, the model in this paper is always stabilized below 0.001, showing extremely high prediction accuracy. The reason is that it is able to optimize the number of neurons contained in the hidden layer and the training period of the model to seek the path with better prediction effect, so as to output the performance of macroeconomic indicators with higher prediction accuracy.

Table 5. Comparison of root mean square errors of models.

Model	Textual	PCA	Logistic regression
E1	0.0054	0.0189	0.0234
E2	0.009	0.0199	0.0182
E3	0.0065	0.015	0.0166
E4	0.0057	0.0129	0.0185
E5	0.0061	0.0183	0.0153

Table 6. Comparison of the average absolute error of the model.

Model	Textual	PCA	Logistic regression
E1	0.0095	0.0177	0.0193
E2	0.0091	0.0164	0.0206
E3	0.0069	0.012	0.0249
E4	0.0012	0.0138	0.0244
E5	0.0024	0.0159	0.0209

5. Conclusion

In this paper, the macroeconomic development prediction model is constructed based on the BP neural network algorithm with the number of employed population, fixed asset investment, financial expenditure, national bank loans and scientific, educational and cultural inputs as the principal components of macroeconomic development. The BP neural network algorithm used shows excellent prediction performance in comparison with similar algorithms, and the prediction error rate is controlled within 0.36. The model also has a forecasting ability far beyond that of traditional forecasting models, with root mean square error and average absolute error <0.001.

The proposed macroeconomic development model utilizes the powerful network learning and function fitting capabilities of neural networks to accurately predict future development trends based on existing macroeconomic information. It assists industries and even regions in determining their overall future regulatory direction and facilitates the development of corresponding macroeconomic control instruments.

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