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Research Article

Research on Sustainable Development Indicator Prediction of Regional Economic Subsystem Based on Artificial Neural Network

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Sustainable development system is a "black box," or at least a "grey box," and it is not very clear whether there is a causal relationship between various factors. Artificial neural network can simulate the system realistically. In this paper, the artificial neural network BP model is used as a tool, and Matlab language is used to predict the indexes of regional sustainable development economic subsystem. Through data collection, network structure model design, program design, and network training, this study drew the indicator forecast chart, analyzes it, and finally puts forward suggestions. The results show that it is feasible to use an artificial neural network to simulate a sustainable economic subsystem.

1. Introduction

The regional sustainable development system is a nonlinear, complex, and open system. It is not clear what the influencing factors are, whether there is a causal relationship among the factors, which is the cause and which is the result, and whether there is both the cause and the result. It can be said that the sustainable development system is still a "black box" or at least a "grey box" [1]. The artificial neural network is characterized by nonlinear, fast, parallel distribution processing, self-learning, self-organization, self-adaptation, and robustness and can simulate real social and economic system realistically. Its structure can be considered as a mapping of the real system [2]. Through the construction of artificial neural network, it can be made to self-learn and "master" the operation parameters of the development process of an economic system in different periods and gradually become the mapping integration of system structure and function [3]. After the network test is passed, parameters of different economic development levels are input into the network, and the dynamic state of economic indexes can be obtained by monitoring the connection weights of each layer of the network and calculating the transfer function, and finally, the prediction results of economic subsystems can be obtained [4]. Therefore, this paper adopts the artificial neural network method to predict the sustainable development of regional economic subsystem, and the prediction is based on the development of indexes in the next few years. With the continuous development of artificial intelligence, not only the economy but also other fields have begun to emerge.

2. Indicator Selection and Data Collection

Sustainable development system involves not only subsystems of economic, social, and ecological environment but also time factors of contemporary and future generations, as well as the status, response, and pressure of the system [5]. However, so far, all indicators or indicator systems have been discussed separately from a certain lens [6].

For example, the D/S/R model of the United Nations Commission on Sustainable Development and the World Bank takes into account the economic, social, and environmental fields but lacks the characteristics of time. To fully and accurately reflect the connotation of sustainable development, the constructed indicators must comprehensively reflect the time, field, and impact [7, 8]. On the basis of analyzing the existing sustainable development indicators and indicator systems as well as their advantages and disadvantages, the author puts forward the following indicator system framework for multidimensional sustainable development evaluation, as shown in Figure 1.

According to this indicator system framework, a sustainable development indicator system composed of 42 indicators is constructed. Considering the data collectability, 29 indicators are used after removing the hard-to-collect ones.

The quality and quantity of data itself have a great influence on the prediction results. If conditions permit, more data should be obtained as much as possible [9]. In the process of data collection for sustainable development prediction, due to management and other reasons, data have different accuracy [10]. Therefore, under the condition that data meet a certain amount, the quality is crucial [11].

The collection of data should be well planned. It can proceed as follows:

(1) Conduct demand analysis; (2) develop data collection forms; (3) determination of data collection methods; (4) data collection.

In the process of data collection, due to the influence of various factors, data loss may occur, resulting in incomplete or discontinuous data and affecting data analysis [12]. Therefore, these situations should be understood so that the analysis results can be modified or used as the basis for the study of assessment methods [13]. In addition, in order to avoid human error in data collection, training should be given to data collection personnel [14].

According to the above steps, 29 indicators were collected for an area for 18 years of data from 1981 to 1998, which served as the basis for prediction. The work of collecting data is a very important part, so the time data we choose are generated according to various surveys.

3. Network Construction

A regional sustainable development system is nonlinear, and the BP network model is selected when considering model construction [15, 16]. The network is a kind of multilayer feedforward neural network in which the transformation function of neurons is an S-type function and the input quantity is a continuous quantity between 0 and 1. It can realize any nonlinear mapping from input to output [17]. After the structure of BP network is determined, the input and output sample set is used to train it, and the network is allowed to learn and adjust its weights and fields so as to realize the given input-output mapping [18]. A trained BP network can also provide the appropriate output for sample uncentralized input [19].

3.1. Network Structure Model Design. In Figure 2, the network structure model is a BP network structure composed of 29 inputs, 29 outputs, and 2 hidden layers. Hidden layer 1 has 4 nodes, and hidden layer 2 has 3 nodes.

Other parameters of the network structure model are as follows:

Network Name: Sustainable artificial neural network.

Number of Layers: 4

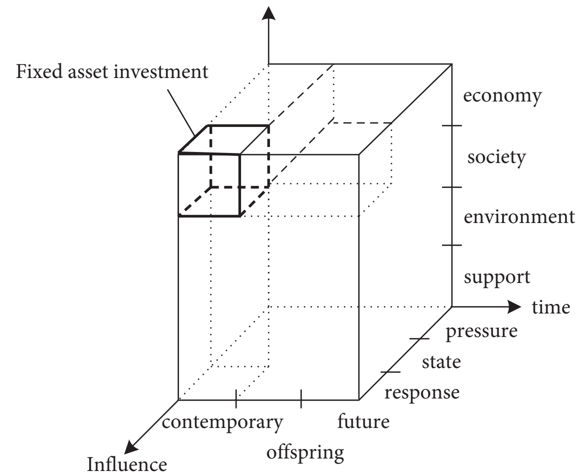

Figure 1: Indicator system framework of regional sustainable development.

Input Layer:

Nodes: 29

Transfer Function: Lingear Hidden Layer 1:

Nodes: 4

Transfer Function: Sigmoid Hidden Layer 2:

Nodes: 3

Transfer Function: Sigmoid Output Layer:

Nodes: 29

Transfer Function: Sigmoid Connections:

FULL

3.2. Program Design. In this study, an artificial neural network toolbox in Matlab language was used as a tool to predict sustainable development [20, 21]. The following programs have been prepared:

net, 30 net = newff ([6 400000 3 000; 20 1 000; −5 30; 0 20; 600 2 000; 1 3; 0 5 000; 10 300; 10 200; 1 600; 10 30; 400 10 000; 20 600; 0 150; 400 600; 0 12; 1 30; 3 20; 60 300; 0 5; 0 10; 100 1 000; 1 60; 0 10; 1 20; 50 100; 20.

500; 1 1 20], [29, 29], <”tansig,” “purelin”}, “traincgb”);

Net. trainParam. show = 40.

Net. trainParam. lr = 0.05.

Net. trainParam. Ir _ inc - = 1.05.

Net. trainParam. mc = 0.9.

Net. trainParam. epochs = 10 000.

Net. trainParam. goal = le − 3.

p = [6.50 1 186 29.53 1 5.010 7.41 6341.07 67.47 25.11 12.08 0 20.00 419.024.00 7 496.0 6.34 5.04 4.86 64.82 4.328.21 146.23 2.75 1.45].

t = [6.39 1 266 31.99 2.120 7.09 680 1.18 79.70 23.47 13.86 1.96 18.90.

[pn, minp, maxp, tn, mint, maxt] = premn-mx(p, t).

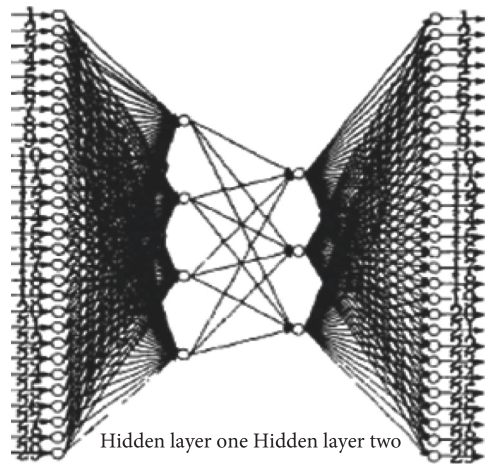

Figure 2: BP network structure model.

net = train (net, pn, tn).

an = sim (net, -pn).

a = postmnmx(an, mint, maxt).

bn = sim(net, an).

b = postmnmx(bn, mint, maxt).

3.3. Training process. In the indicator prediction curve, the curve from 1981 to 1998 was drawn by using the actual data collected, and the curve from 1999 to 2002 was predicted by an artificial neural network.

The training process of the artificial neural network is as follows: first, the data of 29 indicators from 1980 to 1997 are used as the input of the network, and the data of 29 indicators from 1981 to 1998 are used as the output of the network to form a training set to train the network, so that the error of the network can reach a satisfactory degree, and the trained network is used for prediction.

The process of prediction with an artificial neural network is as follows: the data from 1981 to 1998 are used as the input of the network to predict the output of each indicator from 1982 to 1999. Then, the newly obtained data from 1982 to 1999 are used as the input of the network to predict the output of each indicator from 1983 to 2000. Then, the newly obtained data from 1983 to 2000 are used as the input of the network to predict the output of each indicator from 1984 to 2001. Thus, we obtained the predicted values for the years 1999–2002.

It can be seen from the prediction curve of each indicator that a group of training sets are used to train the network first, and then, the trained network is used to predict. The artificial network prediction method has very high accuracy, and the front part of the curve almost overlaps. (Table 1)

3.4. Results after Training

3.4.1. Examples of Network Statistics

Network Name: Sustainable artificial neural network

Iterations: 70 000

Table 1: Training data.

Node	Std dev	Bias	Max error	Correlation
1	9.76747	−0.02422	25.00479	0.99629
2	831.42120	−28.97698	2609.41211	0.99431
3	11.37707	−0.63371	23.03641	0.99932
4	4.08579	−0.16283	9.03857	0.87419
5	0.64729	0.04561	1.63340	0.96011
6	231.28082	−13.68900	607.84570	0.99920
7	0.04034	−0.00055	0.07521	0.99327
8	64.8439	−4.43478	124.14110	0.99880

3.4.2. The Relationship between Training Times and Mean Square Error and Correlation Coefficient. Figure 3 shows the relationship between training times and mean square deviation: with training, mean square deviation gradually decreased. When the training times reached 7,000, the mean square deviation was close to 0.055. Figure 4 shows the relationship between the number of training times and the correlation coefficient: with the increase in training times, the correlation coefficient gradually approached 1. When the training times reached 7,000, the correlation coefficient was close to 0.98. Therefore, the network design is reasonable.

3.4.3. Weights after Training. Examples of weights after training are given in (Table 2).

4. Indicator Prediction

Figures 5–10 are the prediction charts of some indicators. It can be seen from the figure that when an artificial neural network is used to predict regional sustainable development, it has high accuracy, and the front part of the curve almost overlaps. The analysis is given in Figure 5.

Figure 5 Prediction chart of fixed asset investment in the whole society:

Since 1981, the fixed asset investment in the whole society has been on the rise, especially from 1991 to 1995, during the Eighth Five-Year Plan period, when the annual growth rate reached 46.3%. During the Ninth Five-Year Plan period, the growth rate declined. The main reason is that the super-fast development of fixed assets during the eighth Five-Year Plan period enlarged the total base and made it more difficult to continue the rapid development. On the other hand, the buyer's market was formed, and the overproduction of many commodities, including real estate, stalled key aspects underpinning fixed-asset investment growth, such as real estate development. It is expected that fixed-asset investment will fall temporarily after 2001 and then gradually rise again.

Figure 6 Prediction chart of labor productivity of the whole society:

Since 1981, the labor productivity of the whole society has been on the rise, and especially after 1992, it raises rate very fast, and it is expected to reach the peak in 2001 and then show a downward trend.

Figure 7 Forecast of GDP:

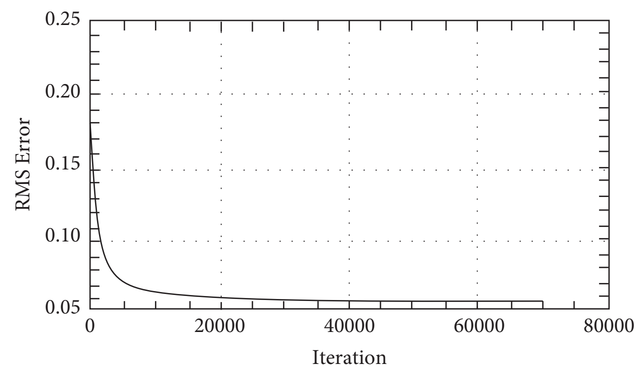

Figure 3: Relationship between training times and mean square error.

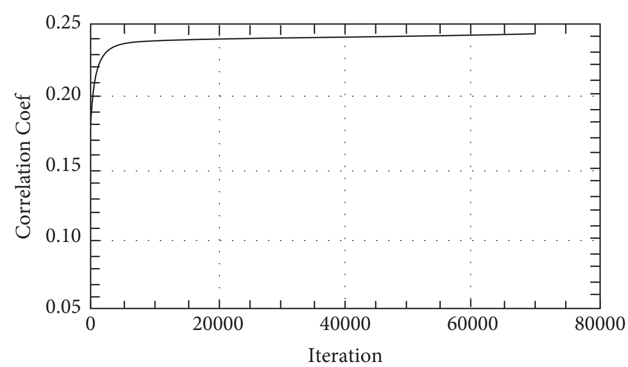

Figure 4: Relationship between training times and correlation coefficient.

Table 2: Training weight comparison table.

Layer	Node	Connection	Weight	Weight delta
2	1	1	−0.91807	−0.000002
2	1	2	−0.78684	0.000001
2	2	1	−1.75736	−0.000008
2	2	2	−1.47432	−0.000002
2	3	1	1.23080	0.000058
2	3	2	−0.67901	−0.000001
2	4	1	−1.29172	0.000003
2	4	2	−1.24301	−0.000010

Gross domestic product is the core index of the national economy. From the perspective of the economic track since the reform and opening up, GDP in China has been continuously growing at a high speed. Between 1981 and 1998, GDP increased by 17%, of which 9% during the Seventh Five-Year Plan period (1986–1990), 21% during the Eighth Five-Year Plan period (1991–1995), and 12% during the Ninth Five-Year Plan period. It is expected that the growth rate will not be so high during the Tenth Five-Year Plan period, but it will still keep increasing momentum.

Figure 8 Forecast chart of the inflation rate.

The inflation rate showed contemporaneous change, and the peak appeared in 1985, 1988, and 1993, respectively. After 1998, it showed a stable situation and is not expected to significantly rise and fall.

Figure 9 Energy consumption forecast of per capita GDP.

The energy consumption of per capita GDP shows a continuous downward trend, indicating that energy conservation has been noticed in production.

Figure 10 Proportion forecast of the tertiary industry:

From the running track of the proportion of the tertiary industry in GDP, it can be divided into two stages: the first stage was before 1990 when the tertiary industry developed relatively slowly, and the structural changes were not obvious. At that time, people's consumption demand was

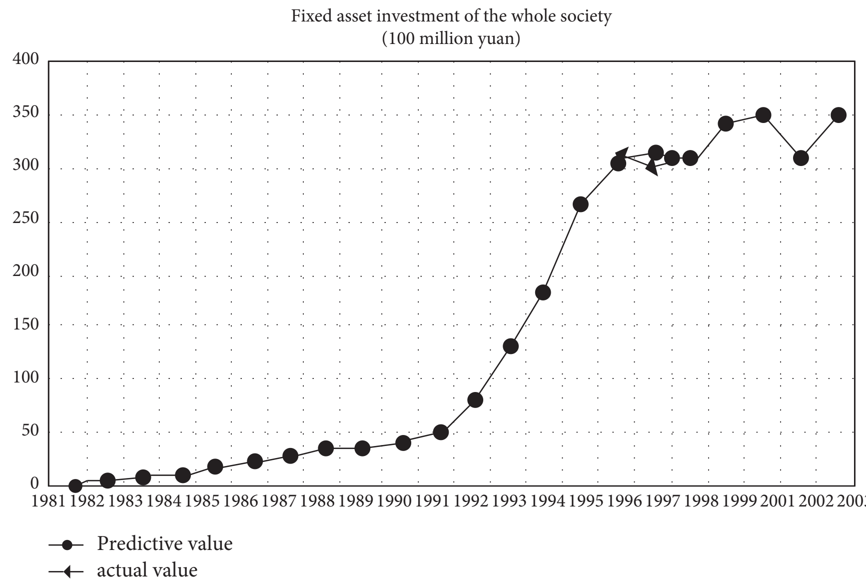

Figure 5: Forecast of fixed asset investment of the whole society.

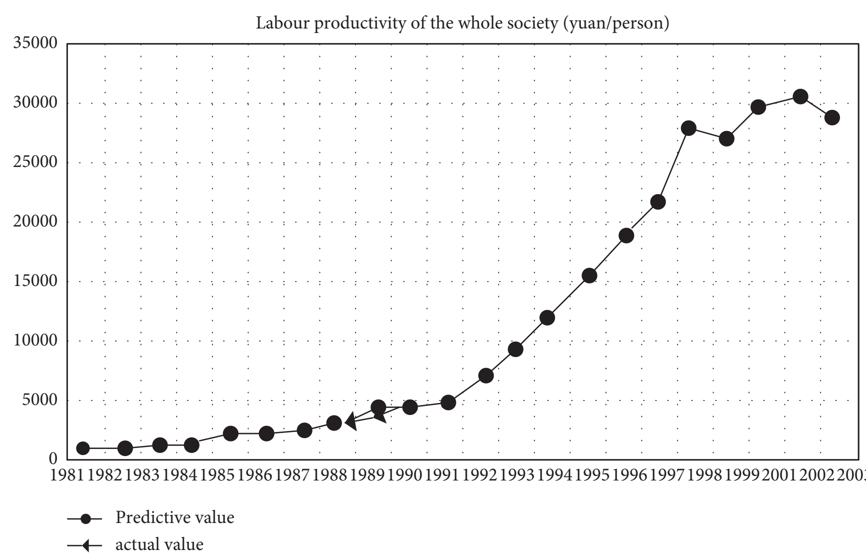

Figure 6: Forecast chart of labor productivity of the whole society.

generally low, mainly concentrated in general industrial consumer goods. Relatively speaking, the tertiary industry was in a state of spontaneous development, and people's attention was not enough. In this stage, the proportion of tertiary industry in GDP rose from 19.6% in 1981 to 20.7% in 1990, a rise of only 1.1% in 10 years. In the second stage, the tertiary industry structure changed significantly after 1991. Especially in 1992, the State Council issued the Decision on Accelerating the Development of the Tertiary Industry, which further promoted the development momentum of the

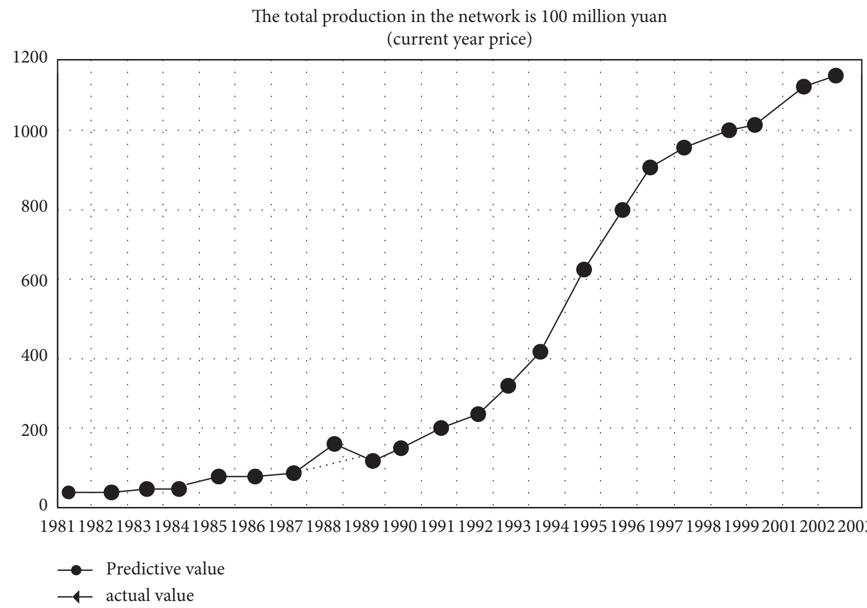

Figure 7: Forecast of GDP.

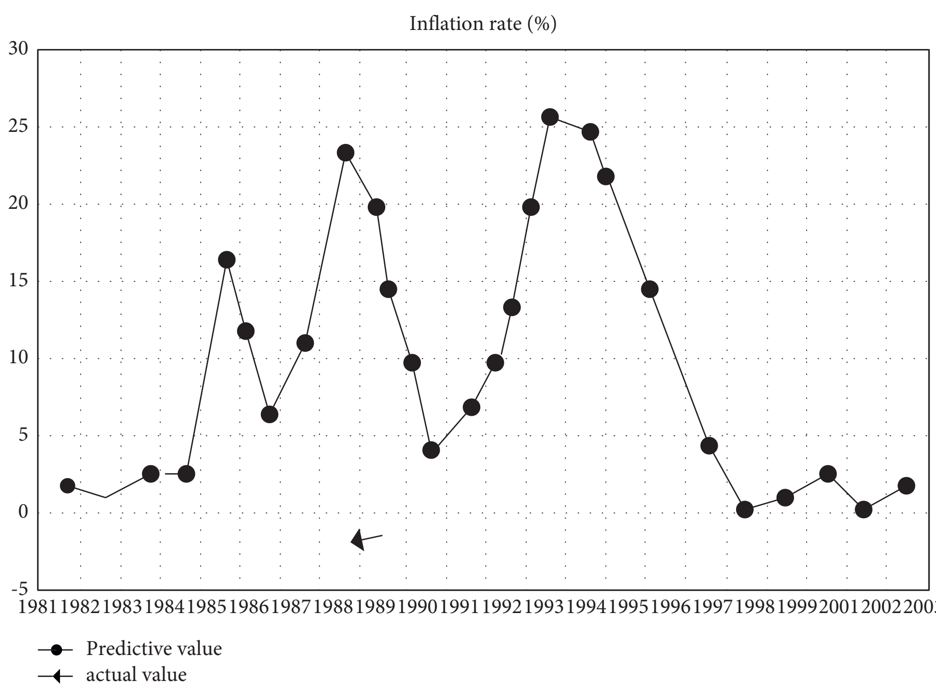

Figure 8: Forecast of the inflation rate.

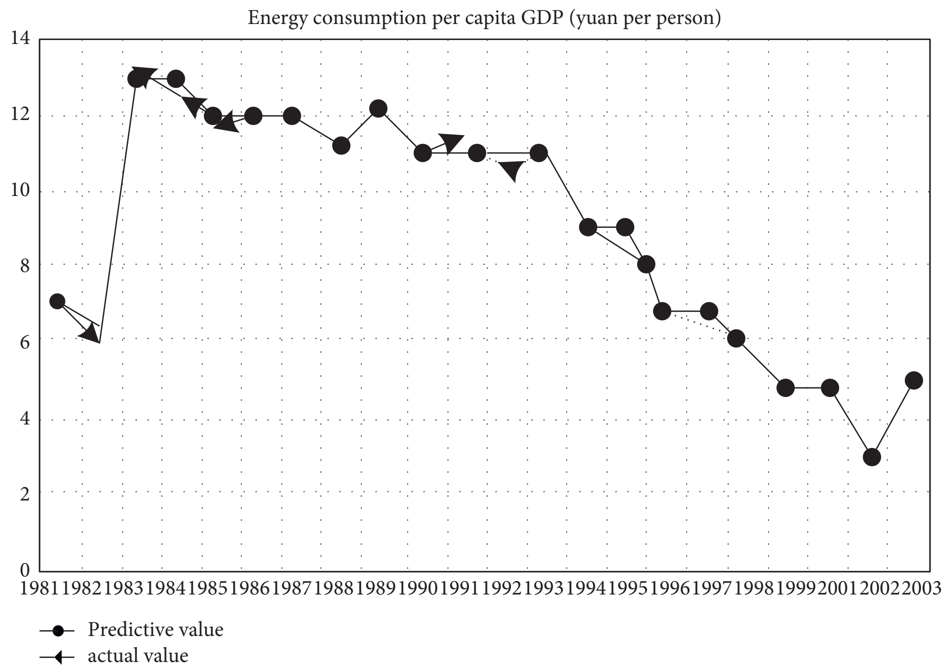

Figure 9: Energy consumption forecast of per capita GDP.

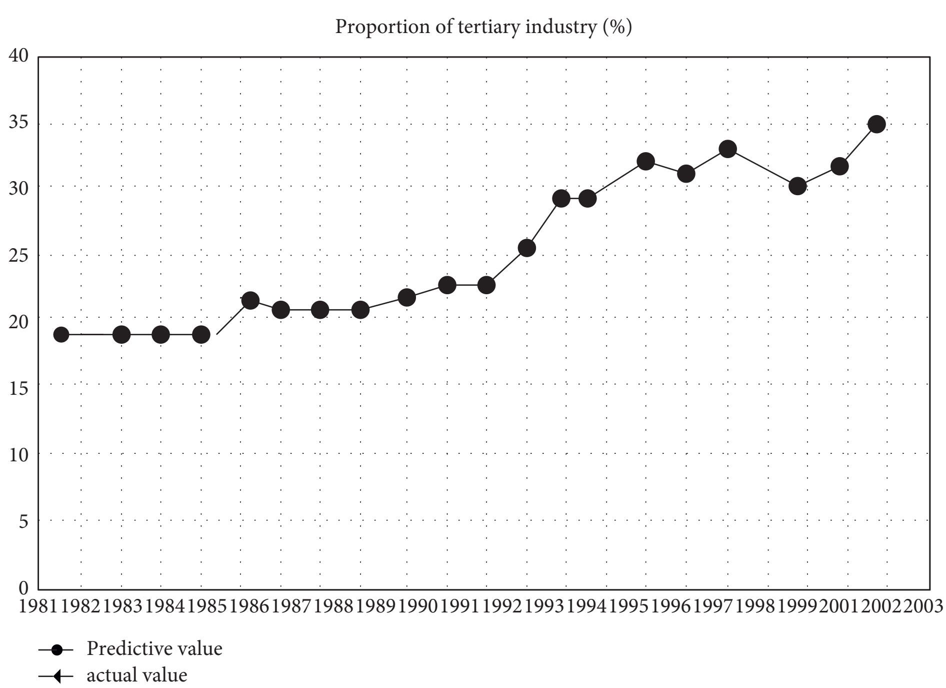

Figure 10: Proportion forecast of tertiary industry.

tertiary industry. The proportion of the tertiary industry in GDP rose from 20.7% in 1990 to 33% in 1998, an increase of 12.3%.

5. Conclusion

Based on the forecast results, we propose the following suggestions:(1) actively deepening the reform, accelerate the construction of housing for ordinary residents, constantly meet the people's growing housing demand, and strive to cultivate the real estate industry into a new economic growth point; (2) accelerating the industrialization, socialization, and marketization of urban public facility services, community services, comprehensive agricultural services, and cultural industries; (3) focusing on developing trade and circulation industry, transportation industry, information service industry, tourism, finance, and insurance industry, and increasing the proportion of tertiary industry in GDP. Using artificial intelligence, machine learning methods to forecast the economy will become more and more important.

Data Availability

The datasets used and/or analyzed during the current study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare no conflicts of interest.

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