Article

Prediction of Enterprise Free Cash Flow Based on a Backpropagation Neural Network Model of the Improved Genetic Algorithm

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Abstract: Enterprises with good long-term free cash flow data often have better prospects than enterprises with good net profit but unstable free cash flow for a long time, and free cash flow prediction is an important part of evaluating the enterprise value of an enterprise. By determining the fitness function, algorithm formula, population, and Backpropagation (BP) neural network design, a BP neural network model based on the improved genetic algorithm is proposed to predict the free cash flow of enterprises. Taking the free cash flow data of G Company from 1 January 2019 to 30 June 2019 as an example, after evaluating the most neurons and the best population, analyzing the relative errors and comparing the average relative errors of different prediction models, the results show that the model has better prediction accuracy. Cash flow forecasting can effectively improve decision making on productions and operations and the investment financing of enterprises, and has important practical significance for studying enterprise fund management.

Keywords: BP neural network; enterprise economy; free cash flow; improved genetic algorithm; prediction

1. Introduction

As an important indicator to measure the future sustainable management ability of enterprises, enterprise value can provide important decision-making information for stakeholders and help to identify enterprises with good prospects [1–7]. At present, enterprise valuation methods mainly include the income method, cost method, and market method, among which the free cash flow discount method is the most widely used [8]. Free cash flow is the remaining cash flow after meeting the needs of business activities and reinvestment, and is the discretionary cash obtained by enterprises [9–12]. The discounted free cash flow method is used to evaluate enterprise value, which includes three steps: predicting the performance and free cash flow, estimating the discount rate, and estimating the continuous value. When forecasting free cash flow, choosing a scientific and reasonable method is an important prerequisite for accurately evaluating enterprise value [13–20].

In past research, the time series forecasting method has been the main method used to forecast free cash flow, including the grey model [21], Markov model [22], neural network [23], BP neural network [24], and so on, but each method has its own applicable conditions and limitations. Luo et al. [21] used the improved grey prediction method as an absolute valuation model to estimate cash flow. Yao et al. [22] provided a general model to investigate stochastic cash flows in both wealth and liability dynamic processes using Markov chain. Rowland et al. [23] presented a methodology based on neural networks that takes into consideration seasonal fluctuations when equalizing time series, using the Czech crown and Chinese yuan as examples. Li et al. [24] proposed a method for predicting using a BP neural network. In addition, there are several other models [25–30]. Jennergren [25]

focused on continuing value with the discounted cash flow model. Décamps et al. [26] developed a dynamic model of a firm facing agency costs of free cash flow. Tabei et al. [27] proposed a new method for forecasting projected cash flow under a fuzzy environment. Weytjens et al. [28] predicted accounts receivable cash flows by employing methods applicable to companies with many customers and transactions. Hsu [29] attempted to innovate by deploying a model of time series prediction for e-commerce cash flow service customers. Wang and Ning [30] proposed a hybrid learning algorithm based on the adaptive population activity particle swarm optimization algorithm combined with the least squares method to optimize the adaptive network-based fuzzy inference system model parameters.

In terms of the prediction effect, because a BP neural network is a multilayer feedforward neural network trained according to the error backpropagation algorithm, it can effectively overcome the shortcomings of a Markov model with few parameters and few prediction levels. Compared with the trend extrapolation method, a BP neural network has a wider application range, and better data prediction and fitting ability, especially in complex conditions such as nonstationary data and a nonlinear environment. However, the shortcomings are a long learning time, long convergence time, and it being easier to find a local optimal solution rather than a global optimal solution. The genetic algorithm can optimize the weights and thresholds of a neural network through computer simulation, reduce the convergence time of a neural network, and obtain better optimization results quickly.

Based on this, this paper puts forward a BP neural network prediction model based on the improved genetic algorithm, and takes the actual data of G Company from 1 January 2019 to 30 June 2019 as an example to test the effect of the model in predicting free cash flow, compare the relative error between the predicted value and the actual value, and compare the average relative error of different prediction models.

The research problem in this paper is to propose a prediction model for the free cash flow of enterprises. On this basis, we evaluate whether the proposed model is applicable to predict the free cash flow of enterprises, and whether it is superior after comparing it with the grey model, Markov model, and BP neural network model. The research objective of this paper is to propose a prediction model that has good applicability and superiority in predicting enterprise free cash flow. The prediction of enterprise free cash flow based on our proposed model has good guiding significance for enterprise value evaluation, and can provide a reference basis for enterprise stakeholders in enterprise value management and investment management.

The rest of the paper is organized as follows. We propose a predicting model for enterprise free cash flow in Section 2. Section 3 presents the experimental results and Section 4 concludes the paper.

2. Model

BP neural network has better data prediction and fitting ability in prediction, and has better training and learning ability in a nonlinear environment, but its learning time is longer, the convergence time is longer, and it is easier to find local optimal solution instead of a global optimal solution. The genetic algorithm can optimize the weights and thresholds of neural networks and reduce the convergence time of neural networks. Therefore, this paper puts forward a neural network prediction model based on the improved genetic algorithm to predict the cash flow of high-tech listed companies.

2.1. Fitness Function

In the process of obtaining the optimal initial weights of neural network by the genetic algorithm, the fitness value of the selected individuals should be larger and larger, so that the global optimization ability of the genetic algorithm is enhanced and the optimization speed will be accelerated. At the same time, it is necessary to ensure that the fitness value of individuals increases when the learning error of fitness function decreases. The formula

for calculating the learning error of each individual is Equation (1), and each E_i is shown in Equation (2):

$$E = \sum_{i=1}^{n} E_i \tag{1}$$

$$E_i = \sum_{s=1}^{m} \left(y_s^i - x_s^i \right)^2. \tag{2}$$

In Equation (2), y_s^i and x_s^i are the predicted output value and actual output value of the s output obtained by training the i-th sample, n is the total number of samples, m is the number of output neurons of the whole neural network, and the square should ensure that the denominator of fitness function should not be 0, so as not to fall into a local optimal solution when optimizing weights by the genetic algorithm. The fitness function is shown in Equation (3):

$$F = 1/E. \tag{3}$$

This can ensure that, the smaller the training error, the larger the fitness function calculated, which is more in line with the actual situation.

The improvement of the crossover and mutation probability formula of the genetic algorithm is as follows:

Before the global optimization of the genetic algorithm, the model should ensure the diversity of the initial population. With the increase in genetic iteration times, the crossover probability of population should change along the decreasing direction, while the mutation probability should change along the increasing direction, which not only ensures the diversity of the population, but can also lead quickly to optimization.

If the population crossover probability is large, individuals with high fitness will be destroyed by crossover operations. If the probability of population variation is too small, the probability of new individuals will decrease. However, the crossover probability should not be too small, and the mutation probability should not be too large. Therefore, it is necessary to use the difference between the highest fitness value and the average fitness value of each generation. When the difference is too small, it shows that the diversity within the population is very small, the fitness is similar, and it is easy to cause local convergence, so it is necessary to improve the population variation probability and reduce the crossover probability. When the difference is too large, it shows that there is great diversity in the population, so it is necessary to reduce the probability of population variation and improve the probability of crossover.

The model needs to design an adaptive crossover probability formula and an adaptive mutation probability formula, which are shown in Equations (4) and (5):

$$P = \frac{1}{\varepsilon + e^{-k_1 \cdot \Delta F}} \tag{4}$$

$$P = 1 - \frac{1}{\epsilon + e^{-k_2 \cdot \Delta F}}. \tag{5}$$

In Equations (4) and (5), k_1 and k_2 are positive numbers, indicating the rate of crossover operation and mutation operation. Initial $k_1 = 1$, initial $k_2 = 1$, $\varepsilon = 1$, $\epsilon = 1$, ΔF represents the difference between the highest fitness value and the average fitness value of each generation, which can be used to control the change speed of cross-mutation probability.

$$\Delta F = F_{max} - F_{avrg} \tag{6}$$

By adjusting the adaptive function and the adaptive crossover and mutation probability formula in Equation (6), the global optimization ability of genetic algorithm can be more effective.

2.2. Design of BP Neural Network

A BP neural network mainly includes three layers: the input layer, middle layer, and output layer. In this paper, the previous 5/10/15/20/25 groups of historical cash flow data

are used as the input of the model, and the current data are used as the output of the model. Therefore, the number of input layers of BP neural network is 5/10/15/20/25, and the number of output layers is 1 for training. During training, the previous 5/10/15/20/25 consecutive vectors are selected as input vectors, and the next one is the target output vector.

The number of neurons in the middle layer of neural network has a great influence on the prediction results of the model. If the number of hidden layers is too large, the model will become complex, the training time will become longer, and the number of hidden layers is too small, which is easy to fit and has no good prediction effect.

The population in the genetic algorithm also has a great influence on the final optimization results. If the population is too small, the whole model will easily fall into the local optimal solution, while if the population is too large, the learning and training time of the model will be too long, and the convergence speed will slow down.

2.3. Implementation Steps of the Model

The implementation steps of the neural network prediction model based on genetic algorithm are mainly divided into two modules, the genetic algorithm part and the BP neural network part. The specific process is shown in Figure 1, and the specific implementation steps are as follows.
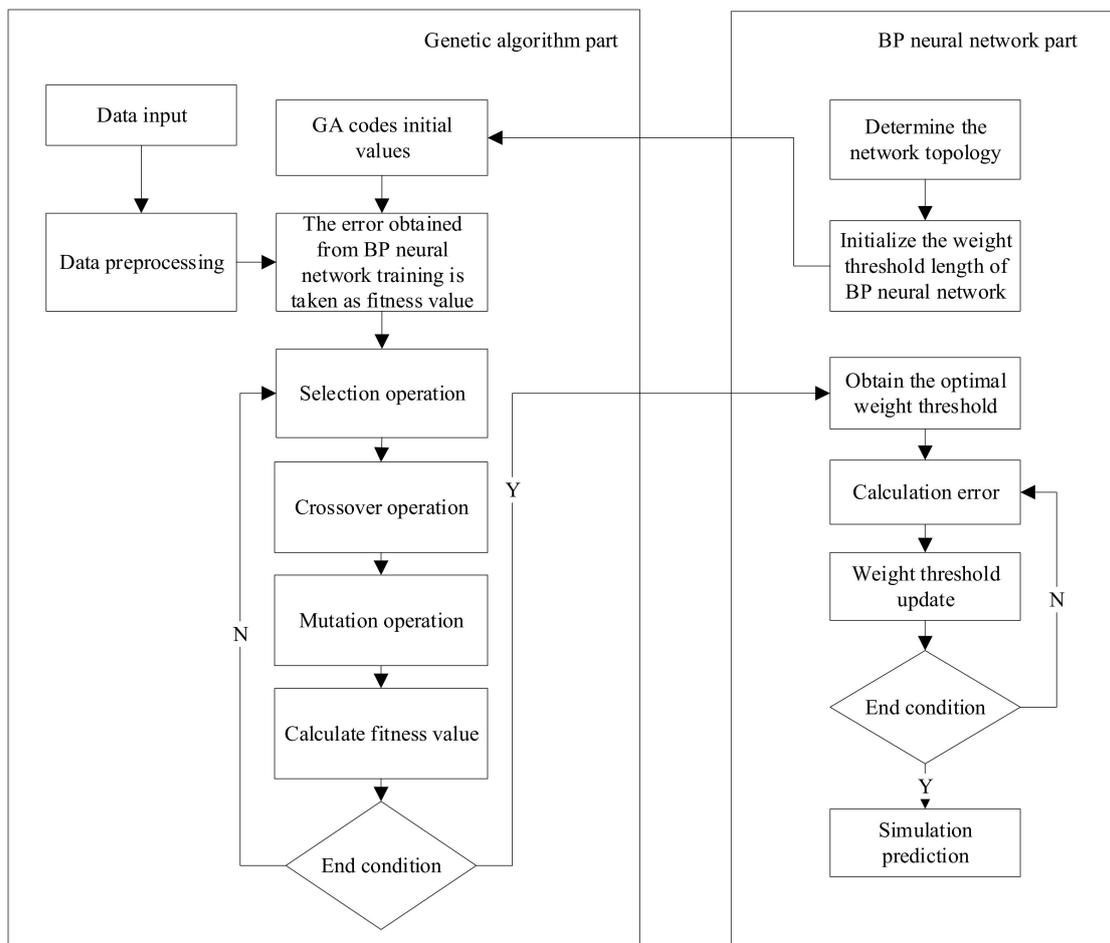
Figure 1. Neural network prediction flowchart based on the improved genetic algorithm.

Step 1: Using the binary coding method, the initial weights and the threshold values of hidden layer and output layer of neural network are coded. Because the optimal number of cells in the hidden layer of neural network can be obtained experimentally, the code includes the weights and thresholds of the network and the binary serial code of the number of cells in the hidden layer of neural network.

Step 2: After the encoding mode and the composition of the binary code are determined, the system randomly generates the initial population, and the initial population number can use the best population obtained from the experiment.

Step 3: According to the definition of fitness function, first calculate the fitness value according to Equation (3). Judge whether the fitness value meets the end condition of genetic algorithm. If so, go to Step 5; if not satisfied, continue the steps in order.

Step 4: Carry out a round of selection operation and cross-mutation operation according to the rules of roulette. The probability of each round is calculated according to the cross-mutation formula. Go back to Step 3.

Step 5: At this time, the optimal initial weights of the BP neural network are obtained, and the forward propagation learning mechanism and error back propagation mechanism of BP neural network are started. The cash flow dataset is divided into three parts: a training set, a verification set, and a test set. The training set and the verification set are used to update the weights and thresholds of the cells in the network until the end condition of updating is met.

Step 6: The best model for prediction is obtained at this time. The test set is used to calculate the prediction error of the model and evaluate the prediction ability of the model.

Step 7: Choose the adaptive function and the adaptive crossover mutation formula, and repeat the above steps. The experimental prediction errors are compared, and the performance of the adaptive genetic algorithm neural network model is observed.

3. Experiments

3.1. Experimental Setup

Supervised machine learning models generally divide the data into three sets when training learning data: a training set, a verification set, and a test set.

Training set: As the data of initial training and learning of the model, the training set needs to set specific initial parameters to establish the model and train the model.

Verification set: Use the model trained by training set to predict the verification set, select the best model weight parameters, adjust the weight parameters and threshold parameters of genetic algorithm neural network, and get the best model.

Test suite: The test suite does not participate in the establishment and selection of models. After validating the optimal model, the test set is used to evaluate the performance of the model and test the generalization ability of the model.

The choice of experimental data has a great influence on the prediction accuracy of the whole prediction model, so the cash flow of a high-tech listed company from 1 January 2019 to 30 June 2019 is used as the test data.

We used the historical cash flow data of the previous 5/10/15/20/25 days as the input of the neural network for training and learning. The previous 5/10/15/20/25 groups of cash flow data were selected as the input, and the current cash flow data were used as the expected value of the model output, so as to build a neural network model based on genetic algorithm. After the training, we input the historical cash flow data of the previous 5/10/15/20/25 days, and compared the simulated cash flow data of the 6/11/16/21/26 days with the real data.

The fitness function selected the objective function of the Matlab package and improved fitness function, and the iteration time was set to 150. The selection operation used roulette, and the crossover probability and mutation probability were as shown in Table 1.

The BP neural network in this paper used the method of momentum gradient descent as the training network. The training function was the Traindm function in Matlab. The activation function, learning rate, training target error, and training times were as shown in Table 2. The input layer of the neural network was 5 neurons, the output layer was 1 neuron, and the hidden layer was 15 neurons. The initial weights and thresholds were the system defaults.

Table 1. Parameters of genetic algorithm.

Initial Parameters of Genetic Algorithm	Value
Population size	30
Number of iterations	150
Crossing probability	0.9
Crossing probability	0.1
Select operation	Roulette
Fitness function	Matlab's own function

Table 2. Parameters of neural network.

Initial Parameters of Neural Network	Value
Number of input layers	5
Number of hidden layers	15
Number of output layers	1
Target error	1×10^{-6}
Training times	10,000
Learning rate	0.01
Training function	Traindm function
Training method	Momentum gradient descent
Activation function	Sigmoid function
Network weights and thresholds	Optimal weights obtained by genetic algorithm

3.2. Experimental Results

In this subsection, we perform three groups of experiments, which are evaluations of optimal neuron number and optimal population, relative error evaluations, and comparative evaluations.

In the first groups of experiments, we performed evaluations of optimal neuron number and optimal population. For the neural network model based on the improved genetic algorithm, it is necessary to determine some fixed parameters to forecast the cash flow data. For the genetic algorithm, we needed to determine the initial population, and for the neural network, we needed to determine the number of hidden layer units. In order to study the influence of the number of neurons and the n chromosome population in the hidden layer of neural network with the best cash flow data on the model optimization results, the number of neurons in the hidden layer of neural network and the number of chromosome population, respectively, were as shown in Table 3 to predict the historical data of cash flow.

Table 3. The errors of selecting different parameters.

Number of Hidden Layer Units	Population	Test Error
5	10	0.136
5	20	0.115
5	30	0.128
5	40	0.125
5	50	0.115
10	10	0.123
10	20	0.115
10	30	0.148
10	40	0.135
10	50	0.131
15	10	0.124
15	20	0.122
15	30	0.105

Table 3. *Cont.*

Number of Hidden Layer Units	Population	Test Error
15	40	0.116
15	50	0.112
20	10	0.135
20	20	0.131
20	30	0.115
20	40	0.108
20	50	0.107
25	10	0.131
25	20	0.125
25	30	0.141
25	40	0.121
25	50	0.111

As shown in Figure 2, the historical cash flow data of the previous 5/10/15/20/25 days were selected as the training test data, and the figure shows the error diagram of the test results. In the neural network model based on the genetic algorithm, the number of hidden layer units and population of the neural network were changed, and the difference between the actual output and the expected output of the test set was observed. The difference between each combination is not large, which shows that the genetic algorithm has a strong global optimization ability and good performance.
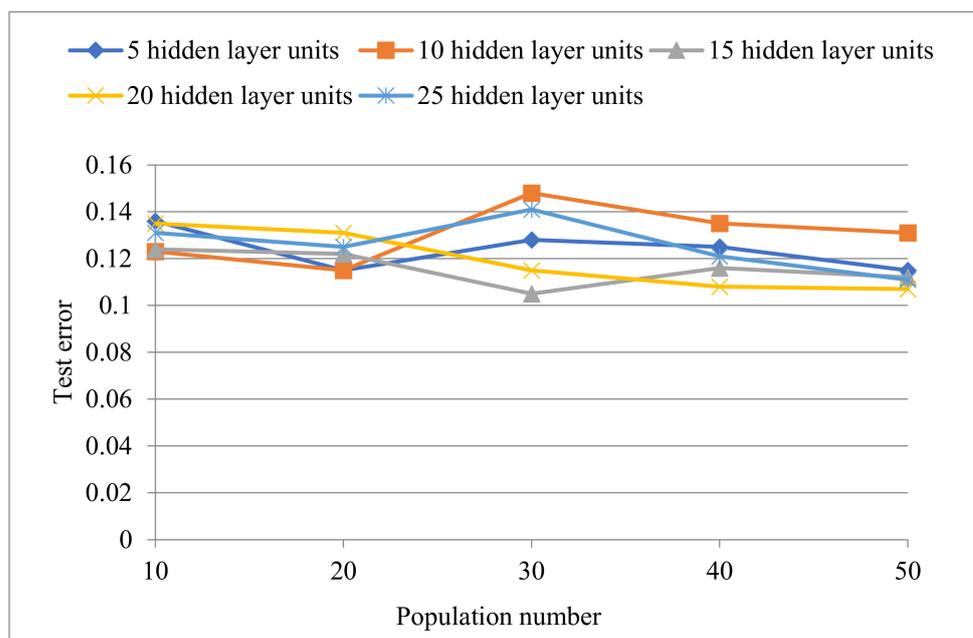
Figure 2. Test error of different populations.

As a result, for the historical cash flow data of the previous 5/10/15/20/25 days, when the population is 30 and the number of hidden neurons is 15, the error of the model is the smallest and the prediction ability of the model is the best.

In the second group of experiments, we performed relative error evaluations. Taking the free cash flow data of G Company from 1 January 2019 to 30 June 2019 as the test data, the relative error was evaluated by using the proposed prediction model, as shown in Table 4 and Figures 3–8. Among them, relative error refers to the ratio of the absolute value of the difference between the predicted value and the actual value of the day to the actual value of the day.

Table 4. Relative errors (RE) of cash flow forecast of G company from 1 January 2019 to 30 June 2019.

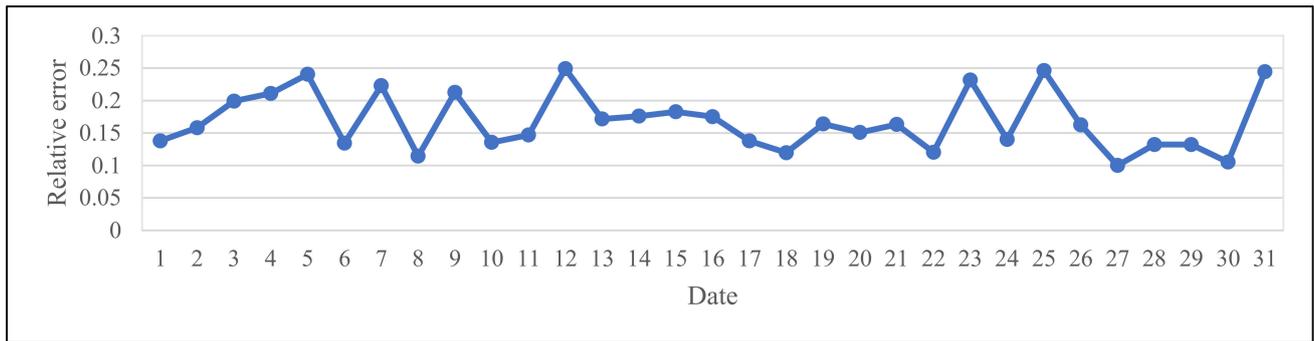| Date	January 1	January 2	January 3	January 4	January 5	January 6	January 7	January 8	January 9
RE	0.1379	0.1582	0.1992	0.2110	0.2405	0.1343	0.2230	0.1143	0.2127
Date	January 10	January 11	January 12	January 13	January 14	January 15	January 16	January 17	January 18
RE	0.1356	0.1470	0.2492	0.1716	0.1761	0.1828	0.1752	0.1378	0.1197
Date	January 19	January 20	January 21	January 22	January 23	January 24	January 25	January 26	January 27
RE	0.1640	0.1509	0.1633	0.1204	0.2318	0.1401	0.2462	0.1625	0.1002
Date	January 28	January 29	January 30	January 31	February 1	February 2	February 3	February 4	February 5
RE	0.1323	0.1323	0.1052	0.2446	0.1454	0.2088	0.2132	0.2296	0.1967
Date	February 6	February 7	February 8	February 9	February 10	February 11	February 12	February 13	February 14
RE	0.1679	0.1655	0.1967	0.2476	0.2245	0.1251	0.1558	0.1056	0.1241
Date	February 15	February 16	February 17	February 18	February 19	February 20	February 21	February 22	February 23
RE	0.1669	0.1694	0.2203	0.1159	0.1177	0.1735	0.1280	0.2063	0.2082
Date	February 24	February 25	February 26	February 27	February 28	March 1	March 2	March 3	March 4
RE	0.2167	0.1570	0.2375	0.1786	0.1693	0.2404	0.1885	0.1098	0.1540
Date	March 5	March 6	March 7	March 8	March 9	March 10	March 11	March 12	March 13
RE	0.1379	0.2483	0.2279	0.1451	0.1854	0.1861	0.1302	0.1458	0.1623
Date	March 14	March 15	March 16	March 17	March 18	March 19	March 20	March 21	March 22
RE	0.1779	0.1740	0.2217	0.2495	0.1287	0.1199	0.2494	0.1178	0.2070
Date	March 23	March 24	March 25	March 26	March 27	March 28	March 29	March 30	March 31
RE	0.1601	0.1847	0.1814	0.1549	0.1772	0.1690	0.1764	0.1974	0.1565
Date	April 1	April 2	April 3	April 4	April 5	April 6	April 7	April 8	April 9
RE	0.1091	0.1625	0.2142	0.1470	0.1734	0.2114	0.2333	0.1289	0.1097
Date	April 10	April 11	April 12	April 13	April 14	April 15	April 16	April 17	April 18
RE	0.2262	0.2290	0.2027	0.1254	0.2329	0.1872	0.1620	0.1548	0.1446
Date	April 19	April 20	April 21	April 22	April 23	April 24	April 25	April 26	April 27
RE	0.1612	0.1011	0.1205	0.1139	0.1464	0.1176	0.1088	0.1767	0.1756
Date	April 28	April 29	April 30	May 1	May 2	May 3	May 4	May 5	May 6
RE	0.1014	0.1556	0.1301	0.1778	0.2072	0.2248	0.1470	0.1235	0.1862
Date	May 7	May 8	May 9	May 10	May 11	May 12	May 13	May 14	May 15
RE	0.1692	0.2379	0.2152	0.1855	0.1012	0.2121	0.1032	0.1896	0.1529
Date	May 16	May 17	May 18	May 19	May 20	May 21	May 22	May 23	May 24
RE	0.1371	0.2294	0.1563	0.1272	0.1616	0.1369	0.1943	0.1391	0.2316
Date	May 25	May 26	May 27	May 28	May 29	May 30	May 31	June 1	June 2
RE	0.1248	0.1354	0.1238	0.2109	0.1152	0.1405	0.1278	0.1243	0.1047
Date	June 3	June 4	June 5	June 6	June 7	June 8	June 9	June 10	June 11
RE	0.1910	0.1531	0.2179	0.1639	0.2220	0.2353	0.2180	0.1189	0.1200
Date	June 12	June 13	June 14	June 15	June 16	June 17	June 18	June 19	June 20
RE	0.2091	0.1935	0.2445	0.1353	0.1649	0.2239	0.1012	0.1120	0.1016
Date	June 21	June 22	June 23	June 24	June 25	June 26	June 27	June 28	June 29
RE	0.2108	0.2154	0.1255	0.1407	0.1597	0.1477	0.2113	0.2283	0.1403
Date	June 30								
RE	0.2369								

Figure 3. Relative error of cash flow forecast of G company in January 2019.

Figure 4. Relative error of cash flow forecast of G company in February 2019.

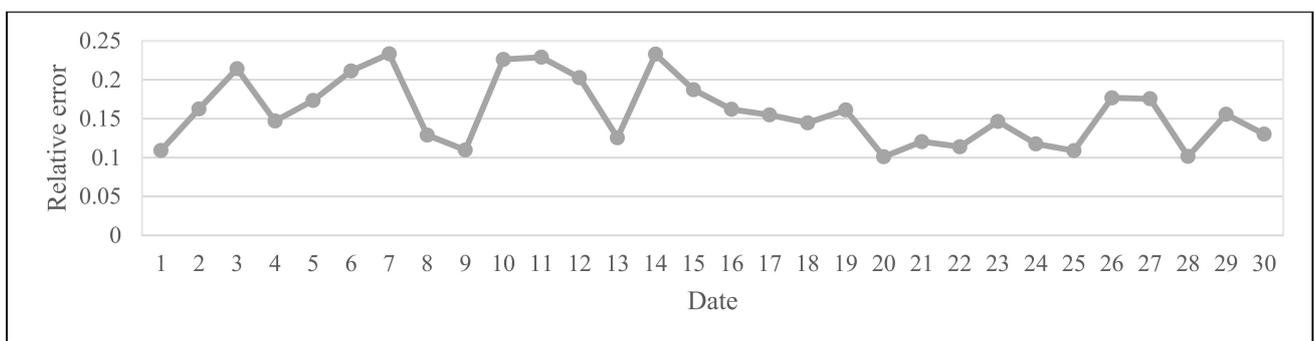**Figure 5.** Relative error of cash flow forecast of G company in March 2019.

Figure 6. Relative error of cash flow forecast of G company in April 2019.
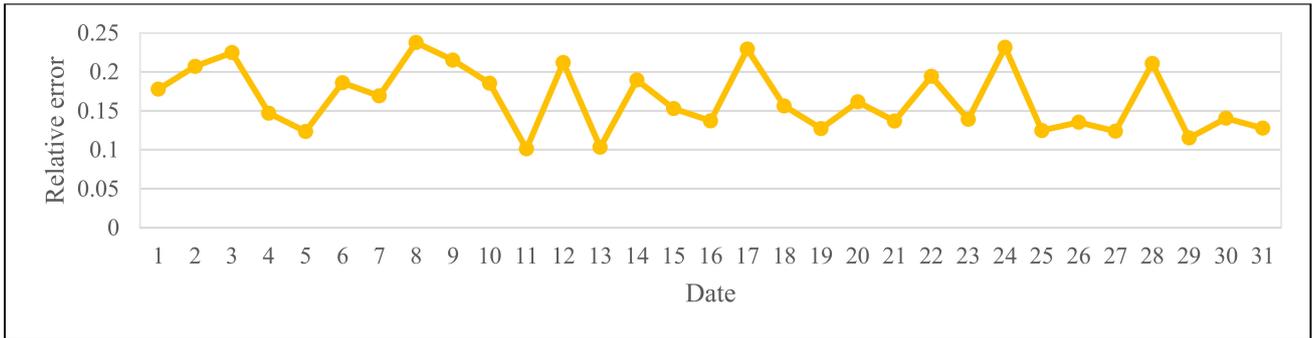
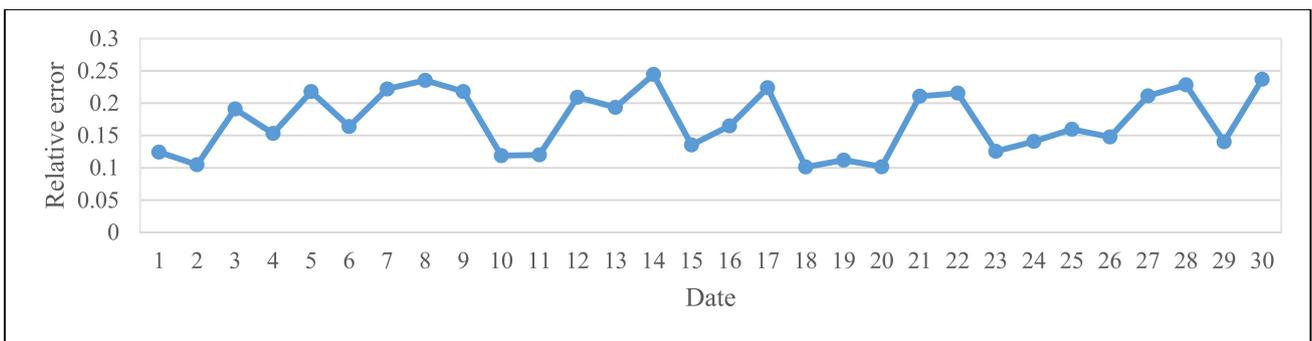**Figure 7.** Relative error of cash flow forecast of G company in May 2019.

Figure 8. Relative error of cash flow forecast of G company in June 2019.

As obtained from Figures 3–8, the minimum value of relative error data is 0.1002, the maximum value is 0.2495, and the average value is 0.1697. From the experimental results, the relative error is small, the predicted value is close to the real value, and the prediction model proposed in this paper can better predict the free cash flow of enterprises.

In the third groups of experiments, we performed comparative evaluations. This group of experiments will compare the relevant free cash flow prediction models, and evaluate the average relative error of free cash flow data of G Company from 1 January 2019 to 30 June 2019. It can be seen from Figure 9 that the average relative error of the forecasting model proposed in this paper is smaller than that of other free cash flow forecasting models from January 2019 to June 2019, so the forecasting model proposed in this paper has a better forecasting ability.
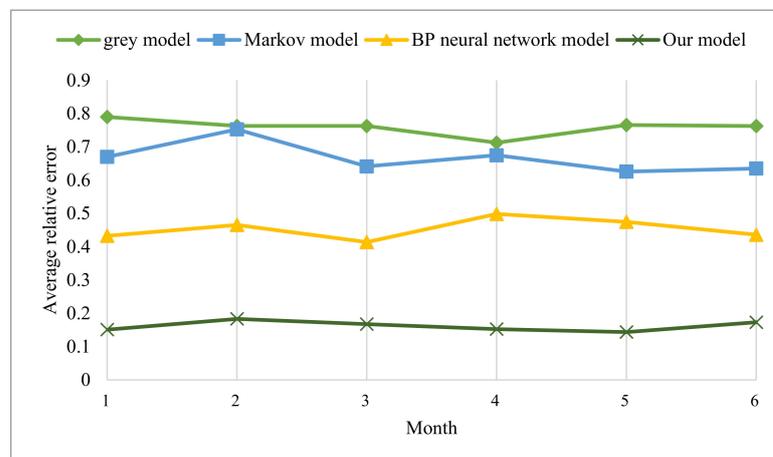
Figure 9. Average relative errors of different prediction models.

4. Conclusions

In this paper, a BP neural network model based on the improved genetic algorithm is proposed to predict the free cash flow of enterprises. Taking the data of G Company as an example, the optimal number of neurons and population and the relative error are evaluated by data preprocessing, the genetic algorithm, and neural network parameter selection. The experimental results show that when the population is 30 and the number of hidden layer neurons is 15, the error of the model is the smallest and the prediction ability of the model is the best. By calculating the relative error, we found that the model has high precision in forecasting free cash flow. Comparing the average relative error of relevant forecasting models shows that the forecasting model proposed in this paper has a better forecasting ability and effect.

The prediction model proposed in this paper provides a new idea for companies to predict free cash flow. On the one hand, it can predict the value of free cash flow more scientifically and objectively, which has better guiding significance for enterprise evaluation. On the other hand, it can provide a reference for company stakeholders of to carry out enterprise value management and investment management.

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