A Research on Neural Network and An Improved Model For Stock Prediction

Tianze Dai *

Department of Economic ESSEX University, Nanjing, China

* Corresponding Author Email: td20644@essex.ac.uk

Abstract. In this paper, Back Propagation Neural Network (BPNN) and Firefly Algorithm-Back Propagation Neural Network (FA-BPNN) are studied for the purpose of stock price prediction. The result shows that, compared with BPNN, the average prediction time of FA-BPNN increases by 3.2239s, the average relative prediction accuracy increases by 1.2739 %, and the corresponding variance decreases by 0.0003. It shows that the prediction accuracy obtained using FA-BPNN is higher. This is because the weighted value of FA-BPNN can effectively find the extreme value of the loss function, thus avoiding local optimum. But the prediction time is slightly longer, because the algorithm needs to sacrifice the tracking time in order to improve the prediction accuracy. Meanwhile, the variance corresponding to the relative prediction accuracy of FA-BPNN is the smallest. This demonstrates that the prediction effect of FA-BPNN is superior, and the prediction results are more stable and robust after each training. The above outcomes demonstrate that the FA-BPNN model has excellent performance in short-term stock forecasting. It has some feasibility and can be of use to stock market investors.

Keywords: Stock Prediction; Neural Network and Improved Model; Accuracy; Stability.

1. Introduction

Because the stock market contributes to the stability and development of global finance, more and more researchers are paying attention to stock price prediction [1]. Among the methods available, the ARMA model [2], the ARIMA model [3] and GARCH model are the most widely and frequently used by these researchers. These financial time series models are considered to be important tools for stock market forecasting, which can basically help investors make accurate judgements. To further improve the forecast accuracy, the combination of the ARIMA-GARCH-M models and other combined models have been proposed and studied [5]. The purpose is to combine and harmonize the models to further improve the prediction accuracy. However, traditional stock predictions are ineffective in turning point prediction. Therefore, with the continuous advancement of machine learning and artificial intelligence, developing lightweight models with high speed while ensuring simplicity and accurate prediction has become the target of research. Machine learning methods are being introduced into stock price prediction [6], such as neural network stock prediction method [7], improved GA-BP neural network prediction model [8], LSTM-Attention neural network prediction model [9], etc. Although these combined models of stock prediction have higher prediction accuracy, not may studies have been conducted with a focus on the prediction time. And there are no detailed studies of the highly nonlinear stock forecasting volatility.

Therefore, this paper studies the Back Propagation Neural Network algorithm and Firefly Algorithm-Back Propagation Neural Network algorithm for stock price prediction and it discusses their accuracy and stability. The above outcomes demonstrate that the model can predict the future stock index more accurately in the short term. It has certain feasibility and can be of great use to stock market investors. At the same time, the model can also provide future researchers with an idea and direction of stock price prediction.

2. Prediction Algorithm

2.1. Firefly Algorithm (FA)

FA is a class of stochastic optimization algorithm constructed by simulating the group behaviour of fireflies. The bionic theory is that the points in the search field are taken to represent individual fireflies in nature, and the search and optimization process is modeled as the attraction and movement of the individual fireflies. The objective function of the solution problem is measured as the superiority or inferiority of the position in which the individual is located, and the process of superiority or inferiority of the individual is analogous to the iterative process of replacing a poorer feasible solution with a good feasible solution in the search and optimization process [10].

In this algorithmic model, the tendency of fireflies to attract each other can be explained by two elements: self-luminance and attractiveness. The degree of luminance of the fluorescence emitted from each firefly will be determined by the target value of its own location. Higher luminance indicates a more favorable location, which means better target value. Attractiveness is correlated with luminance. The brighter the firefly, the more attractive it is. which then attracts other fireflies with weaker luminance to move in this direction. If the degree of luminance is same, fireflies move randomly. Luminance and attractiveness are in inverse ratio to the distance between the fireflies, both reducing with distance. It is the same to simulating the characteristics of fluorescence gradually attenuated by the propagation medium during spatial propagation [11].

As mentioned above, the FA algorithm consists of two factors, luminance and attractiveness. The degree of luminance indicates the location of the individual firefly and decides the direction of its movement, and attraction decides the distance between fireflies. Through the continuous improvement of luminance and attractiveness, the target improvement is realized. The optimization mechanism of the Firefly Algorithm is described mathematically as follows:

$$\beta(r) = \beta_0 e^{-\gamma r_{ij}^2} \tag{1}$$

In the formula:$\beta_0$is the maximum attractiveness;$\gamma$is the light absorption coefficient; $r_{ij}$is the Cartesian distance from firefly$i$ to firefly j. That is:

$$r_{ij} = \|X_i - X_j\| = \sqrt{\sum_{k=1}^{D}(X_{ik} - X_{jk})^2} \tag{2}$$

In the formula: where X_i and $X_j$are the positions of firefly$i$and firefly$j$ respectively; D is the dimension of the variable.

Assuming that the luminance of firefly$i$is higher than that of firefly$j$, the position update formula of firefly$j$attracted by firefly$i$and moved to firefly$i$is

$$X_j(t+1) = X_j(t) + \beta(r)(X_i(t) - X_j(t)) + \alpha(rand - \tfrac{1}{2}) \tag{3}$$

In the formula:$X_j(t+1)$ is the position of firefly $j$at moment$t+1$; $X_i(t)$ and$X_j(t)$ are the positions of firefly$i$and firefly$j$at moment$t$；$\alpha$is the step size factor；$rand$is a random number between[0,1].

2.2. Back Propagation Neural Network (BPNN)

BP is a multilayer feedforward network for back propagation error training, which is by far one of the most widely used network models. BPNN can master and save a great deal of mapping correlations among input and output patterns, without having to debunk and describe a mathematical equation that describes the mapping relationship between input and output before learning and storing [12].

BPNN modifies the weights (W_{mh},W_{hn}) and threshold value (θ_h,θ_n) by error comparison between the results obtained in each training and the expected results. Step by step, we get models that can output results that are consistent with the expected results. The network structure of BPNN is shown in Figure 1.

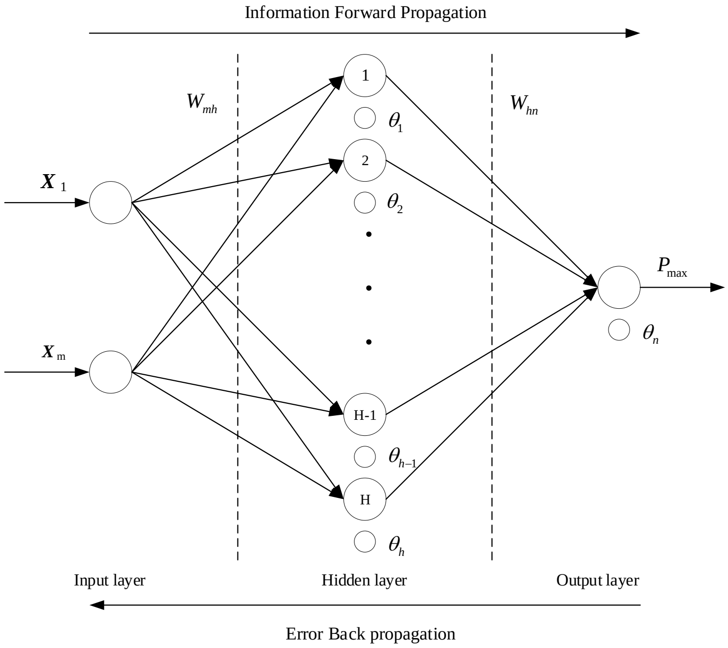

Fig 1. BPNN network structure

In the design, the structure of neural network adopts the classic three-layer structure: the input layer, the hidden layer and the output layer. The input layer is decided by the number of input features, and the output layer is composed of output features.

2.3. FA-BPNN

The major steps of the algorithm are as follows (Fig.2 is the algorithm flow chart):

1) Determine the network structure of the FA-BPNN algorithm according to the experimental object ($M = 5, H = 3, N = 1$).

2) Set the basic parameters of PSO-BPNN algorithm: loss function (MSE function), transfer function (ReLU), training function (descending gradient method), learning rate (0.01), maximum number of iterations (100), solution accuracy (0.001), population size (20), maximum attraction (0.2), light absorption coefficient (1) and the variable dimension (18).

3) Initialize the weights and thresholds value of the BPNN algorithm as the initial position of the FA population particles.

4) Calculate the fitting value (the training error of BPNN is used as the fitness function of FA) to obtain the initial fluorescence luminance of fireflies.

5) Calculate the mutual attractiveness between fireflies to determine the direction of movement of the fireflies.

6) Update the position of the firefly, and calculate the new fluorescence luminance of each firefly again using the fitness function.

7) Determine if the algorithm has achieved the maximum number of iterations or convergence target. If the requirements are met, the optimal individual is output as the initial weight and threshold of BPNN, otherwise go to step 4.

8) Forward propagation: Normalize the training sample set and the prediction sample set using the standard deviation normalization method, then input the training sample and calculate the actual output and training error of the network.

9) Backward propagation: The weights and thresholds of the layers in the BP neural network are updated according to the negative gradient direction of the error function by the descending gradient method.

10) Determine whether the algorithm meets the maximum number of iterations or accuracy requirements. If the requirements are met, end the training and go to step 11, otherwise go to step 3.

11) Input the prediction sample into the network, and the prediction results are output and denormalized.

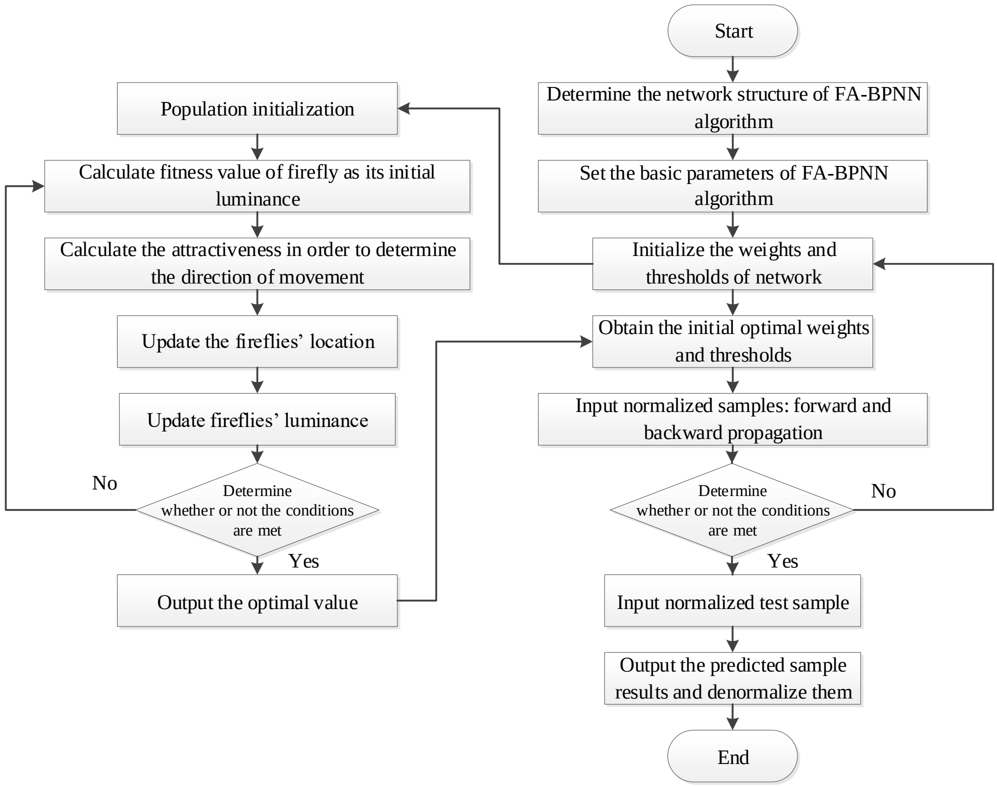

Fig 2. Flow chart of FA-BPNN algorithm

3. Experimental Results and Analysis

To confirm the capability of the proposed model, this paper selects the stock of Shanghai Composite Index in literature [8] as the data set of the algorithm model for training and prediction. The table 1 shows the specific information of the selected stocks.

Table 1. Part of Stock Trading Data

Data	Closing Price	Maximum Price	Minimum Price	Opening Price	Previous Closing Price	The Quantity of Highs and Lows
1406.371	1407.518	1361.214	1368.693	1366.58	39.791	1406.371
1409.682	1433.78	1398.323	1407.829	1406.371	3.311	1409.682
1463.942	1463.955	1400.253	1406.036	1409.682	54.26	1463.942
1516.604	1522.825	1477.154	1477.154	1463.942	52.662	1516.604
1545.112	1546.723	1506.404	1531.712	1516.604	28.508	1545.112
1479.781	1547.708	1468.757	1547.678	1545.112	-65.331	1479.781
1438.02	1489.28	1434.996	1473.761	1479.781	-41.761	1438.02
1424.442	1444.066	1418.814	1437.453	1438.02	-13.578	1424.442
1408.848	1433.474	1401.706	1426.224	1424.442	-15.594	1408.848
1433.33	1433.383	1402.663	1408.988	1408.848	24.482	1433.33

The influencing factors (closing price, maximum price, minimum price, opening price and previous closing price) are used as the input characteristics of BPNN and FA-BPNN models, and the quantity of highs and lows is used as the output. Keeping the other parameters of the algorithm unchanged, the training and prediction sets are divided in the ratio of 8:2, and training and prediction are performed 10 times each. The result is as follows. Figure 3 displays the error convergence curves of the two algorithms during training. Table 2 displays the outcomes of the algorithms after 10 times of training and prediction.

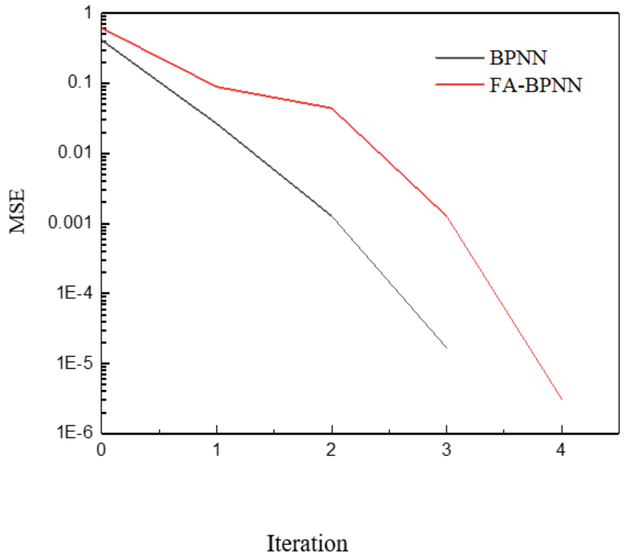

Fig 3. Algorithm Training Convergence Curve

According to Figure 3, Within the set maximum number of iterations, the number of training iterations of BPNN and FA-BPNN is 3 and 4 respectively, and the corresponding MSE is 0.00001684 and 0.000003126 respectively. Compared with BPNN, FA-BPNN reduces training errors by sacrificing the number of iterations. The result shows: The training effect of FA-BPNN is the best because it can effectively avoid the problem of gradient disappearance during training.

Table 2. Average Prediction Accuracy of Algorithms

Algorithm	Average Forecast Time (s) and Variance	Average Relative Prediction Accuracy (%) and Variance
BPNN	0.1788 (±0)	97.9354 (±0.0003)
FA-BPNN	3.4027 (±0.0015)	99.2093 (±0)

According to Table 2, compared with BPNN, the average forecast time of FA-BPNN increased by 3.2239s, the average relative prediction accuracy increased by 1.2739%, and the corresponding variance decreased by 0.0003. The result shows that the average relative prediction accuracy of FA-BPNN is highest. This is because that the weight of FA-BPNN can be used to effectively find the extreme value of the loss function to avoid local optimum. However, the average forecast time is slightly longer because the combined algorithm needs to sacrifice tracking time in order to improve prediction accuracy. Meanwhile, the variance corresponding to the average relative prediction accuracy of FA-BPNN is the smallest. This means that the prediction of FA-BPNN is more effective, and the prediction results are more stable and robust after each training.

4. Conclusion

The volatile nature of the stock market means that it is full of uncertainty, therefore stock price prediction is a challenging issue. There has never been a method to accurately predict stock prices, although many scholars have studied the subject. Though many new methods for stock price prediction have emerged over time, deep learning is still an effective one.

This paper studies BPNN and FA-BPNN for stock price prediction. The study result shows that, compared with BPNN, the average prediction time of FA-BPNN increases, but the average relative prediction accuracy also increases and the corresponding variance decreases. This is because the weighted value of FA-BPNN can effectively find the extreme value of the loss function, thus avoiding local optimum. The prediction time is slightly longer because the algorithm requires sacrificing the tracking time to improve the prediction accuracy. The prediction variance decreases because this algorithm is highly robust.

The above shows that the FA-BPNN produces positive results on short-term stock price prediction. It has a certain feasibility, and can be useful to stock market investors.

However, the FA-BPNN model proposed in this paper has certain deficiencies, and its ability of long-term stock price prediction is limited. We can collect more data, combine it with the time series model for analysis, and to the best of our ability, include more factors affecting the stock market prices into the study, such as the guiding role of the mass media, domestic policies, investors purchase desire, etc. This can provide more accurate long-term stock price predicting ideas and directions for investors with a higher demand.

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