Research on Computer Prediction Model Using SSA-BP Neural Network and Sparrow Search Algorithm

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Abstract. Stock price forecasting has always been a very challenging topic and a hot gamble in the wealth management and its applications. Timely and accurate forecasts can not only provide individuals with excellent investment opportunities, but also help the country's macroeconomic regulation and control. In order to achieve accurate predictions, people have tried various methods, among which machine learning methods have made breakthroughs. In this article, we propose a BP neural network model optimized based on the Sparrow Search Algorithm (SSA), and we use it to forecast the stock market. The experimental results show that the SSA-BP neural network model effectively overcomes the problem that the BPNN and the PSO-BPNN are easy to fall into the local optimum. The accuracy is better than BPNN, PSO-BPNN and LSTM model.

Keywords: Stock market, Wealth management, Sparrow search algorithm, BP neural network.

1. Introduction

Stock market index forecasting has always been the most attractive problems in our life [1]. This is mainly due to the instability, nonlinearity and complexity of dynamic changes in the stock market. In addition, it will be affected and impacted by many factors such as economic policies [2]. Accurate prediction of future stock trends can reduce investors' risks, and at the same time guide the financial market economy at an appropriate time, which can promote a more healthy development of the national economy. How to accurately predict stock market indexes has always been one of the most attractive research topics in wealth management and its applications.

The basic idea of stock prediction is generally to use historical data of stock prices to forecast and simulate the future price trend of stocks. Initially, the technical analysis method was used for stock price forecasting. Through long-term observation of daily and weekly stock prices, the law of stock price volatility was summarized and summarized. Later, scholars tried to establish a time series forecasting model to achieve forecasting. Yang [3] in order to prove that the stock price can be predicted, the Shanghai stock market is simulated by the ARCH model. Wu et al. [4] established an
ARMA model to analyze the historical stock data of China Merchants Bank and predict the stock price situation in the next three days.

However, due to the non-linear fluctuation of stock prices (indexes), traditional models are difficult to deal with when the original trend of stock prices (indexes) reverses. At this time, artificial intelligence technology began to rise, bringing new directions to stock price prediction. Among them, BP neural network has been widely used due to its strong noise data tolerance and nonlinear mapping ability. In 2020, Zhang et al. [5] proposed to use the BP algorithm to classify and predict stock prices. At the same time, in 2020, Yu et al. [6] used BP NN to achieve accurate prediction of individual stocks. However, when the traditional BPNN predicts the stock price, it often falls into the local area, the training time is too long, and the prediction data is inaccurate.

Therefore, in this article, we propose a BP neural network model optimized based on the Sparrow Search Algorithm (SSA) to predict the closing price of the Huatian Technology. The experimental results shows that the SSA-BPNN model effectively overcomes the problem that the BPNN and the PSO-BPNN are easy to fall into the local optimum. The accuracy is better than BPNN, PSO-BPNN [7-8] and LSTM model [9-11].

2. SSA-BP neural network

2.1. BPNN

BPNN is a multi-layer feedforward neural network, and its weight setting is determined by error back propagation [12]. In the 1980s, Rumelhart first proposed the concept of BPNN. Its essence is to combine gradient descent, use error back propagation to dynamically adjust various parameters in the network, and stop iteration when the error reaches the accuracy requirement. The composition of BPNN mainly has three parts: input, output and hidden layer. Take the three-layer BP neural network as an example, the specific structure we can see from the Fig.1.

![BP neural network structure diagram](image)

Figure 1. BP neural network structure diagram.

Where the circle on the leftmost layer of the NN represents the input of the NN \(x_1, x_2, \ldots, x_n\), which is the input layer. The layer formed by all the nodes in the middle is called the hidden layer because it cannot be observed in the sample training set (the hidden layer can have multiple layers at the same time). There is no loop or closed loop in this structure. In order to obtain the final output of the NN, only forward propagation is used to calculate the output of all nodes in each layer step by step. A model like this is called a feed forward neural network [13].

2.2. Sparrow search algorithm

The sparrow search algorithm [14] is a brand-new intelligent optimization algorithm [15], which was first proposed in 2020. Each intelligent optimization algorithm has its corresponding bionic principle, and it is no exception. It is mainly based on the predation behavior of the sparrow population to perform the optimal solution. It effectively overcomes other algorithms such as genetic algorithm (GA) [16, 17], particle swarm optimization (PSO) [18], ant colony algorithm (ACO) [19] etc., which are easy to fall into local optimization when solving optimization problems. In the sparrow search
algorithm, we divide the sparrow population into discoverers, followers and guards. The discoverer is a part of the sparrow with higher self-adaptability, and followers and guards follow the discoverer so as to obtain a higher fitness value. The location update of the discoverer follows the following formula:

\[
X_{i,j}^{t+1} = \begin{cases} 
X_{i,j}^t \cdot \exp \left( \frac{-i}{\alpha \cdot \text{iter}_{\text{max}}} \right) & R_2 < ST \\
X_{i,j}^t + Q \cdot L & R_2 \geq ST 
\end{cases}
\]  

The position update formula of the followers are as follows:

\[
X_{i,j}^{t+1} = \begin{cases} 
Q \cdot \exp \left( \frac{X_{\text{worst}}^t - X_{i,j}^t}{i^2} \right) & \text{if } i > \frac{n}{2} \\
X_{p}^{t+1} + \left| X_{i,j}^{t+1} - X_{p}^{t+1} \right| \cdot A^* \cdot L & \text{otherwise}
\end{cases}
\]

The position update formula of the guards are as follows:

\[
X_{i,j}^{t+1} = \begin{cases} 
X_{\text{best}}^t + \beta \cdot \left| X_{i,j}^t - X_{\text{best}}^t \right| & f_i > f_g \\
X_{i,j}^t + k \cdot \left( \frac{X_{i,j}^t - X_{\text{worst}}^t}{f_i - f_{\text{worst}}} + \varepsilon \right) & f_i = f_g 
\end{cases}
\]

2.3. Sparrow search algorithm optimizes BPNN

BPNN is a multi-layer feed forward neural network, and its weight setting is determined by error back propagation. In the 1980s, Rumelhart first proposed the concept of BPNN. Its essence is to combine gradient descent, use error back propagation to dynamically adjust various parameters in the network, and stop iteration when the error reaches the accuracy requirement. Therefore, the BPNN can be used to learn and simulate the trading mode of the stock market, discover the inherent operating law of the stock, and obtain the functional relationship of the stock price over time. Yet the BPNN is prone to the following problems during training: BP neural network is very sensitive to the initial weights and thresholds. Once the initial weights and thresholds are chosen improperly, it may lead to a local minimum when searching for the global minimum; the smaller the learning rate value will result in a decrease in the system convergence speed and a prolonged training period. These problems will more or less have a certain impact on the prediction accuracy of the model. So as to improve the above problems, the sparrow search algorithm is introduced, and a set of optimal network connection weights and thresholds are searched in a certain range through the sparrow search algorithm as the initial value of the BPNN, which reduces the prediction error of the BPNN and improves the prediction accuracy.

The specific implementation process is as follows:

Step 1: Determine the initial structure of the BPNN and relevant parameters of the BP algorithm.

Step 2: Determine the size of the sparrow population and the maximum mounts of iterations, and initialize the location of the sparrow.

Step 3: Perform neural network training, and use the training error value as the initial self-adaptation value of the each sparrow population.

Step 4: According to the location update formula in the SSA, update the location information of the discoverer, follower, and guard respectively.
Step 5: Verify whether the algorithm meets the termination condition, that is, whether it has reached a maximum number of iterations, if the termination condition of the algorithm is met, the final optimized weight is output. Otherwise, skip to step 3.

Step 6: The optimal initial weights and thresholds output by decoding are used as the initial weights and thresholds of the SSA-BP model, and the data is brought in for model prediction.

The flowchart of optimizing the BPNN using the sparrow search algorithm is shown in Fig. 2.

3. Empirical analysis

3.1. Index selection

In this article, we select the daily data of Huatian Technology Co., Ltd. (002185) from January 2, 2019 to September 19, 2020 for a total of 420 trading days, and a total of 10 indicators are selected as the influencing factors of stock prices, including the opening price (Open), the highest price (Hiprc), the lowest price (Loprc), the closing price (Clsprc), the number of daily individual stock transactions (Dnshrtrd), the daily individual stock transaction amount (Dnvaltrd), the daily market value of individual stocks (Dsmvosd), Diluted earnings per share (Eps), undistributed earnings per share (Upps), and price-to-earnings ratio (PB).

In order to eliminate the influence of dimensions, this paper normalizes the original data, and the normalized formula is as follows:

$$x = \frac{x - x_{\min}}{x_{\max} - x_{\min}}$$  \hspace{1cm} (4)

![Figure 2. SSA-BP neural network.](image)

3.2. Parameter settings

The network structure of BPNN is 10-12-1, the functions of hidden and output layer are the Sigmod function and the purelin function, respectively, the maximum number of training is set to 10000, the learning rate of the network is 0.06, and the target error is set to 0.0001.
The number of sparrows in the sparrow search algorithm is 50, the maximum number of iterations is set to 200, and the proportion of discoverers is listed as 0.2.

3.3. Experimental results
Comparing the fitness curves, we find that the convergence speed and accuracy of SSA-BP are better than PSO-BP.

![Fitness curve](image)

**Figure 3.** Fitness curve.

| Data       | Actual | BP  | PSO-BP | SSA-BP | LSTM |
|------------|--------|-----|--------|--------|------|
| 2020.9.24  | 13.92  | 14.19| 14.17  | 13.92  | 13.72|
| 2020.9.25  | 13.73  | 13.89| 13.73  | 13.77  | 14.17|
| 2020.9.28  | 13.32  | 13.70| 13.51  | 13.67  | 13.78|
| 2020.9.29  | 13.77  | 13.38| 13.16  | 13.41  | 13.82|
| MAE        | 0.30   | 0.27| 0.18   | 0.29   |      |

**Figure 4.** Forecast results.

In this article, we use Mean Absolute Error (MAE) as the standard to evaluate the prediction results of each model, as shown in Table 1.
It can be seen from Table 1 that the SSA-BPNN model proposed in this paper has the best prediction performance, followed by the PSO-BPNN model, and the BPNN model has the weakest prediction performance. Comparing several models, it is found that SSA-BP realizes the optimization of BP neural network, which greatly improves the prediction accuracy.

4. Conclusion
In the paper, we propose a BP neural network optimized based on the Sparrow Search Algorithm (SSA) to predict the closing price of stock exchange. This paper uses the sparrow search algorithm to optimize the thresholds of the BPNN and the initial weights the experimental results indicate that the SSA-BPNN model effectively overcomes the problem that the BPNN and the PSO-BPNN are easy to fall into the local optimum. This accuracy is higher than BPNN, PSO-BPNN and LSTM model. Facts have proved that the SSA-BPNN has made a huge improvement.

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