ISSN 2616-5775 Vol. 5, Issue 7: 1-9, DOI: 10.25236/AJCIS.2022.050701

Financial Time Series Forecasting Based on LSTM Neural Network optimized by Wavelet Denoising and Whale Optimization Algorithm

Xuehan Zhang

College of Finance, Guangdong University of Foreign Studies, Guangdong, Guangzhou, 510000, China

Abstract: *In order to further explore the application of deep learning in predicting financial market time series data and improve the accuracy of the prediction, this paper adopts a financial time series prediction method based on wavelet denoising, whale optimization algorithm and long-short term memory (LSTM) neural network. This article chooses 10 common evaluation indexes in the financial market as the input, the financial time series data are denoised by wavelet analysis. Then the optimal LSTM neural network parameters are obtained by whale optimization algorithm (WOA). Finally, the LSTM neural network algorithm is used for stock prediction to output the predicted closing price. To verify the effectiveness of WP-WOA-LSTM model, three other neural networks are used to compare with the forecasting result. By comparing the prediction accuracy of different methods, it is obvious that the mean absolute error (MAE) of LSTM neural network under whale optimization algorithm can be reduced by 22 % compared with the standard LSTM neural network. Therefore, the results show that WOA-LSTM model has significantly improved the prediction accuracy.*

Keywords: *Financial Time Series Forecasting, LSTM neural network, Whale Optimization Algorithm, Deep Learning*

1. Introduction

Financial time series prediction predicts the future development trend of many financial products in the financial market by establishing models based on historical data. It is important for investors to formulate investment strategies. However, the time series of financial assets is often considered as an unknown random variable sequence, which has many uncertain factors and has the characteristics of nonlinear change and instability. Therefore, it is very essential to select accurate statistical theory and construct effective sequence prediction model in financial time series analysis. Ordinary linear statistical tools cannot meet the complex characteristics of the financial market and have certain limitations. Therefore, machine learning and deep learning can improve the accuracy of data prediction compared with traditional econometric prediction methods, which are widely used. [1]

In the study of financial time series prediction using machine learning and deep learning, scholars in the world have made many explorations. [2] Support vector machine (SVM) is a successful application of machine learning in the field of financial prediction[3], and scholars extends the SVM-GARCH model to improve the accuracy of prediction. [4] At the same time, with the rise of neural network, artificial neural network (ANN) began to become a hit prediction method in financial time series prediction. Sadig Mammadli determined the weights of neural network by Levenberg-Marquardt algorithm and combined with ANN to obtain the time series prediction of stock market. [5] However, ANN has the shortcomings that it is easy to stay in local optimum and cannot effectively deal with financial data noise. [6] Recurrent neural network (RNN) has also been gradually applied to time series prediction, but RNN cannot solve the problems of gradient disappearance and exploding gradient. [7] Therefore, scholars have introduced long-term and short-term memory (LSTM) neural network to solve the gradient problem. [1] The selection of the number of neuron and step size in LSTM neural network is particularly indispensable. However, it is usually depended by past experience, which is subjective and reduces the prediction accuracy. Under this circumstance, this paper selects the whale optimization algorithm to select the optimal results of the number of neurons and the step size. Simultaneously, WOA optimizes the LSTM to make the prediction results more objective, so as to solve the shortcomings of the ordinary LSTM. Moreover, whale optimization algorithm is not easy to fall into local optimum. In addition, this paper uses wavelet analysis for noise reduction decomposition, sym wavelet as wavelet basis, which effectively solves the instability problem of financial market data.

ISSN 2616-5775 Vol. 5, Issue 7: 1-9, DOI: 10.25236/AJCIS.2022.050701

In this paper, wavelet analysis is used to solve the situation of high noise, high volatility and unstable periodicity in financial market. In order to solve the subjectivity of the number of neurons and the step size selected in the LSTM and improve the effectiveness of the prediction, this paper proposes a method to iteratively obtain the two key parameters of LSTM by using the whale optimization algorithm. Therefore, the WOA-LSTM model is used to realize the prediction of the Hang Seng Index (HSI) in Hong Kong, which fills the shortage of the accuracy of LSTM in the current financial time series prediction.

In view of all the above problems in financial time series prediction, in the second chapter, this paper introduces three models, namely, wavelet analysis, whale optimization algorithm and long-term and short-term neural network. Simultaneously, it explains how the model are applied to the financial time series prediction in this paper. In the third chapter, the signal sequence processing data are obtained by using sym wavelet and five-layer noise reduction decomposition. The WOA model is used to find the optimal solution for LSTM neural network, and the prediction results for time series are obtained. At the same time, in order to prove the superiority of WOA-LSTM model, this paper compares it with the other three prediction methods.

2. Model introduction

2.1 Wavelet Denoising

The factors that affect stocks are complex and difficult to distinguish between primary and secondary factors. It is difficult to distinguish the relationship among various Influencing factors and affected factors. Therefore, it is urgent to find a good method to avoid or decrease the influence of these factors. This paper solves these problems by wavelet analysis. Wavelet analysis is called another effective time-frequency analysis method after Fourier analysis, which has the ideological characteristics of multi-resolution analysis.[8] Fourier analysis is best applied to absolute periodic signals, and financial market is a step signal of instantaneous transformation. Therefore, wavelet analysis has a wide range of applications in the signal processing of financial market.

When given a signal $\psi(t)\epsilon L^2(R)$, where $L^2(R)$ is a signal space with limited energy, its standard Fourier change $\psi(\omega)$ satisfies:

$$C_\psi = \int_0^{+\infty} \frac{|\psi(\omega)|^2}{\omega} d\omega < \infty \tag{1}$$

Then, $\psi(t)$ is the mother wavelet function. It can do a series of slip and shrink transformation to get a series of wavelet functions.

When $f(t)\epsilon L^2(R)$ and $\psi(t)$ are admissible, the continuous wavelet of the wavelet function is:

$$(WT)(a,b) = |a|^{-\frac{1}{2}} \int_{-\infty}^{+\infty} f(t)\psi(\frac{t-b}{a})dt, a > 0 \tag{2}$$

In the formula, a is the stretching factor and b is the translational factor. If these two factors are discretized, and $a = 2^m, b = ka2^m$. The definition of discrete wavelet function can be obtained:

$$\psi_{m,n}(t) = 2^{-\frac{m}{2}} \psi(2^{-m}t - n), \quad m, n \in Z \tag{3}$$

In multi-resolution analysis, wavelet transform can be seen as a set of signals through a high-pass filter and low-pass filter decomposition process, the corresponding algorithm is called Mallat algorithm. In this paper, the data are denoised by this algorithm.

2.2 WOA-LSTM

2.2.1 WOA

Whale optimization algorithm is a new bionic optimization algorithm based on the predation behavior of humpback whale. The process of predation into a mathematical model mainly includes the following three stages: circumferential contraction, spiral bubbles and searching for prey.

ISSN 2616-5775 Vol. 5, Issue 7: 1-9, DOI: 10.25236/AJCIS.2022.050701

1) The winding shrinkage process can be expressed by the following mathematical model:

$$D = | C \bullet X^*(t) - X(t) | \tag{4}$$

$$X(t+1) = X^*(t) - A \bullet D \tag{5}$$

Among them, A and C are coefficients, t is the number of iterations, $X^*(t)$ is the optimal position coordinate vector of humpback whale obtained in the current iteration process, which may be updated with the iteration process. $X(t)$ is the current position coordinate vector of humpback whale, $X(t+1)$ is the target vector of the next iteration.

The coefficients A and C can be calculated by the following formula:

$$A = 2ar_1 - a \tag{6}$$

$$C = 2r_2 \tag{7}$$

$$a = 2 - 2 \bullet t / T_{\max} \tag{8}$$

$r_1$and r_2 are the random numbers generated between [0,1], and T_{max} is the maximum number of iterations. It is apparent to know that a decreases linearly from 2 to 0.

2) The spiral renewal process of spiral bubble attack can be represented by the following mathematical model:

$$X(t+1) = D' \bullet e^{bl} \bullet \cos(2\pi l) + X^*(t) \tag{9}$$

Among them, $D' = |C \cdot X^*(t) - X(t)|$ is the distance between the current position and the current optimal position, l is a random number between [-1,1], b is the logarithmic spiral constant.

Since the spiral update and contraction ringing process are carried out at the same time, the probability of occurrence of the two in the predation process of humpback whales is roughly the same, which is represented by P:

$$X(t+1) = \begin{cases} D' \bullet e^{bl} \bullet \cos(2\pi l) + X^*(t), 0 \leqslant P \leqslant 0.5 \\ X^*(\mathrm{t}) - \mathrm{A} \bullet \mathrm{D}, 0.5 \leqslant \mathrm{P} \leqslant 1 \end{cases} \tag{10}$$

3) In order to achieve global optimization, the searching prey stage can be expressed by the following mathematical model:

$$D = | CX_{rand} - X(t) | \tag{11}$$

$$X(t+1) = X_{rand} - A \bullet D \tag{12}$$

where X_{rand} is the randomly selected position vector of humpback whale, and when $|A| < 1$, the optimal position is solved by the method of surround contraction. When $|A| \geq 1$, the optimal position coordinate vector is solved by the above search method.

2.2.2 LSTM

LSTM is a recurrent neural network. The neural network design a memory cell for selective memory, memory of important information, filtering noise. LSTM neural network consists of input gate, output gate and forgetting gate. Its basic network structure is shown as follows:

ISSN 2616-5775 Vol. 5, Issue 7: 1-9, DOI: 10.25236/AJCIS.2022.050701

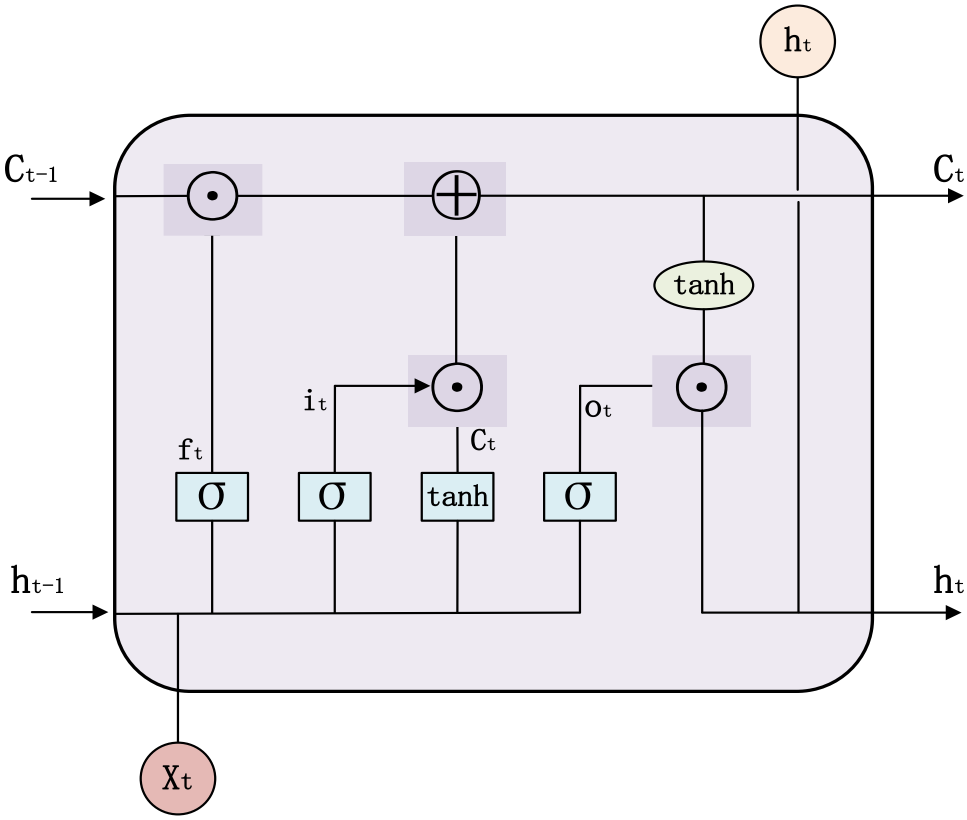

Figure 1: Flow chart of LSTM neural network

The calculation formula of LSTM at time t is as follows:

$$i_t = \sigma(i_t) = \sigma(W_{xi}x_t + W_{hi}h_{t-1} + b_i) \tag{13}$$

$$f_t = \sigma(f_t) = \sigma(W_{xf}x_t + W_{hf}h_{t-1} + b_f) \tag{14}$$

$$g_t = \tanh(g_t) = \tanh(W_{xg}x_t + W_{hg}h_{t-1} + b_g) \tag{15}$$

$$o_t = \sigma(o_t) = \sigma(W_{xo}x_t + W_{ho}h_{t-1} + b_o) \tag{16}$$

$$c_t = c_{t-1} \odot f_t + g_t \odot i_t \tag{17}$$

$$m_t = \tanh(c_t) \tag{18}$$

$$h_t = o_t \odot m_t \tag{19}$$

$$y_t = W_{yh}h_t + b_y \tag{20}$$

2.2.3 WOA-LSTM

LSTM neural network needs to set the number of hidden neurons and the step size before training prediction, and the selection of these values is often judged by experience, which will reduce the accuracy of prediction. Therefore, this paper uses the whale optimization algorithm to obtain the optimal parameters through the values in the random search range, so as to accurately optimize the prediction results of the circular network.

ISSN 2616-5775 Vol. 5, Issue 7: 1-9, DOI: 10.25236/AJCIS.2022.050701

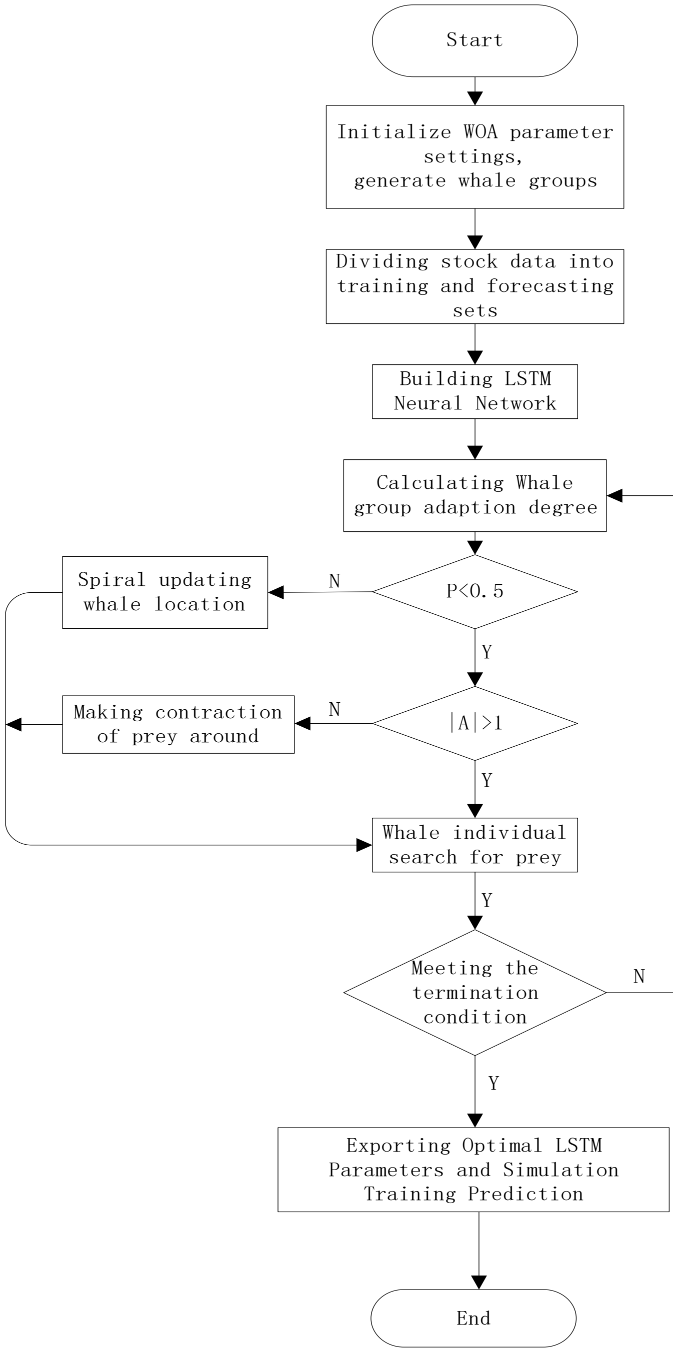

Figure 2: WOA-LSTM neural network flow chart

3. Case study

3.1 Data resource

The data in this paper are from the Hong Kong HSI, using the data from February 9,2015 to April 14,2022. The data include daily opening price (open), closing price (close), trading volume (Volume), maximum price (High) and minimum price (Low). At the same time, this paper also selects 10 indicators as the input variables that may affect the prediction results. They are random indexes (Stochastic % K, Stochastic % D), relative strength index (RSI), pro-potential index (CCI), energy tide index (OBV), 5-day average trading volume (VMA (5)), 20 - day average trading volume (VMA (20)), 5 - day average moving line (MA (5)), 20-day average moving line (MA (20)), and exponential smoothing average moving line (MACD).

ISSN 2616-5775 Vol. 5, Issue 7: 1-9, DOI: 10.25236/AJCIS.2022.050701

3.2 WP

In this paper, sym wavelet is selected as the wavelet base. After the signal is decomposed into five layers, the approximate sequence a and the detail sequence d are obtained.

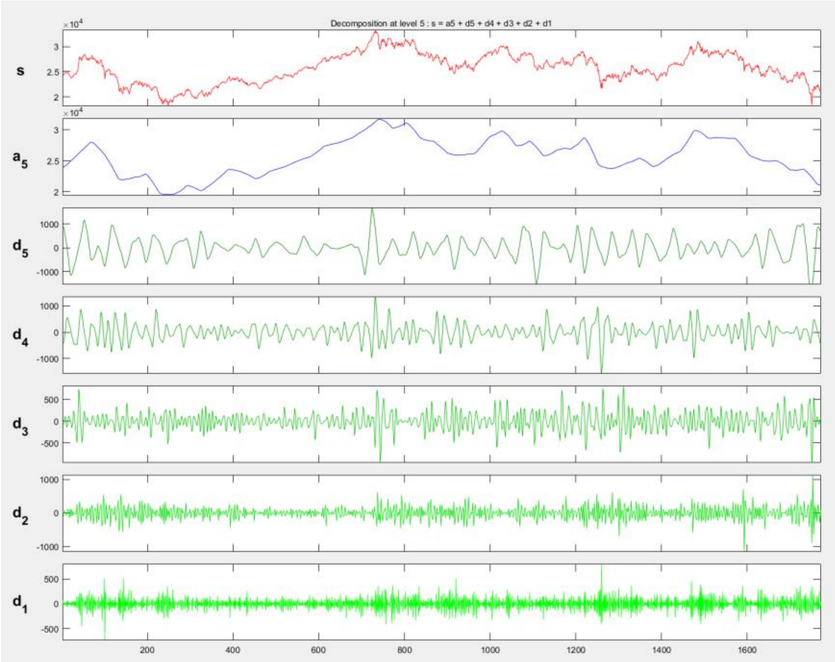

Figure 3: Wavelet analysis result

It can be seen from Figure 3 that the amplitude of high frequency coefficients of denoising wavelet decreases rapidly with the increase of decomposition level, and its variance is the same. With the increase of scale, the wavelet coefficients of real signals increase gradually, while the wavelet coefficients of noise decrease.

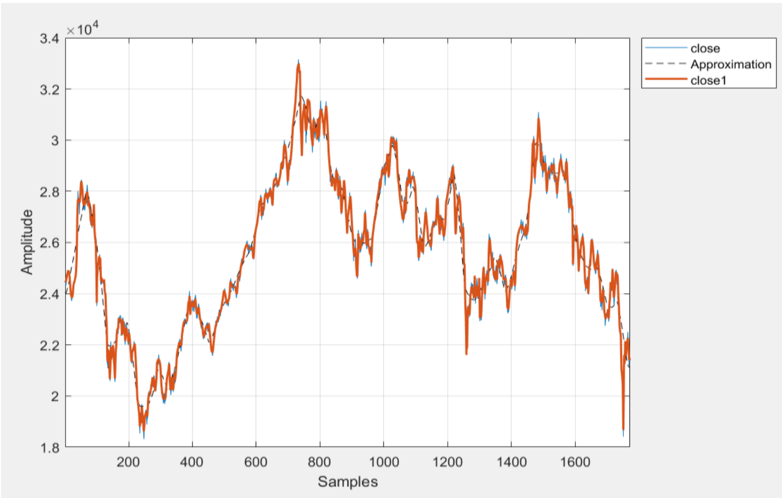

Figure 4: HSI before and after denoising

It can be seen from Figure 4 that the financial time series data reconstructed by wavelet after denoising can effectively smooth the original data and retain its approximate signal, so it is theoretically feasible to establish a prediction model based on the data.

3.3 WOA-LSTM

The prediction results of WOA-LSTM are as following figure:

ISSN 2616-5775 Vol. 5, Issue 7: 1-9, DOI: 10.25236/AJCIS.2022.050701

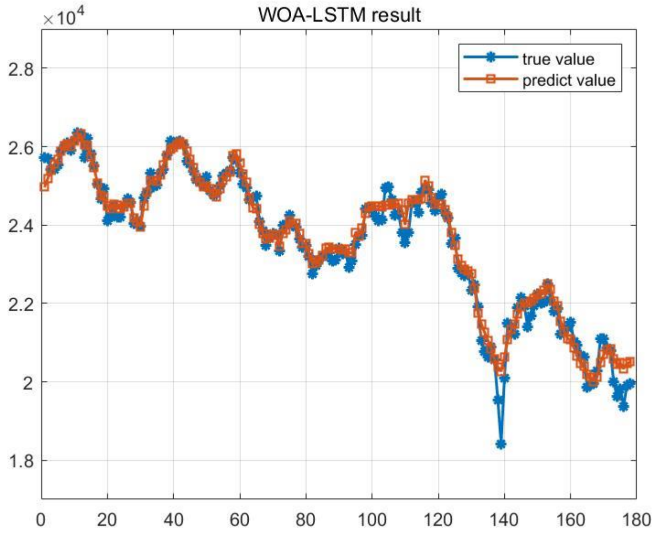

Figure 5: WOA-LSTM forecasting result

It can be seen that the closing price predicted by WOA-LSTM has the same trend with the predicted value, which can be better precisely predicted.

In order to further illustrate the effectiveness of WOA-LSTM model, three other prediction models are selected for comparison, including BP neural network, standard LSTM model and BILSTM model.

The prediction results of these four models are shown in the following figure:

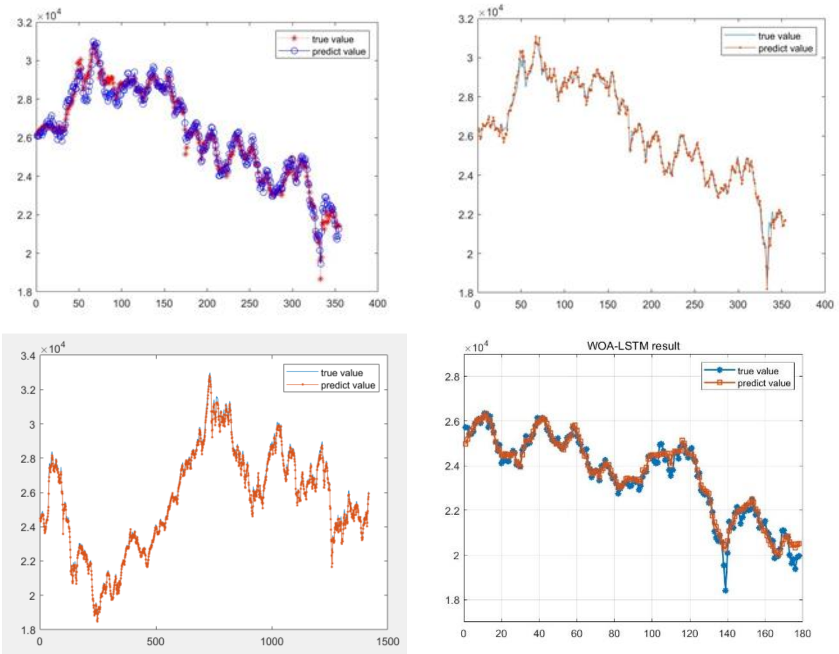

Figure 6: Prediction results of BP neural network, LSTM neural network, RNN neural network and WOA-LSTM neural network

In the prediction of financial time series, this paper adopts the following four error evaluation indexes: mean absolute percentage error (MAPE), root mean square error (RMSE), mean absolute error (MAE) and determination coefficient (R^2).

Among them:

ISSN 2616-5775 Vol. 5, Issue 7: 1-9, DOI: 10.25236/AJCIS.2022.050701

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i - y_i}{y_i}\right| \times 100\% \tag{21}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\hat{y}_i - y_i\right)^2} \tag{22}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|\hat{y}_i - y_i\right| \tag{23}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(\hat{y}_i - y_i\right)^2}{\sum_{i=1}^{n}\left(\overline{y}_i - y_i\right)^2} \tag{24}$$

The smaller the values of MAPE, RMSE and MAE are, the smaller the error is, and the better the prediction effect is. The larger the R^2 is, the better the prediction effect is. The prediction errors of different models are shown in Table 1:

Table 1: MAPE, RMSE, MAE, R^2

	MAPE	RMSE	MAE	R^2
WP-BP	0.9031%	334.1061	239.1629	0.9925
WP-LSTM	0.8205%	281.0223	216.2047	0.9937
WP-BILSTM	0.8057%	263.1023	209.7982	0.9954
WP-WOA-LSTM	0.6125%	201.5062	141.2089	0.9982

According to the above results, WP-BP model has the worst prediction effect. Compared with WP-BP model, MAPE, RMSE and MAE of WP-LSTM model decreased by 9.1 %, 15.89 % and 9.6 %, respectively, and R^2 increased by 0.12 %. Compared with WP-LSTM, WP-BILSTM reduced MAPE, RMSE, and MAE by 1.8 %, 6.3 %, 2.9 %, with an increase of 0.17% in R^2. The performance of WP-WOA-LSTM was the best. Compared with WP-LSTM, WP-WOA-LSTM, MAPE, RMSE and MAE decreased by 25.35 %, 28.29 % and 34.69 % respectively, and R^2 increased by 0.14 %. Therefore, it can be seen that compared with the traditional BP neural network and LSTM neural network, the error of LSTM neural network optimized by WOA algorithm is smaller, and the prediction effect is the best, which is closer to the real results.

4. Conclusions

In this paper, the application of LSTM neural network in financial time series prediction is improved. The whale optimization algorithm is used to optimize the number of neurons of the neural network. At the same time, wavelet analysis is used to denoise financial data, reduce noise interfering prediction results, and improve the prediction accuracy of the sample. Based on the empirical analysis of the Hang Seng Index in Hong Kong, this paper obtains the following conclusions. Firstly, the wavelet analysis is used to denoise the financial time series data, which can effectively improve the prediction effect of the LSTM neural network and more effectively predict the dynamic change trend of the financial time series. Secondly, compared with the traditional BP neural network, LSTM neural network and RNN neural network, the LSTM neural network optimized by whale optimization algorithm has higher prediction ability. This proves that the application of intelligent optimization algorithm in deep learning has strong predictive ability for the trend of financial markets, and it is of great significance to provide decision-making reference for investors under the background of the development of artificial intelligence.

References

[1] OUYANG Hong-bing, HUANG Kang, YAN Hong-ju. Prediction of Financial Time Series Based on LSTM Neural Network [J]. Chinese Journal of Management Science, 2020,28(04):27-35. DOI:

ISSN 2616-5775 Vol. 5, Issue 7: 1-9, DOI: 10.25236/AJCIS.2022.050701

10.16381/j.cnki.issn1003-207x.2020.04.003.

[2] Henrique B M , Sobreiro V A , Kimura H . Literature Review: Machine Learning Techniques Applied to Financial Market Prediction[J]. Expert Systems with Applications, 2019, 124(JUN.):226-251.

[3] Huang W , Nakamori Y , Wang S Y . Forecasting stock market movement direction with support vector machine[J]. Computers & Operations Research, 2005, 32(10):2513-2522.

[4] ZHANG Gui-sheng, ZHANG Xin-dong. A SVM-GARCH Model for Stock Price Forecasting Based on Neighborhood Mutual Information[J]. Chinese Journal of Management Science, 2016,24(09):11-20.DOI:10.16381/j.cnki.issn1003-207x.2016.09.002.

[5] Mammadli, Sadig. Financial time series prediction using artificial neural network based on Levenberg-Marquardt algorithm[J]. Procedia Computer Science, 2017, 120:602-607.

[6] Kim K J , Han I . Genetic algorithms approach to feature discretization in artificial neural networks for the prediction of stock price index[J]. Expert Systems with Applications, 2000, 19(2):125-132.

[7] Hochreiter S , Schmidhuber J . Long Short-Term Memory[J]. Neural Computation, 1997, 9(8):1735-1780.

[8] ZHOU Bo, Yan Hong-sen. Financial time series forecasting based on wavelet and multi-dimensional Taylor network dynamics model[J]. Systems Engineering-Theory & Practice, 2013,33(10):2654-2662.