WEP Warwick Evans Publishing

Transactions on Computer Science and Intelligent Systems Research
ISSN: 2960-1800, eISSN: 2960-2238 | Volume 5
AIDML 2024

Research on Predicting the GBP/USD Exchange Rate Based on BP Neural Network

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Abstract. As global base currencies, the fluctuations in the prices of the pound and dollar have an impact on the global economic situation. The exchange rate of currency not only affects the decline of the economy but also affects the stability and development of political and trade relations in various countries. Due to the numerous and non-linear factors that affect the currency exchange rates between the two countries, the accuracy of existing exchange rate prediction research is still relatively low. This experiment conducted a study on the prediction of the pound to dollar exchange rate, to help deepen the understanding of the operating rules of the international economy and financial markets and take corresponding measures. This experiment selected data on the GBP/USD exchange rate from May 12, 1993, to March 1, 2024, and used MATLAB to establish a Back Propagation (BP) neural network model to study the GBP/USD exchange rate. This article optimizes the prediction performance of exchange rates in this experiment by changing the number of hidden layer nodes as much as possible. The results show that the BP neural network in this experiment has a relative prediction error of less than 0.35 for the pound-to-dollar exchange rate, and has a good fitting effect.

Keywords: GBP; USD; Exchange Rate, BP Neural Network.

1. Introduction

The study of exchange rates can be traced back to ancient times when currency exchange had already begun to emerge. After the 1970s, the emergence of the floating exchange rate system made exchange rate fluctuations more severe, which promoted the development of exchange rate research. Exchange rate fluctuations can have a radiating effect on the price level, balance of payments, trade conditions, employment, output, labor productivity, and industrial structure of any country in the globalization chain [1]. The exchange rate of currency not only affects the daily lives of thousands of households, but also plays a crucial role in macroeconomic indicators such as a country's foreign exchange market, international reserves, and the direction of international capital flows [1]. The British pound and the US dollar, as global standard currencies, influence the global economic direction, and their price fluctuations reflect the political and economic changes in the UK and North America. However, many factors affect the exchange rate between the British pound and the US dollar, such as monetary policy and uncertain factors in trade between the two countries. They exhibit a non-linear relationship and are difficult to predict. Therefore, it is crucial to establish a predictive model for the exchange rate over time. Predicting its trend helps to formulate corresponding scientific response policies and minimize negative impacts.

Due to the influence of various nonlinear factors on exchange rates, early researchers mainly relied on historical data for linear regression analysis of exchange rates, which showed significant limitations. Later, with the deepening of research, fundamental analysis models based on exchange rate determination theory and statistical econometric models based on exchange rate time series characteristics emerged to predict exchange rate trends, but the accuracy still has certain shortcomings.

Using machine learning models that consider the complex characteristics of exchange rates to predict exchange rate trends, compared to traditional models, this model has significant advantages in time series prediction and can effectively improve the accuracy of exchange rate prediction. This model can accurately predict future exchange rates by extracting information hidden in exchange rates. In recent years, artificial intelligence has developed rapidly, and the field of machine learning has developed rapidly. As a branch of machine learning, BP neural networks are more accurate and efficient in many aspects compared to traditional prediction methods. Recently, many studies have demonstrated its superiority in learning and memory. Zhang used the BP neural network as a tool to classify short-term Electrocardiogram signals into emotions, and the average classification accuracy reached 89 14% [2]. The prediction of CO2 adsorption saturation based on the BP neural network showed high accuracy, and the determination coefficient R2 of the calculated test data was 0.9946 [3]. Based on the Back Propagation (BP) neural network, the inversion of water depth in inland reservoirs shows good adaptability [4]. The application of the BP neural network in coal mine gas safety accident prediction has a small error in the results, indicating that the BP neural network has good performance in prediction [5]. Li Ji used a BP neural network for blood pressure monitoring and achieved good results [6]. Based on the above research, the BP neural network has significant advantages in various fields of prediction research. Therefore, this experiment will use the BP neural network to predict the exchange rate of GBP/USD.

Early research on the prediction of the pound-to-dollar exchange rate had certain limitations and inefficiencies. This experiment will use the establishment of a non-linear model called BP neural network to study the prediction of the GBP/USD exchange rate, to fill the current gap in predicting the GBP/USD exchange rate.

2. Method

This experiment used a total of 157539 pieces of data on the GBP/USD exchange rate from May 12, 1993, to March 1, 2024, for model training. During this process, the parameters were set through multiple training and discussions, and the best parameters were selected for training and research. Finally, a relatively small relative error was obtained, which has certain advantages over previous research. The research objective of this experiment is to gain a deeper understanding of the operational laws of the international economic and financial markets by predicting the exchange rate between the British pound and the US dollar, providing a scientific basis for policy-making and investment decision-making. At the same time, this article aims to promote the development of international trade and investment, which will help promote the prosperity and stability of the global economy.

2.1. Data Sources

This experiment selected data on the GBP/USD exchange rate from May 12, 1993, to March 1, 2024, on the Meta Trader 4 (MT4) foreign exchange trading platform. The MT4 platform is widely used to trade various financial products such as foreign exchange, stocks, futures, etc. It has widely recognized safety and professionalism and has high authority. The data for this experiment was trained and optimized using the format of daily exchange rate opening price, highest price, lowest price, and closing price, with a total of 157939 pieces of data.

2.2. Experimental Tools

This article uses MATLAB to establish a BP neural network model for predicting changes in the price of GBP/USD BP neural network is a multi-layer feedforward neural network trained through a backpropagation algorithm, which consists of three parts: input layer, hidden layer, and output layer. It is divided into two parts: forward propagation and backward propagation. Each neuron is connected to the previous neuron for information transmission, using activation functions for nonlinear transformation. It has greater fault tolerance than traditional methods and does not require formula descriptions for complex relationships, allowing for self-learning. This experiment uses incremental rules to train single-layer neural networks on data from around 30 years ago. BP neural network is a highly adaptive nonlinear dynamic system, and through learning BP neural network, a highly nonlinear mapping between input and output can be obtained [7]. It has smaller errors and faster speed than traditional prediction methods and has good adaptability to the influence of complex factors.

2.3. Training Process

In BP neural networks, neurons mimic the characteristics of biological neurons and use activation functions to map input results to a certain range. If the mapped result is greater than the threshold, the neuron is activated. The conversion process for this experiment is as follows: first, initialize the weights and thresholds with appropriate values. Then, the "input" was obtained from the GBP/USD exchange rate database over the past thirty years, and the training data format was {input, correct output}. The "input" was then passed to the neural network model for output, and the correct output was calculated $d_i$and model output y_i error between e_i as follows:

$$e_i = d_i - y_i \tag{1}$$

Then, according to the incremental rule, calculate the update of weights, and adjust the weights. Repeat the iteration multiple times until the error between the predicted value and the true value is less than 10^{-8}.

3. Results and Discussion

3.1. Data

Using MATLAB to construct a single-layer BP neural network and LM algorithm to predict the GBP/USD exchange rate, this article selects 157939 exchange rate data from the MT4 foreign exchange trading platform over the past 30 years. The test set for this study consists of 100 samples. The number of rounds is 1000, the learning rate is 0.01, and the target error is 10-8. This study optimized the training results as much as possible by changing the number of hidden layer nodes. After extensive training, three sets of the most representative hidden layer nodes were selected, namely 9, 12, and 15. The training results are shown in Fig. 1-5, and a set is presented below as a reference.

When the number of nodes is 9:

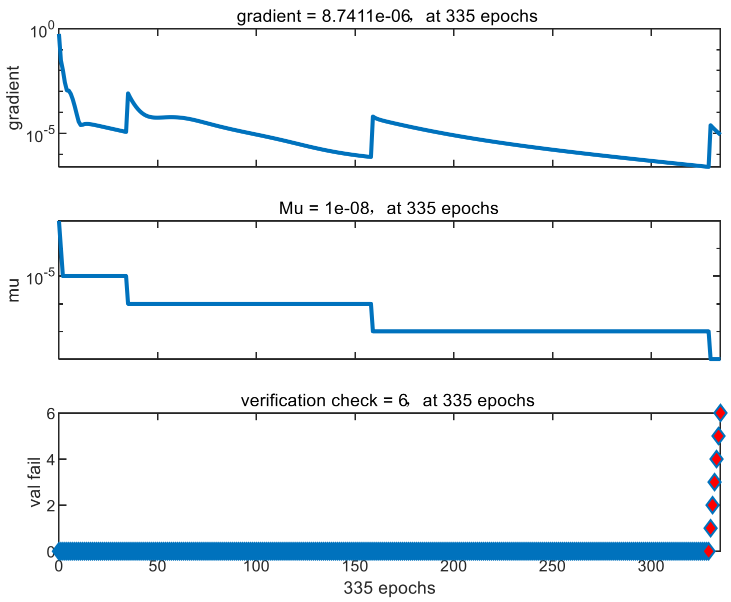

Fig. 1. The plot train of the training model (Photo/Picture credit: Original).

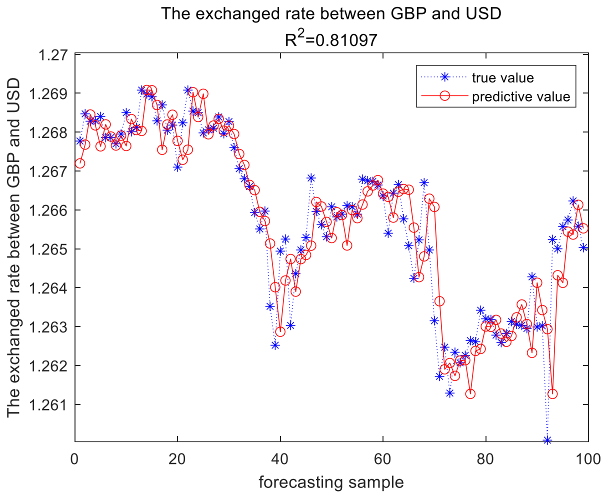

Fig. 2. Line chart of predicted and true values (Photo/Picture credit: Original).

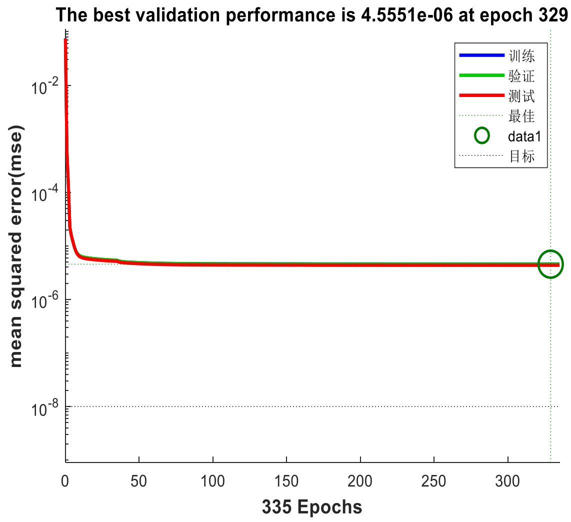

Figure 3. The performance of the training model (Photo/Picture credit: Original).

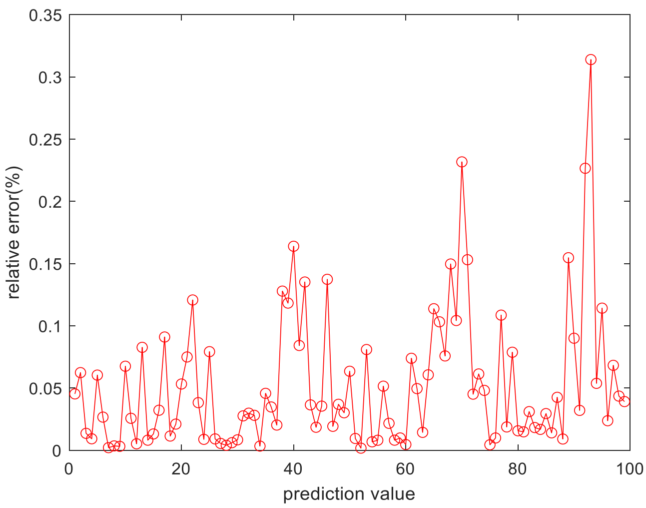

Fig. 4. The relative error of prediction value (Photo/Picture credit: Original).

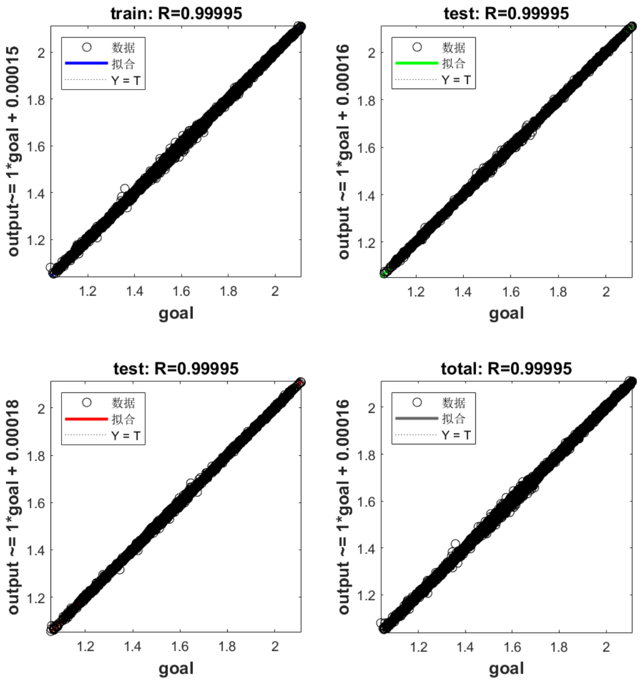

Fig. 5. The plot regression of the training model (Photo/Picture credit: Original).

Table 1. Model performance in each hidden layer nodes

Number of nodes	9	12	15
Linear correlation coefficient	0.81097	0.81075	0.81112
relative error	0~0.35	0~0.35	0~0.35
Fitting effect	0.99995	0.99995	0.99995
gradient	8.7411 × 10-6	6.5665 × 10-6	9.9619 × 10-5
Best validation performance	4.5551 × 10-6	4.586 × 10-6	4.5658 × 10-6
Damping factor	1×10-8	1×10-9	1×10-7
Verify the number of inspection rounds	6	6	6
The optimal number of iterations	335	574	26

3.2. . Data Analysis

This article will analyze from 7 aspects: linear correlation coefficient, relative error, and fitting effect, gradient, optimal validation performance, damping factor, validation check size, and optimal iteration number:

Linear correlation coefficients, as shown in Table 1, are all around 0.81. This indicates a high degree of correlation between predicted values and true values and also suggests that using BP neural networks to predict exchange rates is feasible.

The relative error and fitting effect can be seen from Table 1 that the relative error of the three can be controlled around 0-0.35. However, from Figure 4, it can be found that when the number of nodes is 9, some predicted values of the data are the same as the true values. When the number of nodes is 12 and 15, there are also situations where the true values are the same as the predicted values. In addition, the fitting effect of the three also reaches nearly 100%.

Gradient refers to the partial derivative of the loss function concerning network parameters. The calculation of the gradient is achieved through a backpropagation algorithm, which can effectively calculate the contribution of each parameter in the network to the overall loss. From Figure 1, it can be seen that the overall gradient of the three is decreasing, but in the model with 15 nodes, the lowest gradient is 9.9619 × 10-5, and the maximum gradient among the three is 9.9619 × 10-5. Therefore, the accuracy loss of node 15 will be greater than the other two.

The best validation performance usually refers to the best model selected during the training process, which performs best on the validation set. Note that the optimal validation performance of the three models is around 4.5 × 10-6, indicating that the performance of these three models is roughly the same.

The damping factor is a parameter used to control the speed of weight update. It can help the network converge to the optimal solution more stably during the training process. The overall fluctuation of the damping factors of the three shows a decreasing, gentle, and lowest characteristic, which ensures that the BP neural network can stably converge to the optimal solution during the training process. It is worth noting that the final damping factor with 12 nodes is the smallest, 10-9, and the maximum damping factor with 15 nodes is 10-7. This means that the model with 12 nodes can converge to the optimal solution more stably and accurately.

Finally, there is a validation check, which is a method used to evaluate model performance. It is usually used to monitor the accuracy of the model during the training process and conduct a final evaluation of the model after training is completed. The verification check sizes of the three models show a trend of first flattening and then increasing, indicating that the accuracy of the training model continues to improve. The verification check sizes of the three models are all the same, indicating that the performance of the three models is roughly the same.

The optimal iteration times for hidden layer nodes 9, 12, and 15 are 335574 and 26, respectively. It can be considered that when the number of nodes is 15, the number of training stop iteration rounds is the smallest, and when the number of nodes is 12, the number of training stop iteration rounds is the largest.

3.3. Discussion

In the process of constructing a neural network model, this study did not have a standard for uniformly setting various parameters and functions; Therefore, specific analysis is needed for specific issues. Although this reflects the flexibility of artificial neural network models, it also brings certain problems to the design of the model [8]. In this study, the setting of hidden layer nodes in BP neural networks may be influenced by subjective factors, which is a limitation of BP neural networks in exchange rate prediction. However, through the analysis of the data in the previous text and the structural analysis of the BP neural network, it can be found that the neural network has excellent generalization ability and can learn universal patterns and features from the training data. This is also the advantage of using BP neural networks to predict exchange rates compared to using traditional models. In future research, a generalized regression neural network with the ability to automatically increase the number of hidden layers of neurons, output independent of initial weights, and structure adaptive determination can be selected to predict exchange rates, to reduce the impact of subjective factors on prediction accuracy [8]. Moreover, in this training, we have seen the powerful performance of the BP neural network in exchange rate prediction and also demonstrated its excellent performance in small sample sizes, objectivity, stability, and accuracy [9]. In future exchange rate prediction research, we can further improve its performance by improving sample quality, model indicator system, model parameter optimization, optimization algorithms, and other aspects, thereby improving accuracy.

4. Conclusion

This article specifically studied the application of the BP neural network in exchange rate prediction. Through data analysis, it was found that using the BP neural network to predict exchange rates has high accuracy. In addition, this also indicates that using the BP neural network can discover universal patterns from training data and improve prediction accuracy. This training fully demonstrates the powerful performance of the BP neural network using the LM algorithm in the field of exchange rate prediction. However, due to the limitations of computer performance, it cannot fully reflect the powerful performance of the BP neural network in exchange rate prediction. In addition, there is still room for improvement in the linear correlation coefficient, which reflects the difficulty of predicting exchange rates due to the influence of multiple factors. In future research, BP neural networks can be applied to fields such as market trading, and other deep learning networks can be attempted to predict exchange rates and obtain more accurate results.

Authors Contribution

All the authors contributed equally and their names were listed in alphabetical order.

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