Research on the Exchange Rate Forecast of the Pound Sterling and the Dollar Based on Neural Networks

Jiantao Chen[1], and *Yining* Song[2*]

[1]Kunshan High School, Jiangsu Province, China
[2]Shaanxi University of Science and Technology, School of Mathematics and Data Science, Shaanxi Province, China

Abstract. The dynamics of the British Pound (GBP) and the US Dollar (USD), as reflected in their exchange rate, profoundly shape global trade and investment trends. Traditional forecasting methodologies, grounded in statistical analysis and economic indicators, often struggle with accurately capturing the dynamic fluctuations of this currency's value, given the complex interplay of influencing variables. In response to this challenge, this paper proposes a neural network-based prediction model to forecast future GBP/USD exchange rates. Utilizing Matlab as the computational platform, the paper collects extensive historical exchange rate data and designs a multilayer feed forward neural network architecture. Through meticulous adjustments, the paper determines the optimal number of neurons in the concealed layers to achieve a harmonious equilibrium between the model's complexity and its aptitude for generalization. During the training phase, the back-propagation algorithm is employed to reduce prediction errors, and rigorous cross-validation techniques are utilized to precisely evaluate the model's performance. The optimized model is then utilized to predict future exchange rates, and its accuracy and practicality are validated through comparisons with actual market data. This research not only provides investors with a novel and effective tool for exchange rate forecasting but also paves the way for further exploration and application of neural networks in the realm of financial market prediction.

1 Introduction

With the development of productivity and the globalization of finance, economic interactions between countries worldwide have become increasingly frequent, further promoting the integration of the global economy. Concurrently, a notable recent development occurred in the 1970s and 1980s—the internationalization of world finance, where the depth and breadth of financial penetration were more pronounced and distinctive than in any previous period. The sway of the US dollar's exchange rate significantly shapes international financial dynamics and profoundly affects various sectors of a nation's economy, assuming ever-greater importance in economic development across multiple domains. The US dollar market

* Corresponding author: 202311010611@sust.edu.cn

is highly leveraged, which inherently determines its high-risk and high-return characteristics. Since 1973, significant changes have taken place in the world's major exchange rate systems, with the initial fixed exchange rate regime has been supplanted by a novel floating exchange rate mechanism, exerting a substantial influence on the world economy. Meanwhile, due to the development of the world economy, fluctuations in the US dollar exchange rate have become very frequent, prompting many investors to devise ways to predict changes in the US dollar exchange rate in order to benefit from these fluctuations. Accurate prediction of US dollar exchange rate movements has become a key issue of concern in the international financial market.

Consequently, to delve into the historical forces shaping the US dollar market and to bolster predictive accuracy regarding its future movements, scholars have harnessed a variety of approaches to elucidate trends amidst the volatility of this market. To exemplify, the theory of a random walk suggests that movements within the US dollar market happen without an identifiable sequence or predictability. Analyses utilizing linear models to scrutinize changes in the US dollar's exchange rate have similarly failed to uncover steady patterns, mirroring insights consistent with the random walk hypothesis [1]. Over the course of several years, the investigation into nonlinear models has deepened, leading multiple academics to explore the use of simple time series models for predicting changes in the US dollar's exchange rate. Nonetheless, considering the intricate dynamics of the US dollar, which is profoundly affected by a multitude of unforeseeable factors, its behavior exemplifies a complex nonlinear system. As a result, the forecasts derived from traditional time series models often fall short in accurately capturing these nuances. Building on earlier research, the field of chaos theory has experienced notable growth, empowering scientists to delve deeper into the complexities of nonlinear systems. This advancement has been instrumental in enhancing the deployment of artificial neural networks within the financial industry, driving their adoption and incorporation. Neural networks are renowned for their outstanding capability to learn complex, nonlinear relationships, demonstrating exceptional skills in nonlinear approximation, error correction, and self-learning. Specifically, predicting the U.S. dollar's exchange rate exemplifies a quintessential nonlinear forecasting task, where neural networks showcase unique advantages in addressing challenges marked by nonlinearity.

2 Related works

As far back as the dawn of the 20th century, foreign neural network scholars, in their endeavor to forecast the U.S. dollar market [2], pioneered the utilization of artificial networks. They adhered to the traditional methodology of machine learning, whereby data was meticulously partitioned into training and testing subsets. The testing set, in this context, acted as the conclusive benchmark for validating the efficacy of their predictive models. Upon verification, it was established that artificial neural networks demonstrated a markedly superior ability to correlate with the US dollar exchange rate, outperforming traditional research approaches. Subsequently, Jintao Yao and Chew Lim Tan [3] utilized an error backpropagation (BP) neural network to predict the US dollar exchange rate. A selection of currency pairs, featuring comparisons between the US dollar and both the Japanese yen and the German mark, was chosen for analysis. A specialized neural network system was developed, its foundation rooted in an extensive examination of the US dollar's market behavior. Upon the completion of the system's development, they juxtaposed the forecasted results from different models in order to evaluate the efficacy of the constructed neural network. Their study found that utilizing this engineered neural network for predicting the British pound's exchange rate against the US dollar demonstrated a significant advantage compared to the traditional ARIMA forecasting approach. Additionally, Kuan and Liu [4] also constructed an artificial network to simulate the US dollar market and discovered that the constructed neural network performed well on some currency pairs but "failed" on others. Keith [5] pointed out in his article that it is difficult to discover the inherent laws of nonlinear systems like the US dollar market using traditional prediction methods, while neural networks have unique advantages in this aspect. The author employed a feedforward neural network for modeling the dynamics of the US dollar's exchange rate, incorporating fifteen input parameters, twenty hidden nodes, and three output dimensions. Specifically, within the set of input forecast indicators, the peak price, the nadir price, and the concluding price were chosen for analysis. When juxtaposed against traditional prediction methodologies, the utilization of the Backpropagation (BP) neural network showcased outstanding results. Mark Staley and Pcter Kim [6] indicated in their related papers that artificial neural networks can better predict changes in the US dollar exchange rate. Michael A. Pearson [7] and Hellry G. Green successfully applied artificial intelligence to solve interest problems among multiple currency pairs in the US dollar market, establishing relevant models to support British pound against US dollar exchange rate predictions and forecast price trends. In recent years, there has also been considerable research on this topic in China. Hu Yunquan, along with Hui Xiaofeng [8] and colleagues, employed genetic algorithms for the optimization of a Backpropagation (BP) neural network. They subsequently utilized this refined model for forecasting the exchange rate between the Chinese Renminbi and the United States Dollar. After testing, the constructed neural network model achieved good results in predicting the US dollar exchange rate. Wang Songxi [9] from Shanghai University of Finance and Economics studied data on the Japanese yen, British pound, and Australian dollar against the US dollar for 14 years from 1990 to 2004, selecting the daily highest price as the sample and using MATLAB for data simulation and analysis. The simulation analysis drew relevant conclusions, indicating that technical analysis can be used to predict the US dollar market. A short-term prediction model was established based on econometrics, combined with time series prediction methods, achieving good prediction results. During a sample fitting process spanning seven years, the maximum absolute value of the residual did not exceed 0.02, and the difference rate did not exceed 1.5%. During a prediction period of two months, the average value of the prediction difference (absolute value) was only 0.0045, with a difference rate of only 0.23% (the average actual market volatility was 0.69%); the maximum absolute value of the prediction difference was 0.0098, with a difference rate of 0.51% (the actual market volatility on that day was 1.42%). In their study, Ma Hongbo and Yang Xin [10] focused on predicting the US dollar's exchange rate. They employed a tailored neural network model to forecast the relative value of the German mark against the US dollar. Their methodology encompassed a comparison of the neural network's predictions with those generated by a random walk model. The results demonstrated that the neural network model provided markedly more accurate forecasts than the random walk technique. Wei Weixian [11] and others used five years of trading data from the London and New York US dollar markets to model and analyze the short-term fluctuations of the German mark against the US dollar. The prediction results indicated that, compared to traditional prediction models, neural networks indeed had higher prediction accuracy. Combining the research of relevant scholars both domestically and internationally, it can be seen that artificial neural networks have good performance in fitting nonlinear systems and exhibit many unique properties not found in other traditional models. At the same time, considering the research situation both domestically and internationally, the studied US dollar exchange rate fluctuations generally involve longer time intervals, which can increase uncontrollable factors. Expanding on previous research, this paper utilizes MATLAB to develop a BP neural network with a hidden layer. The objective of this novel methodology is to predict the fluctuating exchange rates between the British pound and the US dollar.

This paper's main objective is to predict the foreign exchange rate involving the British pound sterling and the United States dollar, utilizing a BP neural network distinguished by its singular hidden layer comprising fifteen neurons. Utilizing official statistics procured from an online database, the baseline estimate functions as the starting attribute, with the concluding adjusted figure representing the desired end result. Over a multi-year span, a collection of exchange rate variability metrics is divided into portions allocated for validation, assessment, and successive optimization, based on the performance observed during the learning period.

3 Research methods

3.1 Introduction to the data set

The core of this investigation relies on a neural network architecture operational within MATLAB. The objective is to predict variations in the foreign exchange rates specifically between the British Pound Sterling (GBP) and the United States Dollar (USD). The approach comprises multiple phases: collecting relevant data, constructing the predictive model, instructing the model through this data, and evaluating its effectiveness. By establishing a neural network and training it with historical exchange rate data, the paper aims to predict future exchange rates. Firstly, the paper collected all historical exchange rate data from August 31, 2019, to August 31, 2024, from the website investing.com. The paper downloaded the data into an Excel file named "GBP_USD Historical Data.xlsx". The paper extracted the opening prices as input features and the closing prices as the target outputs. The dataset captures the volatility of exchange rates over multiple years, essential for the model's training to be illustrative. It is partitioned into two segments: one dedicated for the model's training and the other for validation. The training portion serves to instruct the model, whereas the validation set facilitates an accurate assessment of its effectiveness. Utilizing MATLAB's Neural Network Toolbox, the paper embarked on constructing the neural network, methodically setting the node count in the hidden layers, defining the learning rate, and specifying the total number of epochs dedicated to training.

3.2 Experimental steps

The paper's experiment necessitates execution within the Matlab-R2023b framework, leveraging Matlab's Neural Network Toolbox.

Data Import: The paper uses the xlsread function to read exchange rate data from an Excel file.

Data Preprocessing: The dataset undergoes preprocessing steps, including cleaning and normalization. Subsequently, it is partitioned into distinct training and testing datasets.

Neural Network Construction: A feedforward neural network is created using the newff function, and training parameters are set.

Model Training: The training process employs the `train` function, evaluating the model's performance following each training iteration.

Prediction and Evaluation: The trained model forecasts the test dataset, and the relative errors are calculated subsequently. A comparative graph is produced, visually depicting the model's predictions juxtaposed against the actual values.

During the experiment, the paper found that our computer's processing power might be too low, resulting in slow running speeds. The paper attempted to switch to a higher-performance computer and successfully ran the experiment. Additionally, the analysis revealed that while the model demonstrated impressive performance on the training dataset, its efficacy was underwhelming when evaluated on the test set. To rectify this discrepancy, the paper refined the model architecture by incrementally modifying the node count within the hidden layers and fine-tuning the learning rate. These adjustments were aimed at boosting the model's predictive precision for unseen data points.

4 Experimental results

Through the training and assessment of the created neural network, the paper attained an average relative error of 0.24237, indicating that our model exhibits a certain level of accuracy in predicting the volatility of the British Pound's exchange rate relative to the US Dollar. During the assessment of the experimental results, the paper calculated the correlation coefficient between the model's predicted values and the actual measurements, yielding a figure of 0.99808.

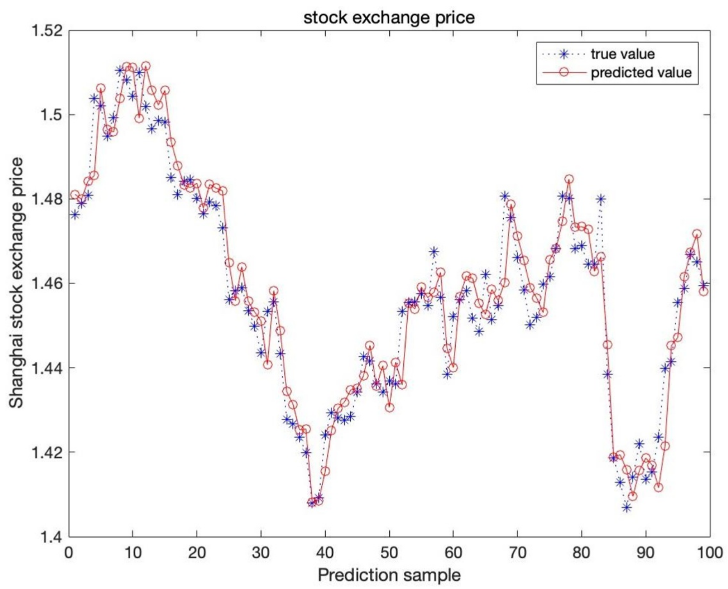

Fig. 1. An image of the actual values versus the predicted values.

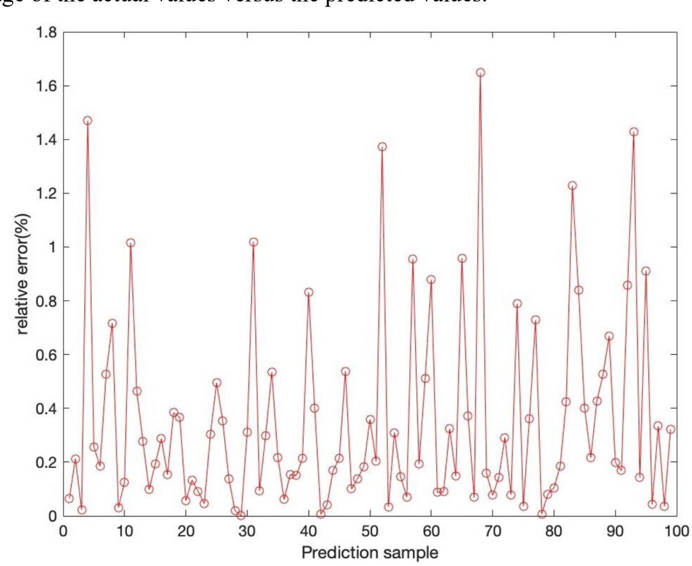

Fig. 2. The difference between the actual value and the predicted value

As shown in Fig. 2, by plotting the relative error graph, the paper can observe the distribution of prediction errors of the model across different samples. The relative errors for most samples remain within an acceptable range, while a few samples exhibit larger errors, which may be related to market volatility or data characteristics. As depicted in Fig. 1, the developed neural network model demonstrates significant effectiveness in identifying the trend of volatility changes in the currency exchange rates between the British Pound and the United States Dollar. However, the prediction performance of the model is still influenced by certain factors, and in some cases, the prediction errors are relatively large. This may be attributed to the data. In some special market conditions, data trends may deviate from other data.

5 Discussion

With the globalization of finance, diverse investment strategies have emerged, and the US dollar market presents significant opportunities. Predicting dollar prices is crucial for investors. However, the US dollar system is complex and nonlinear, influenced by various uncertainties. To address this, the paper collected and preprocessed historical exchange rate data from August 31, 2019, to August 31, 2024, ensuring data quality and representativeness. Using MATLAB's Neural Network Toolbox, the paper constructed a BP neural network with one hidden layer and 15 neurons to predict GBP/USD exchange rates.

Key findings:

(1) The paper designed a neural network model based on prior research and optimized it through multiple trainings. The model exhibited good learning on the training set but initially struggled on the test set. By adjusting parameters such as hidden layer nodes and learning rate, the paper improved its performance on the test set, achieving accurate predictions.

(2) The paper recognize the model's limitations. As discussed, the US dollar system's uncertainties and nonlinearities can result in increased prediction errors during market volatility or unusual data trends. This highlights the need for further optimization of model structure and parameters to enhance robustness and adaptability.

(3) Computer performance significantly affects experimental efficiency. By switching to a higher-performance computer, the paper resolved slow running speeds, enabling future large-scale data processing and model training.

(4) The paper comprehensively introduced the principles of BP neural networks and successfully applied them to predict the US dollar system. Selections of network layers, hidden nodes, learning rates, and training functions were experimentally and theoretically validated, yielding good prediction results on the test set.

In summary, this experiment successfully built a neural network model to predict GBP/USD exchange rate changes, demonstrating its predictive capabilities. Future research will focus on model optimization and improving practical applications. Despite its imperfections, our model provides a valuable tool for investors navigating the complex US dollar system. By acknowledging its limitations and continuously refining the model, the paper aims to enhance its robustness, adaptability, and predictive accuracy to better serve the needs of investors in the ever-evolving financial landscape.

6 Conclusion

It is evident from this paper that the BP neural network, constructed using MATLAB's Neural Network Toolbox, can be effectively applied to modeling for US dollar system prediction. It provides a good approximation for the US dollar price, which is a nonlinear system influenced by multiple factors. However, the research conducted in this paper represents only an initial stage, and there are numerous issues that warrant further investigation:

(1) BP networks deduce the relationships between inputs and outputs through training with input data. Therefore, to better construct a US dollar price prediction system, data collection should be more comprehensive and standardized. If conditions permit, attempts should be made to gather data on various factors that influence the US dollar price for prediction purposes. At the same time, traditional US dollar price prediction is just one aspect of US dollar investment. To truly excel in US dollar investment, it is also essential to conduct fundamental analysis and research on fund management, investment philosophy, etc.

(2) Due to time constraints, this paper could not provide a more comprehensive construction of the US dollar price prediction system. Given the opportunity, data on the main factors affecting US dollar movements, such as political and economic factors, should be collected to build a more holistic US dollar system. Additionally, fundamental analysis could be incorporated to offer better support for investment decisions.

(3) The US dollar price prediction system constructed in this paper is manually updated. In subsequent work, Expert Advisors (EAs) for algorithmic trading could be integrated to achieve automation.

Authors Contribution

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

References

1. Z. Lü. An Exploration of the Weak-Form Efficiency in China's Convertible Bond Market: An Empirical Study of Convertible Bond Indices Based on the Random Walk Theory. Journal of Commercial Economic Research, 26: 64-65 (2022).
2. A. P. Refense, G. Francis, et al. Stock performance modeling using neural networks. A comparative study with regression models. neural networks. (2014).
3. Y. Jingtao, T. chewlim, P. heanlee. Neural networks for technical analysis: A study on KLCI. International Journal of Theoretical & Applied Finance, 2(2) :221-241 (2019).
4. Z. Lu, A. May, K. Liu, et al. How to Scale Up Kernel Methods to Be As Good As Deep Neural Nets. Eprint Arxiv, (2019).
5. P. K. Richard. Theoretical aspects of generalization in feed-forward neural networks. University of Stirling, (2020).
6. M. Staley, P. Kim. Predicting the Canadian spot exchange rate with neural networks // Computational Intelligence for Financial Engineering, 2018. proceedings of the Ieee/iafe. IEEE:108-112 (2018).
7. H. G. Green, M. A. Pearson. Artificial intelligence in financial markets// IEEE International Conference on Neural Networks, (2021).
8. H. Xiaofeng, H. Yunquan, H. Wei. Research on the Application of BP Neural Network Based on Genetic Algorithm in Exchange Rate Forecasting. The Journal of Quantitative & Technical Economics, 19(2): 80-83 (2022).
9. W. Songxi. Exchange Rate Forecasting and Technical Analysis Based on Gene Expression Programming. Shanghai University of Finance and Economics, (2020).
10. Y. Xin, M. Hongbo. Application of Artificial Neural Networks in Medium and Long-Term Exchange Rate Forecasting. Systems Engineering, 17(1): 38-41 (2019).
11. W. Weixian, Z. Chuzhu, J. Zhenghua. Exchange Rate Forecasting Based on Artificial Neural Networks. Systems Engineering - Theory & Practice, 16(6): 13-20 (2022).