Comparative Study of Euro-Dollar Exchange Rate Forecasting Based on BP Neural Network and ARIMA

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Abstract. Effective economic activity prediction is crucial for financial market stability, as accurate exchange rate forecasting can significantly impact international trade and investment decisions. This study aims to anticipate the EUR/USD exchange rate utilizing the automatically picked BP neural network structure with the Autoregressive Integrated Moving Average(ARIMA) model, assessing their efficacy in capturing market dynamics. Traditional models, like ARIMA, often struggle to account for the complexities and nonlinearities of financial markets, which are influenced by various economic and political factors. Advanced techniques, such as BP neural networks, are designed to overcome these limitations by better capturing complex patterns within the data. With a mean squared error (MSE) of 2.8899e-06 and a lower relative error, the results demonstrate that the BP neural network model performs significantly better than the ARIMA model in terms of prediction accuracy. The ARIMA model's forecasts are presented as a horizontal line, which indicates that it performs less well than the BP neural network model. The study demonstrates that the improved neural network designed by BP has greater predictive capacity in terms of anticipating exchange rates. This provides decision-makers in the market for securities with useful information that can be utilized in their practice.

1 Introduction

Exchange rate forecasting is crucial in financial markets and international trade because it affects international trade and investment decisions. Accurate exchange rate predictions can help decision-makers and investors develop more effective strategies. However, due to the fact that exchange rates are affected by a wide range of economic and political factors, The complex market dynamics can be difficult to accurately capture using traditional methods, such as the Autoregressive Integrated Moving Average model. making accurate exchange rate forecasting highly challenging.

Therefore, there is a need to explore more advanced forecasting techniques. Pedro Escudero et al. provided optimal forecasts for the EUR/USD exchange rate over different periods using three methods [1], Jonas Lund Nadj et al. integrated macroeconomic data and technical indicators into a set of alternative LSTM models, allowing for more accurate

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forecasts of daily deviations in the foreign exchange market or any other financial market currency pair [2], Marek Vochozk and associates. Suggested suggested utilizing artificial neural networks to take seasonal fluctuations in equilibrium time series into account. The results showed that additional variables measured in forms such as years, months, mid-month days, and mid-week days improved the accuracy and order of the time series' equilibrium [3], Alexander Jakob Dautel and colleagues the prediction accuracy of direction and profitability of trading models between the use of Long Short-Term Memory Networks (LSTM) and gated repetitive units (GRU) compared to conventional frequent network architectures and feedforward networks. The findings demonstrated that deep networks can be used to predict exchange rates generally, but they also brought attention to how challenging it is to install and fine-tune these specific architectures[4], Cătălina-Lucia COCIANU et al. investigated financial data forecasting with one-step non-linear models with exogenous inputs. The results indicated that the LSTM neural networks suggested for the NARX model provided the best forecasting technique[5], In order to determine the best model for predicting foreign exchange rates and show how to get the closing price one step ahead of time, M. Markova suggested a method for projecting the exchange rate between the euro and the dollar using a nonlinear self-regressive system with external inputs (NARX) [6]. According to Dong Meng's research, a comparison with actual values showed that the ARIMA model had certain shortcomings in terms of relative and absolute error measures, showing that the BP paradigm outperforms conventional linear time series methods in terms of predicting precision, in comparison to the BP neural network approach [7]. Hippert, H.s & Pedreira et al. studied the combination of neural network and ARIMA model and proposed a hybrid prediction system to make hourly temperature forecasts. [8]. Matlab's BP tool functions for BP neural network research were presented by L. Liu, J. Chen, and L. Xu, along with instructions on how to program within them [9]. Shumway, R.H. and Stoffer, D.S. introduced the Box-Jenkins methodology for identifying ARIMA models, techniques for parameter estimation and forecasting with these models, and discussed some theoretical foundations for the use of ARIMA models [10]. The study compares the forecasting performance of the model developed by ARIMA and the BP neural network in order to predict the EUR/USD conversion rate. In order to increase prediction accuracy, the study specifically adjusts the total amount of neurons in the BP neural network's hidden layers. Additionally, experiments are carried out to assess the model's performance. The history of research and its present status is introduced in Chapter 1. Chapter 2 goes into great detail on the basic concepts of the BP neural network topology and its data sources. Chapter 3 presents the results of model training and compares the predicted results with actual data. Chapter 4 summarises the research findings and suggests directions for the study.

2 Research techniques

2.1 Research tools

BP Neural Network is a widely employed approach that trains network weights using a backpropagation algorithm to reduce the discrepancy between predicted and actual outcomes. The basic idea is that input data is processed through multiple layers of neurons to produce an output. By calculating the output error, the weights of each neuron layer are adjusted backward, allowing the network to gradually approach the ideal prediction results"A Backpropagation (BP) neural network is composed of an Input Layer, multiple Hidden Layers, and an Output Layer, where neurons in each layer are connected by weights. Neurons in this layer receive inputs from the previous layer and perform a non-linear transformation using activation functions, such as the Sigmoid function and the Rectified Linear Unit

(ReLU). Fig. 1 shows the specific model of the neural network. The more hidden layers there are, the better the network's ability to fit complex data, but this also increases the difficulty of training and the risk of overfitting. The particular learning process is shown in Fig. 2. There are multiple distinct advantages that come with using the BP neural network.

(1) The neural network developed by BP has high nonlinear modeling capabilities and can handle complicated quadratic issues with an activation function that isn't linear, which is suitable for complex data relationships that cannot be solved by traditional linear methods.

(2) The BP neural network has the ability to generalize well if there is sufficient training data to be well generalized to new data to achieve accurate prediction and classification of unknown data.

(3) Can handle high-dimensional data: BP neural network can deal with multi-dimensional data, feature extraction, and transformation of data through multiple hidden layers, which is suitable for dealing with the high-dimensional, complex structure of the data set. These various reasons make the BP neural network one of the mainstream models at present.

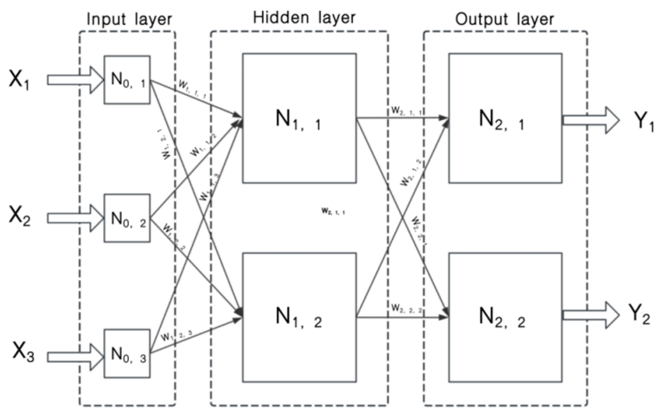

Fig. 1. The structure of neural network models for BP (Photo credit: Original)

One popular approach for time series forecasting is the ARIMA (Autoregressive Integral Sliding Average) model. There are three components that make it up.

(1) This component, called AutoRegressive, represents the linear connection between the time series's current and historical values. The AR component, which denotes a relationship among the present values and historical data, is defined as an autoregressive coefficient. The number of historical values used to forecast the present value is determined by the AR model's order (p).

The expression in mathematics is:

$$X_t = \sum_{i=1}^{p} \alpha_i X_{t-i} + \epsilon_t \tag{1}$$

In this equation, X_t denotes the value at time t, α_i represents the coefficients for the lagged values, and ϵ_t is the error term.

(2) The time series' trend component is taken care of by the integrated component. Applying a differencing operation is necessary to smooth the time series. For instance, the number of differentiation processes determines the integration order. One distinguishing operation, which entails deducting the prior value from the present value, is indicated if d=1.

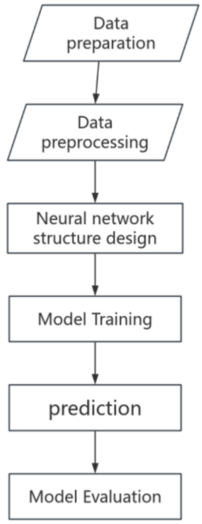

Fig. 2. BP neural network learning flow chart(Picture credit: Original)

The first-order difference formula is:

$$\Delta X_t = X_t - X_{t-1} \tag{2}$$

(3) MA, Moving Average: This component represents the linear relationship between the current value and the past forecast error. The MA component models the effect of the forecast error through a moving average coefficient.

The mathematical expression is:

$$X_t = \epsilon_t + \sum_{i=1}^{q} \theta_i \, \epsilon_{t-i} \tag{3}$$

These include the variance term (ϵ) and the fluctuating average coefficient (θ).

Fig. 3 below shows the ARIMA model learning flowchart of this paper.

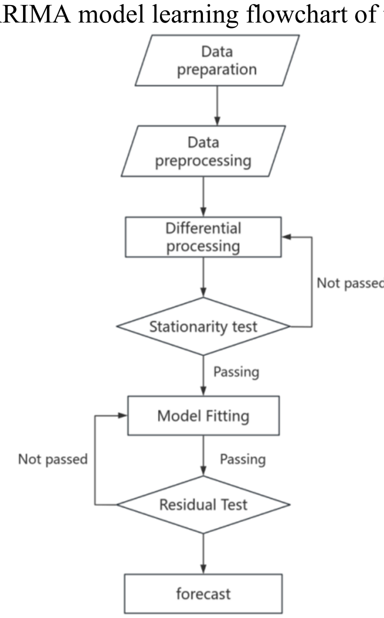

Fig. 3. ARIMA Model Learning Flowchart(Photo credit: Original)

2.2 Data sources and processing

The exchange rate data is obtained from https://investing.com/ as shown in Fig. 4, the Historical data of EUR/USD for the past five years and contains daily closing and opening prices. The data is split into a training set and a test set, where the training set is used for model training and the test set is used for performance evaluation. The input variables are the opening and intraday prices and the output variable is the closing price. The first 80% of the data is used for training and the second 20% is used for testing and validating the predictive ability of the model.

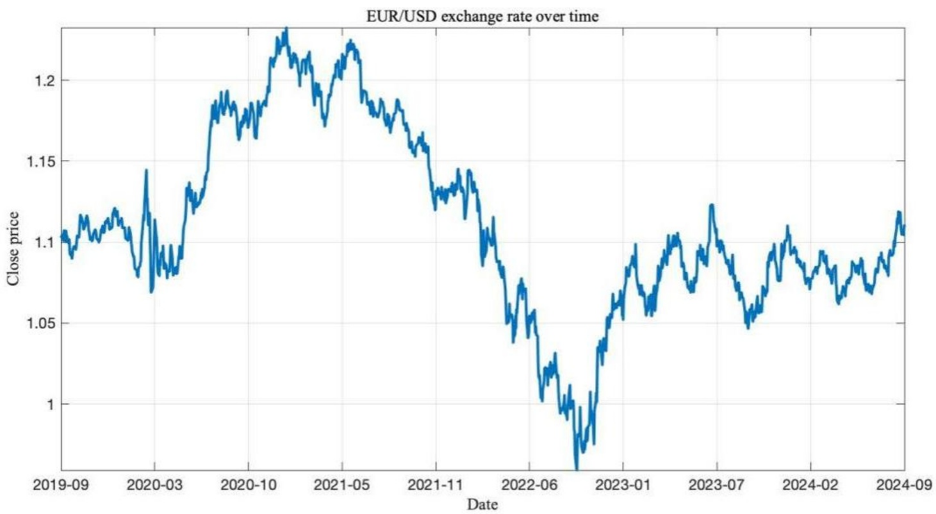

Fig. 4. Image of the exchange rate between EUR and USD from September 2019 to September 2024, drawn by means of Matlab (Picture credit: Original)

2.3 Model training

The ARIMA model and the BP neural network model were used with the neural network toolbox in MATLAB to set the training parameters, including the number of training rounds, the target error (MSE convergence to 10^-8) and the initial learning rate.

After training the ARIMA model, a test set is used to make predictions for future data. The model outputs future exchange rate values and compares them with the real test data. The trained BP neural network is used to make predictions about the set being tested. Using the same evaluation criteria (MSE and relative error), the accuracy output the simulation is assessed by comparing the projected output exchange rate figures once more with the actual exchange rates. After the prediction process is complete, the findings of the ARIMA framework and the BP neural network model are compared using the two metrics of MSE and relative error to evaluate the models' individual benefits and drawbacks.

3 Results and Analysis

3.1 Model training

3.1.1 Comparison between forecasted values and observed values

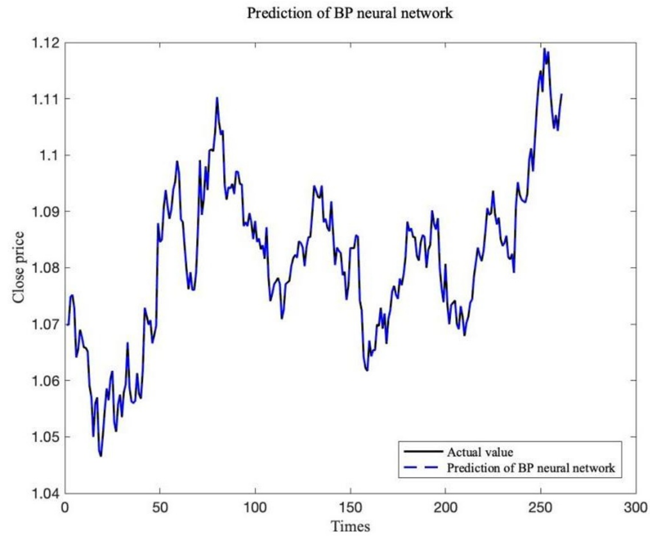

Fig.5. Difference between the actual value and the BP neural network's predicted value (Photo credit: Original)

The model's ability to accurately forecast the euro versus the US dollar trend is demonstrated by Fig. 5, which displays that the BP neural network's predicted value is quite near to the actual value, capturing the features of the data, and predicting the trend and specifics of the data. The model's high-precision prediction highlights its remarkable ability to recognize intricate patterns and non-linear features in the data.

3.1.2 MSE and Convergence Analysis

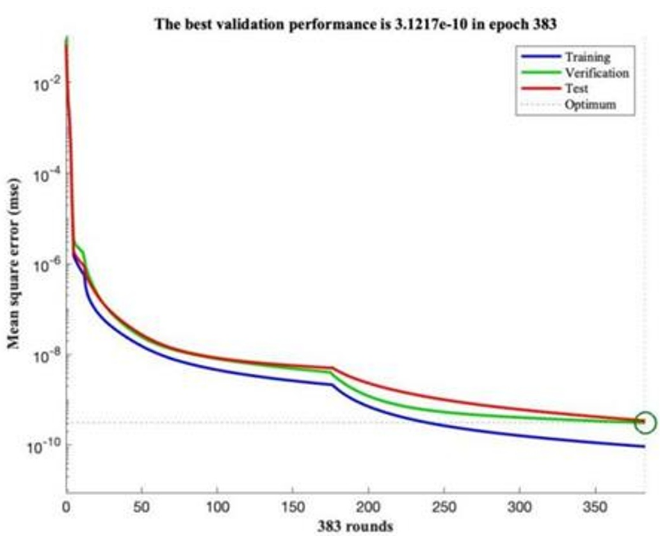

Fig. 6. Image of MSE (Picture credit: Original)

As shown in fig.6, the Mean Square Error (MSE) of the model decreased rapidly across all rounds during training, with a particularly sharp and pronounced decrease in the first 50 rounds. As training progressed, the Mean Square Error of the tray rounds approached zero, with the best performance of the validation group reaching 3.1217×10-103.1217 \times 10^{-10}3.1217×1 0- 10 in the Chapter 383 round. This result indicates that the model training has a very high training efficiency, and has reached a very precise high accuracy level.

3.1.3 Residual Analysis

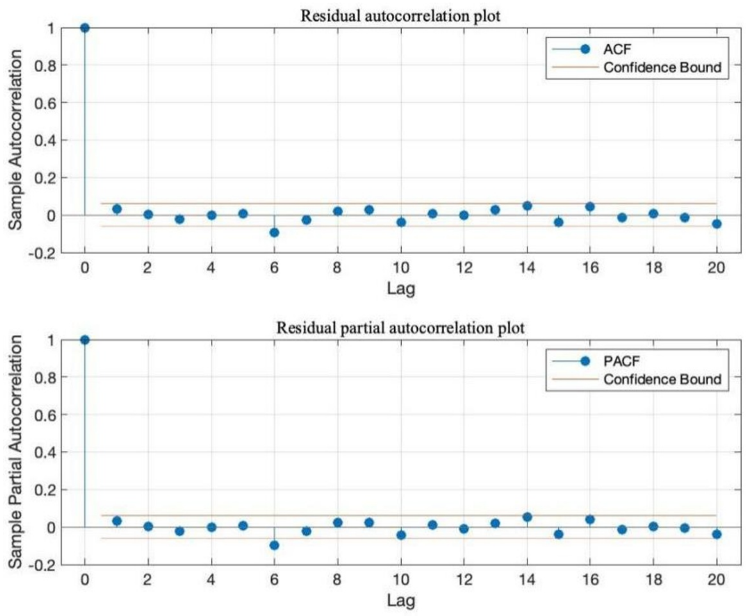

Fig. 7. Residual autocorrelation plot and residual partial autocorrelation plot (Photo credit: Original)

Diagrams of residual autocorrelation: fig.7 plots demonstrate that the residuals for each subsequent operation fall within the confidence intervals for the autocorrelation coefficients (ACFs). This suggests that the model residuals do not exhibit any discernible autocorrelation, which is consistent with the white noise assumption. This result implies the approach has effectively handled the data, indicating the residuals are randomly distributed, and suggesting that no significant patterns remain uncaptured by the model.

The leftovers' partial autocorrelation plot: Because the partial autocorrelation loss for each delay is also strongly positioned inside the residual confidence ranges, the Portion Synchronization Plot of the Differences (PACF) suggests there exists insufficient lagged autocorrelation in the residuals. According to this, the model has successfully eliminated the correlation in the data, demonstrating its suitability and efficacy.

3.1.4 Fitting effect

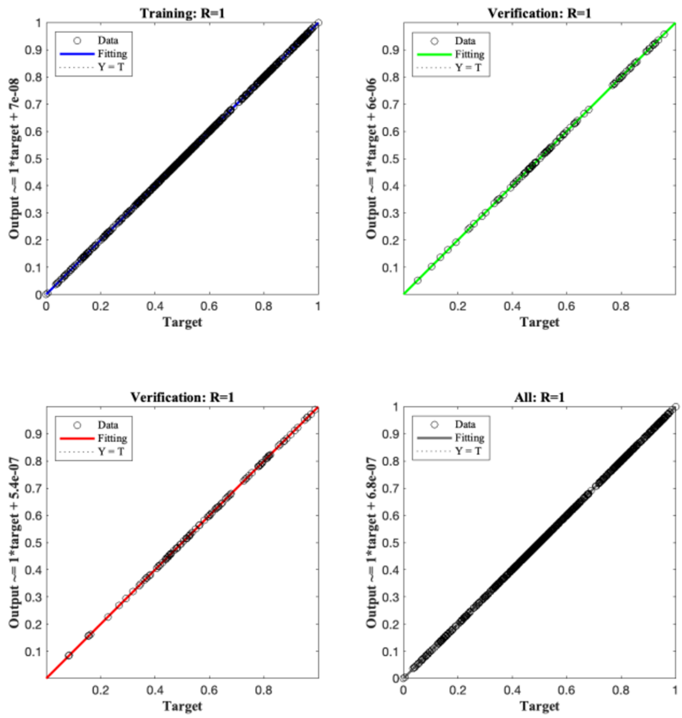

Fig.8. Fitting effect image (Photo credit: Original)

Fig. 8 illustrate the approach's effectiveness throughout the learning phase, validation, and test sets, respectively, as well as the condition of individual observations. Results indicate that this approach performed well across each data set. In each figure, the output values overlap almost completely with the target values, and the coefficient of determination (R) is 1. This suggests that across many datasets, the model's 28 prediction success rate is extremely good. The model has successfully captured the main characteristics of the data, demonstrating an exceptional ability to generalize.

3.2 Forecasting the EUR/USD time series using the ARIMA model

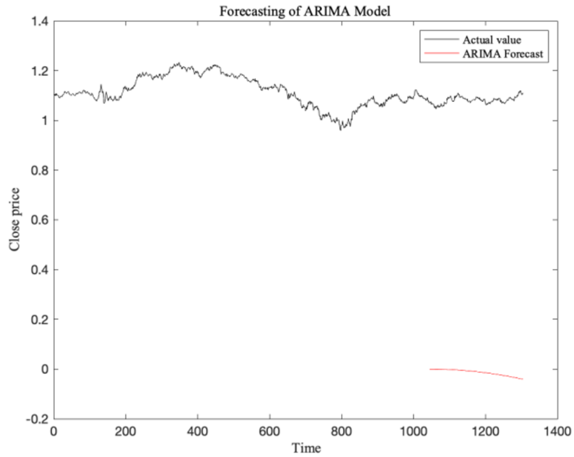

Fig. 9. ARIMA model predicts euro versus US dollar time series

(Photo credit: Original)

As shown in fig.9, There is some discrepancy between the actual value and the ARIMA as a strategy projected outcomes. When processing data with bigger amplitudes, the ARIMA simulation exhibits considerable variation even when the projected trend is quite close to the actual data. In particular, for some fluctuating variables in the time series, the predicted value increases and does not fully capture the complex non-linear relationship in the data. This is related due to the characteristics inherent in the linear mode, and in intricate temporal sequence prediction tasks, it may not be possible to achieve higher prediction accuracy and respect the results of the data.

3.3 Comparison between ARIMA model and BP neural network

Table 1. Comparison of ARIMA model and BP neural network

Model	Constant	AR{1}	MR{1}	Variance	Standard Error	T-Statistic	P-Value	AIC
ARIMA(0,2,1)	-1.1965e-06	N/A	-0.99026	2.7245e-05	1.6857e-06	-0.70978	0.47784	-8004.0634
ARIMA(1,2,1)	-1.1966e-06	0.024741	-0.99044	2.723e-05	1.6659e-06	-0.7183	0.47257	-8002.6981
ARIMA(1,2,0)	-4.4478e-06	-0.48674	N/A	3.9912e-05	0.00019722	-0.022553	0.98201	-7605.5797

(1) ARIMA(0,2,1) has an MA{1} value close to -1, a small standard error and an AIC of -8004.0634.

(2) ARIMA(1,2,1) shows a slight increase in the AR{1} parameter with a comparable AIC value (-8002.6981).

(3) ARIMA(1,2,0) has a lower AIC of -7605.5797, indicating a less favourable fit than the previous two models.

As shown in Table 1, these results provide insight into how each model performs in terms of quality of fit, with ARIMA(0,2,1) showing the best performance based on AIC.

Table 2. Error Metrics for ARIMA and BP Neural Network

Model	Mean Absolute Error(MAE)	Roost Mean Square Error(RMSE)
ARIMA	1.0951	1.0953
BP Neural Network	1.0951	7.7391e-06

(1) With an RMSE of 1.0953 and an MAE of 1.0951, ARIMA has noticeably higher failure ratios.

(2) The BP Neural Network has dramatically lower error metrics, with an MAE of 6.2045e-06 and an RMSE of 7.7391e-06.

As shown in Table 2, the results highlight the superior predictive accuracy of the BP Neural Network over the ARIMA model, suggesting that BP can better capture the underlying dynamics of the exchange rate data.

Table 3. Model Comparison between ARIMA and BP Neural Network

Model	MAE	RMSE
ARIMA	1.0951	1.0953
BP Neural Network	6.2045e-06	7.7391e-06

The error metrics comparison from Table 3 is repeated in this table, giving a direct comparison of the two models.

Compared to the backpropagation neural approach, the ARIMA method displays substantially higher values for MAE and RMSE.

(1) Due to its notably reduced MAE and RMSE scores, the backpropagation neural method shows a clear advantage over ARIMA."

(2) Results reveal that the BP Neural Network performs exceptionally well in this particular forecasted assessment, with much higher prediction accuracy.

4. Conclusion

This study evaluates the exchange rate predicting capabilities of the BP neural network versus the ARIMA model, concluding that the latter performs better. The optimized neural network model outperforms the model developed by ARIMA in currency exchange rate forecasting, as evidenced by its lowest relative error. It is apparent in the difference evaluation that the brain patch (BP) neural network model successfully removes all autocorrelation, thus the residual satisfies the white residual's properties, suggesting that the equation is capable of accurately predicting what was originally data. The noise impact graphic also demonstrates how effectively the BP neural network model can predict the original data. In addition, the noise effect plot shows that the BP neural network model can predict the original data well. The model showed extremely high performance in the three stages of training, verification and testing, and the R-value was close to 1, indicating that the model has a certain prediction ability and generalisation performance. In contrast, although the ARIMA model can reflect the trend of time series data in a certain programming, its performance in predicting drastic data is relatively weak. The Bayesian neural network model's benefits for planning complicated information are confirmed by the somewhat worse performance of the ARIMA model, particularly when it comes to capturing complex non-linear properties. The model performed exceptionally well in the three training, verification, and testing phases, and its R-value was nearly 1, suggesting that it has some capacity for prediction and generalization. On the other hand, the ARIMA model performs poorly when it comes to forecasting dramatic data, even though it may accurately depict the pattern of time series data in a certain programming. The considerably poorer performance of the ARIMA model validates the benefits of this neural network model in detecting complex data, particularly when it comes to capturing complex non-linear properties. Future research can further explore other model combinations and parameter optimisation methods to improve the prediction accuracy and apply them to a wider range of financial market analysis.

The neural network structure and ARIMA model can be further optimised, or other machine learning algorithms such as LSTM models can be tried to improve prediction accuracy. There is also potential to extend the prediction to other currency pairs.

References

1. P. Escudero, W. Alcocer and J. Paredes. Recurrent Neural Networks and ARIMA Models for Euro/Dollar Exchange Rate Forecasting. Applied Sciences, 11(12), 1-8. (2021)
2. J. Lund, N. Daniel, L. Jensen, A. Bo Rønsholdt. Predicting The EUR/USD Exchange Rate: A Deep Learning Approach.1-3. (2024)
3. M. Vochozka, J. Horák and P. Šuleř. Equalizing Seasonal Time Series Using Artificial Neural Networks in Predicting the Euro–Yuan Exchange Rate. JRFM, 12(2),76-79. (2019)
4. D., A.J., Härdle, W.K., Lessmann, S. et al. Forex exchange rate forecasting using deep recurrent neural networks. Digit Finance 2, 69–96 (2020)
5. C. Cocianu and M.S. Avramescu The Use of LSTM Neural Networks to Implement the NARX Model. A Case Study of EUR-USD Exchange RatesMarch 2020Informatica Economica 24(1/2020):5-14
6. M. Markova.Foreign exchange rate forecasting by artificial neural networks. AIP Conf. Proc. 2164, 060010 (2019)
7. D. Meng. Application of BP neural network in short-term exchange rate forecasting. Beijing University of Technology. (2011)
8. H., H.s & Pedreira, C. & Souza, R. Combining neural networks and ARIMA models for hourly temperature forecast. Proceedings of the International Conference on Neural Networks (IJCNN). 4. 414 - 419 vol.4. (2000) 10.1109/IJCNN.2000.860807
9. L. Liu, J. Chen and L. Xu. Realization and Application Research of BP Neural Network Based on MATLAB, 2008 International Seminar on Future BioMedical Information Engineering, Wuhan, China, (2008), pp. 130-133, doi: 10.1109/FBIE.2008.92
10. R. H. Shumway, D. S. Stoffer. ARIMA Models. In: Time Series Analysis and Its Applications. Springer Texts in Statistics. Springer, Cham. (2017) https://doi.org/10.1007/978-3-319-52452-8_3