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Comparative Performance Analysis in Exchange Rate Prediction: The Case Study of MYR/USD

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Abstract

Prediction of currency exchange rates became highly desirable due to its significant role in financial and managerial decision-making processes. The fluctuations in exchange rate affect the economy of a country. Hence, over the years, various statistical models, along with machine learning techniques, were developed to predict the currency exchange rates of different countries with varying parameters. In this paper, we compared the performance of classical forecasting methods with machine learning approaches in the specific context of exchange rate prediction, focusing on the currency pair MYR/USD. A thorough and careful analysis of experimental results was conducted on the models selected for both classical and machine learning methods, which included Holt's Linear Exponential Smoothing, ARIMA, and Neural Networks. Additionally, several performance measures such as RMSE, MAPE, and MAE were used to evaluate the forecast accuracy of these models. Our study revealed that Holt's Linear Exponential Smoothing model exhibited the highest forecasting accuracy compared to ANN and ARIMA models in terms of MAPE and MAE. Conversely, ANN provided the smallest RMSE value, followed by both traditional methods, which yielded the same RMSE value for the series. It is recommended that future studies investigate the incorporation of new methodologies, including the development of a hybrid neural network model, in order to achieve more precise outcomes while tackling social or economic problems.

Keywords:
Exchange Rate, Artificial Neural Network, Prediction

INTRODUCTION

An exchange rate is a term that describes the value of one country's currency with respect to another country's currency (Chen, 2022). In the modern world, exchange rates are mostly flexible, unpredictable, and fluctuate based on market supply and demand. The exchange rate between two currencies is typically influenced by factors such as economic activities, interest rates, GDP, and unemployment rates in the respective countries (Abdoh, Yusuf, Zulkifli, Bulot & Ibrahim, 2016). Rate fluctuations could occur frequently, either on an hourly or daily basis, with minor adjustments or significant changes.

Over the last few years, the COVID-19 pandemic created a significant impact on the global economy, triggering the largest economic crisis in history. This crisis affected currency exchange rates and became a concern in numerous countries (Statista Research Department, 2023). In the case of Malaysia's currency, the Ringgit reached its lowest value against the US dollar in November 2022 due to the Federal Reserve's unprecedented increase in interest rates.

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The uncertainties surrounding the monetary policies of central banks persisted into the new year, resulting in increased volatility in the USD/MYR currency exchange rate. Between February and May 2023, the exchange rate experienced a significant increase of approximately 5% (Chen, 2023).

The foreign exchange market was a large and volatile financial market that was essential to the development of the world economy. Exchange rates were commonly acknowledged as crucial indicators of the economy (Ganti, 2022). Predicting future currency rates was a challenging subject that had been extensively debated for years (Morrison, 2019). The ability to forecast exchange rates held great importance as it provided valuable information for decision-making in various sectors, including international trade, investment, monetary policy, corporate finance, economic analysis, and risk management. Therefore, individuals such as investors and business professionals were always eager to understand the future trend of exchange rates due to the significant impact fluctuations could have on their investments and transactions.

Traditional forecasting techniques, which relied on econometric models and time series analysis, had been employed in exchange rate forecasting for a long time. These techniques included moving average, exponential smoothing, ARIMA, and more. These models were frequently based on linear or stationary relationships in the data and depended on statistical assumptions (Cai, Pipattanasomporn & Rahman, 2019). Despite their widespread use in time series forecasting, they might not have been able to fully capture complex patterns and non-linear interactions that exist in the data. Recent years saw a number of studies develop new theories, techniques, and tools to enhance the modeling of time-series forecasting using machine learning. A subset of artificial intelligence known as "machine learning," the practice of teaching a computer to learn from data, was used to predict future values and events by recognizing patterns and relationships present in the training data. Machine learning could learn and adapt from any amount of data, in contrast to traditional methods that employed a set of predefined rules to create predictions (Wisneski, 2022). Machine learning methods like artificial neural networks, which offer supervised learning, might have filled the theoretical gap under the current state of technology. They had demonstrated the ability to handle massive datasets, capture non-linear patterns, and adjust to shifting patterns.

Numerous academic fields, including biology, physics, psychology, statistics, mathematics, business, and computer science, had been giving artificial neural networks significant attention (Abiodun, Jantan, Omolara, Dada, Mohamed & Arshad, 2018). It had been shown that a neural network could approximately resemble any continuous function, thanks to the classification and prediction abilities of the ANN. The forecasting of financial and economic data series, including currency exchange rates, had been accomplished successfully using neural networks. In terms of accuracy, Artificial Neural Networks (ANN) offered the most favorable forecasting methodologies and methods.

Accurate exchange rate forecasts assisted stakeholders in making well-informed decisions, reducing risks, optimizing operations, and promoting overall economic stability and expansion. Accurate forecasting is crucial for financial decision-making, and advanced models like VaR can improve prediction accuracy by accounting for volatility and risk (Ahmad Baharul Ulum et al., 2012). Therefore, there was an increasing need for studies that could help forecast their indications and boost the economy. Nevertheless, the accuracy of exchange rate estimations remained controversial given the unpredictable nature of currency movements (Remz, 2023). Considering that exchange rates are influenced by a variety of economic and political factors, forecasting exchange rates is a challenging subject from both practical and theoretical perspectives (Beckmann, Czudaj & Arora, 2020). This problem continued to be one of the largest challenges in the field of time series forecasting techniques, despite the fact that several statistical and economic models had been developed over the years by researchers with the purpose of forecasting exchange rates. As we were aware, lowering the risk of currency exchange rate changes involved reducing uncertainty, and an accurate forecast of the outcome required a suitable model. As a result, choosing the best forecasting approach had a significant impact on reducing the process's time, effort, and cost (Menon & Ranjan, 2023). Accordingly, the intent of this study, which focused on the currency pair MYR/USD, was to analyze and compare the performance of classical forecasting methods with machine learning approaches in the specific context of exchange rate prediction.

Due to the quantity of inherent complexities and uncertainties present in the foreign currency market, forecasting exchange rates was a challenging task (Yilmaz & Arabaci, 2021). Thus, issues like what parameter affects the currency rates and how to forecast future value came to light. Both model identification and parameter estimation were involved in time series analysis; however, the majority of researchers acknowledged that it was harder to identify a model (Tangirala, 2018). This was due to the fact that once a model's functional form was defined, determining its parameters was often straightforward. In order to determine whether the model could assist us in achieving the goals we had established, it was assessed based on its capacity to predict future values of the time series.

Despite the importance of exchange rate forecasting in financial decision-making and risk management, there was still a need to compare and evaluate the performance of traditional forecasting approaches and machine learning techniques in this area. Utilizing optimization to identify the optimal parameters and selecting the best method out of numerous traditional methods had been established for over a century and had seen significant improvement. The focus of traditional forecasting approaches was a univariate dataset or a multivariate dataset with finite, countable, and explainable predictions; these techniques were primarily descriptive in nature (Thomas, Johnson & Manoj, 2024). However, a growing body of research indicated that machine learning algorithms could outperform traditional methods because they frequently used more advanced prediction techniques (Menon & Ranjan, 2023). The most significant difference between the two methods lay in the manner of minimization. Even though they were widely used, traditional methods like ARIMA and exponential smoothing might not be capable of fully capturing the complex patterns and non-linear relationships present in exchange rate data. On the other hand, ANN showed promise in managing non-linearity and capturing complex patterns. One additional benefit of machine learning forecasting in this situation was the ability to incorporate a variety of forecasting methods, both linear and nonlinear, resulting in improved accuracy (Ahmad & Chen, 2020). Yet, their performance and applicability in exchange rate forecasting required empirical investigation. Hence, the primary objective of this research was to evaluate and compare the forecasting abilities of traditional techniques and machine learning approaches in the context of exchange rate prediction.

Classical forecasting methods did not always handle well; despite continuous improvement, they failed to perform adequately. In most cases, poor forecasts meant a significant increase in stock or a decrease in service levels (Hewamalage, Ackermann & Bergmeir, 2023). This situation highlighted the need for methods that worked more effectively, using all available data together to work out models that were more reliable. Machine learning was more suitable in this situation because it could aid in automatically analyzing and building such models. Furthermore, machine learning demonstrated its capacity to analyze both structured and unstructured data flows more effectively, swiftly recognizing particular patterns among data massifs (Hou, Kong, Cai & Liu, 2020). Time series forecasting became faster and more precise thanks to the contribution of machine learning (Nix, 2021). As we noticed, traditional approaches could only process previously collected, easily accessible demand history. Hence, it was safe to say that the fundamentals of machine learning in time series forecasting outperformed the traditional time series forecasting approaches.

According to various research, the ANN model provided the most accurate forecast for the nonlinear component among machine learning techniques (Hyndman & Athanasopoulos, 2018). The classical methods used for time series prediction, such as moving average, exponential smoothing, linear regression, ARMA, or ARIMA, assumed that there was a linear relationship between inputs and outputs (Oancea & Ciucu, 2014). The greatest advantage of neural networks was that they could approximate any nonlinear function without requiring prior knowledge of the characteristics of the data series (Cuomo, Di Cola, Giampaolo, Rozza, Raissi & Piccialli, 2022). In light of the statement mentioned earlier, a significant amount of research has been conducted on how particular kinds of machine learning in the field of forecasting, utilizing Machine Learning methods, specifically ANN, can be exploited to improve time series forecasting. Reviewing the findings of (Makridakis et al., 2018), it tried to prove that all machine learning techniques surpassed classical techniques when making comparisons of their performance. This study showed that among all machine learning techniques, Multi-Layer Perceptron (MLP) and Bayesian Neural Network (BNN) achieved the best performance.

Recent studies employed a variety of forecasting techniques, including classical econometric models and machine learning algorithms, to predict fluctuations in exchange rates. Even though some models performed well in in-sample analysis, according to results in the literature, classical models fared poorly in out-of-sample prediction analysis. This issue indicated uncertainty about which model was the most appropriate for the set of data related to currency exchange rates. To analyze the performance of the models in terms of output accuracy, we had to identify the model that made the most accurate predictions and wanted to find out how accurate these models were.

In this paper, various classical and artificial neural network models were established for exchange rate MYR/USD data from 2013 to 2023. The aim was (i) to investigate the accuracy of each model and compare the viability of the results to ensure assessment of the forecast quality of forecasting models, (ii) to identify the most suitable forecasted model for the analysis of MYR/USD which will provide the best output of forecasting which will be beneficial to the government, investors, traders, and more, and (iii) to compare the forecasting performance of artificial neural networks and traditional forecasting techniques in order to anticipate the MYR/USD exchange rate.

LITERATURE REVIEW

Traditional Methods

In terms of choosing the best forecasting model, the exchange rate issue recently caught the interest of many authors. Many scholars held the view that ARIMA was the best model for predicting exchange rates, and there was a growing body of evidence to support this statement. According to Joshi et al. (2020), the authors explored and analyzed the suitability of the ARIMA model for forecasting currency rates in the Indian context, specifically focusing on the rupee/dollar, rupee/euro, and rupee/yen pairs. The findings of this research indicated that the optimal model for predicting exchange rates was identified as ARIMA (1,1,5). Similarly, the research by Asadullah et al. (2020) constructed an ARIMA model to predict future exchange rates of the USD and PR by ensuring the stationarity of the time series through the first difference. The experimental results demonstrated a variance of less than 1% between the predicted and actual values.

In the analysis of the EUR/RON exchange rate, Ionela and Iustina Alina (2019), employed Box-Jenkins models, commonly known as Auto Regressive Integrated Moving Average (ARIMA) models. Their objective was to ascertain the significance of the exchange rate forecast and determine the best-fitting model specification. Furthermore, Nyoni (2019), utilized the Box-Jenkins ARIMA method to forecast annual time series data on the exchange rate between the Indian Rupee and the US Dollar. Diagnostic tests conducted in the study revealed the stability of the ARIMA (0,1,6) model, making it suitable for forecasting the exchange rate between the Indian Rupee and the US Dollar. Finally, in the comparison of the Iraqi dinar to the US dollar, Farhan and Fakhir (2019) proposed time series analysis using the Box-Jenkins method. The authors concluded that the ARIMA (1,1,1) model yielded the most reliable forecasts, suggesting its applicability as a dependable approach for estimating the exchange rate of any foreign currency.

However, there were still some authors who challenged the widely held view and came out with different opinions. Asadullah et al. (2021) and Asadullah, Bashir, et al. (2021), forecasted the exchange rate by a combination of different models. In both contexts, three univariate time series models (ARIMA, Naïve, Exponential Smoothing) and one multivariate model (NARDL) were included. These studies declared that the Naïve model, which had the lowest MAPE value, hence outperformed all other individual and combined time series models. In Ahmed et al. (2021), the authors forecasted the time series currency exchange rate of SAARC countries when converted from USD by using the Random Walk Model, Single Exponential Smoothing, Double Exponential Smoothing, and Holt-Winter Models. According to the accuracy metric, the ARIMA model and the Double Exponential Smoothing model were both capable of accurately predicting and smoothing out the series of currency exchange rates. Rasheed et al. (2020) evaluated and compared the precision of time series and economic forecasting models using the exchange rate of the Pakistani Rupee versus the US Dollar. As a consequence, it was determined that the exponential model, as opposed to the Naïve, ARIMA, and ARDL Co-integration models, offered the greatest accuracy in forecasting. In contrast, Al-Gounmeein and Tahir (2020), took a different approach by suggesting that the Seasonal Autoregressive Integrated Moving Average (SARIMA) model was a better fit for the time series data to predict future points in the exchange rates series than ARIMA based on the result of exchange rate forecasts for the Jordanian dinar vs. the US dollar in their paper.

In conclusion, these literatures indicated that among other classical models, ARIMA and Double Exponential Smoothing stood out as the best-performing methods. ARIMA was a widely used statistical model for time series forecasting, particularly effective in capturing autocorrelation and seasonality in the data. Besides, Double Exponential Smoothing was an extension of the simple exponential smoothing method, capable of handling time series data with trends. It had been found to perform well in scenarios where the exchange rate data exhibited a clear and consistent trend.

Machine Learning

Recent studies provided valuable insight to prove that machine learning contributes to accuracy improvement with an error reduction of 20 to 60% compared to classical forecasting methods such as moving average (Vandeput, 2021). In the literature, many machine learning approaches have been explored in forecasting applications. Specifically, Artificial Neural Networks (ANN) are the most widely implemented strategies in time series analysis. First, in Adekoya et al. (2021), the weekly exchange rate of one Ghanaian Cedi (GH) to three distinct currencies—the United States Dollar, Euro, and British Pound—was predicted using a Long Short-Term Memory Networks (LSTM) architecture. The suggested LSTM model performed better in accuracy and closeness metrics than the Support Vector Regressor (SVR) and Back-propagation Neural Network (BPNN) models, according to the authors' findings. Besides, Pfahler (2021), used artificial neural networks and the XGBoost models to forecast ten currency pairs from the OECD countries. According to this study's findings, the majority of machine learning techniques appear to have strong and extensive predictive power in directional forecasts, especially when applied to nonlinear machine learning models, which also contributes to the body of evidence supporting this claim. Furthermore, research results reported in Dautel et al. (2020), also support the appropriateness of neural networks for forecasting exchange rates. By contrasting LSTM and gated recurrent units with classical recurrent network architectures and feedforward networks in terms of their directional forecasting accuracy model predictions, this thesis successfully explores the potential of machine learning for exchange rate forecasting. Finally, Güler and Tepecik (2019), have shown that ANN is useful for forecasting fluctuations in the foreign exchange and gold markets, and the forecasted outcomes can be employed to foresee crises.

Overall, the literature review supports the proposition that Artificial Neural Networks are the best models for exchange rate forecasting when compared with other machine learning approaches. Their ability to capture non-linear relationships, handle temporal dependencies, and adapt to changing data dynamics makes them well-suited for this complex and dynamic forecasting task, such as exchange rate currency. By selecting ANNs as the best model, the study aims to contribute to the growing body of evidence supporting the efficacy of machine learning approaches in time series forecasting.

Comparison

Earlier research had affirmed that the forecasting capability of machine learning surpasses classical models in terms of precision. To substantiate this assertion, Kaushik and Giri (2020), attempted to develop a multivariate time series approach for forecasting the USD/INR exchange rate. They concurrently evaluated the performance of three multivariate prediction modelling techniques: Support Vector Machine (a Modern Machine Learning Technique), Recurrent Neural Networks (a Modern Deep Learning Technique), and Vector Auto Regression (a Traditional Econometric Technique). The results unequivocally demonstrated that modern SVM and RNN algorithms outperformed the widely used traditional auto-regression approach. Study by Escudero et al., (2021) focusing on the EUR/USD exchange rate, a comparison of short-term accuracy among three forecasting models, included Autoregressive Integrated Moving Average (ARIMA), Long Short-Term Memory (LSTM), and Recurrent Neural Network (RNN) was conducted. The findings revealed that RNN provided the best long-term forecast, while LSTM excelled in short-term predictions, emphasizing the predictive efficacy of machine learning. To differentiate between traditional models (ARIMA) and machine learning techniques such as Recurrent Neural Network (RNN) and Support Vector Machine (SVM). In addition, Liao et al., (2020) employed time series forecasting for the USD to RMB exchange rate. In comparison to SVM and ARIMA, RNN exhibited superior performance. Furthermore, Liang et al., (2022), utilized the ARIMA model to predict linear characteristics in the RMB exchange rate. Conversely, the ARIMA model was integrated with four other machine learning models (CNN, RNN, Elman neural network, and RF) to present nonlinear residual predictions. The authors' analysis indicated a notable enhancement in prediction performance under each machine learning model for trend and periodic sequence predictions compared to the sole use of the ARIMA model.

In general, the neural network (NN) approach demonstrated higher profitability compared to the linear regression model across three distinct performance metrics, as anticipated due to its capacity to identify nonlinear patterns (Karlsso, 2021). The study conducted by Matta et al., (2021), which involved a comparison of the performance of Gaussian process regression (GPR) with two artificial neural networks, namely MLP and Radial Basis Functions Neural Network (RBF), against other forecasting techniques in the realm of machine learning. The results indicated that multi-layer perceptron networks exhibited excellent predictive accuracy for econometric data, with Gaussian process regression models and multi-layer perceptron networks producing the most satisfactory results. In the research conducted by (Stoll et al., 2021), two industrial datasets were analysed using both traditional and machine learning forecasting methods. The traditional methods encompassed moving average, exponential smoothing, and ARIMA models, while the machine learning techniques included K-nearest neighbour, random forests, and neural networks. The results suggested that machine learning models proved to be effective tools for forecasting, delivering results with reasonable Root RMSE and MAPE, and the predicted values closely mirrored the actual behaviour of testing values. Aluko and Liu (2019), conducted a time series study comparing machine learning algorithms used for sales prediction with traditional forecasting methodologies such as Multivariate Linear Regression, K-Nearest Neighbours (KNN) Regression and lastly Artificial Neural Networks (ANN). The results indicated that the Holt-Winters model, along with machine learning models KNN and ANN, produced significantly lower RMSE and MAE compared to other classical forecasting models. Lastly, Uh and Majid (2021) investigated the effectiveness of the ARIMA model and Artificial Neural Network (ANN) in gold price forecasting based on the value of RMSE. The lower value of RMSE in the comparison suggested that ANN could serve as an excellent alternative to ARIMA.

In summary, although ARIMA and Double Exponential Smoothing are considered strong classical forecasting methods in time series forecasting, several pieces of literature reaffirm that ANN offers distinct advantages, especially in capturing non-linear relationships and handling dynamic patterns in exchange rate data. The study aims to compare and contrast these best-performing models to provide valuable insights and recommendations for exchange rate forecasting.

METHODOLOGY

The real data of exchange rate currency of Malaysian Ringgit against the United States Dollar used in this study is secondary data collected on a daily basis. With a total of 10 years of historical data, covering the period from 1 July 2013 to 30 June 2023, the source of the data was downloaded from the official Open DOSM website. All data are easily available and publicly published by the Department of Statistics Malaysia (2023), readily available to develop different time series models that can estimate the MYR/USD currency. The data used in this study consists of historical daily exchange rate currency MYR/USD, which is time series data. The Bretton Woods Agreement made the U.S. dollar the official reserve currency of the globe, backed by the greatest gold reserves in the world (Best, 2023), and it is always compared universally with other currencies. It has also become the reason for this research choosing this pair as the medium. Besides, the dataset contains a total number of 3,833 observations. The observations only contain one independent variable, MYR/USD, and one dependent variable, which is the day. Time series models, as opposed to other types of models, use the target variable as a predictor variable. In this scenario, the outcome will be more effective the more data there is. In conclusion, the closer the forecast value is to the actual value, the more efficient the results can be explained.

Three techniques were used in this research: ANN, Auto-Regressive Integrated Moving Average (ARIMA), and Holt's Linear Exponential Smoothing. Currently, these are the most popular time series forecasting models in time series forecasting, as they have shown better performance in forecasting quality and accuracy.

Holt's Linear Exponential Smoothing

Holt's linear trend method, also known as Double Exponential Smoothing, is an extension of simple exponential smoothing designed to handle data exhibiting a trend by smoothing both the level and trend components when present (Pardoe, 2023). This method incorporates a level component and a trend component at each period. In the context of double exponential smoothing, the components are updated at each period using smoothing parameters, which dictate the rate at which the series' weights decay. Typically, exponential smoothing methods combine the current estimate for a period with a portion of the random error produced in that time interval. Weighted averages of historical data are used in exponential smoothing applications for forecasting. It is anticipated that the impact of recent discoveries will eventually decrease rapidly (Cho, 2003).

Previous academic references state that when a strong trend is present, basic exponential smoothing will eventually lag behind the actual time series predicted values (Hyndman & Athanasopoulos, 2018). By adding a second equation with a second constant, this scenario can be improved (Glen, 2018). It is therefore possible to handle trended data using the advanced versions of exponential smoothing algorithms. When the historical data series is not stationary, this method is also helpful in handling the series.

To forecast into the future using this smoothing methodology, the equation can be written as:

$$\hat{Y}_{t+m} = a_t + b_t m$$

Where the difference between the exponentially smoothed values is represented by a_t,

$$a_t = 2S_t - S'_t$$

and the adjustment factor (b_t) is calculated by using formula,

$$b_t = \frac{\alpha}{1-\alpha}(S_t - S'_t)$$

To find the difference between the simple and double smoothed values (a_t) as a measure of a trend, we must first compute the simple and double smoothed values using the respective formulas:

$$S_t = \alpha Y_t + (1-\alpha)S_{t-1}$$

$$S'_t = \alpha S_t + (1-\alpha)S'_{t-1}$$

Where S_t is the exponentially smoothed value of Y_t and S'_t is the double exponentially smoothed value of Y_t at time t. We are prepared to make the forecast for m periods into the future once we have made the required adjustments to the data.

In this research, Holt's Linear Exponential Smoothing model was run using computer software, SPSS, which is a powerful statistical package.

Autoregressive Integrated Moving Average (ARIMA)

ARIMA, also recognized as the Box-Jenkins model, is a statistical analysis model known as Autoregressive Integrated Moving Average (ARIMA). This method uses time series data to either gain a better understanding of the dataset or forecast future trends (Hayes, 2022). Essentially, when a statistical model forecasts future values by utilizing data from the past, it is termed autoregressive. ARIMA modeling is frequently employed for time series analysis, forecasting, and control, making it a common choice among scholars conducting research on time series forecasting. The effectiveness of the ARIMA model in predicting outcomes based on historical data stems from its assumption that past values have some residual influence on present or future values, utilizing historical data to forecast future events. In particular, ARIMA is a forecasting method grounded in historical time series data. It relies on the statistical concept of serial correlation, asserting that previous data points influence subsequent data points. Additionally, ARIMA uses lagged moving averages to smooth time series data. Instead of using actual values, the model seeks to predict past movements in time series markets by analyzing differences between values in the series.

According to Hyndman and Athanasopoulos (2018), the two most often used techniques for time series prediction are exponential smoothing and ARIMA models, both of which offer complementary solutions to the problem. The main difference between exponential smoothing models and ARIMA models is that exponential smoothing predicts based on a description of the trend and seasonality present in the data, while ARIMA aims to describe the autocorrelations in the data. When comparing ARIMA models with exponential smoothing models, this essential distinction is noticeable.

Following the Box-Jenkins methodology, the ARIMA model is developed in three essential steps: model identification, model estimation, and model validation. In this instance, the SPSS software was utilized to develop the models.

Artificial Neural Network (ANN)

The model of ANN in this study decided to adapt the concept of multi-layer perception. The typical three-layer feedforward network served as the neural network model for this research, with a single output node considered for one-step-ahead forecasting. To experiment with the exchange rate time series ANN model, these models were implemented with the help of MATLAB software and its Neural Networks module. In this research, we train the ANN using the Levenberg-Marquardt algorithm provided by the Neural Network Time Series Tool (ntstool) available in MATLAB (R2023a), which is employed in training and the analysis on the exchange rate currency data using an Artificial Feed-Forward Neural Network with back-propagation principles, following its popularity for being a reliable technique in the field of forecasting (Yusof & Samsudin, 2018). It is acknowledged that Neural Network training performs better with a larger dataset. Therefore, the dataset adapted for this study was deemed suitable for use.

In this study, a nonlinear autoregressive neural (NAR) network was used. The structure of the NAR neural network model was displayed in Figure 1. When only one series is involved, the NAR network (NARN) is a particular kind of dynamic neural network that specializes in time series prediction (Wei et al., 2012). A time series Y(t) can only have its future values predicted given its d previous values. This type of forecast can be expressed as follows.

$$Y(t) = f(Y(t-1), Y(t-2), \ldots Y(t-d))$$

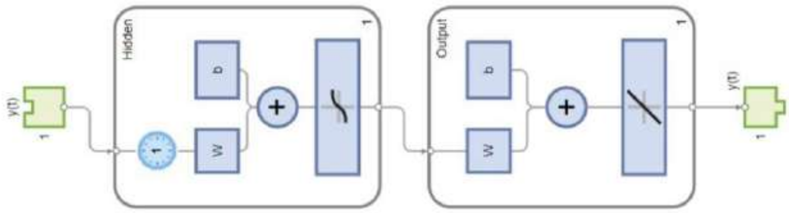

Figure 1: The structure of NAR neural network model

Furthermore, while an open-loop network architecture is beneficial for network training, a closed-loop architecture (as depicted in Figure 2) proves more useful for multi-step ahead predictions. The software MATLAB utilized the function "close loop" to convert the open-loop architecture to a closed-loop model.

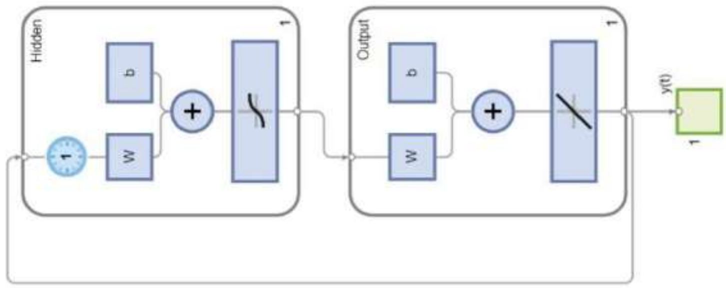

Figure 2: Closed loop architecture of NAR neural network model

Following the study by Reddy (2015), Vika et al. (2016), and Charef and Ayavhi (2016), the structure of a NAR used in the present study is depicted as 70% (2680 observations) of the data, known as the training data, are randomly chosen to train the neural network. The training set contains training data, while 15% (575 observations) of the data, known as the validation data, are used to validate that the network is generalizing and to stop training before overfitting. It will measure the network's generalization by providing it data it has never seen before (Mitrea et al., 2009). Eventually, the remaining 15% (575 observations) of samples, referred to as the test data, provide an independent measure of the neural network's MSE performance used for checking and validating the model for predicting the exchange rates.

In terms of MLP network architecture, it has been proven that most practical issues could potentially be solved with a single hidden layer of neurons (Palmer et al., 2006). One of the most important tasks in developing a network is figuring out how many hidden layers and neurons there are. This is because the number of hidden neurons affects the MLP network's learning ability (Wei et al., 2012). Notwithstanding its significance, there is no single standard that specifies the ideal quantity of hidden neurons to use in a given situation. Neural networks can recognize complicated relationships and capture nonlinear patterns in the data series thanks to the quantity of hidden nodes in the network. Networks containing too few numbers of hidden nodes may not have enough power to effectively model and learn the data. Conversely, networks with excessive hidden nodes could experience overfitting issues, which would make their forecasting performance inadequate (Zhang & Hu, 1998).

In this study, a three-layer network structure (p, d, m, n) was employed for training NAR network models, where p represents the input vectors, d is the feedback delay, m is the number of neurons in the hidden layers, and n is the output vectors. According to Khan et al.

(2015), the neurons in this layer can be changed depending on the performance of the result. We employed the typical technique of numerous starts in neural network training to prevent getting stuck in local minima. Following literature by Wei et al. (2012), the training process started with 1 neuron (m=1) and feedback delay from 1 (d=1), and the number of neurons and feedback delay ranges were increased progressively if the network performance could not be improved after several rounds of training. In the quest to determine the optimal delay and number of hidden neurons, all parameters were set to fixed values, and a trial-and-error procedure was employed to adjust the delay. This iterative process continued until the value providing the network with the best performance was identified, following the methodology outlined by Ruiz et al. (2016). The evaluation criteria for determining the best performance included the significance of time delay, MSE, MAE, and MAPE. As suggested by Agus and Sri Hartati in 2016, the NAR method was subjected to testing using different combinations to ascertain the appropriate number of hidden nodes and delay time.

In addition, the adequacy of the model was assessed by examining the significance of the time delay in terms of the error autocorrelation function (EACF) and input-error cross-correlation function (IECF). The EACF elucidates how simulation errors are correlated over time, while the IECF illustrates the correlation between errors and input sequences. A perfect prediction model is characterized by only one nonzero value in the autocorrelation function, and all input-error cross-correlations should ideally be zero. In cases where the assumptions for a perfect prediction model are not met, as highlighted by Wei et al. (2012), enhancements to the NAR model are typically implemented. This improvement can be achieved by increasing the number of delays or the number of neurons in the hidden layer.

Model Evaluation

To evaluate the accuracy of the model, we compare the current data with the data generated by applying the prediction model to earlier time periods. The difference between the actual and expected values is referred to as the forecast error. The smaller the values of these criteria, the closer the forecasted value is to the actual value (Lin et al., 2012). Therefore, we may conclude that the smaller the forecast error, the more accurate the model is (imVivRan, 2020).

There are several measures used to assess forecast accuracy. Following Lu et al. (2009) and Tay and Cao (2001), the performance measures evaluated in this study include RMSE, MAPE, and MAE, which quantify the deviation between actual and forecasted values.

Mean Squared Error (MSE)

The average of the squared differences between the predicted and actual values is computed by MSE. By calculating the average of the squared forecast errors of the model's prediction, the MSE error measure solves the issue of positive and negative forecast errors offsetting each other. Better accuracy and closer agreement between forecast and actual values are indicated by a lower MSE. However, due to the squaring process, MSE is sensitive to outliers and penalizes greater errors more heavily. As extra knowledge, the value is always positive since it is the square of the difference between the expected value and the desired value.

It is computed as follows:

$$MSE = \frac{\sum_{t=1}^{n} e_t^2}{n}$$

Root Mean Squared Error (RMSE)

RMSE has the same scale as the initial target variable, and is the square root of MSE. It is a helpful statistic since it directly interprets the average error magnitude in the same units as the expected variable. It gives an indication of the typical size of forecast mistakes relative to the data's original scale. When comparing forecasting accuracy across several datasets, RMSE is frequently employed. No matter the time period, RMSE gives each error the same weight. Similar to MSE, RMSE is sensitive to outliers and a lower value denotes better accuracy.

It can be calculated as follow:

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n} e_t^2}{n}}$$

Mean Absolute Percentage Error (MAPE)

The average percentage difference between the expected and actual values is measured by MAPE. When considering forecasting performance, MAPE, which offers a relative measure of accuracy, is often used. A lower MAPE suggests better accuracy when stated as a percentage. As a result, comparisons for a different time period are challenging. This measure has the benefit of accounting for the relative size of the error term in relation to the actual units of observation. But MAPE has its limitations as well, especially when the actual numbers are very near to zero, as this might lead to significant or infinite errors.

We can compute MAPE for the series using formula as follow:

$$MAPE = \frac{\sum_{t=1}^{n} \left| \left(\frac{e_t}{Y_t} \right) . 100 \right|}{n}$$

Mean Absolute Error (MAE)

The MAE method calculates the average magnitude of errors in a set of predictions without considering their direction (Matta et al., 2021). It represents the mean of absolute differences between predictions and actual observations over the test sample, assigning equal weight to all individual differences.

$$MAE = \frac{1}{n} \sum_{t=1}^{n} e_t$$

According to earlier studies, MSE, RMSE, MAPE, and MAE are often used evaluation metrics for evaluating the effectiveness of forecasting models, including those articles that forecast exchange rates. Each metric offers a unique perspective on the models' precision and accuracy. Using a mix of these criteria can give a comprehensive evaluation of forecasting models' performance when used to predict exchange rates. MAPE offers a measure of relative accuracy while MSE and RMSE concentrate on the magnitude of error. When choosing the best assessment criteria, it's crucial to take the unique properties of the exchange rate data and the research goals into account. Additionally, to have a better knowledge of each model's strengths and shortcomings, it is advised to compare the performance of several models using a variety of evaluation criteria.

ANALYSIS AND DISCUSSION

Data Analysis of Holt's Linear Exponential Smoothing

The time series plot of the exchange rate currency Malaysia Ringgit against the United States Dollar plotted in Figure 3 displays a trend; it has no seasonal or cyclical pattern existing, and the growth rate has been changing over time. Because of these characteristics of the series depicted in Figure 3, Holt's Linear Exponential Smoothing method was chosen for this study's adoption in order to compare it with alternative approaches.

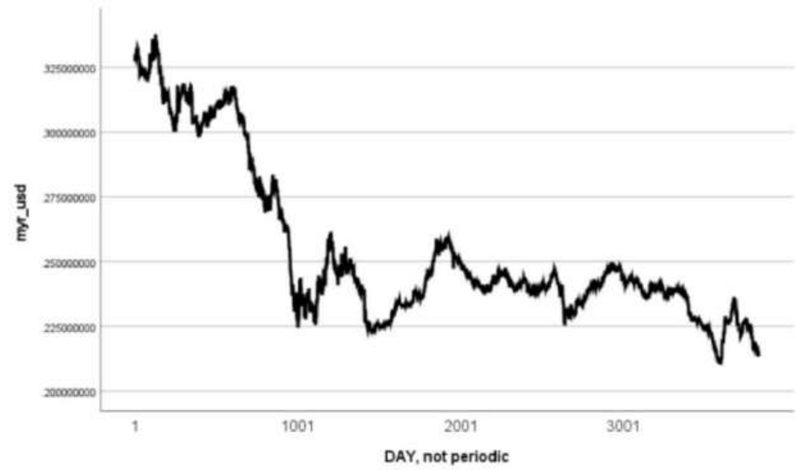

Figure 3: Time series plot of exchange rate currency MYR/USD from year 2013 to year 2023

Table 1: Parameters estimation for holt's linear exponential smoothing

Model			Estimate	SE	t	Sig.
Myr_usd-Model	No Transformation	Alpha (Level)	.960	.016	59.495	.00
		Gamma (Trend)	1.490E-5	.000	.070	.944

Regarding DES, the trend parameter γ used to smooth the slope tries to improve the overall model fit, while the parameter α smooths the level equation. Table 1 summarizes the accuracy results obtained using the best parameters found in our analyses: $\alpha = 0.960, \gamma = 0.00001$. the value was low, it indicated that the corresponding series exhibited stability over the training period. Conversely, a high value suggested that the fluctuation of rates was significant. As shown in Table 1, the parameters of trend smoothing, γ, for the series were nearly zero. This suggested that the slopes of the series remained constant over the training period, or the trend could be adequately represented by a straight line.

Table 2: Error summary for Holt's linear exponential smoothing model

DES parameters	RMSE	MAPE	MAE
$\alpha = 0.960$ $\gamma = 0.00001$	0.001004	0.209946	0.000541

Table 2 shows how the Holt's Linear model works on the data provided. The output for double exponential smoothing results in very good accuracy measures (MSE, MAPE, and MAE) within the known range of data; their forecast accuracy was systematically high.

Data Analysis of ARIMA

Model Identification

The initial step in the analysis involves creating a run sequence plot of the response variable. In this instance, the analysis commences with plotting the given sequence of observations, specifically MYR/USD against days. This initial plot provides insights into the characteristics of the series, aiding in the detection of trends and determining if the series is stationary or non-stationary. Additionally, a run sequence plot can help identify the presence of outliers and seasonal patterns. If non-stationarity is observed, it can often be addressed by differencing the data or fitting a trend curve. Subsequently, attempts are made to fit a Box-Jenkins model to the differenced data or to the residuals after fitting a trend curve.

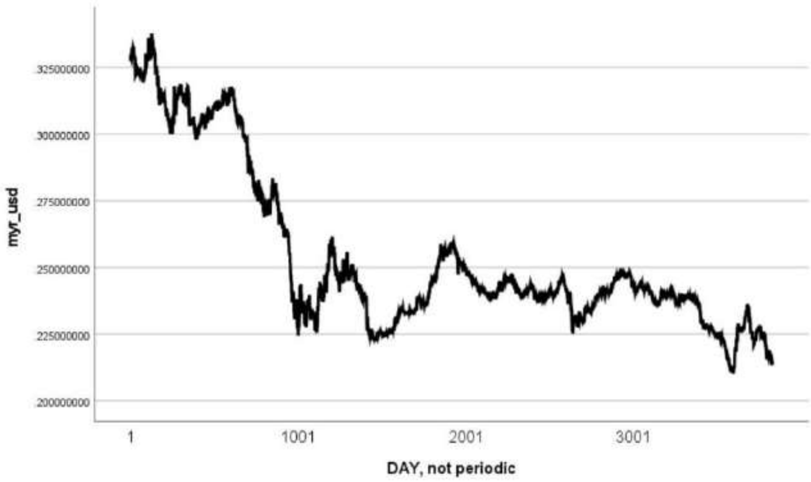

Figure 4: Sequence plot of exchange rate currency MYR/USD from year 2013 to year 2023

The above run sequence plot yielded the following conclusions. Figure 4 distinctly showed that the rate of MYR/USD maintained a fluctuating and decreasing trend over the years. There was no apparent or significant seasonal pattern, but a noticeable downward trend was evident in the data over this period. Moreover, there was no indication of any cyclic behavior. The analysis also concluded that the original pattern of the time series of the index was not stationary, primarily due to the presence of a trend.

Model Estimation

This section describes the estimation of parameters for all selected ARIMA models. The following parameter estimates, p, d, and q, were computed using SPSS for these models based on the differenced data. The chosen parameter values were based on suggestions by literature.

Table 3: Parameter estimation for ARIMA (4,1,0)

					Estimate	SE	t	Sig.
myr_usd-Model_1	myr_usd	No Transformation	Constant		-2.953E-5	1.512E-5	-1.953	.051
			AR	Lag 1	-.042	.016	-2.573	.010
				Lag 2	.024	.016	1.480	.139
				Lag 3	-.011	.016	-.667	.505
				Lag 4	-.044	.016	-2.723	.007
			Difference		1			

ARIMA (4,1,0) can be represented as below equation:

$$\Delta x_t = -0.00003 - 0.042\Delta x_{t-1} + 0.024\Delta x_{t-2} - 0.011\Delta x_{t-3} - 0.044\Delta x_{t-4}$$

Table 4: Parameter estimation for ARIMA (4,1,1)

					Estimate	SE	t	Sig.
myr_usd-Model_1	myr_usd	No Transformation	Constant		-2.954E-5	1.484E-5	-1.990	.047
			AR	Lag 1	.212	.314	.676	.499
				Lag 2	.034	.021	1.647	.100
				Lag 3	-.017	.018	-.930	.353
				Lag 4	-.044	.018	-2.527	.012
			Difference		1			
			MA	Lag 1	.254	.314	.810	.418

The model for the differenced data, ARIMA (4,1,1) is as below:

$$\Delta x_t = -0.00003 + 0.212\Delta x_{t-1} + 0.034\Delta x_{t-2} - 0.017\Delta x_{t-3} - 0.044\Delta x_{t-4} + 0.254\varepsilon_{t-1} + \varepsilon_t$$

Table 5: Parameter estimation for ARIMA (0,1,4)

					Estimate	SE	t	Sig.
myr_usd-Model_1	myr_usd	No Transformation	Constant		-2.953E-5	1.507E-5	-1.960	.050
			Difference		1			
			MA	Lag 1	.043	.016	2.691	.007
				Lag 2	-.026	.016	-1.586	.113
				Lag 3	.010	.016	.607	.544
				Lag 4	.043	.016	2.665	.008

ARIMA (0,1,4) can be represented as below equation:

$$\Delta x_t = -0.00003 + 0.043\varepsilon_{t-1} - 0.026\varepsilon_{t-2} + 0.01\varepsilon_{t-3} + 0.043\varepsilon_{t-4} + \varepsilon_t$$

Table 6: Parameter estimation for ARIMA (1,1,4)

					Estimate	SE	t	Sig.
myr_usd-Model_1	myr_usd	No Transformation	Constant		-2.954E-5	1.488E-5	-1.984	.047
			AR	Lag 1	.214	.340	.628	.530
			Difference		1			
			MA	Lag 1	.257	.340	.754	.451
				Lag 2	-.035	.022	-1.583	.113

continued

	Lag 3	.015	.019	.792	.428
	Lag 4	.042	.018	2.369	.018

The model for the differenced data, ARIMA (1,1,4) is as below:

$$\Delta x_t = -0.00003 - 0.214\Delta x_{t-1} + 0.257\varepsilon_{t-1} - 0.035\Delta\varepsilon_{t-2} + 0.015\Delta\varepsilon_{t-3} + 0.042\Delta\varepsilon_{t-4} + \varepsilon_t$$

R-squared was a statistical measure indicating how closely the data aligned with the fitted regression line. It was represented as the percentage of the response variable variation explained by a linear model. Table 7 displayed the R-squared values for each model.

Table 7: R-squared value for various order of ARIMA model

ARIMA Model (*p*, *q*, *r*)	R-squared
(4,1,0)	0.9989
(4,1,1)	0.9989
(0,1,4)	0.9989
(1,1,4)	0.9989

Based on the output from SPSS, all ARIMA models showed the same R-squared value, which was 0.9989. This value indicates that the model explains 99.89% of all the variability in the response data around its mean. The high R-squared value suggests that all models were considered to have a good fit.

Model Validation

It was required to determine whether the model was appropriate after it had been fitted. Furthermore, by taking into consideration multiple potential models, information-based criteria like the AIC or BIC can be implemented to help in selecting an appropriate model. In order to eventually determine the best-fitted model, we decided to look onto the Bayesian Information Criterion (BIC) for different orders of moving average (q) and autoregressive (p) terms, while maintaining the integrated term (d) at order 1. Table 8 presented the BIC values for different orders of parameters p and q in the ARIMA model for the Malaysian Ringgit against the US dollar.

Table 8: BIC value for various orders of ARIMA

ARIMA Model (*p*, *q*, *r*)	Normalised BIC
(4,1,0)	-13.7976
(4,1,1)	-13.7956
(0,1,4)	-13.7977
(1,1,4)	-13.7955

As observed from the following table, the lowest BIC value is considered the best fit for the model. Hence, ARIMA (0,1,4) is considered the best model for modeling and predicting future values of our time series data in terms of information criteria, as it presented the lowest BIC value of -13.7977.

The residuals from each of these models were then subjected to the Box-Ljung test to see if they were random. Since the p-values for all models were more than the significance level of 0.05, the summary of the Box-Ljung test output for each model in Table 9 indicated that the first 24 lag autocorrelations among the residuals were zero. This proved that the models offered a sufficient fit to the data and that the residuals were random. The results of the two tests above, along with the large p-values, indicated that the null hypothesis was accepted, as all autocorrelation functions in lags 1 to 24 were zero. In other words, our fitted models did not show any evidence of non-zero autocorrelations in the forecast errors at lags 1 to 24.

For instance, the test results showed zero autocorrelation in the residuals from ARIMA (0,1,4) for the first 24 lags. This led us to conclude that there was sufficient evidence to assert that the residuals were random, as indicated by a p-value of 0.313.

Table 9: *p*-value of Box-Ljung test for various orders of ARIMA

ARIMA Model (p, q, r)	Box-Ljung test
(4,1,0)	0.296
(4,1,1)	0.322
(0,1,4)	0.313
(1,1,4)	0.307

Table 10: summarizes the results obtained using various selected ARIMA models

ARIMA Model	RMSE	MAPE	MAE
(4,1,0)	0.001004	0.212494	0.000548
(4,1,1)	0.001004	0.212781	0.000548
(0,1,4)	0.001004	0.212576	0.000548
(1,1,4)	0.001004	0.212738	0.000548

Based on the experimental results, the RMSE and MAE errors are similar across all the models. In the case of currency MYR/USD, ARIMA (4,1,0) achieved the lowest error and it appeared to be the appropriate model as the best in terms of forecast error with the lowest MAPE value (0.212494).

Overall, we concluded that the ARIMA (4,1,0), ARIMA (4,1,1), ARIMA (0,1,4), and ARIMA (1,1,4) were adequate models for the currency data of MYR/USD. However, we decided to choose ARIMA (4,1,0) as our final ARIMA to make a comparison with other methods because this model is performing better than the others after observing several points. ARIMA (4,1,0) satisfied the assumptions and stationary condition, which also yielded a significantly low value of BIC (-13.7976) and the lowest value of forecast error (MAPE=0.2125).

Data Analysis of ANN

To obtain the best model of ANN, it resulted in computing several neural network models with different combinations of neurons (*m*) and feedback delay (*d*), among which we chose the best-fit one to report its training, validation, and testing results. Statistics of error measurement and predictive modeling performance of different combinations of parameters for the NAR network on the dataset for all experimental trials are summarized in the following tables.

Table 11: Performance measure of different parameters with NAR model

d (delay time)	*m* (neuron)	RMSE	MAPE	MAE
1	1	0.001006	0.216576	5.564e-04
	2	0.001009	0.217742	5.605e-04

continued

2	1	0.001003	0.214562	5.516e-04
	2	0.001002	0.214343	5.528e-04
	3	0.001003	0.212646	5.482e-04
	4	0.001001	0.211601	5.459e-04
	5	9.984e-04	0.210720	5.433e-04
	6	0.001007	0.216333	5.587e-04
3	1	0.001004	0.214806	5.523e-04
	2	0.001002	0.214605	5.535e-04
	3	0.001002	0.215250	5.552e-04
4	1	0.001004	0.213827	5.506e-04
	2	0.001002	0.213563	5.509e-04
	3	0.001010	0.219945	5.661e-04

After training the network, the performance can be evaluated using the performance function in MATLAB. The best results were achieved with the NAR model, with a higher number of neurons, as the lowest forecast error involved a minimum of 2 neurons in most cases. According to the information from Table 11, the result regarding the best delay is 2, whereas the worst delay horizons are 1 and 4. In this case, we could conclude that the number of neurons required by NAR to get the best forecast is 5, with the best delay time being 2.

The best result obtained is plotted in Figure with an MSE of 7.7326e-07.

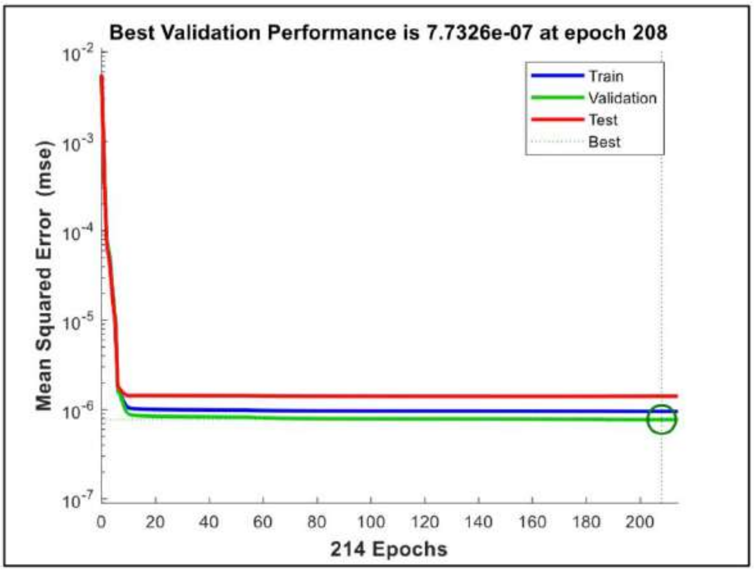

Figure 5: Performance analysis of best NAR model

Figure 5 illustrated the dynamic features of MSE. When the training process reached epoch 208, the training result represented the best performance. Various training algorithms could be chosen to train samples in a neural network.

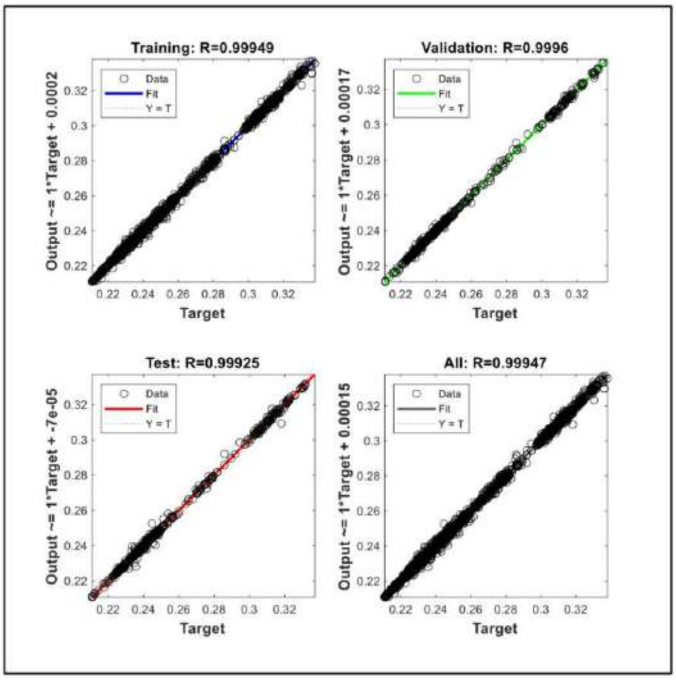

Figure 6: The fitting state of training data

The correlation between the actual and anticipated exchange rates for each training, test, and validation sample was visually displayed in Figure 6. The magnitude of the error, indicating the difference between the actual and anticipated values, was also shown in the illustration too. While the visual representation strongly suggested a good fit of the NAR network in predicting the exchange rate, a quantitative analysis was performed by computing MSE and R values for both the training and test datasets. The presence of high R values and negligible MSE values in both datasets implied the effective predictability of the exchange rate using the NAR architecture.

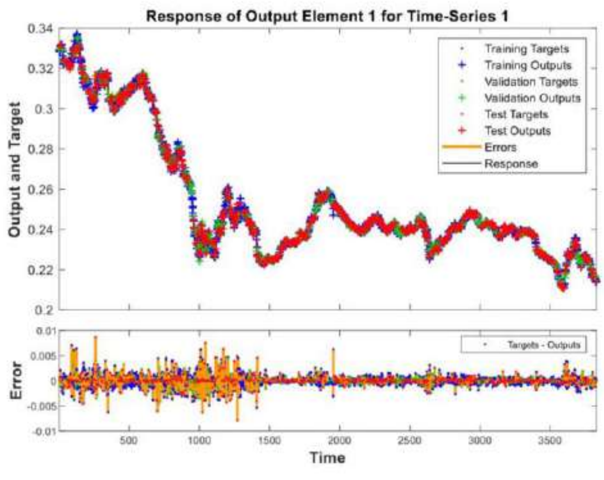

Figure 7: Prediction curve of NAR neural network model

Moreover, two curves were depicted in Figure 7, the actual curve of the original sample data and the prediction curve of the NAR neural network. The actual curve of the original sample data was composed of many red plus signs, while the prediction curve was composed of many blue dot marks. Examining Figure 7 revealed that the two curves exhibited a similar fluctuation tendency, indicating a good fitting effect. The fitting error of the curve, observed to be between -0.01 and 0.01, was relatively small. Therefore, it can be concluded that the NAR model demonstrated a good fitting effect on the nonlinear curve.

Besides, Figure 8 illustrates the plots of EACF for the Best NAR Model.

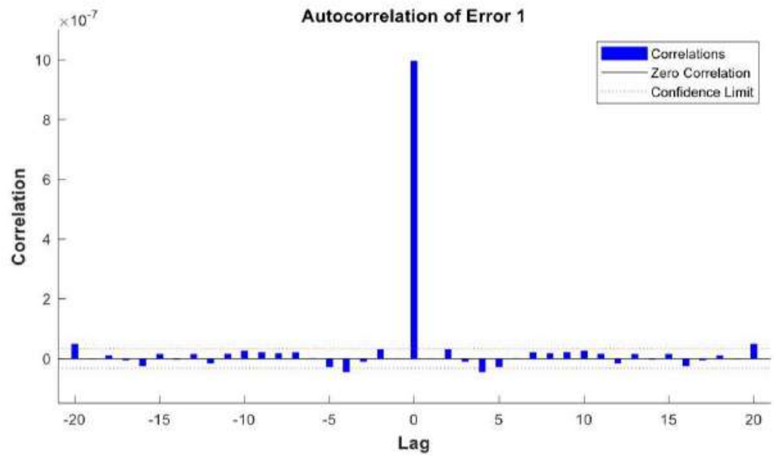

Figure 8: Error autocorrelation function (EACF) of NAR model

With the exception of the one at zero lag in Figure 8, error autocorrelations were approximately within the 95% confidence limits around zero when a feedback delay of 2 (*d*=2) and 5 neurons (*m*=5) were employed in the hidden layer. Hence, we can also report that the time delay is significant since there are only a few error autocorrelations displayed in the figure, which are at lags ±4 and lags ±20. It can be observed that although the autocorrelation of the NAR model fluctuated up and down, it generally remained within the confidence interval. This observation further supports the reasonableness of the NAR model for predicting the time series data (Sun et al., 2020).

Error histogram with 20 bins for the best NAR model was displayed below in Figure 9.

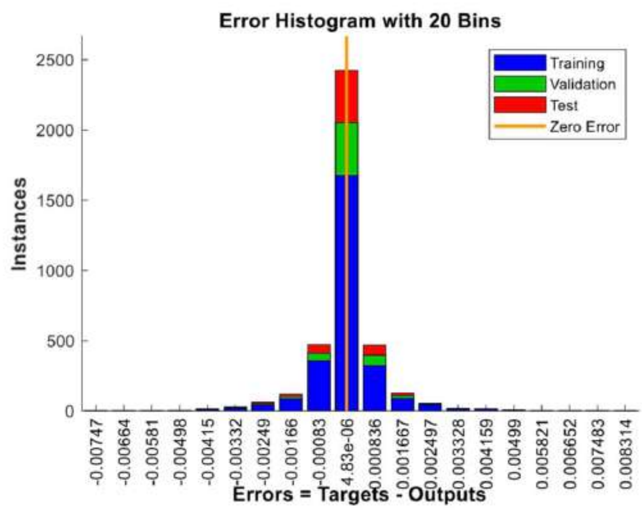

Figure 9: Error histogram of NAR model

It was clear that for the training, validation, test, and whole dataset, the actual exchange rate and the forecasted exchange rate were extremely close. The actual and expected exchange rates displayed a nearly linear trend, supporting the model's effectiveness.

In conclusion, the negligible MSE and high R values indicated that the presented NAR network with 2 delay units and 5 neurons possessed strong forecasting ability to predict the exchange rate as a nonlinear function in the data.

Performance Evaluation

Ultimately, for the purpose of assessing and comparing the performance of each model, various evaluation criteria such as MAE, RMSE, and MAPE were applied. The results of these evaluation metrics are presented in Table 6, enabling a comprehensive comparison between Holt's Linear model, the ARIMA model, and the nonlinear autoregressive neural network. Based on the empirical findings outlined in Table 6, it was evident that the forecasting accuracy of the ANN model, when compared with both classical approaches (Holt's Linear and ARIMA models), exhibited a noteworthy significance.

Table 12: Summary performance measure for all three models

Methods	RMSE	MAPE	MAE
Holt's Linear	0.001004	0.209946	0.000541
ARIMA	0.001004	0.212494	0.000548
ANN	0.000998	0.210720	0.000543

According to the results presented in the table, when using 70% of the data as training input, the Nonlinear Autoregressive Neural Network (ANN) model and Holt's Linear Exponential Smoothing demonstrate superior forecasting performance across multiple evaluation criteria (MAE, RMSE, MAPE). It can be argued that all models performed reasonably well, as indicated by the relatively low forecast errors. Among them, the ANN model produced the smallest RMSE value, followed by both traditional models (Holt's Linear and ARIMA), which reported identical RMSE scores. For MAPE and MAE, however, Holt's Linear Exponential Smoothing yielded the most accurate results. Although the ARIMA model performed well and produced consistently low forecast errors, both the ANN and Holt's Linear models outperformed ARIMA in terms of overall accuracy, as reflected in all three criteria: RMSE, MAE, and MAPE.

Moreover, despite the favorable outcome of MAE indicating a low value for all methods, it is noteworthy that ARIMA reported the highest MAE value, signifying a comparatively lower forecasting ability than the other two methods. The presented results clearly demonstrated the greater robustness and efficiency of the Neural Network and Holt's Linear models in forecasting exchange rates compared to ARIMA models. Holt's Linear model, with a higher frequency of minimal errors, emerged as the method displaying superior performance among the three. Furthermore, the ANN model exhibited better forecasting accuracy than the ARIMA model in terms of performance while maintaining similarity to the Holt's Linear model, albeit with a slightly higher MAE of only 0.000002. The success of exponential smoothing models, which essentially involve weighted averages of past observations, in performing well for MYR/USD data is not surprising.

Certainly, the forecasting accuracy of Holt's Linear Exponential Smoothing surpassed that of ARIMA when comparing classical models. The results consistently demonstrated that Holt's Linear model exhibited superior predictive performance in all cases, with small values of RMSE, MAPE, and MAE throughout the training results. Specifically, the MAPE and MAE were notably higher for the ARIMA model compared to the Holt's Linear model, despite both models obtaining the same RMSE value. This suggests that the exponential smoothing approach to modeling can offer better insights into the trend and seasonality over time, making it a more suitable choice than the ARIMA model.

Conversely, the Holt's Linear Exponential Smoothing model exhibited the highest forecasting accuracy compared to the ANN and ARIMA models in terms of MAPE and MAE. Consequently, the forecasting results underscored the superiority of the Holt's Linear model in predicting daily values of the MYR/USD currency pair. Moreover, the magnitudes of MAE and MAPE highlighted that larger forecast errors were more significant in the case of ARIMA and less so for the Neural Network model and Holt's Linear model. Despite the longer training time of ANN, its forecasting ability was deemed accurate, as evidenced by the lowest RMSE. This suggested that ANN was well-suited and applicable for predicting fluctuating series of exchange rates.

Once again, ANN emerged as one of the best models for forecasting exchange rate data, as it yielded the smallest RMSE. Therefore, this research further validated the contrasting opinions reported in the literature regarding the superiority of the ANN model over the ARIMA model in time series prediction. Additionally, the best performance under MAPE and MAE was achieved using Holt's Linear Exponential Smoothing methods. This was attributed to both methods obtaining fair MAE and MAPE values, signifying that the predicted values closely aligned with the true behavior of the testing values. All performance measures for the ANN and Holt's Linear models were better than those for the ARIMA model, indicating that the ARIMA model exhibited poorer forecasting performance compared to the other two methods.

Obviously, the results established the dominance of the Holt's Linear Exponential Smoothing technique across all measures, excluding RMSE. Likewise, ANN surpassed both classical models in RMSE, affirming the continued superiority of the neural network technique in various empirical research fields. On the contrary, the magnitudes of every criterion indicated that the result of large forecast errors should be treated with more attention when it comes to ARIMA, showing that the model was inappropriate for this series of data.

CONCLUSION

This paper explored the predictability of exchange rates between the Malaysian Ringgit and the United States Dollar using both classical time series methods—ARIMA and Exponential Smoothing—and more complex nonlinear methods such as ANN. Intriguingly, the results and findings presented in this paper diverge from existing literature. Previous studies have affirmed the superior performance of neural network models compared to ARIMA models (Reddy, 2015; Al-Maqaleh et al., 2016). Additionally, Holt's Linear Exponential Smoothing method has been suggested to be successful in forecasting most trend data (Salah et al., 2021; Alias et al., 2016). However, in this study, Holt's Linear Exponential Smoothing performed slightly better than ANN, achieving the lowest forecast error in terms of MAPE and MAE, while the ANN results were considerably better than those of the ARIMA model.

In the comparison between classical methods, exponential smoothing techniques, in some instances, demonstrated superior performance compared to ARIMA models, as they were more adaptable to even the smallest changes in market conditions (Dezsi & Fat Codruta Maria, 2011). Moreover, ARIMA models encountered challenges in estimating and validating the model, and they proved more effective in capturing medium-term trends. Conversely, Holt's Linear models revealed changes in trend more effectively, and forecasting models based on exponential smoothing techniques served as effective tools for those seeking insights into the evolution of exchange rates. As suggested by DeJans (2023), exponential smoothing is suitable when a clear trend or seasonality is present in the data, whereas ARIMA is preferable when dealing with more complex patterns and a sufficiently large dataset to support its complexity.

According to the findings, the feedforward neural network model and Holt's Linear Exponential Smoothing performed better than the ARIMA model. Despite its simplicity, the results implied that the feedforward model provided fairly precise forecasts. These models performed effectively when tested using financial data, offering investors a useful tool to hedge against possible market risks. This was probably due to neural networks' ability to model currency's nonlinear behavior and time dependence using a flexible functional form. One reason of why neural networks worked well in this situation is that they could estimate any kind of nonlinear function.

For several reasons, the neural network model and Holt's Linear Exponential Smoothing method outperformed the ARIMA model in predicting exchange rates. Firstly, the ARIMA model relies solely on past values, providing less information compared to other traditional econometric models. Secondly, if there are nonlinearities in the data, the linear ARIMA model may struggle to capture them effectively, unlike neural network models, which inherently handle nonlinear relationships, as supported by Dematos et al. (1996). Additionally, the ARIMA methodology addresses non-stationarity by applying differencing operations to the time series until stationarity is achieved. However, this process may result in the loss of valuable long-term relationships between the endogenous variable and explanatory variables (Adebiyi et al., 2014).

The feedforward network model showed valuable forecasting capabilities, likely due to its ability to exploit nonlinear dependencies in the data, as it operated as a nonlinear model. This aligned with the findings of Adebiyi et al., (2014), who noted that financial markets, including stock and currency markets, which exhibited nonlinearity, possessed memory and may have been more accurately modeled using techniques beyond traditional linear statistical methods. The nature of neural networks, being flexible and capable of approximating any nonlinear function, aligned with the nonlinear theory of financial markets. This theory challenged the traditional method of time series forecasting, as they usually performed better in handling linearity, suggesting instead that those data series might exhibit nonlinear, unpredictable, and random behavior. The results from the feedforward model supported this perspective, offering evidence for the nonlinear nature of markets (Vika et al., 2016), challenging the prevailing belief in data randomness. If markets indeed exhibited nonlinearity, employing complex models like neural networks, despite their increased complexity compared to traditional linear models, might have offered more accurate results. It was feasible for neural networks to efficiently and simultaneously extract both the model parameters and the nonlinear functional form. Furthermore, they provided substantial assistance for quantitative finance in non-parametric regression-related problems. However, it is also noteworthy that several considerations were involved in setting up neural networks, where parameters and architectures were chosen only through trial and error, with the research by Dhamija and Bhalla in 2010 serving as a reference.

In this study, feedforward neural networks were employed to forecast the daily MYR/USD exchange rate from 2013 to 2023 with the aim of making comparisons. To maintain the model's simplicity and ease of updating, only previous currency transformations were used, aligning with the requirements of forecasters working in the real world. Forecasters sought improved methods for predicting major currencies such as the Malaysian Ringgit because currency trading had been increasing and gaining greater importance. A relatively new method of artificial intelligence, neural networks attempt to simulate the way the brain solves problems and may be applied to the prediction of nonlinear economic time series. Data were analyzed for patterns using neural networks, and these patterns were then taught. By moving the data from input to output, new patterns were categorized, and forecasts were made.

Overall, the results indicate that Holt's Linear performed slightly better than the NAR neural network model in terms of MAPE and MAE performance criteria. Consistent with previous studies, Holt's Linear Exponential Smoothing appeared to be more suitable and convenient for forecasting this type of data compared to machine learning algorithms, although the neural network model still outperformed in terms of RMSE. Commonly, classical methods excel when past trends are expected to extend into the future, with exponential smoothing placing greater weight on the most recent observations (Hyndman & Athanasopoulos, 2018), unlike neural networks, which function as black boxes in forecasting (Salah et al., 2021). Additionally, increased variation in the data may have contributed to the lower accuracy observed across forecasting methods.

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