Heliyon 9 (2023) e16335

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Research article

Forecasting real exchange rate (REER) using artificial intelligence and time series models

Moiz Qureshi [a], Nawaz Ahmad [b,c], Saif Ullah [d,*], Ahmed Raza ul Mustafa [e]

[a] Department of Statistics, Shaheed Benazir Bhutto University, Pakistan
[b] Department of Business Administration, Shaheed Benazir Bhutto University, Pakistan
[c] University of Aveiro, Portugal
[d] Department of Management Technology and Information Science, ZUFESTM, Ziauddin University, Pakistan
[e] Department of Economics, Shaheed Benazir Bhutto University, Pakistan

ARTICLE INFO

JEL classification:
C12
C22
C45
C53
E47

Keywords:
REER
Forecasting
Machine learning
Multi-layer perceptron model
Exponential smoothing
Extreme learning machine
ARIMA

ABSTRACT

Forecasting is an attractive topic in every field of study because no one knows the exact nature of the underlying phenomena, but it can be guessed using mathematical functions. As the world progresses towards technology and betterment, algorithms are updated to understand the nature of ongoing phenomena. Machine learning (ML) algorithms are an updated phenomenon used in every task aspect. Real exchange rate data is assumed to be one of the significant components of the business market, which plays a pivotal role in learning market trends. In this work, machine learning models, i.e., the Multi-layer perceptron model (MLP), Extreme learning machine (ELM) model and classical time series models are used, Autoregressive integrated moving average (ARIMA) and Exponential Smoothing (ES) model to model and predict the real exchange rate data set (REER). The data under consideration is from January 2019 to June 2022 and comprises 864 observations. This study split the data set into training and testing and applied all stated models. This study selects a model that meets the Key Performance Indicators (KPI) criteria. This model was selected as the best candidate model to predict the behaviour of the real exchange rate data set.

1. Introduction

Over the past decades, it has been acknowledged that machine learning (ML) algorithms are the dominant tools and techniques for forecasting and predicting time series data. It is universally accepted that forecasting/prediction of time series data is a hot topic in any study domain because no one knows the data-generating process. Although mathematical models and functions can guess, machine learning models serve to forecast and predict the underlying phenomena. The exchange rate plays a crucial role in determining the dynamics and trends of the foreign exchange market [16,18]. The exchange rates modelling is assumed to be a complex task of financial time series forecasting for the reason that it is unpredictable; this is because different macroeconomic factors, like economic growth, interest rates, inflation, fiscal policy and monetary policies, etc. that affect the value at which national (local) currencies are operated in international markets [4,12]. As a result, the exchange rate significantly determines the foreign exchange market

* Corresponding author.
E-mail addresses: moizqureshi@sbbusba.edu.pk (M. Qureshi), nawazahmad1976@gmail.com (N. Ahmad), saifullah_142@yahoo.com (S. Ullah), ahmedrazamustafa@sbbusba.edu.pk (A. Raza ul Mustafa).

https://doi.org/10.1016/j.heliyon.2023.e16335
Received 7 October 2022; Received in revised form 10 May 2023; Accepted 12 May 2023
Available online 18 May 2023

dynamics.

This study develops and compares the precision of machine learning and time series models, namely, the Multi-layer perception model (MLP), Autoregressive integrated moving average (ARIMA), Extreme Learning Machine (ELM) and Exponential smoothing techniques (EST) to predict the real exchange rate of United States Dollar against Pakistani Rupee (USD/PKR) daily. To compare these models, this study uses the function of lagged values of the exchange rate data set. These past lagged functions are the autocorrelation plot (ACF) and partial autocorrelation plot (PACF). After finding the best fit, this study accommodates some statistical measures to select the best methodology for forecast accuracy.

The objective of this study is to consider the multiple econometric models (Artificial Intelligence) to forecast the Real Effective Exchange Rate (REER) from the perspective of Pakistan. The research question is how Artificial Intelligence effectively forecasts the REER in the case of Pakistan. By considering the research objective, the study attempts to test the hypothesis as given below:

Nul Hypothesis: H_0: Artificial Intelligence is not effective in forecasting the REER.

Alternative Hypothesis: H_1: Artificial Intelligence has significantly forecast the REER.

This study will enhance the literature on forecasting REER via artificial intelligence to better understand Pakistan's financial market dynamics. Literature shows a gap regarding REER forecasting using artificial intelligence.

In the remaining part of this manuscript, section 2 reviewed the literature on exchange rate dynamics and its volatility. Then, section 4 gives a detailed description of the research methodology and the source of the data set. Finally, empirical results and the discussions are part of section 5, while section 6 describes the conclusion and the policy discussions.

2. Literature review

This work compares the machine learning algorithms with the traditional time series forecasting methods for real exchange data [13]. compared the traditional time series model and the neural network model and found that the neural network models are more dominant than the existing time series models [15]. used an artificial neural network model with a sliding window technique to model the time series data and used the key performance indicators (KPI) to evaluate the model and found it satisfactory [22]. suggested new machine learning algorithms forecast the non-linear time series phenomena [5]. suggested a feature selection method for time-series prediction and found their method efficient in the feature selection of a time-series model [3]. discussed the ensemble operators for time series data and found that these three ensemble operators are best concerning the data structure [2]. used an artificial neural network to develop asymptotic forecast intervals for ANN and exhibited how the prediction intervals can be used to select node numbers in the ANN [14]. used an extreme learning model (ELM) to forecast the time series data and found this machine learning model dominant in different fields.

[19] compared the machine learning models in predicting strength for cotton ring-spun yarn and found that the DE-ELM outperformed in forecasting the Back Propagation (BP) model [21]. in this work, the authors used machine learning models, such as extreme learning models, to forecast hospital admissions for respiratory diseases. They found that the proposed neural networks proved more relevant to solving problems of health risks [24]. developed a hybrid SARIMA-MLP mode, compared it with SARIMA-MLP and originated that the proposed methodology performs better than the existing one [11]. in this article, the authors used machine-learning models to predict web traffic.

[20] utilised a multi-layer perceptron network using the Levenberg– Marquardt (MLP) algorithm to model quantitative values of (SPI) of drought at five synoptic stations in Iran. The models were evaluated based on RMSE and R-square criteria to forecast the standardised precipitation index (SPI) [17]. this study was based on hybridising the ARIMA model with the MLP model. In this work, the models are selected based on accuracy measures: MAPE, MAE, and RMSE [8]. utilised three neural network methods and an Adaptive Network-Based Fuzzy Inference System (ANFIS) to forecast the Tehran stock exchange [7]. used the neural network model to predict the new COVID-19 confirmed cases. They found the potential of the multi-layer perceptron neural network (MLPNN), which shows a high accuracy compared with the other models [6]. used the different time series models, compared them with the machine learning models MLP and ELM, and found that they outperformed the existing time series models [10]. The author presents a comparative analysis of various machine learning algorithms for economic data sets in this work.

[25] projected a hybrid ARIMA and Neural network models to improve the forecasting accuracy [9]. used ARIMA and SARIMA to model the fuel price in Turkey [1]. incorporate the ARIMA model to forecast the Nigeria Stock Exchange (NSE) and New York Stock Exchange (NYSE) [23]. used the ARIMA model for reliability forecasting and analysis of time series data [27]. made a comparative analysis based on ARIMA and multi-layer perception model to forecast the monkeypox death cases. This comparison was based on the performance indices such as MSE, RMSE, and MAE. The results revealed that the machine learning model outperforms the classical time series method.

[28] proposed a method based on a hyperparameter selection algorithm linked with ARIMA and compared the proposed method with the existing classical model to forecast the stock exchange data. The results revealed that the anticipated method best fits the existing methodology [29]. forecasted the price of bitcoin for ten years of data by utilising the classical time series and machine learning models. The results exhibited that machine learning models outperformed the existing comparative models [30]. An extended short-term memory model was used to forecast the stock prices' time series data. The author uses the LSTM with the Adam Optimiser (AO) and sigmoid function to achieve this end. The selection of the model is based on the lowest RMSE and MAPE. The result showed that the LSTM model obtained a better fit and achieved the highest accuracy than the conventional data analytical techniques.

[31] in this work, the authors suggested two hybrid models forecasting stock prices. The model selection is based on RMSE, and the output revealed that the proposed model based on (Fast RNNs) outperformed the other existing models [32]. used both linear and non-linear models to forecast stock prices. The result revealed that the proposed Deep Convolutional Generative Adversarial Network

(DCGAN) model to forecast the FTSEMIB (Financial Times Stock Exchange Milano Indice di Borsa) got the highest accuracy compared to the other traditional models [33]. in this article, the authors made a comparative analysis by applying the ANN and SVM models to predict stock prices. The results revealed that both models are significant in achieving the highest measure of accuracy compared to the other underlying models.

For more discussions, readers are suggested to cite in reference [34]. After reviewing the literature, it found that several econometric and statistical models effectively used by artificial intelligence to forecast the REER that will be further useful to understand the dynamics of the financial markets from the perspective of Pakistan.

3. Research methodology

This section explains the concepts and methods used to model the daily exchange rate data. The exchange rate data collected from the State Bank of Pakistan under consideration is from January 2019 to June 2022 and comprises 864 observations. Forecasting equations are stochastic functions utilised to guess the strange behaviour of a phenomenon, which aids in decision-making. We use the past information, i.e. Y_{t-1} lag of the variable and predict the Y_t present value to know this behaviour. The process is used to find a mathematical function F that sufficiently draws the inputs and results in desired output result, as mentioned in Equation 1

$$\hat{y}_t = F(y_{t-1}, y_{t-2}, \ldots, y_{t-k}) \tag{1}$$

It is important to note that the function F can be examined through the linear or non-linear approach. This study uses the linear models (Exponentially smoothing techniques (EST), Box-Jenkins methodology, also known as ARIMA and Multi-layer perception model (MLP), and Extreme Learning Machines (ELM). One of the significant challenges of this study is to determine the function F and select the best subset of the past lagged observations (inputs).

3.1. The method of exponential smoothing techniques (EST)

Exponential smoothing techniques (EST) are primarily used for time series data analysis because of their simplicity of algorithms, application and implementation and efficient prediction results. These exponential smoothing techniques are used according to the nature of the data. We discuss here some widely used smoothing techniques, i.e. the first one is the simple method, which is used when there is no trend in the data; stated differently, we use the simple method when the series is stationary, and there is no need for the transformation. The second approach is Holt's Double Exponential smoothing method, utilised when there is cyclicity and a trend but no seasonality. This approach consists of two parameters which range from 0 to 1. Mathematically this technique can be written as equation (2);

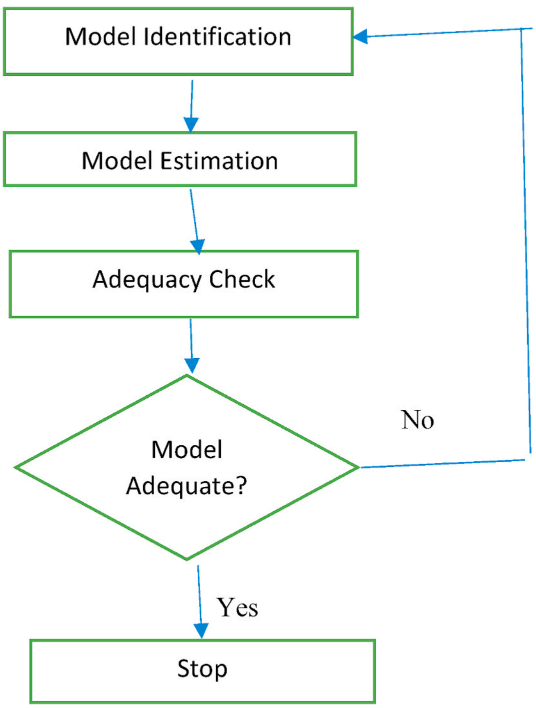

Fig. 1. Flow chart of Box-Jenkins Methodology Source (home.ubalt.edu).

$$\widehat{Z}_{t+n} = L_t + nT_t \tag{2}$$

where the terms L_t and T_t are defined as in equations (3) and (4).

$$L_t = \alpha Z_t + (1-\alpha) * (L_{t-1} + T_{t-1}) \tag{3}$$

where $0 \leq \alpha \leq 1$.

$$T_t = \beta(L_t - L_{t-1}) + (1-\beta) * T_{t-1} \tag{4}$$

where $0 \leq \beta \leq 1$.

The value $\widehat{Z}_{t+n}$ in Equation (2) is the estimated value of the exchange rate for the next (t + n) periods. The last one is the Holt-Winters Exponential Smoothing method (HEST), which is utilised when the seasonal effect is present in the data. In the exponential smoothing technique, two seasonal effects are counted in the calculations (additive and multiplicative) depending on the data's nature.

3.2. Autoregressive integrated moving average model (Box- Jenkins models)

This methodology combines the Autoregressive (AR) and Moving Average (MA) models. These models are dominant in the time series when the time series variables are univariate and can efficiently predict the future values of the time-series data. This model aims to capture the autocorrelation pattern by using the model's moving average part (MA) and checking the series that depends on its past using the autoregressive part (AR). To find both parts, we draw a correlogram of the data and specify the order to estimate the model for the underlying phenomena. This model is frequently used when the data is non-stationary; if it is stationary, we can use any part of it accordingly. Mathematically, this model can be written as equation (5):

$$y_t = \varphi_0 + \varphi_1 y_{t-1} + \ldots + \varphi_p y_{t-p} + \theta_1 \varepsilon_{t-1} + \ldots + \theta_q \varepsilon_{t-q} + \mu_t \tag{5}$$

The flow chart of the methodology is given as in Fig. 1.

3.3. Multi-layer perceptron (MLP)

The multi-layer perceptron (MLP) machine learning model is the most attractive and flexible mathematical algorithm in its potential applications. By this sophisticated nature, the multi-layer perceptron (MLP) model helps approximate any continuous, differentiable, non-linear, and limited function. Therefore, this model is considered a universal approximation.

The multi-layer perceptron (MLP) model comprises the input, output, and one or more hidden layers, also called intermediate layers. Artificial neurons are the function of these layers by which these layers process the information. First, the input layers provide information to the hidden layers. Then, they forward the information nonlinearly to another space. This transfer of information depends on the study problem. Finally, this information goes into the output layer, generating the network answer (response).

The network structure is based on no reappearance or stated differently that it has a feed-forward information algorithm, and connected layers are disjoint, although the neurons are incommunicable. Mathematically the signal processing of the network is given by equation (6).

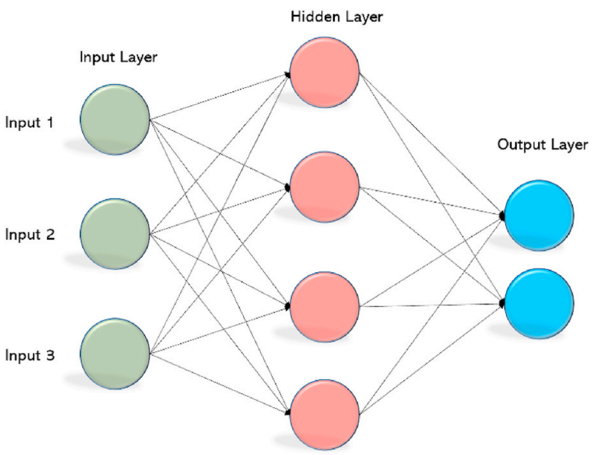

Fig. 2. Architectures of MLP with a single hidden layer Source (https://becominghuman.ai).

$$y = f_s\left(\sum_{k=0}^{k} W_{1k}^{0}\left(f\sum_{n=0}^{n} W_{kn}^{i} U_n + b_n\right)\right) \tag{6}$$

where in equation (6), network inputs are represented by U_n, the network's bias is denoted by b_n. In contrast, the f represents the activation function of the intermediate layers; the output layer activation function is denoted by f_S and the last one, which is the output signal denoted by y. In equation (6), it should be noted that W_{kn}^{i} are the weights for the middle layer, and W_{1k}^{0} represents the connections of the output (productivity) neurons. The diagrammatical structure of this model is shown in Fig. 2 below.

3.4. Extreme learning machines

The speed and improvement in the efficiency of the time series data can be achieved through an algorithm [26]. proposed an algorithm based on hidden layers' biases and random selection of the input weights and by which the efficiency and the speed of an ANN can be enhanced and named an extreme learning machine (ELM). This model was tested in several fields, i.e. forestry and medical studies, and found dominant compared to the other existing models. The mathematical structure of this model is given in equations (7) and (8):

$$X^h = f^h\left(W^h u + b\right) \tag{7}$$

$$Y = W^{out} X^h \tag{8}$$

where **U** is the input signal and, $\mathbf{W^h}$ is defined as the weighting matrix of the intermediate layer, **b** stands for the bias of each neuron. $\mathbf{F^h(s)}$ is used as the activation function of hidden neurons, and $\mathbf{W^{out}}$ is the matrix of the output layer. To determine the output layer weights, the method Moore-Penrose pseudo-inverse is used.

3.5. Key performance indicator (KPI)

There are various criteria to compare the performance and choose the best method among the underlying algorithms; some of them are Root Mean Square Error (RMSE), Mean Square Error (MSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). All these criteria are used to evaluate the performance of the model in this work.

The MSE measures the coefficient of error terms in statistical models. It assesses the average square of the differences between the actual and predicted data values. The zero value of the error term means the MSE equals zero, whereas the root of the MSE is known as RMSE, and MAE is used to calculate the mean error between the predicted and the observed value. Lastly, the MAPE is used to measure the absolute mean percentage error for the data. Mathematically these models can be written in equations (9)–(11):

$$MSE = \frac{1}{N_s}\sum_{n=1}^{N_s}(d_n - y_n)^2 \tag{9}$$

$$MAE = \frac{1}{N_s}\sum_{n=1}^{N_s}|d_n - y_n| \tag{10}$$

$$MAPE = \frac{100}{N_s}\sum_{n=1}^{N_s}\left|\frac{d_n - y_n}{d_n}\right| \tag{11}$$

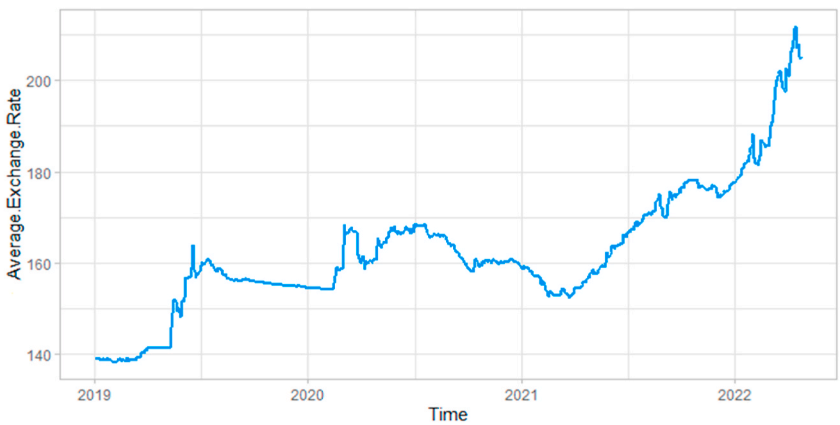

Fig. 3. Graphical display of the daily Exchange Rate data set.

3.6. Data analysis and processing

This study aims to compare the performance of the time series models and the Machine learning techniques for the daily stock exchange data set. The data set is split into the training and the testing model. To check out the behaviour of the series as there is a trend or non-stationarity component, we apply some statistical tests which capture these components. The Dicky-Fuller test is applied to check whether the series is stationary, and if it presents, the difference is used to normalise the data as Y_t -Y_{t1}. After this, we move to the next step, which is the selection of an appropriate model for the series; for this, we make the correlogram which is the graphical demonstration of the autocorrelation function (ACF) and partial autocorrelation function (PACF) for both the methods, i.e., time series and Machine Learning. After this step, we move toward the diagnostic checking of the model. If any candidate model satisfies the stated criteria, we select this as an approximate model for the series. For all the stated models, the predictions within samples are performed for 40% and 20% of the test data set.

4. Empirical results and discussions

The analysis begins with visualising the graph of the exchange rate data set; this gives us an idea about the behaviour of the series. After this, we apply the stationarity test to confirm whether the series needs transformation. Fig. 3 shows visual displays of the exchange rate data set and the Dicky-Fuller test.

In this graph, there is a gesture that presents a non-stationarity component. To confirm this, we apply the statistical test.

- **Augmented Dickey-Fuller Test**

Data: Exchange rate data.
Dickey-Fuller = −0.18753, Lag order = 9, p-value = 0.99
alternative hypothesis: stationary
by applying the test, it is confirmed that the series is not stationary, as the p-value is greater than the significance level. To make it stationary, we apply the transformation. We take the first difference of the series, which makes the series stationary. After this, we make a correlogram of the series to find the order of the candidate model for both machine learning and the time series methods.

The exchange data set's correlogram and other necessary graphical displays are shown in Appendix. However, the numerical results from the candidate models based on key performance indicators (KPI) are given below in Tables 1 and 2.

We begin with the multi-layer perceptron model (MLP) to forecast the exchange rate data set and then move toward the following models accordingly. First, we apply the MLP model with a single hidden layer and 10 hidden neurons with 100 repetitions on 60% of the training data set. If this model gives us the smallest MSE, we use this model to predict 40% of the test data set. The results show that the model with a single hidden layer and 10 hidden neurons with 100 repetitions gives us the minimum MSE of 1.07 on the training data set, so we use this model for prediction. Next, we also apply the ELM model with the same parameter to the training data set and found that the MSE of this model is 1.36, which is greater than the MLP.

The visual display of the model is shown in Appendix (A); it is interesting to note that the MLP model needs two univariate lags to model the series with no need for the difference in series; we also use the same model to predict the 40% of the data and then we use the ELM model to predict the behaviour of the series on and among all the models it is found that the multi-layer perceptron model (MLP) model outperforms and satisfies the key performance indicators (KPI).

The visual display of all the models for 40% of the testing data set is shown in Appendix (A). After this, we apply all these models to 80% of the training data set. The results show that the multi-layer perceptron (MLP) model is dominant in predicting 20% of the test exchange rate data. Therefore, the results for 20% of the test data set are shown in Table 1, and the visual display of the exchange rate data set is shown in Appendix (B).

5. Conclusion and policy Recommendations

This work applied four models (two classical time series models and two machine learning models), and the results obtained through these models were compared. This study splits the data set into training and testing and then selects the best one that fulfils the KPI conditions to apply these models and find the best model. The feed-forward method predicts 40 and 20% of the real exchange rate data set in machine learning models. The best model based on the key performance indicators (KPI): MSE, RMSE, MAE, and MAPE were selected. According to the stated model selection criteria, the machine learning model Multi-layer Perceptron model MLP outperforms

Table 1
MSE, RMSE, MAE, and MAPE for all models for 20% of the test data.

Candidate Models	MSE	RMSE	MAE	MAPE
MLP	**267.51**	**16.35**	**12.29**	**7.17**
ELM	317.31	17.81	14.58	8.60
ARIMA	318.85	17.85	14.37	8.47
ES	319.31	17.86	14.37	8.49

Table 2
MSE, RMSE, MAE, and MAPE for all models for 40% of the test data.

Candidate Models	MSE	RMSE	MAE	MAPE
MLP	**212.05**	**14.59**	**10.09**	**5.83**
ELM	212.93	14.59	10.09	5.83
ARIMA	214.08	14.63	10.02	5.79
ES	213.90	14.62	10.02	5.81

the existing models in both cases when data is split into 40 and 20% of the testing set.

The application of artificial intelligence and econometric model provides a depth overview of forecasting the REER dynamics. However, the REER is sufficient to understand the macroeconomic dynamics and their implications. The study is limited to comparing artificial intelligence models forecasting and traditional time series model forecasting. Many other macroeconomic variables and culture shocks can also affect this forecasting but are not considered in this study. In this regard, future studies can work on the literature gap in which artificial intelligence and econometric modelling can be used to forecast the other indicator that will be helpful for better understanding.

Funding statement

This research received no specific grant from funding agencies in the public, commercial, or not-for-profit sectors.
The authors declare no competing interests.

Author contribution statement

Moiz Qureshi: Conceived and designed the experiments; Performed the experiments; Wrote the paper. Nawaz Ahmad: Conceived and designed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper. Saif Ullah: Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper. Ahmed Raza ul Mustafa: Performed the experiments; Wrote the paper.

Data availability statement

Data will be made available on request.

Additional information

No additional information is available for this paper.

Declaration of competing interest

The Authors declare NO conflict of interests.

Acknowledgments

The authors would like to thank anonymous reviewers and editors for their suggestions and comments.

Appendix (A)

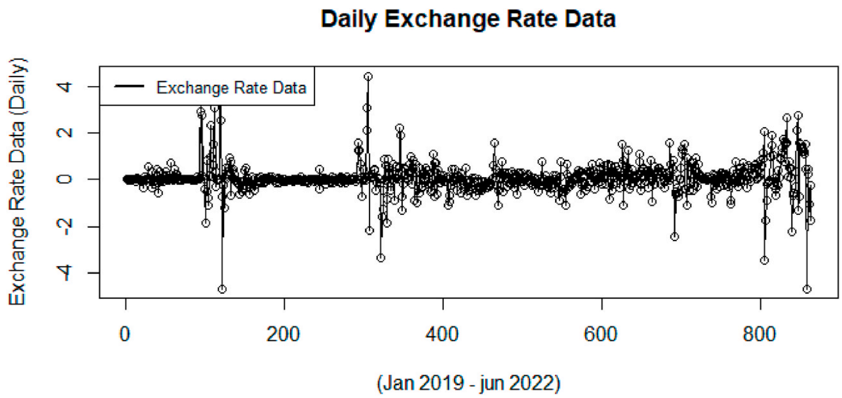

Fig. 1. 1st Difference of Daily Exchange Rate Data (Jan 2019–June 2022)

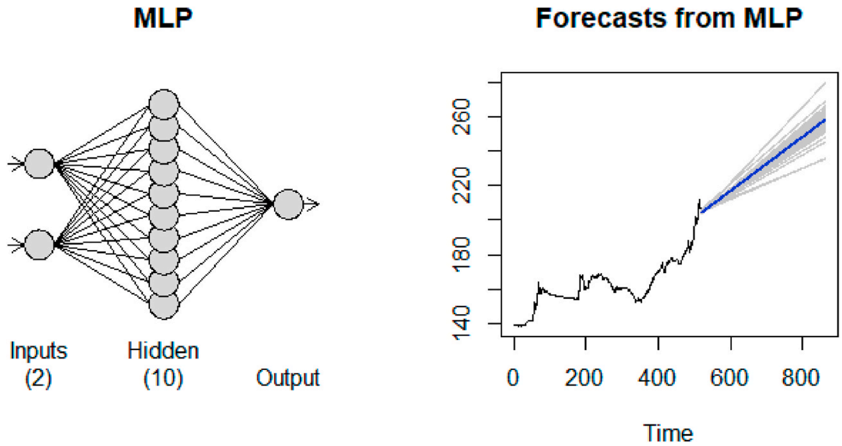

Fig. 2. Forecast from Multi-layer Perceptron Model

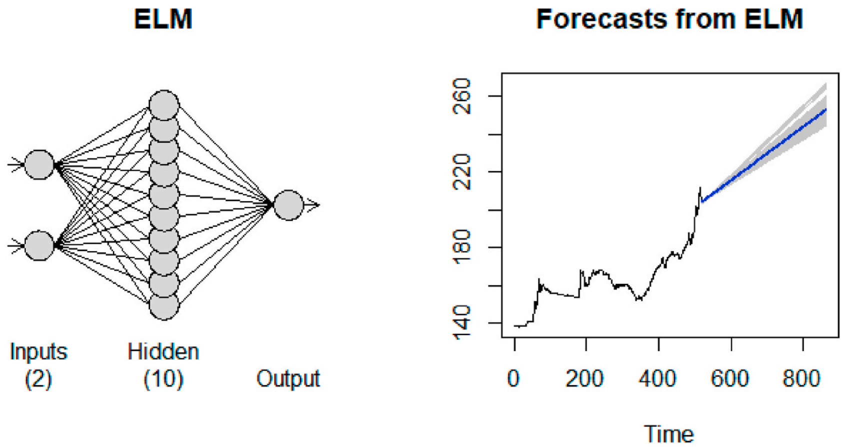

Fig. 3. Forecast from Extreme Learning Machine Model

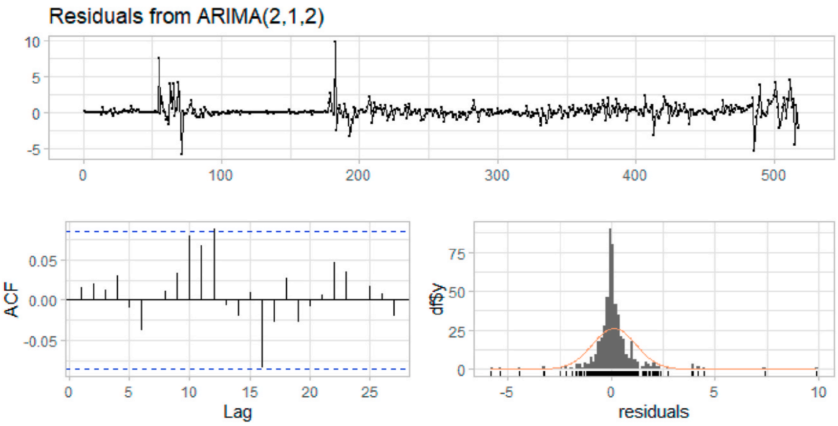

Fig. 4. Diagnostic checking for ARIMA (2,1,2)

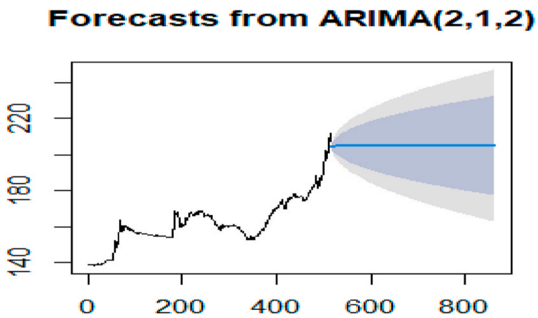

Fig. 5. Forecast from ARIMA (2,1,2)

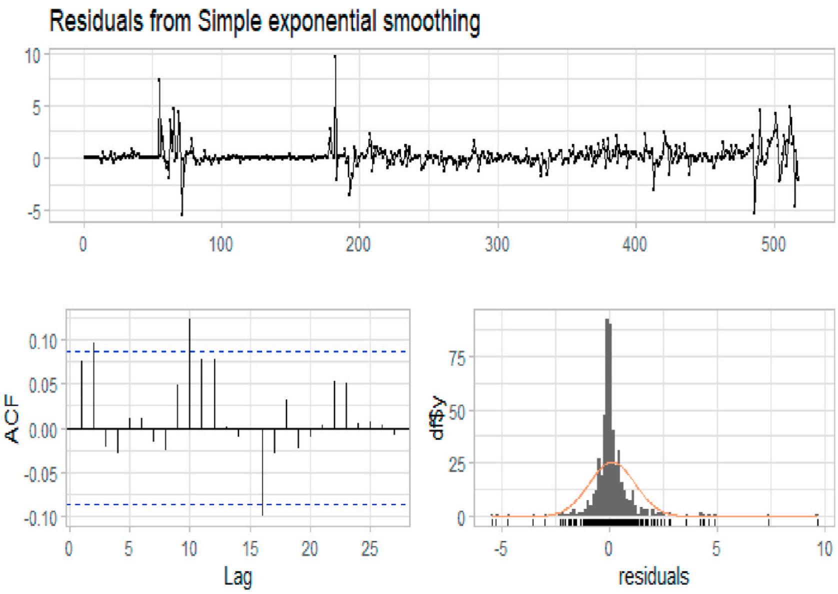

Fig. 6. Diagnostic Plot from Simple Exponential Smoothing (SES)

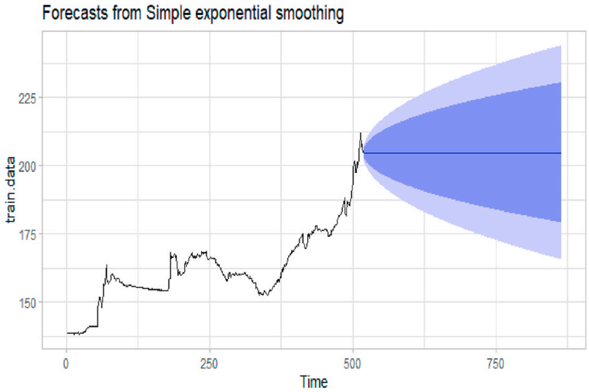

Fig. 7. Forecasting from Simple Exponential Smoothing (SES)

The above results are shown for 40% of the testing data set; the rest for the 20% of the data set are below.

Appendix (B)

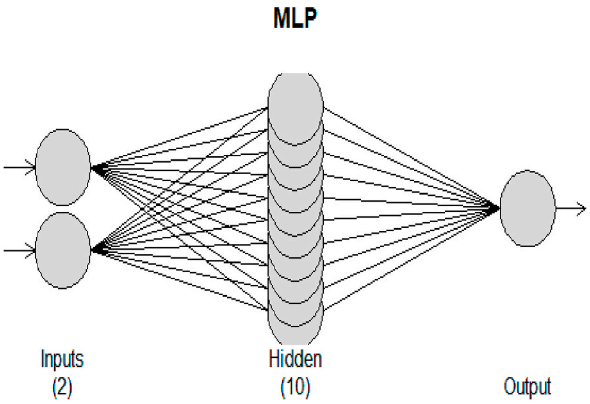

Fig. 8. MLP fit with 100 hidden nodes and 100 repetitions. Series modelled in differences: D1

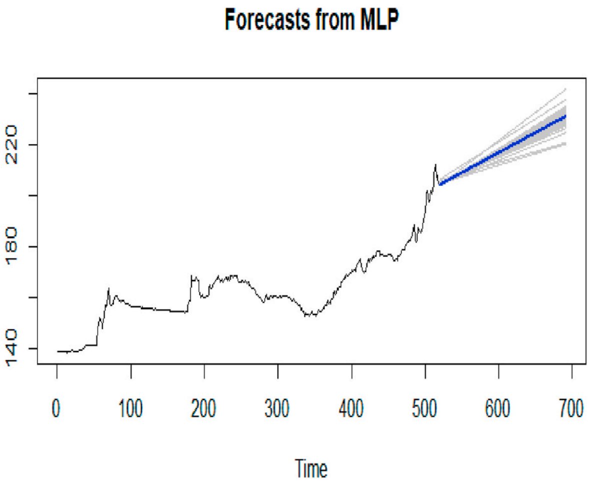

Fig. 9. Forecast for Multi-Layer Perceptron Model

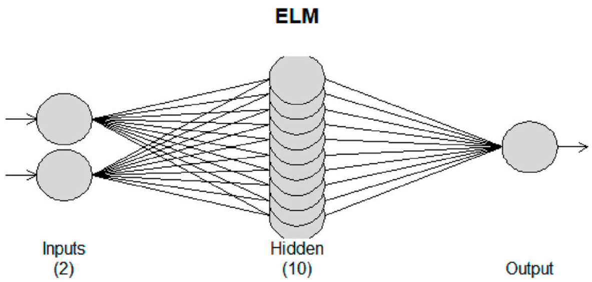

Fig. 10. ELM fit with 10 hidden nodes and 100 repetitions. Series modelled in differences: D1.

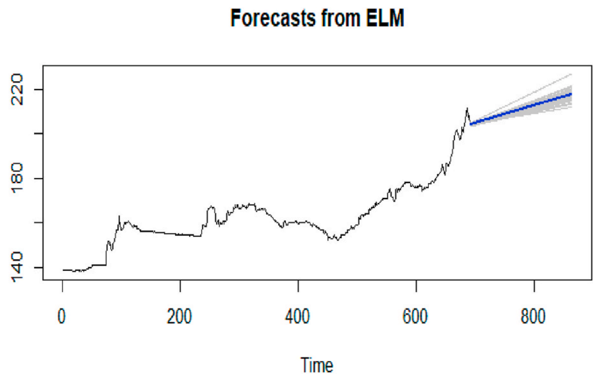

Fig. 11. Forecast from Extreme Learning Machine (ELM)

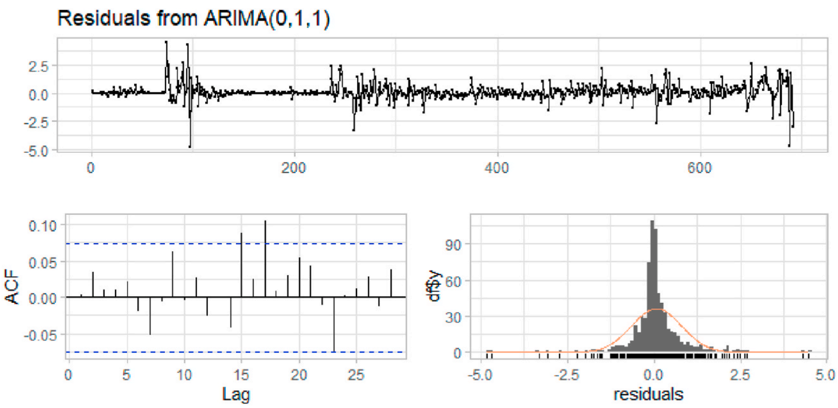

Fig. 12. Diagnostic plot from ARIMA (0,1,1)

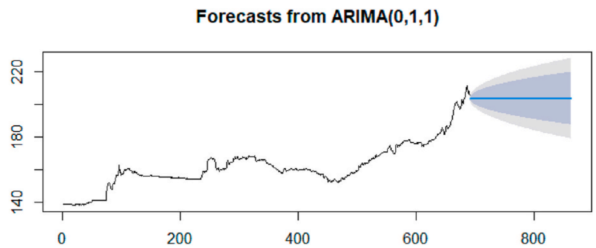

Fig. 13. Forecast from ARIMA (0,1,1)

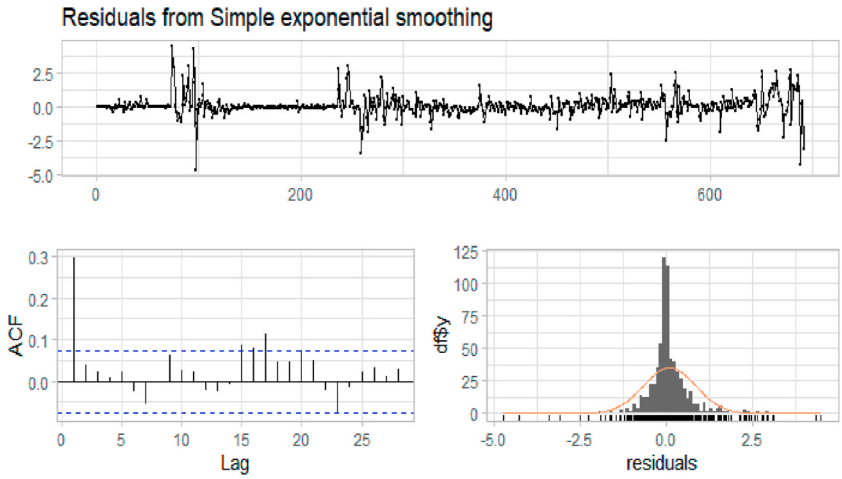

Fig. 14. Diagnostic plot from Simple Exponential Smoothing (SES)

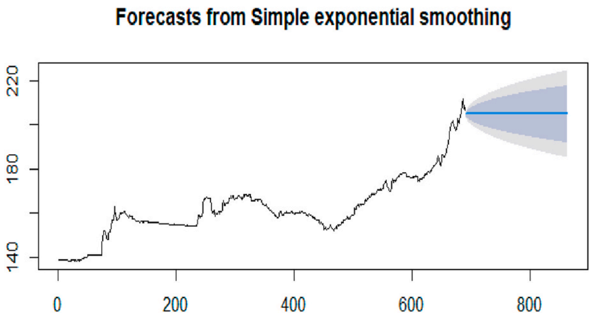

Fig. 15. Forecasting from Simple Exponential Smoothing (SES)

References

[1] A.A. Adebiyi, A.O. Adewumi, C.K. Ayo, Stock Price Prediction Using the ARIMA Model. Proceedings - UKSim-AMSS 16th International Conference on Computer Modelling and Simulation, UKSim, 2014, pp. 106–112, https://doi.org/10.1109/UKSim.2014.67, 2014.

[2] Allende, H. E. C. T. O. R., Moraga, C., & Salas, R. (n.d.). ARTIFICIAL NEURAL NETWORKS IN TIME SERIES FORECASTING : A COMPARATIVE ANALYSIS 1. vol. 88, 685–707.

[3] Barrow, D. K., Crone, S. F., & Kourentzes, N. (n.d.). An Evaluation of Neural Network Ensembles and Model Selection for Time Series Prediction.

[4] W. Chen, H. Xu, L. Jia, Y. Gao, Machine learning model for Bitcoin exchange rate prediction using economic and technology determinants, Int. J. Forecast. 37 (1) (2021) 28–43.

[5] S.F. Crone, N.K. Ã, Neurocomputing Feature selection for time series prediction – a combined filter and wrapper approach for neural networks, Neurocomputing 73 (10–12) (2010) 1923–1936, https://doi.org/10.1016/j.neucom.2010.01.017.

[6] C. Deina, M. Henrique, C.H. Rodrigues, M. Scoczynski, R. Martins, F. Trojan, S. Luiz, S. Jr, H. Valadares, A methodology for coffee price forecasting based on extreme learning machines, Inform. Process. Agric. xxxx (2021), https://doi.org/10.1016/j.inpa.2021.07.003.

[7] M. Djeddou, I.A. Hameed, A. Hellal, A. Nejatian, Predictive Modelling of COVID-19 New Confirmed Cases in Algeria using Artificial Neural Network, 2021.

[8] R. Ebrahimpour, H. Nikoo, S. Masoudnia, M.R. Yousefi, M.S. Ghaemi, Mixture of mlp-experts for trend forecasting of time series: a case study of the Tehran stock exchange, Int. J. Forecast. 27 (3) (2011) 804–816, https://doi.org/10.1016/j.ijforecast.2010.02.015.

[9] V.Ş. Ediger, S. Akar, ARIMA forecasting of primary energy demand by fuel in Turkey, Energy Pol. 35 (3) (2007) 1701–1708, https://doi.org/10.1016/j.enpol.2006.05.009.

[10] C. Eliane, N. Maria, P. Bianchesi, M. Silva, D. Oliveira, A comparative study of forecasting methods using real-life econometric series data, 5411, https://doi.org/10.1590/0103-6513.20210043, 2021.

[11] M. Gupta, A. Asthana, N. Joshi, P. Mehndiratta, Improving time series forecasting using mathematical and deep learning models, in: Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), vol. 11297, LNCS. Springer International Publishing, 2018, https://doi.org/10.1007/978-3-030-04780-1_8.

[12] Q. He, J. Liu, C. Zhang, Exchange rate exposure and its determinants in China, China Econ. Rev. 65 (2021), 101579.

[13] T. Hill, M. O'Connor, W. Remus, Neural network models for time series forecasts, Manag. Sci. 42 (7) (1996) 1082–1092, https://doi.org/10.1287/mnsc.42.7.1082.

[14] Hine, M. A. C. (n.d.). Predictive Analytics Using Extreme Learning.

[15] H.S. Hota, R. Handa, A.K. Shrivas, Time series data prediction using sliding window based RBF neural network, Int. J. Comput. Intell. Res. 13 (5) (2017). http://www.ripublication.com.

[16] R. Jammazi, C. Aloui, *Cyclical Components and Dual Long Memory in the Foreign Exchange Rate Dynamics: the Tunisian case*(No. 2014-198), 2014.

[17] M. Khashei, Z. Hajirahimi, A comparative study of series arima/mlp hybrid models for stock price forecasting, Commun. Stat. Simulat. Comput. 48 (9) (2019) 2625–2640, https://doi.org/10.1080/03610918.2018.1458138.

[18] S. Kumari, S.K. Oad Rajput, R.Y. Hussain, J. Marwat, H. Hussain, Optimistic and pessimistic economic sentiments and US Dollar exchange rate, Int. J. Financ. Eng. (2021), 2150043.
[19] J.I. Mwasiagi, The Use of Extreme Learning Machines (ELM) Algorithms to Prediction Strength for Cotton Ring Spun Yarn, Fashion and Textiles, 2016, https://doi.org/10.1186/s40691-016-0075-8.
[20] M. Rezaeian-Zadeh, H. Tabari, MLP-based drought forecasting in different climatic regions, Theor. Appl. Climatol. 109 (3–4) (2012) 407–414, https://doi.org/10.1007/s00704-012-0592-3.
[21] Y.D.S. Tadano, P. Grossa-pr, H.V. Siqueira, P. Grossa-pr, Admissions for Respiratory Diseases, 2016.
[22] A. Tealab, H. Hefny, A. Badr, Forecasting of non-linear time series using ANN, Fut. Comput. Inform. J. 2 (1) (2017) 39–47, https://doi.org/10.1016/j.fcij.2017.05.001.
[23] T.H.E. Use, O.F. Arima, M. For, A the Centre for Quality, Ngee Ann Polytechnic, Singapore. 535, Clementi Road, Singapore 599489, b Department of Industrial and Systems Engineering, National University of Singapore. 10, Kent Ridge Crescent, Singapore 119260. Science, 1998, pp. 213–216, 35(98).
[24] K.J. Waciko, B. Ismail, SARIMA-ELM hybrid model versus SARIMA-MLP hybrid model 5 (2) (2020) 1–8.
[25] P.G. Zhang, Time series forecasting using a hybrid ARIMA and neural network model, Neurocomputing 50 (2003) 159–175, https://doi.org/10.1016/S0925-2312(01)00702-0.
[26] G.B. Huang, Q.Y. Zhu, C.K. Siew, Extreme learning machine: theory and applications, Neurocomputing 70 (1–3) (2006) 489–501.
[27] M. Qureshi, et al., Modeling and forecasting monkeypox cases using stochastic models, J. Clin. Med. 11 (2022), https://doi.org/10.3390/jcm11216555, 21.
[28] R. Kumar, P. Kumar, Y. Kumar, Multi-step time series analysis and forecasting strategy using ARIMA and evolutionary algorithms, Int. J. Inf. Technol. 14 (1) (2022) 359–373, https://doi.org/10.1007/s41870-021-00741-8.
[29] I.H. Shakri, Time series prediction using machine learning: a case of Bitcoin returns, Stud. Econ. Finance 39 (3) (2022) 458–470, https://doi.org/10.1108/SEF-06-2021-0217.
[30] G. Bathla, R. Rani, H. Aggarwal, Stocks of year 2020: prediction of high variations in stock prices using LSTM, Multimed. Tool. Appl. (2022), https://doi.org/10.1007/s11042-022-12390-5.
[31] K. Yadav, M. Yadav, S. Saini, Stock values predictions using deep learning based hybrid models, CAAI Trans. Intell. Technol. 7 (1) (2022) 107–116, https://doi.org/10.1049/cit2.12052.
[32] A. Staffini, Stock price forecasting by a deep convolutional generative adversarial network, Front. Artif. Intell. 5 (2022) 1–16, https://doi.org/10.3389/frai.2022.837596. February.
[33] A. Kurani, P. Doshi, A. Vakharia, M. Shah, A comprehensive comparative study of artificial neural network (ANN) and support vector machines (SVM) on stock forecasting, Ann. Data Sci. 10 (1) (2023) 183–208, https://doi.org/10.1007/s40745-021-00344-x.
[34] M. Qureshi, M. Daniyal, K. Tawiah, Comparative evaluation of the multi-layer perceptron approach with conventional ARIMA in modeling and prediction of COVID-19 daily death cases, J. Healthc. Eng. 2022 (2022), https://doi.org/10.1155/2022/4864920.