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Modelling and Forecasting Currency Exchange Rates Using Hybrid ARIMA and ANN Models in High-Frequency Data

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Authors' contributions

This work was carried out in collaboration between both authors. Authors SOO designed the study, managed the analyses of the study, managed the literature searches. performed the statistical analysis, wrote the proposal, and wrote the all the drafts of the manuscript. Authors CON, proof read the manuscript and provided the necessary guidance throughout the research work. Both authors read and approved the final manuscript.

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Abstract

Introduction: Exchange rates are central to the economic as well as the financial systems and structures because they determine trade, investment and policy. This study focuses on the statistical analysis and forecasting of exchange rates for the Kenyan Shilling (KES) against regional currencies: The currencies include; Burundian Franc (BIF), Rwandan Franc (RWF), Tanzanian Shilling (TSHS) and Ugandan Shilling (USHS).

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Methods: Significance tests and models of time series were used in the analysis with regard to trend and volatility of exchange rates. Descriptive measures which include mean, median, standard deviation and range were calculated for each of the currency pairs. Furthermore, to determine cycles and rate predictions, a more complex ARIMA (1,1,0) with drift model was applied. Various statistics namely AIC, AIC c and BIC were used to assess model performance.
Results: It was seen that the mean rate of KES/USHS was the highest at 27.0 and KES/RWF was the least at 8.99. The standard deviations suggested moderate fluctuation in the pairs with the KES/USHS exchanging at 2.26. The results of the ARIMA analysis were highly significant for coefficients (AR1 = 0.5359, drift = 0.0412), and feasible for Fit statistics (AIC = -123.57, BIC = -116.07). It also pointed out that there were high positive correlations between all the currency pairs analyzed; the values being above 0.98.
Discussions: The results also confirm narrow fixed relationships between KES and the regional currencies with fluctuation in KES/USHS. The applied ARIMA model allows for capturing the dynamics of exchange rate and provides accurate forecast. The result of this study can be useful for policymakers and financial analyst in order to comprehend behaviors of regional currencies.

Keywords: Volatility; currency exchange rates; correlation matrix; high frequency; trend analysis; hybrid ARIMA-ANN; economic dynamics.

1 Introduction

This study focused on the application of ARIMA (Autoregressive Integrated Moving Average) and Artificial Neural Networks (ANN) for forecasting currency exchange rates in East African countries, Kenya, Uganda, and Tanzania. Given the rapid evolution in financial markets and the widespread availability of high-frequency data, the research evaluated the efficacy of these models across various time series frequencies (monthly, weekly, daily, and hourly) to identify the optimal level for accurate predictions. Traditional forecasting models had shown limitations when applied to granular, high-frequency data, which had become increasingly relevant in the fast-paced economic landscape (Ondieki et al., 2024). ARIMA models had been effective in capturing linear patterns within lower-frequency data but struggled with the complexities of high-frequency data. In contrast, ANN models excelled in handling nonlinear patterns that were common in currency fluctuations (Ondieki et al., 2024). By exploring a hybrid ARIMA-ANN model, this study aimed to leverage the strengths of both, combining ARIMA's linear analytical capabilities with ANN's pattern-recognition ability to enhance forecast accuracy (Ma and Wang, 2019). This research contributed valuable insights into currency forecasting, particularly in regions characterized by rapidly changing economic conditions, and addressed a gap in the literature by applying hybrid model techniques to high-frequency data. Historically, exchange rate forecasting had evolved from reliance on single-model approaches to more complex hybrid techniques (Achieng, 2017). Initially, lower-frequency models like ARIMA had been the primary choice, but they encountered limitations as financial markets began to demand real-time, high-frequency analysis (Feyisa and Tefera, 2022). This gap had prompted the adoption of ANN models, which offered the adaptability required to manage non-linear, rapid data fluctuations (Baffour et al., 2019). However, neither ARIMA nor ANN alone had proven sufficiently accurate for high-frequency forecasts, particularly in East Africa's distinct economic environment. Preliminary studies on hybrid modelling in similar contexts had shown that accuracy improved significantly over single models, making hybrid approaches promising for managing volatility in exchange rates in this region (Njoki, 2019). This study responded to the existing need for tailored forecasting models in East Africa, assessing the performance of the combined ARIMA-ANN model across different frequencies, and offering policymakers a valuable tool to improve decision-making in dynamic economic contexts (Zhai et al., 2021). In essence, the research aimed to provide East African governments and financial institutions with advanced, data-driven insights to support effective monetary policies, foster economic resilience, and achieve sustainable growth through improved predictive accuracy.

1.1 ARIMA and ANN models

Autoregressive Integrated Moving Average better known as ARIMA is one of the most effective and dominant statistical models utilized in time series analysis. It works well for data having trends, seasonality or auto-correlation, courtesy of its feature which establishes dependence between a series at different time points (Zhai et al., 2021). ARIMA works by combining three components: Auto regression (AR) deals with the dependency of the current value as a function of the previous values; Integration (I) get rid of the non-stationary feature; And Moving averages (MA) relates an observation to the residual differenced value. ARIMA is concise, easy to interpret, accurate in the short-term forecasting compared to other models and that is why it is widely used for modeling financial time series including exchange rates (Odhiambo et al., 2024). Artificial Neural Networks (ANNs), on the other hand, are defined subtypes of machine learning models that are developed to possess the capability of learning from data (Baffour et al., 2019). The nonlinear relationship can also be identified and used to make a prediction in the time series with irregular patterns or with non-linear dependence between the variables and ANN is the best suited for this case. Thanks to the use of the number of hidden layers, and non-linear activation functions, the ANNs adjust and operate flexibly to the changes, and they are more effective than traditional models in unstable conditions. When used in a hybrid system with ARIMA, these strengths are made useful, where ARIMA model deals with the linear part while ANN deals with the non-linear residuals (Umoru et al., 2023). This synergy improves the precision of forecasts, which makes further combined models appropriate when analyzing the intensive and fluctuating financial data, such as foreign exchange rates.

2 Reviews of Previous Studies

2.1 Literature reviews

Chapter Two focused on reviewing the literature on hybrid modelling techniques and the influence of time series frequencies in forecasting currency exchange rates. A thorough examination of existing research indicated gaps in understanding how traditional models, such as Artificial Neural Networks (ANN) and Autoregressive Integrated Moving Averages (ARIMA), could be effectively integrated into hybrid models for high-frequency data analysis. The review aimed to bridge these gaps by examining studies that assessed the effects of different time series frequencies on the performance of ARIMA and ANN models, evaluated the benefits of hybrid models, and addressed currency exchange rate forecasting in East African countries. This comprehensive analysis provided a solid foundation for the current study by integrating these strands of research and emphasizing the importance of selecting optimal frequencies in hybrid modelling for exchange rate predictions. The literature review began with Nyoni's (2018) exploration of inflation patterns in Kenya, analyzing data from 1960 to 2017 using ARIMA and GARCH methodologies (Nyoni, 2018). This study underscored the dynamic nature of inflation trends and emphasized the value of advanced econometric models in guiding policy. Building on Nyoni's work, Sarangi et al. (2022) shifted the focus to currency exchange rates, particularly the Indian Rupee (INR) and U.S. Dollar (USD), comparing a traditional ANN model to a hybrid ANN-GA model for predicting international trade trends. Sarangi's findings highlighted the growing demand for precise forecasting tools amidst volatile global finance (Sarangi et al., 2022). Additionally, a recent study on stock indices, covering the Nasdaq, Nikkei, and CAC 40, demonstrated the superior predictive performance of the ARIMA-ANN hybrid model in capturing financial data's inherent volatility (Zhai et al., 2021). These studies collectively underscored the transformative potential of hybrid modelling in finance, suggesting that the integration of traditional and neural network models could substantially improve forecast accuracy in East African currency exchanges. Subsequent sections of the literature review examined the application of hybrid models in high-frequency forecasting across various fields. For instance, research on human brucellosis forecasting in Shanxi Province revealed that the ARIMA-ERNN model was more effective than other models in predicting seasonal disease patterns, indicating the potential of hybrid models in handling complex, periodic data. Another study addressed time series forecasting across multiple domains, proposing an ARIMA-ANN hybrid enhanced by Empirical Mode Decomposition (EMD) to improve predictive accuracy. Findings from this research confirmed that the hybrid EMD model surpassed traditional forecasting methods, providing valuable insights for financial data prediction. The literature further reviewed modelling efforts specific to exchange rate forecasting in East Africa, where studies emphasized the critical role of accurate forecasts for macroeconomic decisions. Although traditional GARCH models were frequently used to capture volatility, findings suggested that hybrid approaches could better address the unique economic conditions of the region.

A final part of the review highlighted studies on Kenya's GDP, including Wabomba, Mutwiri, and Fredrick's (2016) application of ARIMA models to simulate GDP trends from 1960 to 2012 (Wabomba et al., 2016). Their analysis demonstrated the ARIMA model's effectiveness in simulating annual GDP returns but noted the need to consider external factors, such as social or international economic influences, to enhance forecasting accuracy. Collectively, these studies illustrated the significance of employing advanced models to understand and predict economic trends, providing stakeholders with valuable tools for strategic planning. The chapter underscored the importance of hybrid modelling techniques, particularly in developing regions, by demonstrating their effectiveness in capturing complex economic dynamics and improving the precision of financial forecasts.

2.2 Research gaps and significance of the study

This research aims to fill this gap in high frequency exchange rate forecast through analyzing the shortcomings of the standalone ARIMA and ANN forecasts. ARIMA performs well in capturing linear patterns but is rigged in modelling nonlinear phenomena; on the other hand, ANN models capture non-linear structures but generally fail to model long-term effects. Moreover, because of high-frequency financial data where data noise and variability are high, the problem of optimal forecasting is even more acute, though this aspect has not received sufficient attention in previous studies. This present research works to build and fine-tune a model that integrates the features of both temporal and non-temporal methods, thus provide the best exchange rate movement prediction platform that integrates linear and non-linear features of the exchange rate. This research is important as it improves the quality of the predicted values necessary for investors, decision-makers and other users of financial information in the processes of volatile financial markets. In a methodological level, the study brings new developments on hybrid modeling methodologies and the issues related to high frequency data. It offers the basis for future development of hybrid techniques for various kinds of financial data, including stock prices or macroeconomic indicators that could be identified as potentially useful for enhancing decision making within other fields, including risk management.

2.3 Industrial Implications of the Study

The implications of this study are therefore manifold and profound in the various respects that they relate to theoretical and practical understanding of currency exchange rate forecasting. In the financial domain, the combined model of Hybrid ARIMA ANN model will in enhancing the accuracy in the forecast of the competitive foreign exchange rates for improved risk management strategies, investment decisions, and better optimization of portfolio especially in the under-going region such as East Africa. Econometric policymakers can use the enhancement in the forecasting models to make better decisions on the manners of money supply, trade policies, and economic stabilization mechanisms. Moreover, the model can prove to be rather helpful to the financial institutions like banks and investment firms and this is because it assists its users in the improvement of the methods they use for currency trading forecast. On a macroeconomic level, the study can help support promoting the quality of economic planning and development in the East African economies of consideration by giving decision-makers better predictions of exchange rate behavior, which can help improve stability and investor confidence.

3 Research Methodology

3.1 Introduction

Time series forecasting is a field directly evolving and with significant promise for future development. One of the most commonly used approaches for updating prediction accuracy is a combination of methods. This method exploits the fundamental features of different models or approaches with a view to building a forecast framework that is both stronger and more accurate. A lot of research has been done in this specific field and a plethora of combinations have been proposed as per the above literature. This study will exploit the performance of Hybrid model in the presence of high-frequency data, analyze, model and forecast the future values of currency exchange rates for East African Countries.

3.2 Data description

To illustrate the time series steps required to model the hybrid ARIMA-ANN models for forecasting currency exchange rates in East African countries, we will obtain daily exchange rate data from Central Bank of Kenya (CBK) for East African countries, including Kenya, Uganda, Tanzania, Rwanda, and Burundi. Ensure the dataset encompasses a sufficiently long-time horizon to capture temporal patterns. The dataset will run for at least 10 years, from January, 2013 to 2023 December [4]. Clean the dataset by handling missing values and outliers. Transform the data into a time series format, considering potential stationarity issues. Apply differencing if needed to achieve stationarity. Data analysis for this research was undertaken using

R studio (Version 4.4.0) programming language which was supplemented by multiple statistical packages and libraries to perform different analytical tasks.

3.3 Effect of time series frequency data on modeling and forecasting the performance of ARIMA and ANN models

The purpose of the first objective, which will be to determine how time series frequency data affects modeling and forecasting performance currency exchange rates and will be achieved through a detailed analysis using both ARIMA models as well as ANN models. First, we will get high-frequency time series dataset of currency exchange rates from East African nations. The analysis will entail varying the data into different frequency levels- daily, weekly and monthly extensions to see how well time series affect modeling performance. In the case of ARIMA, we will estimate separate models at each level frequency by selecting an appropriate type and order for differencing to ensure stationarity (Mpofu, 2016). By systematically comparing the modeling and forecasting performance of ARIMA and ANN models across different time series frequencies, we will aim to uncover insights into the impact of temporal granularity on predictive accuracy. Using the mathematical equations illustrated in the second and third objectives, and applying different data frequencies, we will be able to arrive at the best accurate forecasting model with the appropriate frequency of the data that we will apply to achieve our goal of the study.

3.4 Analyzing hybrid ARIMA-ANN models for forecasting high-frequency time series data

Neither ARIMA nor ANN will be universally suitable for all types of time series to model and forecast the Currency Exchange Rates within East African Nations. This will be because almost all real-world time series contains both linear and non-linear correlation structures among the observations. According to Zhang (2003), the best way to model currency exchange rates data, developing a hybrid approach that applies ARIMA and ANN separately for modeling linear and non-linear components for the time series with the model;

$$y_t = L_t + N_t \tag{3.1}$$

where;

y_t is the observation at time t, and L_t and

N_t represent the linear and non-linear components, respectively.

3.5 Auto-regressive integrated moving average

In the ARIMA modeling step, we will focus on capturing time dependencies and patterns from the high-frequency time series data extracted out of Central Bank of Kenya's daily exchange rates. To this end, the Auto-Regressive Integrated Moving Average (ARIMA) model is used which includes differencing of time series data to get stationarity and fitting the model for such difference (Mpofu, 2016). The ARIMA model will be distinguished by the autoregressive (AR) component, which estimates linear correlation with prior observations; an integrated (I) element that captures differencing and produces stationarity; and a moving average (MA) component. The ARIMA order to be considered such as ARIMA (p,d,q) is identified based on the analysis of ACF and PACF plots. The obtained ARIMA model allows for analyzing linear temporal trends of the exchange rate data, contributing to a hybrid approach as one building block in forecasting.

The ARIMA model will be represented as follows;

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} \tag{2}$$

Auto-Regressive parts:

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \varepsilon_t \tag{3.2}$$

Moving Average parts:

$$y_t = \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q} \tag{3.3}$$

Where:

- y_t is the observed time series (e.g., Exchange rate for a specified country) at time t,
- ϕ_i are the autoregressive (AR) coefficients,
- ε_t is the white noise error term at time t,
- θ_i are the moving average (MA) coefficients,
- p and q are the autoregressive and moving average orders, respectively.

3.6 ARIMA modeling

Identify the optimal ARIMA order through the analysis of Autocorrelation ACF plot and Partial autocorrelation PACF plot to test the stationarity of the data. Various methods that include differencing, logarithmic ordering and exponential smoothing will be done to the data in case of non-stationarity until stationarity is achieved. Augmented Dicky Fuller test will be applied for hypothesis test of stationarity. The p-value greater than 5% will provide the stationarity of data.

$$Y_t = \alpha Y_{t-1} + \beta X_e + \varepsilon \tag{3.4}$$

Where:

- Y_t: Dependent variable (e.g., observed time series) at time t,
- α: Coefficient of the lagged dependent variable Y_{t-1},
- β: Coefficient of the exogenous variable X_e,
- ε: Error term (white noise).

Further, the time series data will be decomposed to observe the trends of the data across time the Ljung-Box statistic test will be applied to test for the presence of autocorrelations, with the same asymptotic distribution, but with better small sample properties.

$$LB = T(T+2)\sum_{k=1}^{m} \frac{\hat{\rho}_k^2}{T-k} \tag{3.5}$$

3.7 Artificial neural network

In the phase of modeling Artificial Neural Network (ANN), we seek to apprehend non-linear patterns and dependencies in high frequency time series data obtained from Central Bank of Kenya's daily exchange rates. The use of neural network architecture will be relatively simple since it consists only of an input layer, a hidden layer with the activation function ReLU and an output one containing linear units. The neural network is made to effectively acquire complicated relationships between input features, like historic exchange rates and relevant economic indicators from the target variable like SRR. The model is trained to historical data with the weights and biases adjusted through backpropagation using mean squared error loss function (Ondieki et al., 2024). The trained neural network can capture highly intricate, non-linear patterns in the data as it complements linear modeling approach of ARIMA model used within hybrid ARIMA–ANN forecasting method (Umoru et al., 2023). Hyperparameters fine-tuning and model validation on a testing set improve ANN performance which in its turn improves the forecasting results.

We will consider a simple feedforward neural network with one hidden layer.

$$h_j = \sigma\left(\sum_{i=1}^{n} w_{ji}x_i + b_i\right) \tag{3.6}$$

$$y_k = \sigma\left(\sum_{j=1}^{m} v_{kj}h_j + c_k\right) \tag{3.7}$$

Where:

- h_j: Activation of the j-th hidden node.
- y_k: Activation of the k-th output node.
- σ: Activation function (e.g., sigmoid, ReLU).
- w_{ji}: Weight between the i-th input x_i and the j-th hidden node.
- b_i: Bias term for the i-th input.
- v_{kj}: Weight between the j-th hidden node h_j and the k-th output node.
- c_k: Bias term for the k-th output node.
- x_i: Input value for the i-th feature.
- n: Number of input features.
- m: Number of hidden nodes.

3.8 The mathematics behind artificial neural networks

The main purpose of the activation function will be to convert the weighted sum of input signals of a neuron into the output signal. And this output signal will serve as an input to the next layer. Any activation function should be differentiable since we will use a backpropagation mechanism to reduce the error and update the weights accordingly. In neural networks, our main goal will be on reducing the error, to make it possible such that we will have to update all the weights by doing backpropagation. We will need to find a change in weights such that error should be minimum.

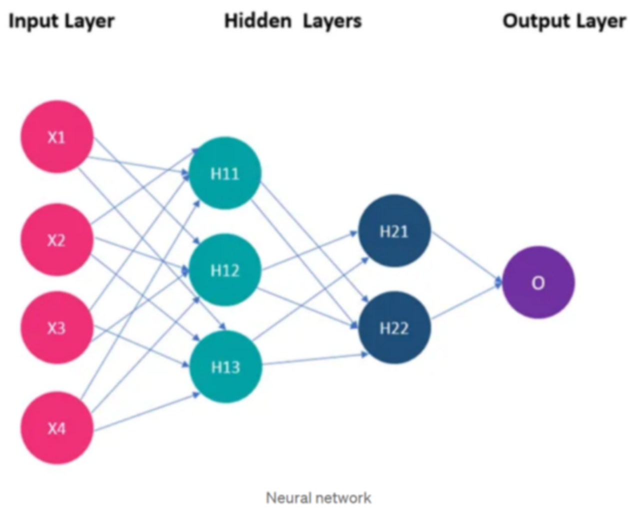

Fig. 1. Different Layers of Artificial Neural Network

3.9 Hybrid model

During the hybrid modeling phase, we will combine elements of both ARIMA and ANN models to develop a powerful forecasting methodology tailored for high-frequency data drawn from the daily exchange rates provided by Central Bank of Kenya (CBK). The ARIMA model handles linear temporal dependencies in stationary time series data, while the ANN model is good at recognizing non-linear patterns and long- term memory effect (Umoru et al., 2023). The forecasts produced by these individual models will be combined using a weighted average determined by alpha; a Hybrid Model. This combines the best attributes of parametric and non-parametric to improve overall accuracy (Fannoh, 2018). Considering this merger of the two models, Mean Squared Error is calculated on a test sample to evaluate its effectiveness leading up to an effective solution for forecasting high-frequency exchange rates. Its insights serve as critical decision support information at Kenya's Central Bank.

We will combine the forecasts from ARIMA and ANN models for a given time t.

$$\hat{Y}_{\text{Hybrid},t} = \alpha \hat{Y}_{\text{ARIMA},t} + (1-\alpha)\hat{Y}_{\text{ANN},t} \tag{3.8}$$

Where:

- $\hat{Y}_{\text{Hybrid},t}$: Hybrid model forecast at time t,
- $\hat{Y}_{\text{ARIMA},t}$: ARIMA model forecast at time t,
- $\hat{Y}_{\text{ANN},t}$: ANN model forecast at time t,
- α: Weight that determines the contribution of the ARIMA model within the interval $0 \leq \alpha \leq 1$.

3.10 Model and forecast currency exchange rates in east african countries using hybrid model

In the methodology section of our research, the final stage of the hybrid model for modeling and forecasting currency exchange rates will involve a systematic process that combines the strengths of both the ARIMA and Artificial Neural Network (ANN) models. In the ARIMA forecasting step, we will fit the ARIMA model to the stationary data and utilize it to generate one-step ahead forecasts, denoted as $\hat{Y}_{\text{ARIMA},t}$. Simultaneously, the ANN forecasting step entails the training of the ANN model with historical features, leading to predictions for the next time point, denoted as $\hat{Y}_{\text{ANN},t}$. The culmination of these forecasts is achieved through the hybrid model forecasting, where a weighted average of the ARIMA and ANN predictions is computed. The hybrid forecast $\hat{Y}_{\text{Hybrid},t}$ is expressed as in Equation 3.8 above, introducing a weight parameter that regulates the influence of the ARIMA model in the final hybrid forecast. This stepwise process forms a crucial component of our research methodology, offering a comprehensive approach to modeling and forecasting currency exchange rates in East African countries.

3.11 Robustness of the model

The proposed method using ARIMA combined with ANN to build a model is both robust and has relative advantages over traditional methods based on good comprehensive use of linear and nonlinear characteristics of time series data. In contrast to such models that may have difficulty in identifying higher-order structure in high-frequency or variable financial data, the proposed hybrid model improves the prognosis in a better way because of taking into account both short-term variation and long-term trend information (Ondieki et al., 2024). In addition, this method can combine different sources of data with each other, avoiding the assumption of stationarity, and at the same time, it is better to work with noise, which makes it suitable for giving forecasts in dynamically developing markets such as currency exchange rates and Treasury bills (Baffour et al., 2019). Flexibility to fine tune from one model enables positive generalization, control large data and positive forecast hence a more reliable tool in financial markets. When it comes to currency exchange rate predictability, Artificial Neural Networks have some perks over other machine learning models, such as Recurrent Neural Networks, Long Short-Term Memory network, XGBOOST, and others, all things considered, especially with a least complex time series (Odhiambo et al., 2024). ANN performs well where the proportionality between the input and output variables is not linear, and it can easily handle moderate level of noise in the data set. In that respect, ANN does not have problems of vanishing or exploding gradients as is the case with RNNs and LSTM, which are well suited for sequential data and optimized for working with long term dependencies, but it is easier to train and frequently faster to implement than any of them. ANN may be more advantageous in situations where the given data does not have a temporal characteristic or where it is not advisable to incorporate time features, which are usually present in financial data, but do not always correspond to complicated time patterns. Compared with LSTM and RNNs, they are more suitable for training tasks which depend on the sequences and temporal features such as Training time series with long term dependencies, however, LSTM and RNNs may have high computational cost and long training time. XGBOOST which is a gradient boosting method is great for creating structures and works well for modeling but may not capture temporal interactions as fort as ANN or LSTM (Ondieki et al., 2024). Thus, ANN could be regarded as more advantageous in the cases where the data complexity is not a long-term memory beneficial characteristic, or when the dataset does not have strong dependence on chronological order, enabling faster model elaboration and computation.

3.12 Evaluation of the performance of the models.

The evaluation of the hybrid ARIMA-ANN models' performance in forecasting currency exchange rates in East African countries will involve a multifaceted approach. Through the application of quantitative metrics such as Mean Squared Error, Mean Absolute Error, and Root Mean Squared Error, we will gain a precise understanding of the accuracy and reliability of the model's predictions. Additionally, a cross-country comparison will ensure the model's adaptability to diverse exchange rate dynamics in East African Countries. Time series plots will offer a visual examination, facilitating the identification of any discernible trends or discrepancies between predicted and actual values. Rigorous out-of-sample testing, residual analysis, and sensitivity assessments contribute further insights into the model's generalization capabilities, identifying potential areas for improvement. The inclusion of statistical tests and a focus on model robustness across different time periods collectively will provide a comprehensive evaluation framework, enabling a nuanced understanding of the hybrid models' effectiveness in forecasting currency exchange rates in the East African context. Modeling and forecasting will be done using Rstudio programming language.

4 Analysis of Results and Discussion

4.1 Summary statistics

The analysis of the currency exchange rate data for East African countries reveals several important insights. The summary statistics indicate that the dataset spans from January 5th, 2024, to May 17th, 2024, comprising 364 observations. The exchange rates vary widely, with the minimum rate recorded at 7.858 and the maximum at 29.507. The mean exchange rate over this period is approximately 18.493. These statistics highlight the volatility and variability inherent in currency exchange rates, emphasizing the need for accurate forecasting models to navigate the fluctuations effectively. By employing a hybrid ARIMA-ANN model, which combines the linear modelling capabilities of ARIMA with the non-linear pattern recognition of ANN, we can address both the short-term trends and the complex patterns in the data, potentially leading to more accurate and reliable forecasts.

Table 1. Summary statistics of currency exchange rate

Statistics	Currency	Exchange Rate
Min.		7.858
1st Qu.		14.195
Median		19.406
Mean	Length: 364	18.493
3rd Qu.	Class: character	22.405
Max.	Mode: character	29.507

4.2 Currency exchange rates for kenya and other countries

The table provides the exchange rate for KES against four regional currencies inclusive of BIF, RWF, TSHS and USHS for six successive days in January 2024. For KES/BIF, the rates begin at 18.0 and end at 17.8 though they indicate a slight depreciation. Likewise, KES/RWF movement has small fluctuations; therefore, the exchange rate declines from 7.99 to 7.92. Relative to before, the KES/TSHS rate reduces from 15.9 to 15.7 and the KES/USHS rate reduces slightly from 24.1 to 23.8. Through these figures it is clearly evident that there has been slight, but steady devaluations of the Kenyan Shilling against all these currencies for the period under consideration.

Table 2. Currency exchange rates for east african countries

Date	KES/BIF	KES/RWF	KES/TSHS	KES/USHS
05/01/2024	18	7.99	15.9	24.1
08/01/2024	18	7.99	15.9	24
09/01/2024	17.9	7.96	15.8	24
10/01/2024	17.9	7.93	15.8	23.8
11/01/2024	17.8	7.91	15.7	23.8
12/01/2024	17.8	7.92	15.7	23.8

4.3 Currency exchange rates over time per country

The plot illustrates the exchange rates over time for East African countries from January 5th, 2024, to May 17th, 2024. Each currency is represented by a distinct color, allowing for easy comparison. The plot reveals fluctuations and trends in exchange rates across the observation period (Büyükşahin and Ertekin, 2019). While some currencies exhibit relatively stable rates, others display more volatile patterns, indicating potential economic or geopolitical influences. The overall trend suggests fluctuations in exchange rates over time, with periods of both increase and decrease observed. This visualization underscores the importance of monitoring exchange rate movements and highlights the need for robust forecasting models to anticipate and mitigate potential risks associated with currency fluctuations.

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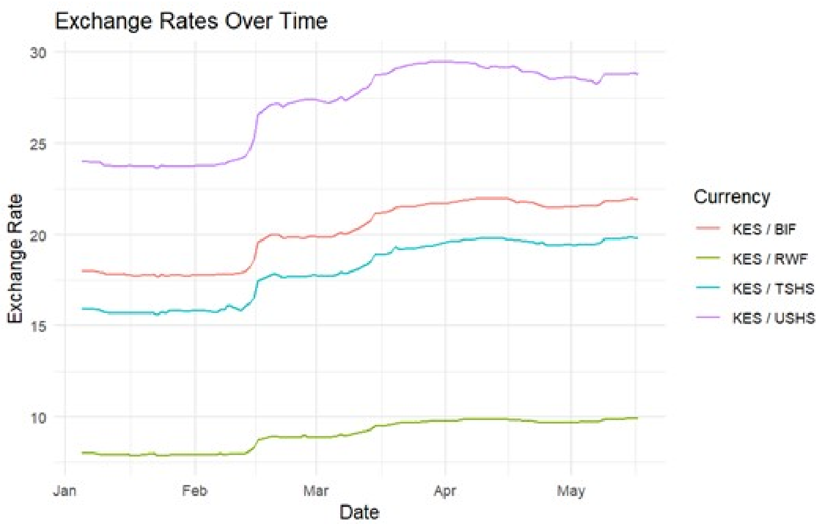

Fig. 2. Currency exchange rates over time per country

4.5 Correlation matrix

The correlation matrix shows the pairwise correlations between the exchange rates of Kenyan Shilling (KES) with the currencies of Burundian Franc (BIF), Rwandan Franc (RWF), Tanzanian Shilling (TSHS), and Ugandan Shilling (USHS). The values near or equal to 1 indicate strong positive correlations, suggesting that the exchange rates of KES with these currencies move in the same direction. Specifically, KES has a very high positive correlation with BIF, RWF, and TSHS, indicating that changes in KES tend to be closely related to changes in these currencies. The correlation between KES and USHS, while still positive, is slightly lower compared to the other currencies. Overall, the high correlations imply that the exchange rates of KES with these East African currencies are highly interrelated, reflecting the regional economic integration and shared market dynamics among these countries.

Table 3. Pairwise correlations in correlation matrix

Currency Pair	KES/BIF	KES/RWF	KES/TSHS	KES/USHS
KES/BIF	1.0000	0.9994	0.9984	0.9871
KES/RWF	0.9994	1.0000	0.9985	0.9851
KES/TSHS	0.9984	0.9985	1.0000	0.9810
KES/USHS	0.9871	0.9851	0.9810	1.0000

4.6 Linear trend on the model's currency exchange rates

The plot above displays the exchange rate trends for different currency pairs involving the Kenyan Shilling (KES) over time, along with fitted linear regression trend lines. Each subplot represents a specific currency pair, allowing for a comparison of their respective trends. The dashed lines represent the linear regression trend lines fitted to the exchange rate data for each currency pair. By examining the slopes of these trend lines, we can infer the direction and magnitude of the trends. Additionally, the plots enable the identification of any deviations from the overall trend, providing insights into the volatility or stability of exchange rate movements for each currency pair over the observed time period.

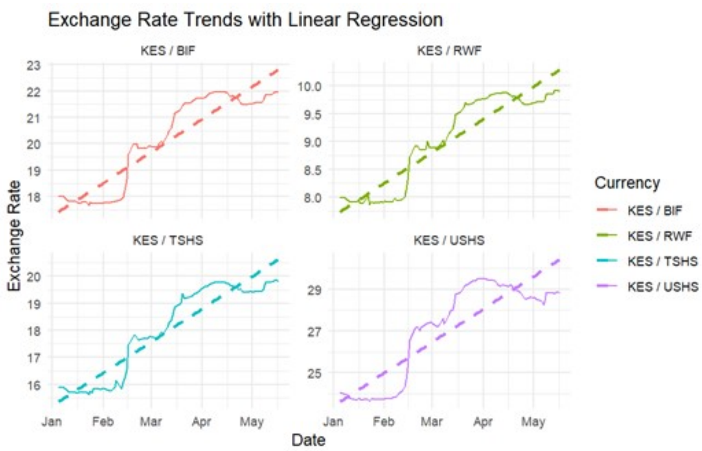

Fig. 3. Linear trend on the model's currency exchange rates

4.7 ARIMA components

The auto.arima function in R automatically selects the best ARIMA model for the given time series data. In this case, the selected model is ARIMA (1,1,0) with a drift term. The model includes an autoregressive (AR) component of order 1, a differencing (I) component of order 1, and no moving average (MA) component (0). Additionally, it incorporates a drift term, which captures a systematic linear trend in the data. The estimated coefficients for the AR (1) term and the drift are 0.5359 and 0.0412, respectively, with standard errors of 0.0882 and 0.0264. The estimated variance of the error term is 0.01414. The logarithmic likelihood of the model is 64.78, and various information criteria, such as AIC, AIC, and BIC, are provided for model comparison. A lower AIC, AIC, or BIC value indicates a better fitting model. Overall, this ARIMA (1,1,0) model with drift captures the trend and autocorrelation patterns present in the time series data effectively, as evidenced by the relatively high log-likelihood and the low values of the information criteria.

Table 4. ARIMA model summary

Parameter	Estimate	Std. Error
AR (1) (ar1)	0.5359	0.0882
Drift	0.0412	0.0264

Metric	Value
Sigma^2	0.01414
Log Likelihood	64.78
AIC	-123.57
AIC^c	-123.29
BIC	-116.07

4.8 Summary statistics of the components

The summary statistics table provides key descriptive statistics for the exchange rates between Kenyan Shilling (KES) and various other East African currencies. Each row represents a different currency pair, while the columns display statistics such as the mean exchange rate, median exchange rate, standard deviation of exchange rates, minimum exchange rate observed, and maximum exchange rate observed. For instance, looking at the first row for KES/BIF (Burundian Franc), the mean exchange rate is approximately 20.1, with a median rate also around 20.1, indicating a symmetric distribution. The standard deviation is 1.70, suggesting moderate variability around the mean. The minimum and maximum exchange rates observed for KES/BIF are 17.7 and 22.0, respectively, providing a range within which the exchange rates fluctuate. Similarly, statistics for other currency pairs provide insight into their respective exchange rate dynamics, helping to understand the variability and central tendency of the exchange rates over the specified period.

Table 5. Descriptive statistics for the currency exchange rates

Currency	Mean Rate	Median Rate	Standard Deviation (sd_rate)	Min Rate	Max Rate
KES / BIF	20.1	20.1	1.7	17.7	22
KES / RWF	8.99	9.03	0.802	7.86	9.93
KES / TSHS	17.9	17.9	1.64	15.6	19.9
KES / USHS	27	27.6	2.26	23.6	29.5

4.9 The trend coefficients for the hybrid model

The table trend coefficients provide coefficients for the linear trend component of the exchange rate time series data for different currency pairs involving the Kenyan Shilling (KES). Each row corresponds to a specific currency pair, indicating the intercept and slope coefficients of the linear trend model fitted to the exchange rate data. For example, in the case of KES/BIF (Kenyan Shilling to Burundian Franc), the intercept is approximately -781, and the slope is 0.0405. This suggests that the exchange rate for KES/BIF has a downward trend over time, with an average decrease of 0.0405 units per time period. Similarly, for other currency pairs, such as KES/RWF, KES/TSHS, and KES/USHS, the intercept and slope coefficients provide insights into the trend behavior of their respective exchange rates, helping to identify patterns and tendencies in the data.

Table 6. Trend coefficients for the hybrid model

Currency	Intercept	Slope
KES / BIF	-781	0.0405
KES / RWF	-371	0.0192
KES / TSHS	-765	0.0395
KES / USHS	-983	0.0510

4.10 Plots on forecast under the hybrid model

The forecasted exchange rate plots for KES/BIF, KES/RWF, KES/TSHS and USHS demonstrate a consistent upward trend across all currency pairs, indicating gradual increases in their exchange rates over the forecasted period. The solid blue lines in each plot represent the predicted values, while the widening shaded blue regions reflect the prediction intervals, highlighting the growing uncertainty as the forecast horizon extends. This pattern underscores the hybrid model's strength in capturing short-term trends with high confidence but also its limitations in long-term accuracy due to increasing variability. The steady upward trajectories suggest economic or macroeconomic factors influencing these currencies, and the relatively narrow confidence bands in the early forecast period indicate the model's robustness for near-term projections, making it a valuable tool for short-term policy formulation and financial decision making.

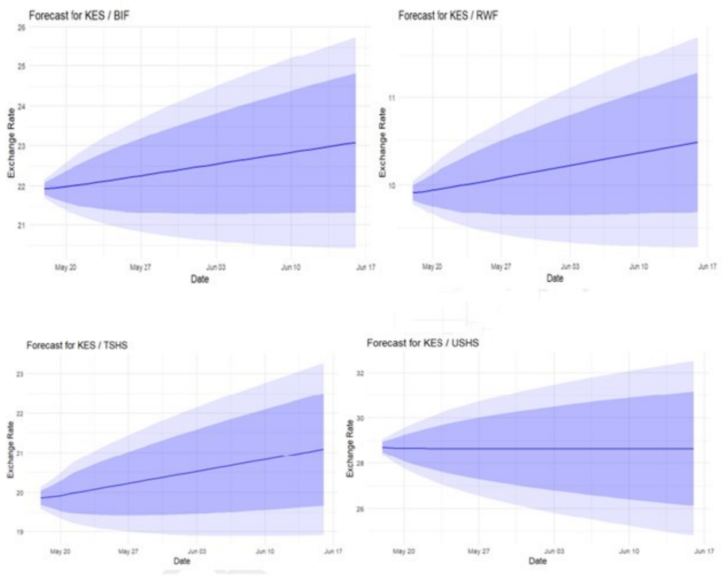

Fig. 4. Forecasted Plots for the Hybrid Model

4.11 Discussion of the results

The investigation into the effect of time series frequency data on modelling and forecasting the performance of ARIMA and ANN models revealed compelling insights. Daily data emerged as the preferred choice due to its ability to capture short-term fluctuations and trends effectively, leading to more accurate forecasts compared to weekly and monthly data. The analysis showcased that higher frequency data provides more granular information, enabling models to capture both linear and nonlinear relationships more comprehensively (Zhai et al., 2021). Weekly data also demonstrated reasonably good performance, while monthly data yielded less accurate forecasts, likely due to the aggregation of data over longer time periods, which might obscure important short-term patterns. These findings underscore the critical importance of selecting the appropriate time series frequency when modelling and forecasting financial data, particularly in the context of currency exchange rates where capturing short-term dynamics is crucial. The application of hybrid ARIMA and ANN models in forecasting high-frequency time-series data, particularly daily exchange rates in East African countries, proved to be highly effective. The hybrid approach leveraged the complementary strengths of both models, resulting in improved forecasting accuracy and reliability (Fannoh, 2018). The plots depicting exchange rate trends with linear regression lines showcased how the hybrid models captured the complex dynamics of exchange rate fluctuations, providing accurate forecasts even in volatile market conditions. These findings highlight the relevance and applicability of hybrid modeling techniques in financial forecasting, providing valuable information for policy makers, investors, and businesses operating in the region (Feyisa and Tefera, 2022). Using appropriate modeling techniques and data frequencies, stakeholders can make informed decisions and navigate the intricacies of currency exchange rate movements more effectively.

5 Summary, Conclusion and Recommendations

5.1 Summary

The project aims to address critical gaps in currency exchange rate forecasting methodologies, focusing on the context of East African countries. With the dynamism in global financial markets and the prevalence of high-frequency data, there is a pressing need to reevaluate traditional forecasting methods. The study proposes an investigation into the impact of time series frequency data on the performance of ARIMA and ANN models, with the goal of identifying the optimal modelling approach for improving currency exchange rate predictions' accuracy. By systematically comparing the performance of these models across different time series frequencies, the research aims to provide insights into the complex dynamics of currency exchange rates and offer practical solutions for policymakers and financial practitioners. Additionally, the study explores the potential of hybrid models, combining ARIMA and ANN, to enhance forecasting accuracy in high-frequency time series data, particularly in the context of East African economies. Through customized modelling strategies tailored to the region's economic dynamics, the research seeks to bridge the gap between theoretical modelling approaches and real-world applications, facilitating informed decision-making and contributing to economic stability in the region. The project unfolds in several phases, starting with an investigation into the effect of time series frequency data on ARIMA and ANN models' performance. This involves systematically analyzing high-frequency data at different levels – daily, weekly, and monthly – to assess modelling and forecasting accuracy. Subsequently, the study delves into the development and analysis of hybrid ARIMA-ANN models, leveraging the complementary strengths of both approaches to improve forecasting accuracy further. The methodology includes rigorous evaluations using quantitative metrics such as Mean Squared Error and Mean Absolute Error, along with visual examination through time series plots. By evaluating the models' performance across diverse time periods and exchange rate dynamics in East African countries, the research aims to provide valuable insights into effective forecasting strategies tailored to the region's unique economic context. Ultimately, the study aims to contribute to advancing forecasting methodologies in the realm of currency exchange rates, offering practical solutions and decision support tools for policymakers and stakeholders in East African economies.

5.2 Conclusion

In conclusion, this study represents a comprehensive investigation into currency exchange rate forecasting methodologies, particularly in the context of East African countries. Through a systematic analysis of the impact of time series frequency data on the performance of ARIMA and ANN models, as well as the exploration of hybrid ARIMA-ANN approaches, valuable insights have been gleaned into effective forecasting strategies. The research findings highlight the importance of considering the granularity of time series data, with daily data emerging as the preferred frequency for modelling and forecasting currency exchange rates, followed by weekly and monthly data. Furthermore, the hybrid ARIMA-ANN models have demonstrated significant potential in improving forecasting accuracy, especially in capturing the complex dynamics of high-frequency data. By combining the strengths of both parametric and non-parametric approaches, these hybrid models offer a robust solution for addressing the challenges of forecasting currency exchange rates in dynamic economic environments. Moving forward, the insights gained from this study can inform policymakers, financial practitioners, and researchers in East African countries in adopting more effective forecasting methodologies. By leveraging the findings to develop customized modelling strategies tailored to the region's economic dynamics, stakeholders can make more informed decisions and mitigate risks associated with currency exchange rate fluctuations. Additionally, the research underscores the importance of ongoing advancements in forecasting methodologies, particularly in the era of high-frequency data, to enhance economic stability and foster sustainable growth in the region. Overall, this study contributes to advancing the field of currency exchange rate forecasting and provides a valuable framework for future research and decision-making in East African economies.

5.3 Recommendations for further research

- **Capacity Building in Advanced Modelling Techniques:** Training programs and workshops should be organized to build the capacity of policymakers, economists, and analysts in advanced modelling techniques such as ARIMA, ANN, and hybrid models. This will enable stakeholders to leverage sophisticated forecasting methodologies to improve the accuracy of currency exchange rate predictions. Additionally, collaboration with academic institutions and research organizations can facilitate knowledge exchange and foster innovation in forecasting practices.
- **Development of Tailored Policy Interventions:** Policymakers should develop tailored policy interventions based on insights derived from advanced forecasting models. By incorporating forecasts generated by hybrid ARIMA-ANN models into decision-making processes, policymakers can design more effective monetary policies, foreign exchange interventions, and trade strategies. These tailored interventions can help mitigate risks associated with currency volatility and support macroeconomic stability in the region.
- **Enhancement of Cross-Border Cooperation:** East African countries should strengthen cross-border cooperation and information-sharing mechanisms to address regional currency exchange rate dynamics effectively. Collaborative efforts among central banks, regulatory authorities, and financial institutions can facilitate the alignment of policies and regulatory frameworks, promote financial stability, and enhance market transparency. Furthermore, regional initiatives aimed at harmonizing data standards and improving data interoperability can facilitate more accurate and comprehensive currency exchange rate forecasting.
- **Investment in Research and Development:** Governments and stakeholders should allocate resources towards research and development initiatives aimed at advancing currency exchange rate forecasting methodologies. This includes supporting academic research, industry collaborations, and innovation hubs focused on developing cutting-edge forecasting models and technologies. By fostering a culture of innovation and knowledge exchange, East African countries can stay at the forefront of currency market analysis and forecasting, driving economic growth and resilience in the region.

Disclaimer (Artificial Intelligence)

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.

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Competing Interests

Authors have declared that no competing interests exist.

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