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DEPARTMENT OF STATISTICS AND MATHEMATICS

A COMPARATIVE ANALYSIS OF TIME SERIES AND NEURAL NETWORKS MODELS IN FORECASTING ZWL/USD EXCHANGE RATES.

BY

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DEDICATION

To my dearest family, whose unwavering love, encouragement, and understanding have been my guiding light throughout this academic journey. Your support has given me the strength to persevere through the challenges and the inspiration to reach my goals.

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ABSTRACT

This research is a comparative analysis of FFNN and ARIMA model in forecasting exchange rate volatility in Zimbabwe. The study applied FFNN [1(5,5)1] and ARIMA (0,1,2) models in forecasting ZWL/USD exchange rates volatility using performance evaluation techniques such as RMSE, Symmetric MAPE, AIC, and BIC. The major objective was to compare the performance of these models in predicting future exchange rates. The research used data of weekly exchange rates extracted from the Reserve Bank of Zimbabwe's website to come up with models. Data used was for the period February 2022 to December 2023. Forecasting was based on In-Sample and Out-Of-Sample predictive horizon. The research findings selected FFNN model since it had the lowest Symmetric MAPE, RMSE, AIC, BIC and RMS values. The FFNN model predicted values were adjacent to the actual data. Based on the findings, the study indorses the use FFNN model for forecasting exchange rates since it can predict large volumes of data in a given data set.

Key words: Time Series Forecasting, Exchange Rates, ARIMA, FFNN, Neural Networks.

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ACRONMYS

ARIMA - Auto Regressive integrated Moving Average

FFNN – Feed Forward Neural Network

RBZ - Reserve Bank of Zimbabwe

BIC - Bayesian Information Criteria

AIC - Akaike Information Criteria

RMSE - Root Mean Squared Error

MSE - Mean Squared Error

MAPE – Mean Absolute Percentage Error

ACF - Auto correlation Function

PACF - Partial Auto correlation Function

ADF - Augmented Dicky Fuller Test

GA - Genetic Algorithm

BVAR - Bayesian Vector Auto-regression

GDP - Gross Domestic Product

PPP – Purchasing Power Parity

IRP - Interest Rate Parity

IFE - International Fisher Effect

MIDAS - Mixed Data Sampling

CHAPTER 1: INTRODUCTION

1.1 Introduction

Given how dynamic currency markets are and how many variables affect exchange rate changes, forecasting exchange rates is a difficult undertaking. Nevertheless, advancements in machine learning methods, especially in the domains of neural networks and time series analysis have offered useful instruments for more accurate currency exchange rate prediction. Time series analysis have been used for a significant amount of time in exchange rate forecasting to use trends in previous data. With this method, it is assumed that historical exchange rate behaviour offers insightful information about upcoming changes. Because they can represent non-linear dynamics and intricate interactions in data, neural network models have drawn a lot of interest lately.

1.2 Background of the study

Exchange rate forecasting has a long history that dates to the late 19th and early 20th centuries. Initially, forecasters relied on fundamental analysis, which involved examining economic factors like interest rates, inflation rates, government policies, and economic indicators to predict currency movements. However, this method had limitations and often failed to accurately predict exchange rate fluctuations.

In the 1970s, with the introduction of computer technology, technical analysis gained popularity in exchange rate forecasting. Studying past pricing data, chart patterns, and various other indications is how this method finds trends and projects future changes in exchange rates. Technical analysts are able to forecast based on previous trend since they think that past price patterns can repeat.

During the 1980s and 1990s, researchers began exploring the use of econometric models to forecast exchange rates. These models employ statistical techniques and economic theories to estimate exchange rate movements. The Purchasing Power Parity (PPP) model is one well-known notion that suggests exchange rates require to be adjusted for the corresponding prices of goods between two countries.

In the 2000s, machine learning and artificial intelligence started playing a significant role in exchange rate forecasting. These advanced techniques utilize large datasets and tools for spotting trends and forecasting outcomes. The models can consider factors beyond traditional macroeconomic indicators, to provide more accurate forecasts.

Currently, exchange rate forecasting continues to evolve as technology and research progress. Hybrid approaches that combine fundamental analysis, technical analysis, and machine learning techniques are gaining popularity. Moreover, the incorporation of big data, natural language processing, and sentiment analysis has provided new insights for predicting exchange rate movements.

However, it's important to note that accurately predicting exchange rates remains challenging due to the complex and unpredictable nature of global financial markets, despite the improvements in forecasting techniques over time.

1.3 Statement of the problem

According to the World Bank, the Zimbabwean dollar is recognized as one of the poorest-performing currencies in the global foreign exchange market. The events of 2008 and the current struggles with the foreign auction system in 2020 indicate a crisis in the market and a severe economic downturn. The volatility of exchange rates creates uncertainty for investors, making it challenging to forecast the future value of their investments. These fluctuations can have a significant impact on investment returns and profitability, making long-term planning difficult. The prolonged financial crisis also leads to economic, labour, and industrial unrest, as evidenced by the incapacitation of both formal and informal workers throughout the country and protests within the healthcare and education sectors.

1.4 Research Objective(s)

The researcher objectives were as follows:

1. To develop an ARIMA and a Feedforward neural network model for predicting exchange rates.
2. To test and evaluate the performance of tentative models based on ARIMA and FFNN approaches for forecasting exchange rates.
3. To assess the performance of time series and neural network models in predicting exchange rates (USD/ZWL).

1.5 Research question(s)

The analysis aims to answer the following:

1. How do developed ARIMA model and Feedforward neural network model perform?
2. Which tentative ARIMA and FFNN models is the best in forecasting exchange rates?
3. How does the neural network approach compare to the ARIMA model in exchange rate prediction?

1.6 Scope of the study

The research focuses on utilizing historical data obtained from the Reserve Bank of Zimbabwe regarding USD/ZWL exchange rates. The data will undergo analysis employing time series methods and neural networks techniques to assess the performance of each model. Additionally, the study will investigate the potential utility of time series and neural network models in predicting exchange rates under various economic conditions, including periods of economic growth, recession, or inflation. The study will primarily involve a comparative analysis between time series and neural network models and will not incorporate other types of models.

1.7 Significance of the study

The study is projected to benefit the following stakeholders who are;

1.7.1. The researcher

Conducting this research allows the researcher to deepen their understanding of time series analysis, neural network models, and exchange rate forecasting techniques. The researcher gains expertise in applying statistical methods, data analysis, and model evaluation techniques specific to this domain. This enhances their skills and knowledge in the field of forecasting and quantitative analysis.

1.7.2. The General Academic community including other researchers and students

The study donates to the existing body of information in the field of exchange rate forecasting. By conducting this study, the researcher adds to the academic literature and offers insights and findings that can be referenced by other researchers and scholars.

1.7.3. Policy Makers and related stakeholders

Policy makers and related stakeholders can utilize the findings of the study to make informed decisions. By understanding which forecasting model performs better in predicting exchange rates, they can make more accurate assessments and design effective policies. This can lead to improved economic planning, better resource allocation, and more targeted interventions.

1.8 Assumptions of the study

ARIMA model assumptions

1. The time series data is stationary and can be made stationary through differencing.
2. Residuals are normally distributed.
3. The variance of residuals is constant over time.
4. Residuals are uncorrelated with each other.

FFNN models assumption

1. The amount of training data is sufficient to learn the underlying pattern.

1.9 Limitations of the study

The absence of literature on the Time Series modelling of exchange rates in Zimbabwe was a challenge. For this reason, the researcher used international articles and journals for the literature review. Due to differences in economies some ideas do not fit well in the Zimbabwean economy. As stated in the research, the researcher used secondary data on the central bank's (RBZ) website of which the researcher is not familiar with the data collection processes and the methodology used and how well it was done. Apparently, data collection processes, error writing and lack of observation cannot be traced.

1.10 Delimitations of the study

- Source of data

The data is delimited to the Reserve Bank of Zimbabwe website from February 2022 to December 2023.

- Time Period

The study is delimited to a range of historical exchange rate data from February 2022 to December 2023.

- Currency pairs

The research is delimited to ZWL/ USD exchange rates to minimise the complexity of the study and provide a extra focused comparison.

- Model Architectures

The study focuses on a predefined set of time series and neural network models, excluding other alternative forecasting approaches to maintain comparability and consistency in the analysis.

- Evaluation Metrics

Predictive analysis of time series data with ARIMA and FFNN models. Also, Comparative analysis with model selection criterion is based on AIC, BIC, MSE, RMSE and Symmetric MAPE tests.

- Technique (tools)

RStudio was used for prediction computation and analysis

1.11 Definition of terms

- Neural Network (NN)

is a machine learning system with interconnected processing components like to the cerebral cortex that is modeled after the human brain's architecture. (Tokui, et al., 2015).

- Time series forecasting

is a method that examines patterns derived from historical data collected on frequent intervals to estimate future values (Torres, et al., 2021).

- Exchange rate

is the price at which one currency can be exchanged for another. It is the monetary value of a particular country measured in terms of the currency of another (Frenkel, 2019).

- ARIMA

is a time series analysis tool employed for predicting future data forecasts by using previous information (Shumway, et al., 2017).

- Feed-Forward Neural Network (FFNN)

is a sort of neural network architecture applied in multiple fields for different applications (Yaseen, et al., 2016).

- AIC

  The Akaike information criterion is an estimate of prediction error and is used in determining model quality for a given set of data (Aho, et al., 2014).

- BIC

  Bayesian information criterion (BIC) is a criterion for model's selection based in part, on the likelihood function (Delattre, et al., 2014).

- MSE

  It is used to measure the forecast accuracy of a model and it stands for mean squared error (Sara, et al., 2019).

- RMSE

  It is a valuable measure for calculating forecast accuracy and it reveals how distributed residuals are. It stands for rooted squared error (Hodson, 2022).

- MAPE

  Mean absolute percentage error is a statistic that leverages relative mistakes to enable you to compare forecast accuracy between time-series models (Kim & Kim, 2016).

1.12 Chapter Summary

The chapter introduced the basic concepts, ideas and information related to the background of the study, statement of the problem, research question, assumptions, limitations and delimitation. The study seeks to answer the question, which model performs better in forecasting ZWL/USD exchange rates data, from February 2022 to December 2023, regarding weekly forecasting results in comparison of FFNN and ARIMA? The following chapter discusses theoretical and empirical studies that are related to the one that is being conducted.

CHAPTER 2: LITERATURE REVIEW

2.0 Introduction

This chapter primarily aims to provide further details on a collection of literature on the subject of the investigation. Relevant data regarding exchange rate prediction employing various models utilized by numerous academics is presented. Chapter 2 examines all relevant theoretical and empirical literature in the field of the exchange rates market and identifies the research gap that prompted the current study. This research paper expands upon the limited empirical research on the utilization of forecasting models and seeks to determine the most effective model for enhancing accuracy. The literature gathered in the chapter aided the researcher in finding the appropriate model for the study.

2.1 Theoretical Literature

As they govern the relative worth, exchange rates between one currency and another are vital to finance and trade between nations and have an enormous effect on national economic growth. Theories concerning exchange rates seek to elucidate the factors that shape and cause fluctuations in exchange rates. These theories can be broadly classified into three primary approaches, the PPP approach, the IRP approach, and the IFE.

2.1.1. Exchange market

The trading of currencies occurs on the exchange market, also referred to as the foreign exchange market, an international and decentralized market. Exchange rates are essential to many aspects of international trade, stock index price forecasts, exchange rate prediction models, and trade imbalance phrases, claim Nagurney et al., (2023). Research shows that in order to investigate the effects of exchange rates on the market, currency rates are included into multicommodity trade models. Moreover, the connection between trade imbalances and misalignments of exchange rates is investigated, indicating little and transient impacts on current account balances in surplus and deficit countries.

2.1.2. Purchasing Power Parity (PPP) Theory.

In the field of PPP theory has bearing on exchange rates. It implies that in the long run, currency exchange rates should alter to guarantee that, if converted to a common currency, a basket of goods and services has the same price in all countries (Rogoff, 1996). PPP theory suggests that exchange rates ought to represent the relative buying power of various currencies.

The Absolute PPP variant holds that the ratio of the price levels of two currencies should determine the exchange rate between them. Relative PPP (Kamal, 2018), over time fluctuations in inflation and currency rates are taken into account. It implies that the difference in the rates of inflation of two currencies should be equal to the rate of change in the exchange rate between them.

PPP does not, however, always hold true in practice because of an array of issues such taxes, trade barriers, transportation costs, and variances in legislation and preferences. In the long run, PPP also usually holds up better than in the short term. PPP is nevertheless a valuable idea for comprehending the basic factors of exchange rates and determining whether currencies are overvalued or undervalued in relation to their buying power, despite its drawbacks.

2.1.3. Interest Rate Parity (IRP) theory

Introduced by Gustav Cassel, a Swedish economist, in the early 20th century. The theory focuses on the connection between interest rates and exchange rates in the financial markets. The principle is that the expected shift in the exchange rate of two countries' currencies should be equal to the difference in interest rates between them.

IRP comes in two primary indications; the Uncovered Interest Rate Parity (UIRP) posits that the expected percentage change in the exchange rates between two countries should be equal to the actual difference in interest rates between them (Çorakçı, et al., 2017). Put otherwise, investors would anticipate a currency depreciation in Country A relative to the currency of Country B that would reduce the interest rate disparity if the interest rate in Country A is higher than in Country B.

The idea is extended to the forward exchange market by Covered Interest Rate Parity (CIRP). It implies that the difference in the forward and spot exchange rates between two countries should be equivalent as the interest rate differential. Put otherwise, the forward exchange rate should fluctuate to account for the difference in interest rates between Country A and Country B, hence eliminating any potential for arbitrage (Niu, et al., 2016).

But much like PPP, IRP theory frequently fails miserably in real life because of things like transaction costs, government involvement, and risk perceptions. Particularly, variables including market expectations, shifts in risk attitude, and capital flow dynamics might cause departures from IRP.

Though it has many drawbacks, IRP theory offers significant insights into the connection between interest rates and exchange rates that are essential to comprehending the workings of financial markets and the determination of exchange rates. Investors and politicians frequently use it to control foreign exchange risk and evaluate the attractiveness of other currencies.

2.1.4. International Fisher Effect

Introduced by the American economist Irving Fisher in 1930, The theory states that variations in nominal interest rates between two countries will be countered by changes in the exchange rate, so that, after accounting for expected shifts in exchange rates, the real returns on comparable assets are equalised between countries. If one nation has a higher nominal interest rate than another, its currency should eventually appreciate to the point where the interest rate differential is eliminated.

The theory takes into account, Interest Rate Differential. The IRD assume that the nominal interest rate in Country A is higher than that in Country B. Investors would look to Country A for larger profits, the IFE predicts, which might raise demand for its currency (Chen, 2015). The higher demand for the currency of Country A would cause its value to appreciate in relation to that of Country B.

The IFE takes into account projected changes in exchange rates in addition to the interest rate differential as of this moment. Investors may change their investments if they believe that the currency of the higher interest rate nation will weaken in comparison to the currency of the lower interest rate nation. It is possible that this expectation will affect the exchange rates now.

The IFE suggests that there should be few chances for arbitrage. Investors might take use of a persistent interest rate disparity between two nations without matching changes in exchange rates by trading currencies, which would cause market corrections in line with the IFE (Ali & Qureshi, 2023).

In practice, though, the IFE does not always hold true precisely because of a number of variables including transaction costs, government actions, and market mood. Beyond only interest rate differentials, a number of other variables, such as market mood, geopolitical events, and economic development prospects, can also affect expectations about future exchange rate movements.

2.1.5. Time series Analysis

Time series analysis comprises the examination of sequentially gathered data throughout time, with time being a major aspect in the reference (Abdalla et al., 2023) This technique has significant use in areas involving economics, accounting, and natural disaster projections. Using deep learning methods like ARIMA, GARCH, Recurrent Neural Networks, and Long Short-Term Memory complex data is handled and forecast accuracy is improved. The basics of time series analysis is forecast future values based on existing data, making it a significant tool in decision-making and trend analysis.

2.1.6. Exchange rates forecasting

Economics and finance have done a significant amount of study on exchange rates. Exchange rate movement is analysed and forecasted by models developed by researchers. Behavioural, microsystems, and macroeconomic modelling are among the many methods used in the literature on exchange rate modelling. The Mundell-Fleming model is among the oldest and most widely used models of exchange rate computation. The model includes, in an open economy context, the impact of fiscal and monetary policy on exchange rates (Wang & Hu, 2015). Money demand and supply are highlighted in monetary modelling, another known technique to exchange rate modelling.

2.1.7. ARIMA Model

Developed by Box and Jenkins in the 1970s, the model is a commonly employed time series forecasting technique. To identify patterns in the data, the model integrates moving average (MA), autoregressive (AR), and variance (I) components (Gui et al., 2023). With over thousand citations in several research and studies, the ARIMA model has emerged as the most well-known models since their creation. Making the difference is the mix of moving averages and auto-regressive difference. Power modelling capturing volatility with an auto-regressive integrated moving average. The number of Auto-regressive (AR) terms is denoted by p, the number of taken differences by d, and the number of moving averages (MA) terms by q. Importantly, this approach takes variance to be constant.

2.1.8. Neural Networks Analysis

The human brain influences the building and running of this neural network model. They are made of strata of connective tissue, or synthetic tissue. The idea of neural networks was initially put forth in the 1940s when McCulloch and Pitts (1990) developed the first artificial neural network. nevertheless, neuromuscular research progressed significantly in the 1950s and 1960s. The perceptron was a major contribution of Rosenblatt (1957), who mostly studied the asymptotic behaviour of prediction errors for deterministic systems with spectral density properties. The prediction error acts strangely if the spectral density vanishes inside an interval, and it behaves like a power function when n approaches infinity, the speaker emphasized. Moreover, coefficients for the Rosenblatt distribution have been derived using a lot of numerical study. Academics highly value the substantial contributions Murray Rosenblatt made to time series analysis.

2.1.9. Feedforward Neural Network (FFNN) Model.

A popular machine learning method, feed-forward neural networks (FFNNs) are applied to data aggregation and picture categorization among other things. It runs on data traveling across several layers without creating neuronal cycles. FFNNs usually modify weights and biases by backpropagation, however this method can be sluggish to converge and heavily reliant on earlier solutions. The Arithmetic Optimization technique (AOA) has developed as a viable metaheuristic search technique for training FFNNs to overcome these constraints, providing a high for global search capability. Furthermore, FFNNs have shown their usefulness in prediction tasks by being effectively applied to the prediction of the remaining usable life (RUL) of bearings in machines. Feed-forward neural networks provide an idea for predicting exchange rates because of its capacity to capture nonlinear correlations, respond to changing market conditions, and enable feature learning (Rumelhart et al., 1986). Considering specific challenges like such data needs and model complexity, continuous study and developments in neural correlation methods are enhancing their usefulness in exchange rate forecasting. A comprehensive assessment of feedforward neural networks and its uses in deep learning is given by Goodfellow, Bengio, and Courville, (2016). Discussed are the computational underpinnings, training algorithms, and useful theories for using feed-forward neural networks in domains as diverse as speech recognition, natural language processing, and image recognition.

2.1.10. Comparative Analysis

Forecasting exchange rates have benefits and drawbacks for both neural networks and time series analysis. Although it provides a well-established framework with understandable models, time series analysis could find it difficult to identify intricate patterns. Conversely, although at the expense of interpretability, neural networks offer flexibility and adaptability, which may result in more precise projections. Availability of data, forecasting horizon, and the significance of interpretability in decision-making determine which of the two methods out performs the other. Exchange rate forecasting might be made more reliable by combining both methods and by utilizing ensemble techniques.

2.2 Empirical Literature Review

This is a subset of research in which findings of previous studies on a certain subject being methodically studied and analysed. The review attempts to give a thorough summary of the state of knowledge on the subject as well as to point up the gaps in the body of current study.

2.2.1 Develop an ARIMA and FFNN model for predicting exchange rates

Islam & Chowdhury (2022) modelled and anticipate exchange values in Bangladeshi Taka (BDT) between seven currencies (US dollar, Euro, Pound sterling, Australian dollar, Japanese yen, Canadian dollar, and Swedish krona) using the ARIMA time series model. Using daily currency exchange rates from January 2018 to December 2018, they estimated one-month rates for January 2019. The Durbin-Watson test indicated daily foreign exchange rate autocorrelation, while the

Augmented Dickey-Fuller test confirmed unit roots and non-stationarity, remedied by first differencing (d=1) within the ARIMA model selection of ARIMA (1, 1, 0) models was done using Ljung-Box, root mean square error, mean absolute percent error, mean absolute error, and R-square values. Predicted rates were compared with actual rates, validated using the Chi-Square test, MAPE, MSE, and RMSE. Results supported ARIMA (1, 1, 0) models for forecasting Bangladeshi foreign exchange values.

Using causal models and time series, Batóg & Batóg (2021) modeled and examined traditional forecasting methods for regional government income. Reliability of three models time series models, dependency models, and structural forecasting—was investigated using data spanning the years 2000–2018. The study found that the best techniques for estimating local government revenue were structural forecasting utilizing the ratio of regional GDP to GDP study and exponential smoothing with the exponential trend.

Ticona et al. built and applied a hybrid model based on GAs and NNs for a multi-step tax revenue prediction in a 2017 work using exogenous and endogenous factors. Including the exogenous variables improved the precision of the prediction. Data from January 2000 to December 2014 from the Federal Revenue of Brazil (RFB) are used in this work. Out of them, test data (2014), validation data (2003), and training data (years 2000–2012) were produced for various uses of the NNs. The study's findings showed the hybrid GA/NN model worked well for tax revenue collection projections. The results also shown to be more precise than the RFB's indicators technique.

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2.2.2. Test and evaluate the performance of tentative models based on ARIMA and FFNN approaches for forecasting exchange rates.

With application to the ASE20 Greek stock index, Karathanasopoulos et al. (2016) introduced a novel hybrid approach for financial asset direction prediction. The work specifically predicted and traded the ASE20 Greek stock index using an alternative computational method known as evolutionary support vector machine (ESVM) stock predictor, so expanding the universe of the studied inputs to include autoregressive inputs and moving averages of the ASE20 index and other four financial indices. A hybrid method fusing evolutionary algorithms with support vector machines evolved to overcome the shortcomings of the existing methods and provide effective short-term trading models. The trading performance of the ESVM stock predictor was benchmarked using a multilayer perceptron neural network model in conjunction with four common strategies: a buy and hold strategy, a moving average convergence/divergence, a naïve approach, and an autoregressive moving average model. As it occurs, the proposed strategy improves trading performance in terms of annualized return and information ratio even during the financial crisis time and provides information about the relationship between the ASE20 index and the DAX30, NIKKEI225, FTSE100, and S&P500 indices.

In a separate work, Khan & Khan (2020), examine in-depth the advantages and disadvantages of neural network and time series models for exchange rate forecasting. The capacity of time series models to capture historical patterns and trends in currency movements is one of its advantages, the authors pointed out, in projecting exchange rates. Autoregressive integrated moving average (ARIMA) and vector autoregression (VAR) are time series models that work well for examining historical exchange rate data and spotting possible trends that could recur in the future. These models offer a comprehensive framework for forecasting and also let the inclusion of various economic factors and components that influence changes in exchange rates. In exchange rate forecasting, however, neural network models provide unique benefits, particularly in their capacity to handle complex interactions among variables and non-linear correlations. Because neural networks can learn from data patterns and change with the market, they can identify complex linkages that are difficult for conventional time series models to see. The writers come to the conclusion that although time series models are quite good at capturing past trends and including economic indicators, they could find it difficult to handle abrupt changes in exchange rates. Conversely, neural network models may not be transparent and may be overfitting prone, but they provide flexibility in managing complicated relationships. Using the DCC-MGARCH model and a copula technique, the study by Sebai, et al. (2015) also looks at the connection between oil prices and the US dollar exchange rate. The Clayton copula was shown to be the most effective model with a conditional dependency structure for estimating the connection between exchange rates and oil markets. They also show for every relationship a notable and asymmetric tail dependence. Moreover, a declining dollar corresponds with a rise in the price of oil. The portfolio simulations demonstrate from a forecasting standpoint that taking extreme coevolution into account increases market risk forecast accuracy. Furthermore, the DCC-MGARCH model indicates that in times of crisis, the dynamic conditional correlation between copulas rises.

2.2.3. Evaluate the performance of time series and neural network models in predicting exchange rates (USD/ZWL).

Scholars investigated at the extent to which these models capture the intricacy of changes in currency rates and how well they forecast. Abdoli, (2020) carried undertaken one excellent study on this subject. The study admits that it is unknown how dependent or independent factors are, and that developing trustworthy predictive models will be more difficult than in other nations. Though data indicating anomalies in the monetary system should be disregarded, the linearization nonlinear multivariate economic time-series to predict can yield results. Further methods of artificial neural networks (ANNs) make it easier to build prediction models that store data properties. This work uses intraday data from the Tehran Stock Exchange (TSE) for the past ten years to show the upcoming two months. The ARIMA model and selected LSTM from ANN are compared. In terms of accuracy error, the results demonstrate that LSTM significantly outperforms ARIMA even when the prediction accuracy of both models decreases with long-term forecasting.

With reference to complex time series models Wang and Hu (2015) estimate the winds using an integrated approach that combines various models anticipating short-term wind speeds; prediction engines are integrated; and the GPR enhances wind speed forecasts. Applying the GP technique to the candidate models yields more precise pricing and probability information consistent with forecasts based on predictive distributions of probability. The use of three analytical measures (MAE, RMSE, and MAPE) characterize the performance that the most likely value prediction achieves, or is close to. The industry can benefit from the possible information the integrated model offers in order to incorporate wind turbines and wind energy into the power grid. A further significant contribution to the field is "Forecasting and Control", (Box, et al., 2015). Time series analysis techniques are thoroughly covered in this classic course, which also covers model analysis and forecasting techniques. The writers go over the difficulties in modelling exchange rate data and offer some understanding of how well time series models capture its genetic variability. In his thorough study of neural network applications in financial forecasting, Refenes (2016) covers exchange rates.

Medel et al. (2015) aims to examine the out-of-model behaviour of a collection of monetary and statistical models for the purpose of forecasting exchange rates (FX) regarding the United States for the UK, Japan, and the Euro Area. Special focus has been placed on the financial crisis of 2008–2009 and the inflation of 2007–8. Using a monthly dataset from 1981.1 to 2014.6, they investigated the forecasting performance of six economies combined with three statistical models when forecasting from one to 60 feet-ahead. They first look into the predicted errors up to the middle of 2006 and then contrast them with the ones up to the middle of 2014. The study identified differences and increases in model performance over time by comparing anticipated errors up to the middle of 2006 with those up to the middle of 2014.

2.3 Research Gap

Despite the widespread use of both time series and neural network models in exchange rate forecasting, there is a lack of comprehensive comparative analyses examining the relative performance of these approaches across different currency pairs, time horizons, and market conditions. Furthermore, most existing studies have focused on in-sample evaluation, neglecting the crucial aspect of out-of-sample forecasting performance. This research addresses this gap by conducting a systematic comparison of time series and neural network models in exchange rate forecasting, evaluating their accuracy, robustness, and computational efficiency in both in-sample and out-of-sample settings, and exploring the implications for practitioners and policymakers.

2.4 Proposed Conceptual model.

According to Swaen & George (2022), conceptual framework is an illustration of a relationship that a researcher expects to see amongst the research variables that are under study. Sacdeva

(2023), added that conceptual framework is the link between concepts, theories, assumptions and beliefs behind a research project and it presents them in a pictorial, narrative, or graphical format. Therefore, conceptual framework defines overall objectives of the research process and deduce how they converge to draw coherent conclusions. The conceptual framework of the research is laid out in the following sections.

2.4.1. Data Collection and preprocessing

The first step in the proposed conceptual model is the collection of historical USD/ZWL exchange rate data. This data can be obtained from the Reserve Bank of Zimbabwe. The collected data undergoes preprocessing, which may include cleaning, normalization, and transformation to ensure its suitability for analysis.

2.4.2. Time Series Analysis

Application of traditional methods of statistical analysis to patterns, trends, and seasonality in the exchange rate data constituted the time series analysis component of the model. A method used to find underlying patterns in the time period data is to use ARIMA modelling.

2.4.3. Neural Network Modelling

In parallel with time series analysis, the neural network modelling component utilized artificial neural networks (ANNs) to capture complex nonlinear relationships within the exchange rate data. This may involve the use of feedforward neural networks.

2.4.4. Feature Engineering and Model Training

As part of the conceptual model, feature engineering techniques were applied to extract relevant input variables for both the time series and neural network models. These features may include lagged values, technical indicators, macroeconomic variables, and sentiment analysis from news sources. Using historical data, the models were then trained to learn the underlying patterns and links.

2.4.5. Model Evaluation and Comparison

An assessment framework was developed after model training in order to evaluate the time series and neural network models' anticipating performance. The accuracy and robustness of the forecasts produced by each model are compared using commonly used metrics like MAE, MSE, and RMSE.

2.4.6. Ensemble Forecasting

In addition to individual model evaluation, an ensemble forecasting approach can be integrated into the conceptual model. This involves combining forecasts from both time series and neural network models using techniques such as simple averaging, weighted averaging, or more sophisticated ensemble methods like stacking or boosting.

2.4.7. Visualization and Interpretation

To facilitate a comprehensive comparative analysis, visualizations such as time series plots, forecast trajectories, prediction intervals, and error distributions are generated. These visualizations aid in interpreting the strengths and limitations of each modelling approach in forecasting USD/ZWL exchange rates.

Below is a visual presenting the suggested conceptual model for analysing time series and neural network models in USD/ZWL exchange rate forecasting:

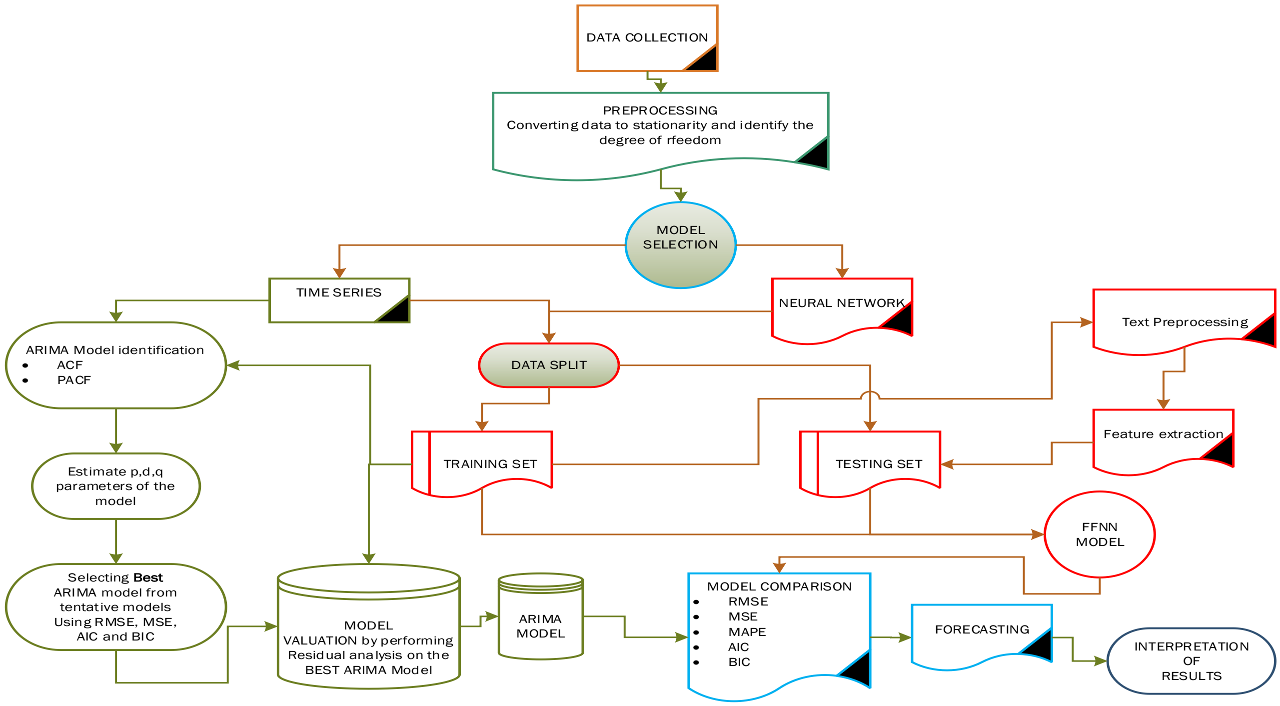

Figure 2. 1 Conceptual framework

Within the suggested conceptual framework, this diagram graphically illustrates the sequence of tasks involved in data collecting, preprocessing, modelling, assessment, ensemble forecasting, visualization, interpretation, conclusion, and suggestions.

2.5 Chapter Summary

The complicated foreign exchange market makes forecasting exchange rates a challenging effort. Traditional time series models and more sophisticated neural network models have been among the models created throughout the years to forecast changes in exchange rates. The pertinent literature on assessing the study of time series and neural network models in exchange rate forecasting is reviewed in this thorough analysis. This chapter compares neural network and conventional time series models to further understanding of exchange rate forecasting. It has clarified relevant studies conducted by other academics and offered useful data to companies, governments, and academics. The next chapter examines the research process, including how data was acquired and how it would be examined.

CHAPTER 3: RESEARCH METHODOLOGY

3.0 Introduction

This chapter provide an outline of the research methods applicable to this topic. In particular, it defines the research strategy, including sample selection and factors included in the study. In addition, it also specifies the procedures utilized for data gathering, including the sources of the data and any preparation or pre-processing techniques used. The paper then includes a full overview of the data analysis methodologies used, including statistical approaches and model definitions. This gives for a better grasp of the statistical procedures utilized to analyse the data. In addition, any limitations and ethical problems relating to this work was highlighted. By doing so, this assures that the review is done with transparency and diligence that the results drawn from the evaluation are reliable.

3.1. Research design.

The prediction of exchange rates using time series and neural network models were evaluated in this study using a quantitative and predictive research design. The performance of each model was assessed statistically using metrics for forecasting accuracy, such as RMSE and AIC matrices.

3.2. Data Sources and methods of collecting data.

Historical exchange rate data for the period February 2022 to the end of December 2023 collected from the Reserve Bank of Zimbabwe included range of components, providing a comprehensive picture of currency trading activity. Included in the exchange rate data observations, the data showed currency pair being traded (such as USD/ZWL), which is the current exchange rate for the currency pair. Additionally, the data included the bid rate (the rate at which the bank is willing to buy the base currency), the ask rate (the rate at which the bank is willing to sell the base currency) and the midrate (the average of the bid and ask). The data specify the rate type (such as bid, ask, or midrate) and the tenor (the duration of the exchange rate contract, such as overnight, 1-week, or 1-month). Finally, the study made use of the weekly mid-rate to carry out the analysis.

3.3. Target population and sampling procedure.

In order to conduct a thorough analysis of the exchange rate data, it is essential to define the target population and outline the sampling procedures used to select the data points.

3.3.1. Target population

The research was to build a forecasting model and to compare performance of the time series of forecasting or forecasting USD/ZWL weekly exchange rates from the Reserve Bank of Zimbabwe. A sample of 99 historical secondary data on weekly ZWL/USD exchange rates from February 2022 to December 2023 was extracted from the Reserve bank database. In this comparative analysis, the data was sufficient to explain the model's performance in predicting exchange rate fluctuations.

3.4. Research Instrument

Research tools are basic tools used for data acquisition, measurement, presentation, and analysis of data related to research in general. There are a variety of tools that make it possible to access, measure, and analyse data. Statistical software was used to extract historical exchange rate data for the US$/ZWL currency pairs from Reserve Bank of Zimbabwe database. There are several statistical software packages that can be used for data management. In this study, R programming language, Microsoft Excel and Python were used to prepare and conduct data analysis. These tools provide a wide range of functions for time series analysis and neural network modelling.

3.5. Description of variable

Clear description of variables and their expected relationships provides a foundation for understanding research findings and drawing meaningful conclusions about cause-and-effect relationships.

Table 3. 1, Description of variable

Variables	Symbol	Indicator	Source
Exchange rates	Exch	Exchange rates	Reserve Bank of Zimbabwe

3.6. Data Presentation and Analysis.

In this research, findings were presented in tables and visual graphs. The researcher used tables, graphs, descriptive and inferential statistics to draw reasonable conclusions of comparative analysis. To ensure reliability and better results, the following preliminary tests were carried out: stationarity test, auto correlation test and error test. Presenting the data in this section using text, tables and graphs provided a clear visual understanding.

3.6.1. Stationarity test

Stationarity of time series data is crucial for modelling and analysis. Various statistical tests like the Augmented Dickey Fuller, and Phillips-Perron tests are employed to test stationarity. These tests help determine if a time series exhibits a consistent mean, variance, and autocovariance over time, aiding in the selection of appropriate models like AR, MA, ARMA, or ARIMA (Wickham & Wickham, 2016). Over-differencing non-stationary data can lead to loss of important information and inferior results in analyses. The presence of non-stationarity in time series data, can have significant implications for climate modelling and policy development. Understanding and managing the stationarity of time series data is essential for accurate predictions and effective decision-making in various fields. While stationarity is crucial for time series analysis, models like RNNs, FFNNs are more versatile and can handle a wide range of data types without strict stationarity requirements.

3.6.1.1. Augmented Dickey Fuller Test

When analysing data and models, it's important to assess how well they align with each other. In covariance structure analysis, the ADF test statistic, originally proposed by Browne in 1984, is the most used metric. Unlike other models, the ADF statistic can evaluate models without relying on specific assumptions about the distribution, like the multivariate normal distribution that applies to observed data.

Research has shown that the ADF statistic lacks power in practical applications unless the sample sizes are exceptionally large. To determine whether to accept or reject the null hypothesis of a unit root, the test statistic with critical values was compared. These critical values are determined based on the significance level chosen for the test. Typically, significance levels of 0.05, and 0.01 are used.

If the computed test statistic is lower than the critical value, the null hypothesis is rejected, indicating that the data is stationary. If the test statistic exceeds the critical value, the null hypothesis is rejected, suggesting that the data is non-stationary.

3.6.1.2 Normality test

In statistics, normality testing is an essential practice especially if one is in the finance, quality control and epidemiological fields, among other job specialties that close or deal with data. The tests include but not limited to Jarque-Bera, Anderson-Darling, Shapiro-Wilk, and Lilliefors tests among others. The purpose of these tests is to determine whether your data is normally distributed or not. In this research work, Jarque-Bera test was used. If the p-value is less than the significance level, reject the null hypothesis conclude that the data does not follow a normal distribution. In conclusion, the data follows a normal distribution, if p-value is greater or equal to the significance level

3.6.1.3. Independence test

The independence of residuals is crucial for valid model inference and accurate conclusions. To assess independence, the Ljung-Box test is often employed in addition to using ACF and PCA residuals in normal linear models. This test allows to determine if there is any remaining autocorrelation or pattern in the residuals.

By combining the use of ACF, PCA residuals and conducting the Ljung-Box test, thorough examining the independence and adequacy of the model. Independent and identically distributed residuals, along with no significant autocorrelation, reinforce the reliability and trustworthiness of model's analysis. This provides a solid foundation for making informed decisions and drawing reliable insights from the data.

3.6.1.4. Heteroscedasticity

Testing homoscedasticity is crucial in a comparative analysis of time series and neural network models in forecasting exchange rates because it ensures that the variance of the residuals is constant over time. If the residuals are not homoscedastic, it can lead to biased estimates of model parameters, inaccurate predictions and invalid inference and conclusions.

The Breusch-Pagan (BP) test is used to detect homoscedasticity. It tests whether the variance of the residuals is constant over time. If the test indicates non-constant variance (heteroscedasticity), it suggests that the model assumptions are violated, and alternative models or transformations should be considered.

3.7. Model validation

Training and Testing In statistical modelling, a dataset is often divided into two separate sets for training and validation purposes. This division allows us to assess and compare the predictive performance of different models without being concerned about the risk of overfitting the training set. A typical split ratio is 80:20, where 80% of the data is used for training and 20% for testing. This ratio is derived from the well-known Pareto principle (Twomey, et al., 1997)

The dataset under consideration consists of 99 observations, covering weekly exchange rates from February 2022 to December 2021.The dataset is divided into two parts: the first 120 observations (week 1 to week 79) are used for training the model, while the remaining 20 observations (week 80 to week 99) are reserved for validation. The forecast was made using the 99 observations from the training set and evaluated against the 20 observations from the validation set. The performance of the models was assessed using criteria such as RMSE, Symmetric MAPE, AIC, BIC, and MAE.

3.7.1. Model Selection

To decide which model is more suitable for a given time series forecasting problem, it is required to undertake a detailed assessment of their relative strengths and limitations. One way to do this is through model selection.

Model selection entails analysing the performance of different models on a certain dataset and picking the one that performs best. In the context of time series forecasting, this often involves computing several performance indicators, such as MSE, RMSE, and MAPE, for each model and comparing their values. In addition to the matrices, the AIC was established by Hirotaka Akaike in 1973 as an extension of maximum likelihood estimation. AIC is defined as:

$$AIC = -2\, log - likelihood + 2\, number\ of\ parameters \ldots\ldots\ldots\ldots\ldots\ldots (Equation\ 3.1)$$

where log-likelihood is the maximal value of the log-probability function for a given set of data and parameters, and the number of parameters refers to the number of free parameters in the statistical model being studied. The AIC score is used to assess different statistical models fit to the same data by penalizing more complex models with additional parameters. The model with the lowest AIC score is regarded to be the best fit to the data.

The Bayesian Information Criterion (BIC) was established by Schwarz in 1978 as a version of AIC that integrates previous knowledge about complexity into the selection criterion. BIC is defined as:

$$BIC = -2\, log - likelihood + ln(n)\, number\ of\ parameters \ldots\ldots\ldots\ldots (Equation\ 3.2)$$

where n is the sample size and ln(n) are the natural logarithm of n. Similar to AIC, BIC penalizes more complicated models with additional parameters, but it does so more heavily than AIC, favouring simpler models over more complex ones. The model with the lowest BIC score is deemed to be the best fit to the data.

Residual Analysis, evaluating the residuals of a model can provide useful insights about the model's fit. Residual plots, such as ACF and PACF of residuals against projected values or time, can assist uncover patterns or deviations from assumptions (Fox & Weisberg, 2018). A good model should have randomly distributed residuals with no identifiable trends.

3.8. Model Specification

The study compares time series models against Neural network models on Performance capability to identify the best performing models in predicting exchange rates. To evaluate the effectiveness of the forecasting performance several error measurements are used, and AIC and BIC are also considered.

3.8.1. ARIMA (p, d, q)

ARIMA model, acclaimed for its straightforwardness and user-friendliness, enjoys popularity in exchange rate forecasting. Represented as a linear composition of prior observations and stochastic disturbances, it is designed as the use the capabilities of autoregressive and moving average components to project future exchange rate. In the ARIMA (p, d, q) model, p stands for the number of autoregressive terms, d denotes the number of differences required to stabilize the series, and q represents the number of moving average terms. This model offers flexibility in selecting either purely AR terms, MA terms or a combination of both, known as ARMA models, allowing it to accommodate diverse data patterns. ARIMA models rely heavily on the assumption that the input time series is stationary, meaning its mean and variance remain constant throughout the observed period. By leveraging this property, the model can extract useful insights from the data and accurately forecast future values. In other words, the stationarity of the time series allows the ARIMA model to identify patterns and trends in the data and generate predictions based on those patterns. The ARIMA model defined as

$$y_t = \alpha + \sum_{i=1}^{p} \beta_i \, y_{t-i} + \sum_{j=1}^{q} \gamma_j \epsilon_{t-j} + \epsilon_t \;\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (\,Equation 3.3)$$

where yt is the time series α is the intercept term β_i are the coefficients for the AR terms, $\gamma_j$are the coefficients for the MA terms,$\epsilon_t$is a sequence of uncorrelated random variables with zero mean and constant variance and ϵ_{t-j} are the lagged error terms. The ARIMA modelling process consists of three stages, as suggested by Box and Jenkins (1976), identifying the appropriate model estimating its parameters, and verifying its accuracy through diagnostic checks. First, the model identifications stage involves examining the ACF and partial PACF characteristics of the time series data to determine the most suitable ARIMA model. Next, various models are estimated, and the best one chosen using a selection criterion such as the Akaike Information Criteria (AIC).

3.8.1.1. ARIMA Process

As a generalized random walk model, it removes all residual auto correlations. As a generalized exponential smoothing model, it incorporates long-term trends and seasonality Use the lags of the dependent variable and/or the lags of prediction errors as regressors.

3.8.2. Feed Forward Neural Network

Artificial neural networks that are feed forward are those in which nodes do not create loops. The idea that all information is only transmitted forward makes this kind of neural network. They are also referred to as a multi-layer neural network. Input nodes receive data during data flow, which passes via hidden layers before leaving to exit output nodes. There are no networks connections that could become accustomed to receiving information back from the output node. This is how a feedforward neural network approximates functions:

classifiers are computed by algorithms utilizing the formula y = f(x).

Thus, input x is put in category y.

The FFNN model states $y = f\ (x;\ \theta)$. This value determines the minimum approximation of the function.

3.8.2.1 Structure of FFNN

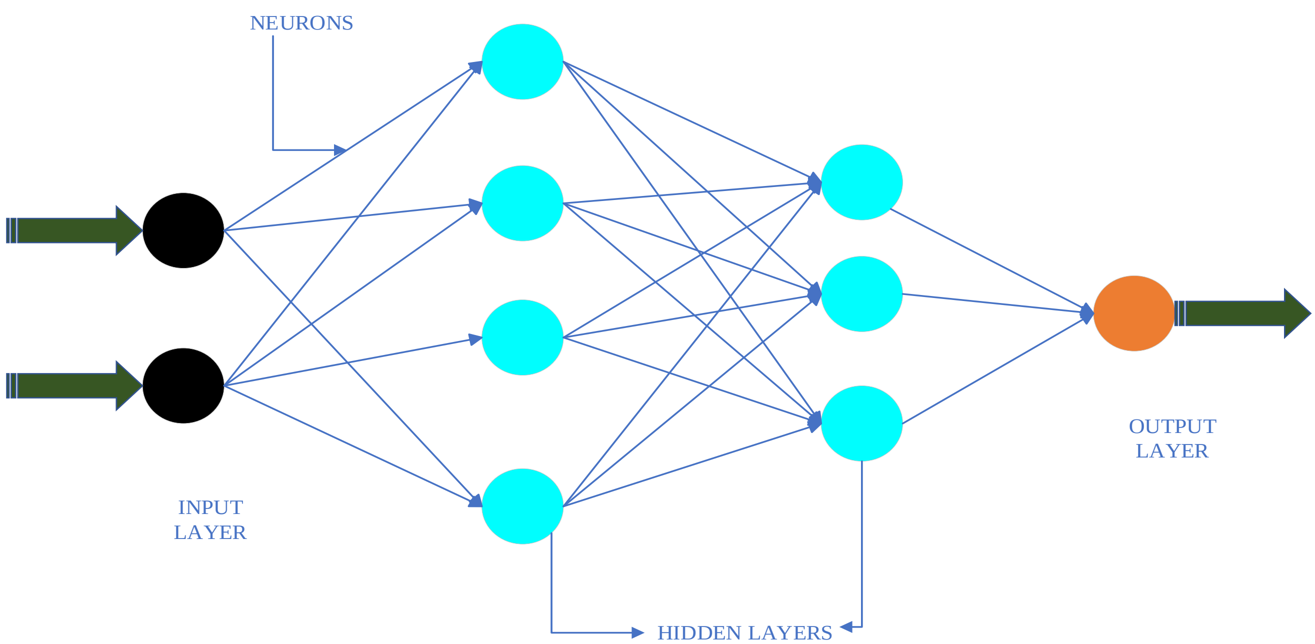

Figure 3. 1 FFNN Structure

The structure of a FFNN model typically involves multiple layers with specific configurations.

1. Input Layer

This is the initial layer of the network where data is fed into the neural network. It represents the features or variables of the problem at hand. Each node in the input layer corresponds to a specific feature, and the values from these nodes are passed forward into the subsequent layers.

2. Hidden Layers

These layers exist between the input and output layers and are responsible for processing the input data. Each hidden layer comprises multiple nodes or neurons, which perform transformations on the input by applying weights to the incoming signals and passing the results through activation functions. These weights and activation functions help the network to learn the underlying patterns and extract relevant features from the data.

The complexity of the problem determines the number of hidden layers and neurons are in each layer. Deeper networks with more hidden layers can capture intricate relationships and representations in the data, while wider networks with more neurons in each layer can learn more fine-grained details.

3. Output Layer

On the basis of the processed data from the hidden layers, this layer of the network generates the intended prediction. The kind of problem at hand will determine how many nodes are in the output layer. For example, whereas in multiclass classification there can be several nodes corresponding to each class, in binary classification problem there might be just one node expressing the probability or class label.

The connections between the layers are established through weighted connections, which allow the information to flow from one layer to the next (Alwan & Kashmar, 2023). During the training phase, the network adjusts these weights through a process called backpropagation, optimizing them to minimize the difference between the predicted output and the actual output. This iterative process of adjusting the weights continues until the network achieves satisfactory performance.

3.10 Chapter Summary

The methods followed during the study is described in this chapter. The field of investigation, the research methodology, the methods of data gathering, the data presentation and analysis procedure were described. The study talked about the tests that had to be done on data analysis before using the data for model fitting. Furthermore, explained in terms of their general fitted model equations were the model selection and the FFNN and ARIMA models to be fitted. The performance evaluation methods to suggest on the optimal model for predicting exchange rate volatility were finally described. Data representation, analysis, and discussion take up the next chapter.

CHAPTER 4: DATA PRESENTATION, ANALYSIS, AND INTERPRETATION

4.0 Introduction

The chapter discuss in detail the analysis and interpretation of the findings of the exchange rate data from time series analysis. Timeseries analysis was conducted on the data in comparing the traditional time series model (ARIMA) and the neural network model (Feedforward neural network). By examining the performance of these models, the chapter provide evidence-based benchmark against the research observations and questions. The Chapter express focus on the analytical presentation of Financial Modelling, forecasting, performance evaluation and interpretation of results. Evaluation and decision-making are based on the theory of measurement error.

4.1 Descriptive Statistics/Summary Statistics

This study examined the Zimbabwean Dollar (ZWL), relative to the US Dollar (USD). To capture the complex interactions between these currencies and economic variables, this study employed a time series framework that incorporates the relationship of the currencies. Descriptive statistics of the currencies are shown below.

Table 4. 1, Descriptive Statistics

Mean	1967.78054
Standard Error	223.8542007
Standard Deviation	2227.321174
Sample Variance	4960959.614
Kurtosis	-0.823214502
Skewness	0.982927674
Range	6833.7159
Minimum	115.4223
Maximum	6949.1382
Sum	194810.2735
Count	99

The exchange rates (exch) data have 99 observations in total. In the context of exchange rates, a positive mean (1967.78054) and skewness (0.982927674) indicating an appreciation of exchange rates and a general upward trend in the currency`s value. The standard deviation of 2227.321174 suggests that the exchange rates have experienced large fluctuations or volatility over the given period. This means that the exchange rates have deviated considerably from their average value, indicating potential instability or uncertainty in the currency markets. In the context of statistical analysis, a high standard error (of 223.8542007) suggests that there is a wide range of potential values around the estimated value, and therefore, the estimate may be less precise or reliable. It indicates that there is considerable variability in the data points, which can affect the accuracy of the estimate. A negative kurtosis value of -0.823214502 suggests that the probability distribution or dataset is relatively flat or platykurtic compared to a normal distribution. It indicates that the dataset has lighter tails and a lower peak compared to a normal distribution. However, it is important to note that a kurtosis value of -0.823214502 is relatively close to zero, which means the departure from a normal distribution may not be substantial.

4.2 Pre-tests / Diagnostic tests

Pretesting is an essential step in the research process, when working with statistical models. It involves checking the data for conditions or assumptions that must be met for the model to be applied correctly. In the context of FFNN and ARIMA modelling, pretesting typically include Stationarity tests (Augmented Dickey-Fuller test, Normality tests (Jarque-Bera test), Homoscedasticity tests (Breusch-Pagan test), Autocorrelation tests (Durbin-Watson test)

If the data fails any of these pretests, it may indicate that the assumptions of the ARIMA model are not met, and additional steps may be necessary to transform the data or select a different model. Pretesting helps ensure that the results of the analysis are reliable and interpretable.

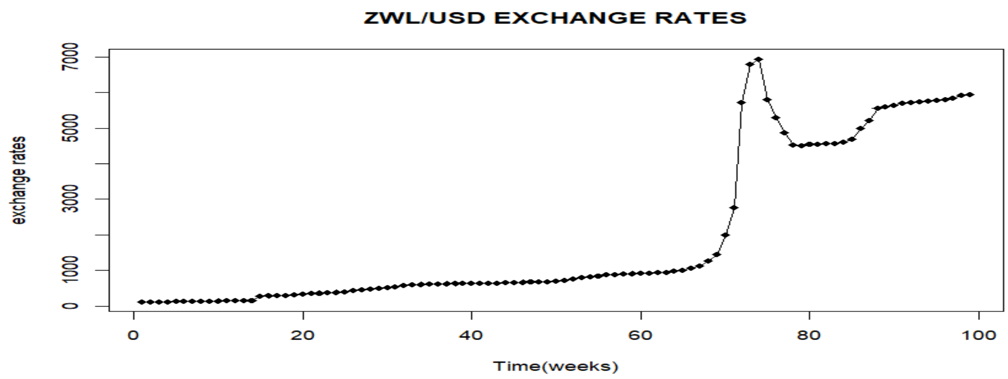

Figure 4. 1 Original Exchange Rate data.

The exchange rate time series illustration was used to figure out if the data was stationary ahead to considering any statistical test. Plot shows that there was an ongoing increase from week 1 to week 70, a dramatic rise in week 75 and a fall in week 80, and once more a steady little rise in yield throughout the year and an overall decline in yield pattern up to 2015. Constant fluctuation within the dataset indicates that the time series data is non-stationary. Still, as Figure 4.1 shows, there was a rising momentum.

As shown in Figure 4.1 the data showed an increasing trend, hence the data failed to meet the requirements for time series modelling. The following test made to check if the data meets the time series modelling requirements.

4.2.2 Stationarity test

As mentioned earlier, the identified an increasing trend component in the exchange rate data, suggesting non-stationarity.

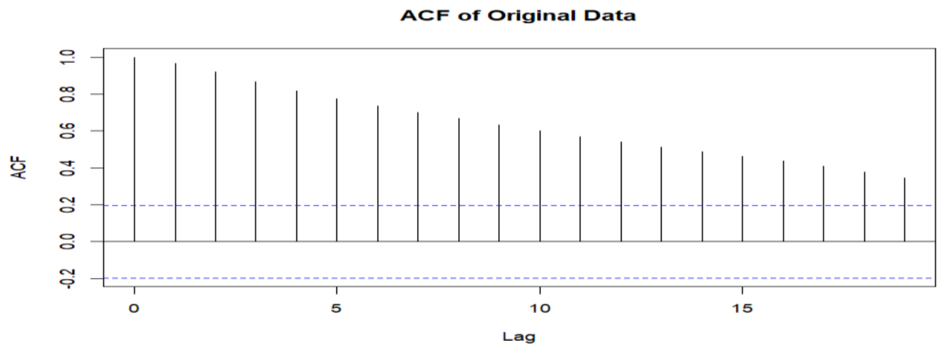

Figure 4. 2 ACF of Original Data

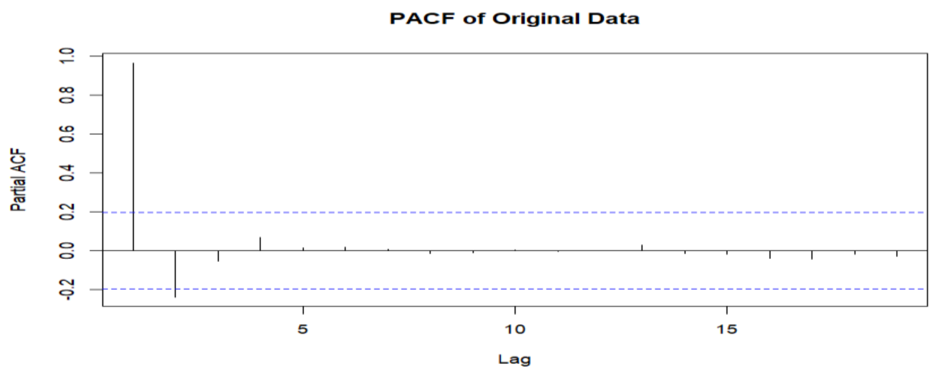

Figure 4. 3 PACF of Original Data

With the help of a correlogram the stationarity of the series is in doubt, as shown by the ACF and PACF of the original data in Figure 4.2 and 4.3. Figures 4.2 and 4.3 above shows that there were spikes outside the preferred zone, that is, $\pm 1.92/\sqrt{n}$ (±0.193244) where n =99 and the series is not stationary

4.2.2.1. Augmented Dickey- Fuller (ADF) Test

To formally test the stationarity of the data, ADF test was applied. The ADF test is a popular tool in econometric analysis to detect the presence of unit roots and, thereby, non-stationarity in time series data.

As anticipated, the results of the ADF test in table 4.2 confirmed the non-stationary nature of the series. The ADF was performed above showed the p-value 0.4727 which is greater than 0.05, hence arrive at the conclusion that the data is non-stationary and fail to reject the null hypothesis.

Table 4. 2 ADF of Original Exchange Rate Data

Augmented Dickey-Fuller Test
data: ts_data Dickey-Fuller = -2.251, Lag order = 4, p-value = 0.4727
alternative hypothesis: stationary

4.2.2.2. Archiving stationarity

To archive stationarity, the researcher moved to the next step of differencing the time series data.

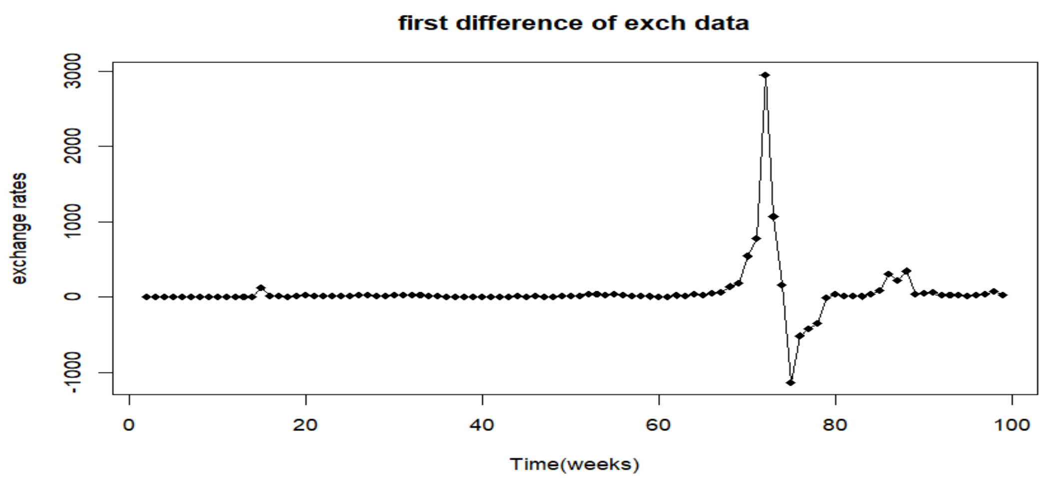

Figure 4. 4 First Difference of the Data

Both mean and variance of the data were found to remain constant after initial differencing (Figure 4.4). For the ARIMA model (p, d, q), there was therefore no need to perform additional differencing (d=1) since the data centered on zero. ACF, PACF and ADF tests were carried out on the differenced series once more after the differencing process.

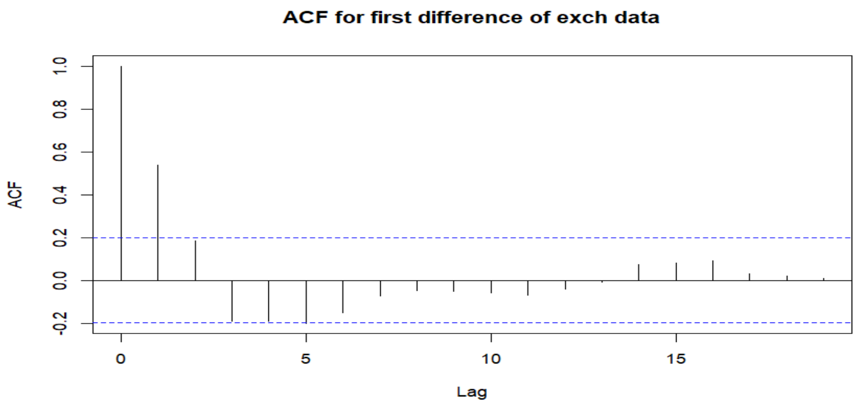

Figure 4. 5 ACF of Differenced Exch data.

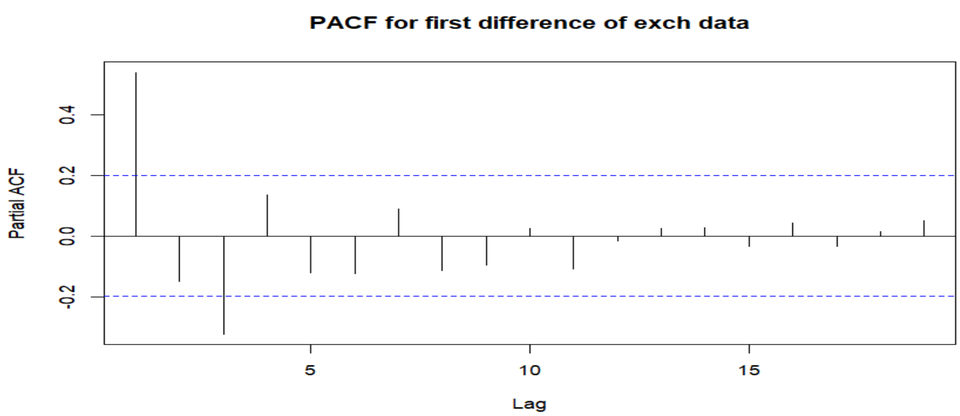

Figure 4. 6 PACF of Differenced Exch data.

Plotting the ACF and PACF for the differenced Exch data in Figures 4.5 and 4.6, respectively, shows that, after first order non-seasonal difference, the series is now stationary in both the mean and variance. The supply data can be captured properly using ARIMA models, which could also be utilized for estimating the next exchange rate statistics. Most sample autocorrelation coefficients of residuals are among the bounds of $\pm 1.96/\sqrt{n}$, or ± 0.193244, where n=99.

The results confirmed that the transformation was successful, and obtained a stationary time series data. The mean and variance of the exchange rate data became constant at d = 1 as the data revolved around zero.

Table 4. 3 ADF for first difference

Augmented Dickey-Fuller Test
data: ts_data_diff Dickey-Fuller = -4.7254, Lag order = 4, p-value = 0.01
alternative hypothesis: stationary

4.3 Model output / Results

In the comparative analysis, seek to identify the best performing model between ARIMA and FFN in forecasting exchange rate volatility. The ARIMA model can be specified differently given the choice of auto regressive component (AR) and moving averages component (MA). After identifying various tentative ARIMA (p, d, q) models, p (number of lags for the dependent variable from the AR model), q (Number of lags for the error term from MA) and d (number of times the series differs from its stability correction), then the best ARIMA model is estimated. To identify this specific ARIMA (p, d, q) model, ACF and PACF plots are drawn to determine the AR and MA lags. On the other hand, in the context of FFNN model selection is often carried out using out of sample performance. This approach involves evaluating the performance of different models on data that was not used during the training process. During the training, the model utilizes a back propagation algorithm to minimize the error between the predicted and the actual outputs. Once trained, the network can then be used to forecast future values based on new input data.

Before choosing the best model, the data was tested to check whether the time series assumptions were met and also if the models captured all the information.

4.4 Model identification.

Model identification was a crucial step in statistical modeling that involved selecting and specifying a model that best described the dataset. This process began with exploratory data analysis (EDA) to understand the data distribution, followed by choosing an appropriate model type, such as time series. Next, model parameters and assumptions were specified. Finally, the model's goodness of fit and accuracy were validated using techniques such as correlation analysis, time series analysis, cross-validation, information criteria (AIC, BIC), and the Wilcoxon test.

4.4.1 ARIMA Modelling

One needs stationary data in both variance and mean to fit an ARIMA model. As clearly illustrated in Figure 4.5 and 4.6 the correlogram shows some significant auto correlations that are outside the standard error bound (broken lines) or the 5% confidence interval and the auto correlation exponentially decay from lag 1 up-to lag 22 on the ACF. The lags are very significant, and the decline is very gradual. While the PACF shows significance on the first lag while others cut off.

Table 4. 4 Tentative ARIMA models

Model	AIC
ARIMA (2,1,2) with drift	1394.091
ARIMA (0,1,0) with drift	1435.693
ARIMA (1,1,0) with drift	1404.575
ARIMA (0,1,1) with drift	1412.175
ARIMA (0,1,0)	1436.256
ARIMA (1,1,2) with drift	1391.987
ARIMA (0,1,2) with drift	1391.387
ARIMA (0,1,3) with drift	1391.766
ARIMA (1,1,1) with drift	1405.786
ARIMA (1,1,3) with drift	391.481
ARIMA (0,1,2)	1390.038
ARIMA (0,1,1)	1411.76
ARIMA (1,1,2)	1390.783
ARIMA (0,1,3)	1390.663
ARIMA (1,1,1)	1404.484
ARIMA (1,1,3)	1392.046
Best model: ARIMA (0,1,2)	

In decision criteria, the appropriate model should have the most significant coefficients, lowest AIC. Looking at the table, ARIMA (0,1,3) meets the required conditions as they have the lowest AIC so it can be selected as the best model. However, ARIMA (0,1,2) have the lowest AIC making it the best model. Having identified the ARIMA model the next step is to perform some diagnostic checking to be certain that there is no uncaptured information by plotting the correlogram of the residuals.

4.4.2. Feed Forward Neural Network Modelling

To fit a Feed Forward Neural Network (FFNN) model, several key components and steps are essential. It is crucial to define the architecture of the FFNN, including the number of layers, nodes in each layer, and activation functions. Selecting an appropriate training algorithm, such as backpropagation, and a suitable loss function to quantify prediction disparities is necessary. Hyperparameter tuning, which involves adjusting parameters like learning rate and batch size, as well as implementing a validation strategy to assess the model's performance on unseen data, are also vital. Lastly, the training process involves iteratively feeding input data through the network, calculating loss, and updating parameters until convergence is achieved, collectively contributing to the successful fitting of the FFNN model.

4.5 Diagnostic Checking

Under diagnostics checking the ideal model (ARIMA (0,1,2)) is tested to be certain that there is no uncaptured information by plotting the correlogram of the residuals. An ideal correlogram for the residuals should be flat, that is the lag structures should be within the standard error bound. If a lag is significant, that is outside the standard error bound, the model is re-estimate trying not to overfit the model.

As can be seen from the correlogram Figure 4.5 and 4.6, the estimated model has managed to capture all the information, thus a flat correlogram with all lags falling within the standard error bound or the 95% confidence interval, showing that the residuals are white noise indicating that the model is a good fit. Now conclude by saying that the ARIMA (0,1,2) model is the most ideal. This is the model which will be used for forecasting.

4.6 Model validation tests/ Model fitness tests

Model validation and fitness testing are essential components of the model development process in machine learning and statistical modelling. They play a role in assessing the performance, robustness, and generalization ability of a model, ensuring its reliability and effectiveness in real-world applications. By validating the model, the model gives confidence in its predictive power and make informed decisions about its deployment and usage.

4.6.1. ARIMA Model validation tests

To have confidence in ARIMA (0, 1, 2), the researcher carried out validation test to ensure the model holds true rather than depending on the error matrices. The residual model was used to validated the selected ARIMA model.

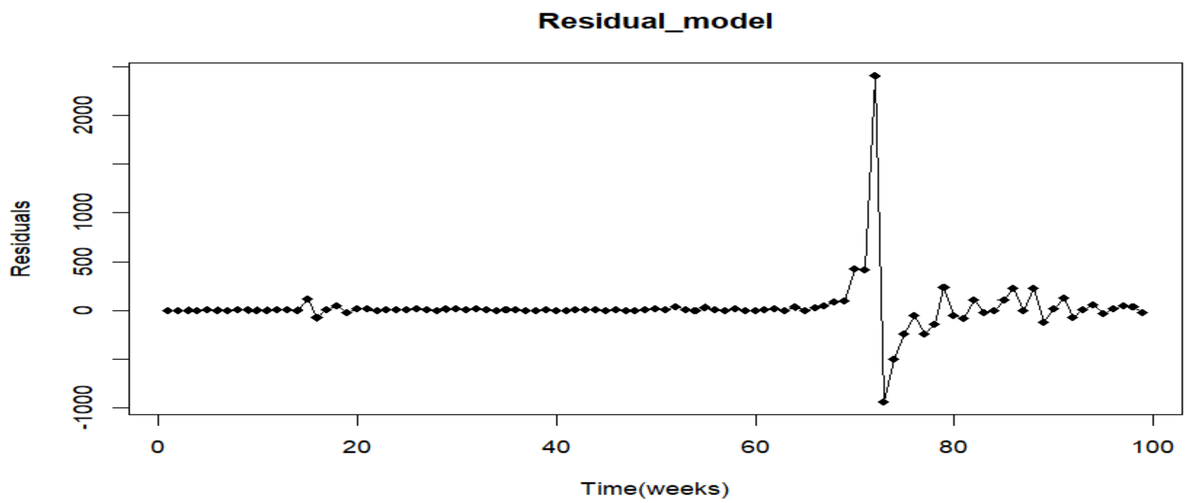

Figure 4. 7 Residual plot

As shown in the Figure 4.7 above, both mean and variance are constant. Therefore, the residuals of ARIMA (0,1,2) model revolved around zero. To formally accept the residuals, the ACF, PACF plots were conducted again on the ARIMA model.

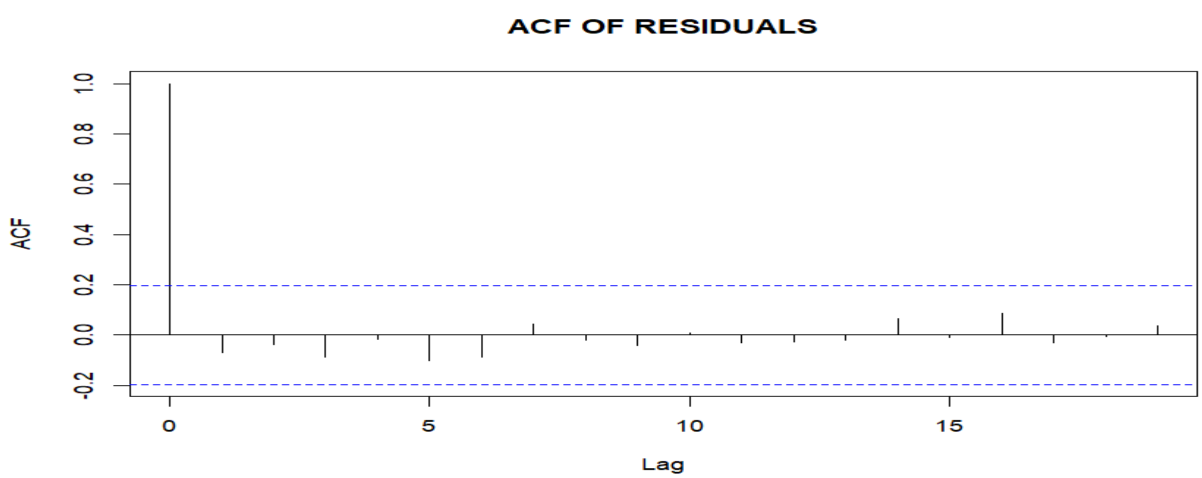

Figure 4. 8 ACF of residuals

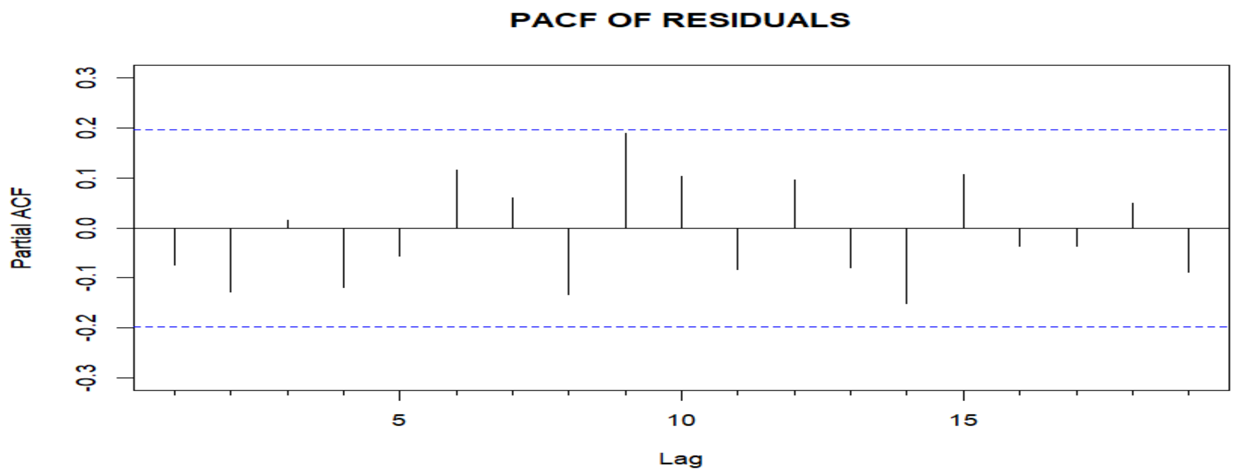

Figure 4. 9 PACF of Residuals

After fitting an ARIMA (0,1, 2) model, the residuals were analysed to assess if any patterns or autocorrelation remain relevant. Residual analysis helps verify if the model captures all the relevant information in the data. As shown by the ACF and PACF plots in figure 4.8 and 4.9, the ARIMA (0,1,2) model is significant as it successfully removed any autocorrelation from the time series, with the residual exhibiting white noise characteristics. White noise indicates a constant power spectral density over all frequencies, indicating the absence of periodic components or trend in the data.

4.6.1.1. Independence of Residual Model

To fully accept the ACF and PACF, the Ljung box (Portmanteau) test was used to test the independence of residuals. To evaluate the independence of residuals, the test was carried out by examining the autocorrelation at different lags.

Table 4. 5 Ljung box test (independence test)

$ljung\_box\_p\_value$
$[1]\ \mathbf{0.5867627}$

The p value of 0.5867627 ($p > 0.05$) indicates that the residuals are independent, which is desirable for the model to be valid.

4.6.1.2. Normality of Residual Model

A quantile-quantile (Q-Q) plot is a graphical tool which was used to evaluate the normal distributional assumption of the residuals. Plotting of residual quantiles vs theoretical distribution quantiles. By examining the Q-Q plot, you can identify any systematic deviations from normality, such as heavy tails or skewness. If significant departures from normality are observed, it may suggest the need for further model refinement or consideration of alternative distributions.

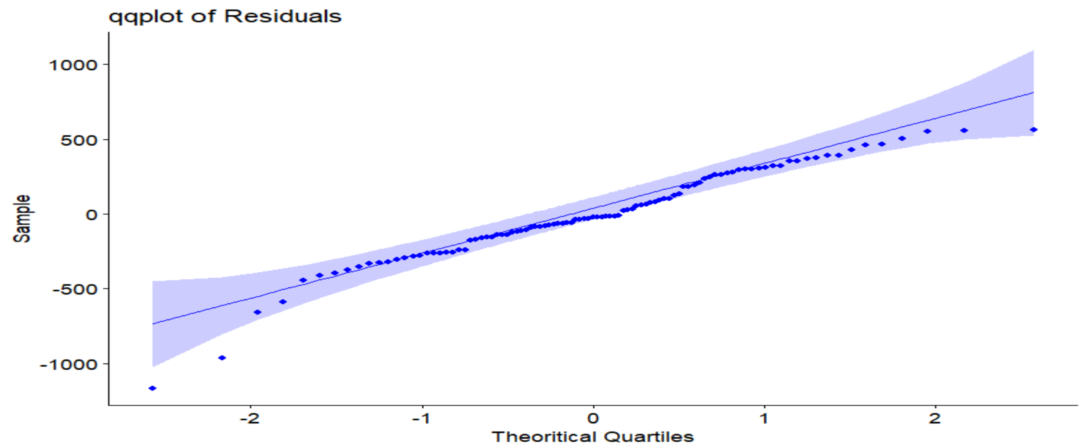

Figure 4. 10 Normal Q-Q plot.

Observed in Figure 4.10, the residuals follow a normal distribution which indicates model adequacy or validation of normality assumption.

Table 4. 6 Jarque Bera test (Normality test)

$jarque\_bera\_test\$p.value$
[1] 0.6432462

The Jarque Bera p value 0.06432462 ($p > 0.05$) the null hypothesis holds true.

The data follows a normal distribution hence, conclude that the model to be valid.

4.6.1.3. Heteroscedasticity of Residual Model

Table 4. 7 Breusch Pagan test (Heteroscedasticity test)

studentized Breusch-Pagan test
data: y ~ x BP = 20.962, df = 1, p-value = 4.684e-06

The BP statistic of 20.962 indicates significant heteroscedasticity in the data. The P-value of 4.684e-06 (essentially zero) indicates that this heteroscedasticity is statistically significant, with a very high degree of confidence.

4.6.2. FFNN Model Validation Test

The validation and fitness of a Feedforward Neural Network model involves performing train-test split or cross-validation, calculating appropriate error metrics, and monitoring for overfitting. These steps provide insights into the model's ability to generalize to unseen data, quantify the performance, and ensure it does not suffer from overfitting.

Table 4. 8 FFNN Models

ACTUAL	FFNN [(1(5)1]	FFNN [1(5,3)1]	FFNN [1(5,5)1]	FFNN [1(5,8)1]	FFNN [1(6)1]
4547.60	4509.009	4481.178	4553.898	4571.279	4560.816
4557.11	4518.79	4490.783	4563.522	4580.044	4570.353
4568.39	4530.401	4502.203	4574.935	4590.438	4581.659
4575.54	4537.781	4509.471	4582.181	4597.037	4588.835
4610.39	4573.832	4545.079	4617.503	4629.2	4623.789
4695.45	4662.559	4633.466	4703.895	4707.882	4709.118
4996.97	4984.674	4962.77	5011.849	4989.772	5011.653
5215.96	5224.122	5214.251	5236.489	5198.552	5231.285

	5562.00	5604.252	5617.656	5590.521	5537.114	5577.45
	5594.38	5639.505	5654.943	5623.445	5569.355	5609.741
	5638.34	5687.192	5705.273	5668.059	5613.279	5653.545
	5698.96	5752.551	5774.01	5729.387	5674.115	5713.864
	5720.31	5775.443	5798.007	5750.926	5695.611	5735.081
	5741.89	5798.516	5822.149	5772.669	5717.381	5756.518
	5761.46	5819.378	5843.938	5792.362	5737.16	5775.949
	5778.44	5837.418	5862.744	5809.416	5754.336	5792.791
	5801.47	5861.808	5888.121	5832.515	5777.672	5815.623
	5841.39	5903.851	5931.718	5872.45	5818.218	5855.159
	5919.55	5985.211	6015.51	5950.214	5897.913	5932.386
	5946.44	6012.887	6043.824	5976.829	5925.421	5958.899
MSE		45.79758	19.1282	13.0185*	21.27614	28.93239
RMSE		48.42033	22.50263	14.44697*	22.76846	29.03915

The error metrics can be used to compare several models or FNN variations and provide quantitative measures of the model's performance based on the results shown in table 4.8. Out of sample anticipated results yielded the best FFNN model, FFNN [1(5,5)1].

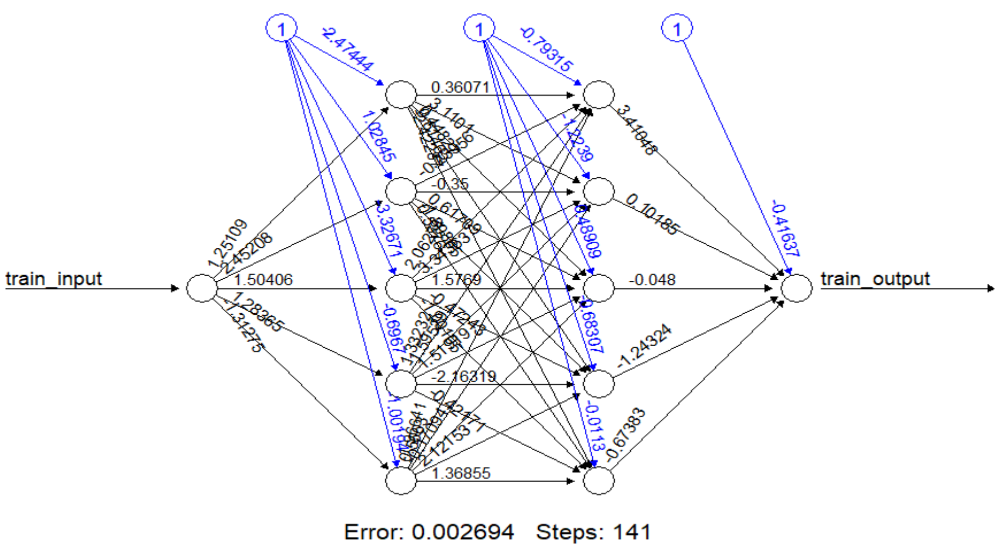

Figure 4. 11 FFNN [1(5,5)1] structure.

4.7 Discussion of findings

When comparing the ARIMA with the FFNN model for time series analysis, numerous performance measures and findings have been discussed in this study.

4.7.1 Performance Measures and Selection Criteria

Performance measures and selection criteria of the ARIMA and FFNN models have been a subject of discussion in the study. These measures are crucial for evaluating the effectiveness and suitability of each model for specific forecasting tasks. As observed in Table 5 and 6, ARIMA (0,1,2) and FFNN [1(5,5)1] are the best models based on MSE, RMSE, AIC and BIC. This matric enabled continuation of comparative analysis as it aimed to discover the best model for forecasting exchange rates.

4.7.2 Experimental Results and Discussion

Experimental results and discussions have been conducted to compare the performance of the ARIMA and FFNN models. As shown in Table 3.3 and 4.3, tentative models were obtained using the matrices for ARIMA models and the split of the data into training and testing matrices were used to select the best models. This marked the selection of FFNN [1(5,5)1] and ARIMA (0,1,2) as the best models.

Table 4. 9 In-sample comparison

Week	Actual	ARIMA	FFNN
70	4547.60	4479.63	4549.02
71	4557.11	4460	4559.4
72	4568.39	4440.37	4571.71
73	4575.54	4420.73	4579.51
74	4610.39	4401.1	4617.54
75	4695.45	4381.47	4710.27

In sample results in Table 4.9 above shows that ARIMA forecasts are gradually deviating from the actual data while FFNN forecasts are closely in line with the actual data. From the results FFNN model predicted the in-sample data accurately.

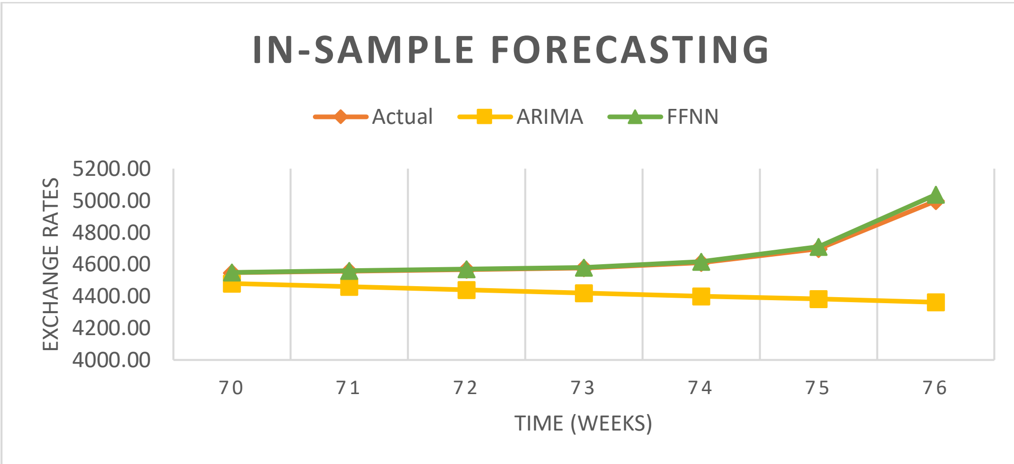

Figure 4. 12 In-sample forecast

Figure 4.12 shows that the forecasts for the volatility of exchange rates in ARIMA model is underestimating from the actual values. The forecast of FFNN model closely align to the actual data. It can be concluded that ARIMA (0,1,2) failed to predict in-sample data because, in comparison with previous exchange rate movements in Zimbabwe, the actual values of the exchange rate differ from the predicted values.

4.7.3 Comparative Studies

Comparative studies have been carried out to evaluate the predictive capabilities of the ARIMA and FFNN models in various domains. In this study the FFNN outperformed the ARIMA model. These discussions often involve the assessment of accuracy, measured by metrics such as MAE, RMSE, BIC and AIC. The researcher introduced MAPE to enable the best model in forecasting in-sample of the testing data.

Table 4. 10 Comparing models using matrices

	MATRICES				
MODEL	MSE	RMSE	MAPE	AIC	BIC
FFNN	0.00012	0.01103	0.56%	-178.3	-177.3
ARIMA	642230	801.392	12.07%	1123.55	1130.62

Based on the provided metrics, the FFNN model appears to outperform the ARIMA model. The FFNN model demonstrates significantly lower MSE, RMSE, AIC, and BIC values compared to the ARIMA model, indicating better accuracy, fit, and model selection criteria. Therefore, based on these metrics, the FFNN model is the preferred choice for forecasting in this scenario.

4.7.4. Model Comparison in Forecasting out of sample.

The comparison of the ARIMA and FFNN models in forecasting tasks has been a focus of discussion, with some studies highlighting the superior performance of the FFNN model over the ARIMA model for specific forecasting horizons. Since both models were very good at predicting (in sample) exchange rate returns, now the question is how good and which model managed to do it the best way.

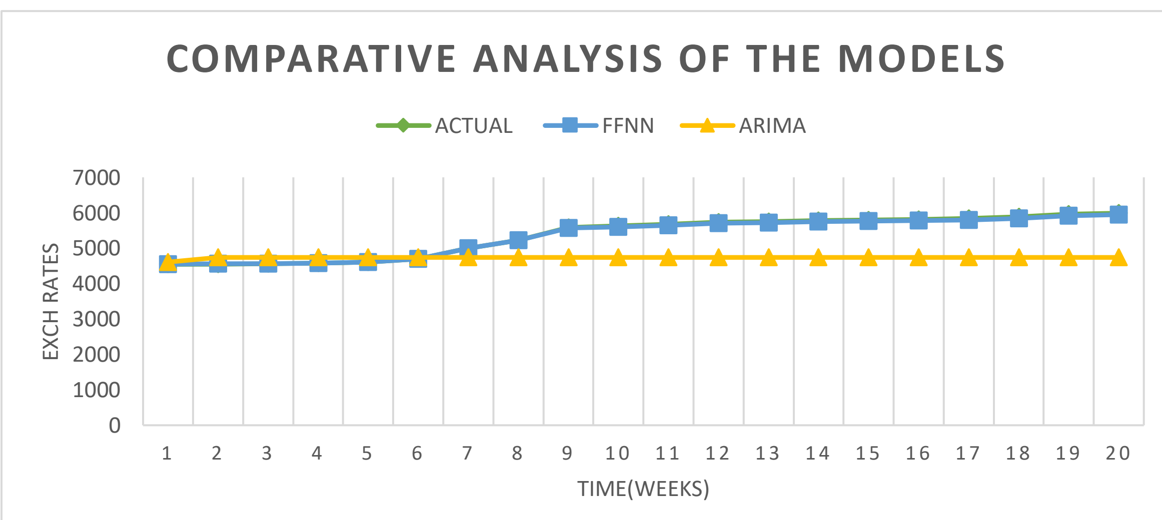

Figure 4. 13 Out of sample forecasting.

From the chart above, the forecast graph shows good performance by the FFNN model with almost exact forecast values as the actual values compared to the ARIMA model. Only between week 1 and week 7, the forecast graph of ARIMA model was close to the actual values. From week 8 to week 20 the ARIMA model deviated from the actual by predicting low values than the actual. From Table 4.10, the FFNN model is significantly efficient than ARIMA model for predicting the time series data. FFNN's MSE and RMSE are almost zero (0.00012 and 0.01103), indicating a very accurate model. ARIMA's MSE and RMSE are very high (642230 and 801.392), indicating a poor fit. FFNN's MAPE is only 0.56%, indicating a very small percentage error. ARIMA's MAPE is 12.07%, indicating a significant error. FFNN's AIC and BIC are negative (-178.3 and -177.3), indicating a good fit. ARIMA's AIC and BIC are high (1123.55 and 1130.62), indicating a poor fit. Based on these metrics, the FFNN model is the clear winner. Its accuracy and goodness of fit are significantly better than the ARIMA model. Therefore, the best model for predicting this time series data is the FFNN model.

7.4.5. Wilcoxon Test

The Wilcoxon test is a vital tool in comparative analysis as it offers a non-parametric approach to comparing distributions, detecting differences in medians, and identifying shifts in distribution. Unlike parametric tests, the test does not require normality or equal variances, making it a robust choice for non-normal data. Overall, the Wilcoxon test provides a reliable and robust way to com pare

distributions and make inferences about the data, making it an essential tool in comparative analysis.

Table 4. 11 Wilcoxon rank Test for ARIMA Model

Wilcoxon rank sum test with continuity correction
data: test_data and ts_data W = 1696, p-value = 5.332e-07 alternative hypothesis: true location shift is not equal to 0

Based on the Wilcoxon test result for the ARIMA model, the p-value is extremely low ($p < 0.05$), indicating that the ARIMA model is performing significantly better. The test statistic (w) is also high, indicating a large difference between the predicted and actual values.

Table 4. 12 Wilcoxon rank test for FFNN Model

Wilcoxon rank sum test with continuity correction
data: test_input and ts_data W = 0, p-value = 2.035e-12 alternative hypothesis: true location shift is not equal to 0

Therefore, the overall conclusion is that the FFNN model is the best model for predicting the time series data. Its superior performance indicates that it is better at capturing the underlying patterns and relationships in the data, and is therefore more suitable for making accurate predictions.

4.8 Chapter Summary

The chapter presented the results obtained using RStudio. The chapter presented findings regarding the fluctuations of exchange rates within the specific setting of Zimbabwe. The data is transformed into a returned series, which is recommended mainly because of its attractive statistical properties. Stationarity is then checked using ACF, PACF and ADF test, the data was stationary (p-value =0.01) at the 5% significant level. Using the ARIMA method, Adjusted ARIMA (0,1,2) was used after examining the Box-Jenkins model procedure for model identification, model estimation, model evaluation, and model prediction. Similarly, for a FFNN approach, FFNN [1(5,5)1] was used after observing minimum MSE, RMSE and predictions of the test data (20% of the total data) which were close to the actual data. In comparative analysis, the FFNN [1(5,5)1] model proved to be the best model as it produced the minimum AIC and BIC values compared to ARIMA (0,1,2). The next chapter presents a summary of the studies and recommendations.

CHAPTER 5: SUMMARY, CONCLUSIONS AND RECOMMENDATIONS.

5.0 Introduction

This chapter is a concluding summary of the research paper, the comparative analysis of time series and neural network models in forecasting ZWL/USD exchange rates. The research findings provided the author with deep understanding and interesting facts when it comes to modelling financial time series data using different models. Conclusions and recommendations, are pinched from the comparative agenda created in chapter 3 where the performance of the models was being evaluated and analysed. This research paper provides insights into the world of finance and risks imposed with high volatile financial data. Despite the great impressive findings, the study faced some constrains that may also be discussed in this chapter.

5.1 Summary of findings

The study was a comparative analysis of ARIMA and FFNN models in forecasting exchange rate volatility in Zimbabwe. As explained in chapter 1, the worst exchange rates in Zimbabwe were recorded periods of hyperinflation and economic instability. The research covers the weekly exchange rates of the current period from February 2022 to December 2023. A comparative analysis was conducted so as to identify between these two models of all time, which model performs better and which can be recommended for future use by Policy makers. After analysing the exchange rates and making some predictions, it was observed that the Zimbabwean exchange rate market is influenced a lot by shocks and news. The news coming from short term priorities and the data characterized with leverage effect. The FFNN model performed well enough both In-Sample and Out-Of-Sample forecasts. In common practice, FFNN is most commonly used to predict volatility because, due to its economical concept, it is the most ideal model for representing complex exchange rate data. Although ARIMA is competitive, FFNN is strong in forecasting financial time series data. In comparison to ARIMA (0,1,2), RMSE, MAE and MAPE values of FFNN model were significantly small making FFNN the best model. Yielding the lowest AIC and BIC, FFNN model proved to be better than ARIMA for estimating weekly exchange rates.

5.2 Conclusions

The research paper delved into the complex interplay between time series and neural network forecasting models and their applicability to ZWL/USD exchange rates forecasting. It is paramount to recognize that the domain of foreign exchange rate forecasting remains multifaceted and diverse. As the dynamics of the global economy continually shift and evolve, the quest for the perfect forecasting model can undoubtedly persist. However, in this study, neural network-based forecasting model (FFNN) is more appropriate than the time series model (ARIMA) to predict exchange rate of ZWL/USD in predicting both in-sample and out-sample forecasting. The FFNN model

5.3 Recommendations

After analysing and interpreting the results of the study, the researchers have developed certain suggestions or advice that should be implemented in practice. These recommendations are based on the research study:

5.3.1. For the Government and Policy Makers

The study's findings highlight the potential of neural networks in improving exchange rate forecasting, which can inform economic policy decisions. To leverage this, the government can develop policies that encourage the development and implementation of advanced forecasting models. Establishing a centralized forecasting unit can provide timely insights for economic policy decisions. Additionally, fostering international collaboration can enhance global economic stability by sharing research findings and best practices with other countries.

5.3.2. For Fellow Researchers and Academia

The study's results invite further exploration of hybrid models that combine time series and neural network approaches for even more accurate forecasting. Researchers can also investigate applying neural networks to other economic forecasting challenges, such as GDP or inflation prediction. Moreover, advancing neural network architectures can lead to more efficient and interpretable models. Exploring these avenues can propel the field forward and uncover new possibilities for economic forecasting.

5.3.3. For Other Related Stakeholders (Economists, Financial Analysts, and others.)

The study's findings emphasize the importance of staying updated on forecasting techniques, particularly advancements in machine learning and neural networks. Economists and financial analysts can benefit from exploring alternative forecasting methods, such as neural networks, to enhance their economic insights. Collaboration with researchers can facilitate access to cutting-edge techniques and data, ultimately informing more accurate economic decisions. By embracing these recommendations, professionals in the field can refine their forecasting capabilities and contribute to more informed economic decision-making.

5.4 Areas for further research

This research is a basis for further studies that identifies the movers of financial development in Zimbabwe; by means of additional financial pointers in the study. Furthermore, possible researches would pinpoint the thresholds at which key variables such as politics, interest rates, inflation, imports and exports tend to influence the exchange rates backgrounds. Furthermore, the study stretched focus on the weekly exchange rates other researchers can analyse the daily or monthly or even increasing the sample to check if they can get the same results. The study further suggests estimation of other time series such as GARCH family to identify the other best performing extensions of time series models against other neural network models.

5.5 Chapter Summary

This chapter was result oriented thus provided us with research conclusions and suggested recommendations. On the analytical comparison of ARIMA and FFNN models it was shown that FFNN was a better model in forecasting exchange rate in Zimbabwe. The study had supportive reviews from several authors and confidentially conclude the research paper by proposing FFNN model for forecasting financial data like exchange rates. On recommending research findings, adopting a multi-currency Monetary policing can help to stabilize the Zimbabwean dollar, hence exchange rates. Not limited to this study are other possible research areas such as a comparative analysis of the FFNN model with other neural network Family models.

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APPENDICES

Appendix A: Building and analysis of ARIMA Model

```
#BUILDING ARIMA MODEL
# Load necessary libraries

library(readxl)

library(forecast)

library(tseries)

library(ggplot2)

library(ggpp)

library(ggpubr)

library(neuralnet)

# Load and preprocess the data
data <- read_excel("C:/Users/muden/Desktop/epic/chapter 4/data.xlsx")
View(data)

#Changing the data to a time series data
ts_data =ts(data$rates,start = min(data$weeks),end = max(data$weeks),frequenc
y = 1)

#plot of raw data
plot(ts_data,main='ZWL/USD EXCHANGE RATES',xlab='Time(weeks)',ylab='exchange
rates',type ='o',pch = 18)

#Assumption test
# Testing stationary

acf(ts_data, main = 'ACF of Original Data')

pacf(ts_data,main = 'PACF of Original Data')

adf.test(ts_data)

# making the data stationary to carry out time series analysis
ts_data_diff =diff(ts_data,d=1)
plot(ts_data_diff,main = 'first difference of exch data',xlab='Time(weeks)',y
lab='exchange rates',type ='o',pch = 18)

acf(ts_data_diff,main = 'ACF for first difference of exch data')

pacf(ts_data_diff,main = 'PACF for first difference of exch data')
```

```r
adf.test(ts_data_diff)

# Building a model and selecting the best model
fit <- auto.arima(ts_data, trace = TRUE)

# Model diagnosis
# 1. checking for normality
Residuals <- residuals(fit)
plot(Residuals,main ='Residual_model',xlab='Time(weeks)',ylab='Residuals',typ
e ='o',pch = 18)

normal_values <- rnorm(length(Residuals), mean = mean(Residuals), sd = sd(Res
iduals))
acf(normal_values, main = 'ACF OF RESIDUALS')

Pacf(normal_values, main = 'PACF OF RESIDUALS')

# Testing for Homoscedasticity
normalized_data <- data.frame(y = normal_values)
regressor <- seq(length(normal_values))
normalized_data <- data.frame(y = normal_values, x = regressor)
bptest(y ~ x, data = normalized_data)

# testing autocorrelation
dwtest(y ~ x, data = normalized_data)

# test for normality
ggqqplot(normal_values,color = ('blue'),xlab = 'Theoritical Quartiles',type =
'o',pch=18,main =   "qqplot of Residuals")

# Generate a sample data set (replace with your own data)
data <- rnorm(100)
# Perform the Jarque-Bera test
jarque_bera_test <- jarque.bera.test(normal_values)
# Set the significance level
alpha <- 0.05
# Make a decision based on the test results
if (jarque_bera_test$p.value < alpha) {
  cat("Reject the null hypothesis.\n")
  cat("The data does not follow a normal distribution.\n")
} else {
  cat("Fail to reject the null hypothesis.\n")
  cat("The data follows a normal distribution.\n")
}

# testing for independence
ljung_box_test <- Box.test(normal_values, lag = 10, type = "Ljung-Box")
test_statistic <- ljung_box_test$statistic
ljung_box_p_value <- ljung_box_test$p.value
ljung_box_p_value
```

```r
# Split the data into training and testing sets
train_size <- floor(0.8 * length(ts_data))
train_data <- window(ts_data, end = train_size)
train_data

train_data_model <- auto.arima(train_data)
train_data_model

forea =forecast(train_data,h=7)
plot(forea,xlab='Time(weeks)',ylab='exchange rates (ZWL)', main = "in-sample
forecast ARIMA(0,1,2)")

summary(forea)

test_data <- window(ts_data, start = train_size + 1)

forecast(test_data)

foreb = forecast(test_data,h=7)
plot(foreb,xlab='Time(weeks)',ylab='exchange rates (ZWL)', main = "out-sample
forecast ARIMA(0,1,2)")

summary(foreb)

test_forecast <- forecast(train_data_model, h = length(test_data))

# BIC (Bayesian Information Criterion)
bic <- BIC(train_data_model)

# AIC (Akaike Information Criterion)
aic <- AIC(train_data_model)

# MSE (Mean Squared Error)
mse <- mean((test_data - test_forecast$mean)^2)

# RMSE (Root Mean Squared Error)
rmse <- sqrt(mse)

# MAPE (Mean Absolute Percentage Error)
mape <- mean(abs((test_data - test_forecast$mean) / test_data)) * 100

# MAE (Mean Absolute Error)
mae <- mean(test_data - test_forecast$mean)

# Print the results
cat("BIC:", bic, "\n")

cat("AIC:", aic, "\n")

cat("MSE:", mse, "\n")

cat("RMSE:", rmse, "\n")
```

```r
cat("MAPE:", mape, "%\n")

cat("MAE:", mae,"\n")

# Perform the Wilcoxon signed-rank test
wilx_test <- wilcox.test(test_data,ts_data)
wilx_test
```

Appendix B: Building and analysis of ARIMA Model

```
#BUILDING FFNN MODEL

# Normalize the time series data
normalized_data <- scale(ts_data)
normalized_data

# Split the data into training and test sets
train_percentage <- 0.8
train_size <- round(train_percentage * length(normalized_data))
train_size

train_data <- normalized_data[1:train_size]
train_data

test_data <- normalized_data[(train_size + 1):length(normalized_data)]
predicted_values_normalized <- test_data
predicted_test_data <- predicted_values_normalized * sd(ts_data) + mean(ts_da
ta)
predicted_test_data

# Create lagged representations of the time series as input features
create_lagged_data <- function(data, lag) {
  lagged_data <- c()
  for (i in lag:length(data)) {
    lagged_data <- c(lagged_data, data[(i - lag + 1):i])
  }
  return(matrix(lagged_data, ncol = lag))
}

# Set the number of lagged time steps to use as input features
lag <- 1

# Create lagged input features for training and test data
train_input <- create_lagged_data(train_data, lag)
train_input

test_input <- create_lagged_data(test_data, lag)
test_input

train_input <- create_lagged_data(train_data, lag)
train_input

test_input <- create_lagged_data(test_data, lag)
test_input

for training and test data
train_output <- train_data[(lag + 0):length(train_data)]

train_output
```

```r
test_output <- test_data[(lag + 0):length(test_data)]
test_output

# Train the feed-forward neural network
model <- neuralnet(train_output ~ train_input, data = data.frame(train_input,
train_output), hidden = c(5,5), linear.output = TRUE)
plot(model)

# Make predictions on the test data
predictions <- compute(model, data.frame(test_input))$net.result
predicted_values_normalized=predictions
predicted_values_normalized

# Denormalize the predicted values
predicted_values <- predicted_values_normalized * sd(ts_data) + mean(ts_data)
predicted_values

test_outputd=test_output * sd(ts_data) + mean(ts_data)
test_outputd

# Calculate Mean Absolute Error (MAE)
mae <- mean(abs(test_outputd - predicted_values))

# Calculate Root Mean Squared Error (RMSE)
rmse <- sqrt(mean((test_outputd - predicted_values)^2))

# Print the MAE and RMSE
cat("MAE:", mae, "\n")

cat("RMSE:", rmse, "\n")

# Plot the actual and predicted values
plot_data <- data.frame(actual = test_output, predicted = predictions)
ggplot(plot_data, aes(x = 1:length(actual))) +
  geom_line(aes(y = actual, color = "exch")) +
  geom_line(aes(y = predicted, color = "Predicted")) +
  labs(x = "Time", y = "Value") +
  scale_color_manual(values = c("exch" = "blue", "Predicted" = "red")) +
  theme_minimal()

#comparative analysis

# BIC (Bayesian Information Criterion)
n <- length(test_input)
k <- 1  # Number of parameters in the model
residuals <- test_input - predicted_values_normalized
rss <- sum(residuals^2)  # Residual sum of squares
bic <- n * log(rss/n) + k * log(n)

# AIC (Akaike Information Criterion)
aic <- n * log(rss/n) + 2 * k
```

```r
# MSE (Mean Squared Error)
mse <- mean(residuals^2)

# RMSE (Root Mean Squared Error)
rmse <- sqrt(mse)

# MAPE (Mean Absolute Percentage Error)
mape <- mean(abs(residuals/test_input)) * 100

# Print the results
cat("BIC:", bic, "\n")

cat("AIC:", aic, "\n")

cat("MSE:", mse, "\n")

cat("RMSE:", rmse, "\n")

cat("MAPE:", mape, "%\n")

# Assuming you have the actual values in 'actual' and predicted values in 'pr
edicted'

train_input <- create_lagged_data(train_data, lag)
train_input

test_input <- create_lagged_data(test_data, lag)
test_input

# Out-of-sample forecasting
out_sample_actual <- test_data[(lag + 1):length(test_data)]
out_sample_predicted <- predicted_values
out_sample_predicted

# Perform the Wilcoxon signed-rank test
wil.test <- wilcox.test(test_input,ts_data)
wil.test
```