Exploring the Utilization of Neural Networks in Forex Market Forecasting: A Comparative Analysis of Nonlinear Autoregressive Neural Network and Autoregressive Integrated Moving Average

Lappeenranta–Lahti University of Technology LUT

Bachelor's Programme in Strategic Finance, Bachelor's thesis

2023

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Examiner: Post-doctoral Researcher Mahinda Mailagaha Kumbure

ABSTRACT

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Bachelor's thesis

2023

48 pages, 12 figures, 5 tables, and 7 appendices

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Keywords: Neural networks, Forex market, deep learning, machine learning, time series forecasting, NAR, ARIMA, forecasting, time series, comparative analysis, foreign exchange rates, Exchange rate movements.

This bachelor's thesis explores and analyses the utilization of Neural Networks in foreign exchange market forecasting and compares it with another statistical time series analysis model. The foreign exchange market is the largest and most liquid marketplace in the world, making it difficult to predict future movements of exchange rates. This research was conducted by introducing the theory, benefits, and possibilities of neural networks in forecasting foreign exchange rate markets. Nonlinear Autoregressive neural network (NAR) and Autoregressive Integrated Moving Average (ARIMA) models selected for the study were reviewed and presented in more detail. The literature review concluded with a general review of the exchange rate market and a summary of previous studies was presented.

In the Empirical section of this study, a NAR neural network and an ARIMA model were built utilizing MATLAB computer software to predict future exchange rate movements for two exchange rate pairs. Historical exchange rate data between the currency pairs of EUR/USD and EUR/GBP within the timeframe of 2013-2022 have been utilized to conduct this research. The data contains the daily closing rate for both currency pairs.

The results of this study show that both the NAR neural network and the ARIMA model can predict foreign exchange rate markets and selected currency exchange rates. Based on the selected performance metrics mean squared error (MSE) and root mean squared error (RMSE), the NAR neural network performed with better accuracy, but the accuracy of the results may be disrupted by the challenging nature of the foreign exchange market.

TIIVISTELMÄ

Lappeenrannan–Lahden teknillinen yliopisto LUT

LUT-kauppakorkeakoulu

Kauppatieteet

Jan Rindell

Neuroverkkojen hyödyntäminen Forex-markkinoiden ennustamisessa: vertaileva analyysi epälineaarisesta autoregressiivisestä neuroverkosta ja autoregressiivisestä integroidusta liukuvasta keskiarvosta

Kauppatieteiden kandidaatin -tutkielma

2023

48 sivua, 12 kuvaa, 5 taulukkoa ja 7 liitettä

Tarkastaja: Tutkijatohtori Mahinda Mailagaha Kumbure

Avainsanat: Neuroverkot, syväoppiminen, Valuuttamarkkinat, koneoppiminen, aikasarja ennustaminen, NAR, ARIMA, ennustaminen, aikasarjat, vertaileva analyysi, Valuuttakurssit, Valuuttakurssiliikkeet.

Tämä kandidaatin tutkielma tutkii ja analysoi neuroverkkojen hyödyntämistä valuuttakurssimarkkinoiden ennustamisessa ja vertaa sitä toiseen tilastolliseen aikasarja analyysimalliin. Valuuttamarkkinat ovat maailman suurin ja likvidein markkinapaikka, mikä vaikeuttaa tulevien valuuttakurssimuutosten ennustamista. Tämä tutkimus tehtiin esittelemällä neuroverkkojen teoriaa, hyötyjä ja mahdollisuuksia valuuttakurssi markkinoiden ennustamisessa. Tutkimukseen valitut Nonlinear Autoregressive neural network (NAR) ja Autoregressive Integrated Moving Average (ARIMA) -mallit käytiin läpi ja esiteltiin yksityiskohtaisemmin. Kirjallisuuskatsaus päättyy valuuttakurssimarkkinoiden yleiseen tarkasteluun ja yhteenvetoon aiemmista tutkimuksista.

Tämän tutkimuksen empiirisessä osassa rakennettiin NAR-neuroverkko ja ARIMA-malli käyttäen MATLAB-tietokoneohjelmistoa ennustamaan tulevia valuuttakurssiliikkeitä kahdelle valuuttakurssiparille. Tämän tutkimuksen tekemiseen on hyödynnetty valuuttakurssi parien EUR/USD ja EUR/GBP historiallista valuuttakurssi dataa vuosilta 2013–2022. Käytetty data sisältää molempien valuuttakurssiparien päivittäisen päätöskurssin.

Tämän tutkimuksen tulokset osoittavat, että sekä NAR-neuroverkko että ARIMA-malli voivat ennustaa valuuttakursseja ja valikoituja valuutanvaihtokursseja. Valittujen suoritusmittareiden mean squared error (MSE) ja root mean squared error (RMSE) perusteella NAR-neuroverkko suoriutui paremmalla tarkkuudella, mutta tulosten tarkkuus voi häiriintyä valuuttamarkkinoiden haastavan luonteen vuoksi.

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1 Introduction

Markets for financial securities are among the most complicated systems on the entire globe. It is vulnerable and sensitive to a wide range of factors, including economic news, political activities, and international significance. This market area is difficult to perceive because of its non-stationary, non-linear, and time-changing nature. Perhaps one of the most significant financial markets worldwide is the foreign exchange rate market alternatively recognized as the Forex market. This marketplace has grown rapidly with an average daily volume of $6.6. trillion from the diversification of the foreign exchange market and the increased use of currency derivatives among financial traders and institutions throughout the previous years. (Dakalbab et al., 2023, 196), (Sharpe, 2012, 35-38)

Apart from the other financial markets, the forex markets function on a decentralized platform, and the forex market operates five days a week around the clock in four different time zones. Owing to these reasons and the high forex market volatility and risk, it is almost impossible to monitor and participate in trading operations successfully for a human being. (Dakalbab et al., 2023, 197) Due to the complexity of forecasting the movements and prediction for currencies in the forex markets the emphasis moves to find other price movement prediction tools and models such as machine- and deep learning and their capabilities. (Ayitey et al., 2023) Especially for different businesses that are involved in international investments and trading the importance of risk management, reduction, and prediction cannot be emphasized enough for currency derivative hedging options. This is to lower the negative impacts of high volatility or interest rate risk. (Zamzamir et al., 2021)

Financial forecasting is currently an increasingly important topic and issue that engages a significant number of different researchers and specialists. Especially financial time series forecasting algorithms (TSF) have been utilized in many different fields, such as econometrics, statistics, and quantitative finance and this has proven to be a successful way of analysis, with the core goal of predicting different things, such as future values. (Iqra et., 2022) Financial issues and challenges are attempting to be resolved by these researchers by implementing various machine and deep learning algorithm-based models both long-term and short-term. (Kurujitkosol et al., 2022) Prospective models created by researchers related to the foreign exchange market have been extensively studied by the research community, but there is not enough information on how to implement exchange rate forecasting in the forex market according to Ayitey et al. (2023). This gap will be explored in this study.

This thesis will focus on foreign exchange rate prediction based on a neural network model and other statistical analysis time series forecasting methods to compare the performance of forecasting the historical exchange rate movements. Deep learning techniques can automatically learn high-level characteristic benefits of recognizing emotions, especially through their multi-layered network structure (Kananen et al., 2019) Because of this, their properties differ effectively compared to traditional methods. For this reason, neural networks are utilized in many different disciplines. The advantages help to automatically detect intricate structures and high-level characteristics extraction based on input data. (Zhang et al., 2024)

1.1 Research objective and questions

The primary objective of this thesis is to introduce Neural Networks and discover the use of the selected feed-forward neural network model of the Nonlinear Autoregressive Neural network (NARNN) to forecast currency exchange rate movements based on the historical exchange rate movements and compare the results with the Econometric statistical analysis time-series forecasting method Autoregressive Integrated Moving Average (ARIMA). The hypothesis around this research will contain the assumption that carefully selected and constructed models can be used to form future development and trends by utilizing historical exchange rate movements. The commonly recognized theory of efficiency markets hypothesis (EMH) will include the assumption that the market prices comply with the "random walk -effect" meaning that the prediction of markets and price movements cannot be estimated or forecasted from past movements (Vukovic, 2013). Another objective of this research with above mentioned EMH is to examine whether forecasts from historical exchange rates made using these models can be considered useful given the effectiveness of the foreign exchange rate market. The selected model will be analyzed utilizing a Nonlinear autoregressive Neural Network (NAR) and Autoregressive integrated moving average (ARIMA). The Research questions for this thesis have been constructed to aid in the achievement of the research's primary objectives.

The primary research questions:

1. In what ways can neural networks be effectively employed in forecasting currency exchange rates?

Secondary research questions include:

2. How does the chosen NAR neural network model perform compared to the ARIMA model in forecasting currency exchange rates?

3. To what extent the information from currency exchange rate forecasting developed from the NAR and ARIMA models can be useful in the light of EMH theory in the forex market?

1.2 Delimitations

Considering the structure and the scope of the research, which is to investigate the effectiveness of neural networks and compare it to another time series forecasting model in predicting currency exchange rate movements, the delimitations will be required to be defined properly. The main restrictions will be to focus on the Euro's historical exchange rate with another selected currency to evaluate the data as currency pairs. According to Fisichella and Garolla (2021), there are a couple of optional approaches available for forex market analysis: fundamental analysis and technical analysis. According to Pornwattanavichai et al. (2022), the fundamental analysis concentrates on political and economic factors that influence change in prices and technical analysis primarily utilizes the historical exchange rate data. There are three types of financial exchange rate forecasting methods, econometric methods, time series models, and machine/deep learning techniques (Galeshchuk and Mukherjee, 2017). In this research by considering the above-mentioned factors, the study is being conducted as a technical analysis utilizing the NAR neural network and ARIMA time series model because the prediction of future prices is based solely on historical data.

This thesis will include an introduction to neural networks, and the comparative analysis is constructed from a selected neural network model and another statistical time-series forecasting method. The used data is collected from historical currency exchange rates. The focus of this research will be on the following currency pairs, EUR/USD and EUR/GBP historical daily data within the period beginning from 2013 to the end of 2022. This will offer a long-term period to evaluate the data.

1.3 Structure of the Thesis

The structure of this research complies with LUT University's guidelines on the typical bachelor's thesis structure including five distinct chapters with subheadings. This thesis will conduct three main chapters including theoretical background, data & methodology, and empirical study. These three chapters will cover the entity needed to execute the process of this research. The second chapter will cover the theoretical background with the literature review. This section will offer the path to the empirical study and results to ensure that this research's underlying theory, models, and key concepts of this study. The third chapter will cover the necessary data introduction from historical exchange rates between the currency pairs EUR/USD and EUR/GBP and the methodology for efficiently building models and critical elements such as data preparation and performance measures to conduct the empirical study. The fourth chapter will conclude the empirical study based on the theoretical background and literature review part. The fourth chapter will include the execution of the selected models and the results from the execution with a comparison of the results of the models. The requirement is to determine which model is the most or more suitable for the chosen currency exchange rate forecast and future rate development. The more suitable model can be determined with the chosen performance measures. The fifth and final chapter comprises the conclusions covering the entire study.

2 Theoretical background

This section of the study will cover the theoretical background with essential key elements of the Neural networks in theory and models to be used in financial forecasting with currency exchange rates. Following this section, the reader will grasp the primary concepts and models that will be implemented and compared in the thesis empirical study. The purpose of a literature review is to be as accurate as possible to make the complex context easier to perceive. With this theoretical background, the interpretation of methodology and empirical research is made more understandable.

2.1 Neural Networks

A neural network (NN) also referred to as an Artificial neural network (ANN) is a subset of deep learning constructed from both machine learning and deep learning algorithms. A deep learning algorithm is a neural network that seeks to mimic the human brain's and nerves' functioning and the network essentially learns via experience. The human brain contains various amounts of neurons which are also a part of neural network functioning. (Sako et al., 2022) This implies that neural networks can learn patterns and act as humans do due to given examples of action throughout the learning process. (Hamid and Habib, 2014) The learning process is arranged in a supervised or unsupervised manner. The supervised learning method means that weight modifications are done by comparing the weights with some target output and the unsupervised vice versa means that weight modifications are not done based on some target output and companion them with each other (Yadav et al., 2015, 33-34).

Neural Networks are constructed up of interconnected sequential mathematical equations and the so-referred artificial intelligence derives from weighting factors (Kananen et al., 2019, 128-130). The weighted factors indicate how strong the connection is and these factors can be found by training the model and weights (Joshi, 2023, 61). The models drawn from various neural networks are particularly operational with a large set of data to be processed through the process (Islam et al., 2019). A neural network is an effective data modeling tool capable of capturing and representing complicated input/output connections according to

Adewole et al. (2019). Neural networks are popular forecasting tools due to their capacity to find correlations across hundreds of variables and they offer a powerful tool for developing nonlinear data models, particularly when the underlying principles driving the system are unclear according to Hamid and Habib (2014), and Walczak (2001).

Primarily, the network structure is an incredibly influential machine for computing. Being a powerful tool, it is exceedingly efficient, and the network does not need astonishing programming exploits, thus it is capable of learning and applying from data that is trained. The structure can tolerate various complications caused by variables. (Sheikh and Unde, 2012)

Deep learning can be utilized and activated in a variety of distinctive fields of science. These models can be found utilized for example Risk management, Sales Forecasting, investment management, prediction of stock prices, and thrift failures. (Sharma, 2021; Xiao et al., 2022; Dautel et al., 2020; Sako et al., 2022) All of these have a single characteristic in common, the capacity to forecast any type of issue with the assistance of artificial neural networks and multiple types of different algorithms according to Sharma (2021). The applications of deep learning methods and artificial intelligence can be discovered in the use of visual effects as an example of recognizing images and voice recognition. (Kananen et al., 2019, 130)

The interest in the possible applications of deep and machine learning, and the use of neural networks has risen rapidly during the past century, due to increased computational resources, for instance, the growth and availability of data. (Yin et al., 2017) It is impossible to conceive a society without quick language translators or fast song-recognizing applications (Rivas and Montoya, 2020, 1). According to a variety of researchers, a deep neural network model can outperform several other traditional learning methods in significant challenges such as numerous demanding classification issues (Özgür and Orman 2023; Vukovic, 2023; Adewole et al., 2019). Deep neural networks (DNN) are a form of ANN consisting of numerous layers that connect the input to the output (Sako et al., 2022).

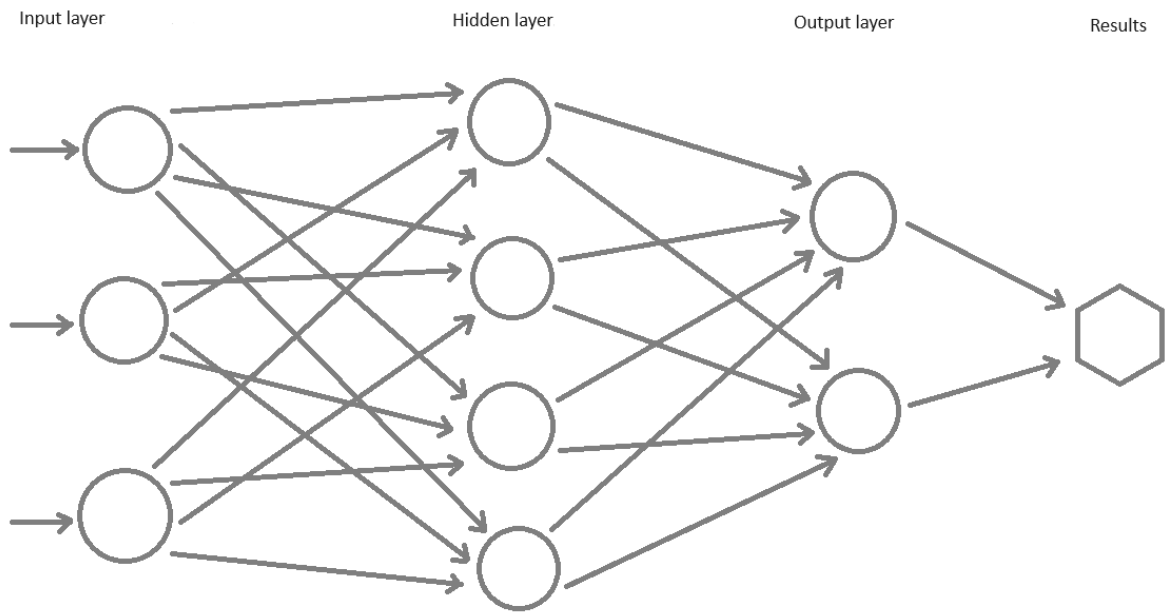

Figure 1: Example of Feed-forward Neural Network with 1 hidden layer (Özgür and Orman, 2023).

2.2 Structure of the Layers

The structure of the artificial neural network is constructed from distinctive layers connected to innumerable networks. Each layer unit in a neural network is built from neurons. The arrangement inside of the neural network model is the layers of “input”, “hidden” and “output”. The nodes are structured as a layer as in the example in Figure 1. Among the most prominent and widely utilized models for neural networks is the feedforward structure, with at least three distinguished levels of layers. Each layer in the structure receives synapses from another neuron, and each layer is connected to another with the weighting factors. The given data is processed through the layers. The number of used layers inside of the model specifies the use of the data and model and the predicting accuracy. (Gurney, 1997)

According to Kananen et al. (2019, 134), the synapses between every layer and neuron are modeled as weights or numbers because of how much every synapse is multiplied by the weights along the way through the framework of the neural network design. In Figure 1, the synapses and the weights are modeled as arrows and the weight is also referred to indicate the importance of that specified neuron.

The input layer of the neural network receives inputs to the nodes from the outside of the model and this layer from the model communicates with the outer world and receives the information as an example of distinctive values. The output layer reacts and starts to generate the final structures. immediately to the input layer when the data is introduced at first sight.

After the inputs have surpassed the input layer the information of the data continues as weighted synapses to the hidden layers of the model. These hiding layers are the interlayers across the input and output layers. The hidden layer is a significant component of the network as it processes the given information and participates in the learning part and depending on the given problem the number of hidden layers varies between distinctive networks. The techniques implemented in the number of hidden layers suggest that less than three layers usually cause a loss in the accuracy of prediction in the network. (Özgür and Orman, 2023) The optimal stage of reducing the complexity and accuracy of the network can be found by using three or more layers inside the model. Summarizing the findings on the use of hidden layers can improve the model's performance during the training session and with the improvement of time complexity. (Walczak, 2001)

The final component of the neural network model's structure is the output layer. The output layer has intercourse with the outer world such as the input layer but slightly distinctive way. The hidden layer transfers the training data to another layer with small neurons and in the output layer, the neurons have an immediate connection with the matter and its convoluted nature. After hidden layers have processed the information the output layer will have the results to show progress and the end figure of the model to the outer environment. (Uzair and Jamil, 2020; Gardner and Dorling, 1998) Challenges are caused based on the count of hidden layers selected for the build model in certain circumstances. These difficult conditions are referred to as overfitting and underfitting condition issues. These conditions negatively affect the time complexity and efficiency of the built network model. Overfitting arises when the network model utilizes more layers than the occurred problem requires and when the training error is continuously reducing, while the testing error begins to increase. This can be discovered by the properties of having low bias and high variance in the network. Underfitting develops when the number of layers is less than the occurred problem requires and when the neural network hasn't been thoroughly trained and the patterns in the training data haven't been entirely recognized, according to Uzair and Jamil (2020), and Khan et al. (2020).

2.3 Neurons

As we've descended into the field of deep learning and neural networks, it is appropriate to concentrate on the functioning and structure as displayed in Figure 2. of neurons beneath the network. The neural network reflects the functioning of the individual's brain with neurons inside it. Especially when focused on the neurons and biological neurons that are accountable for an individual's intelligence. On the foundation of this fundamental conventional presumption, it is permissible to assert that artificial neurons are the core components of artificial intelligence. (Joshi, 2023, 57)

Artificial neurons are referred to as perceptrons in the academic literature and these perceptrons are the foundations of the neural networks. The initial achievement of neurocomputers and perceptrons was developed by Frank Rosenblatt in 1957 as they were utilized for solving linear problems with an expanded computation structure. (Yadav et al., 2015, 13) This perceptron contained only one neuron and in comparison, to several alternative neural network models, the structure was the most straightforward. (Joshi, 2023, 58)

The artificial neuron collects and receives the information due to the problem given by data. The single perceptron in the model processed the given data in the way the model has been trained to resolve the information. According to Joshi (2023, 58), each neuron in the model transmits information to other neurons, which are subsequently processed in the manner prescribed per the model. Every neuron has its core, which receives unique synapses, and the core can activate the neuron depending on how the feeding simulates the neuron. The impulses evolved to other neurons through dendrites generating a connection of neurons. Neurons can be activated or inactivated, which means whether the input passes between layers in the model or not. (Rivas and Montoya, 2020, 6)

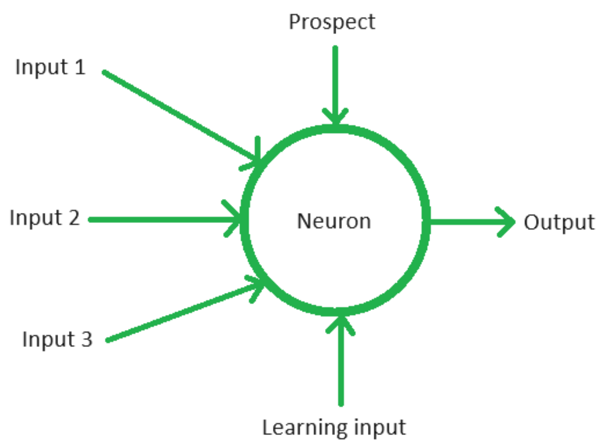

Figure 2: A Structure of artificial neuron (Yadav et al., 2015, 20).

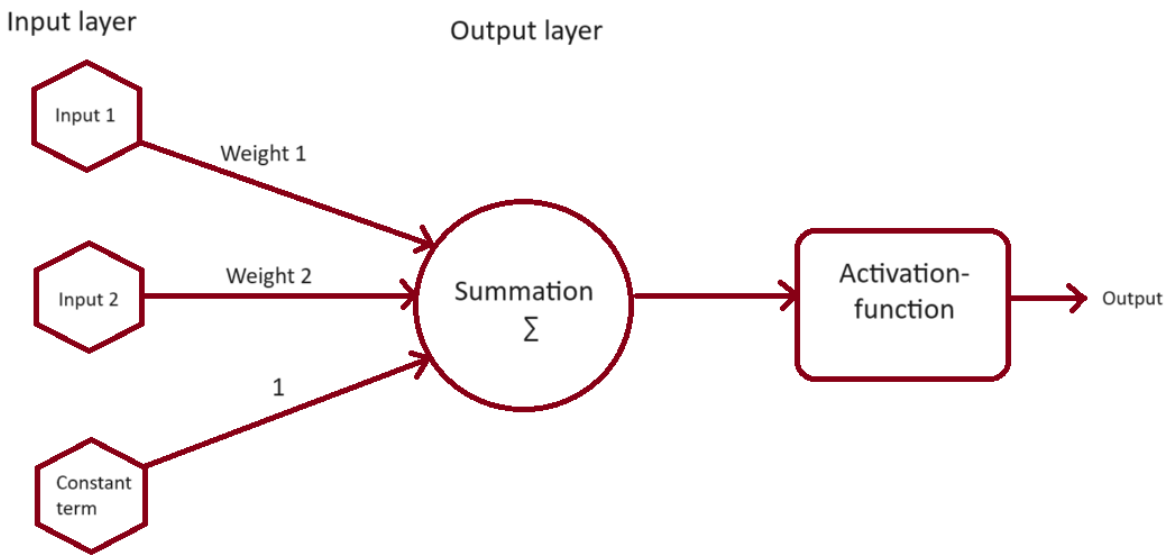

Figure 3: The mathematical structure of a neural network (Yadav et al., 2015, 20).

The fundamental structure of an artificial neuron is displayed in Figure 2. It develops from the weighted inputs and constant term with constant weight forming synapses to the summation of the model and the activation function before the information is processed and shown in the output as seen in Figure 3 (Yadav et al., 2015, 19). According to Sako et al. (2022), Adewole et al. (2019), and Goyal et al. (2018, 40-41), the summation of the model and activation function as a Sigmoid function can be presented as follows in the equations.

The summation of the inputs and weights of the synaptic connections:

$$y = f(\sum_{i=1}^{n} x_1 \cdot w_1 + x_2 \cdot w_2 + x_3 \cdot w_3 \ldots x_n \cdot w_n + 1 \cdot w_b) \quad (1)$$

The equation (1) is explained as, where x_n is the input of the neuron, w_n is the weight of the single input, and w_b is the weight of the constant bias.

The activation function as Sigmoid function formula:

$$f(x) = \frac{1}{1+\mathrm{e}^{-x}} \quad (2)$$

The function (2) is explained as, where e is the Euler's number.

Depending on whether the neuron is activated or not each neuron can receive multiple different inputs yet merely generate one output. The temporary nodes, which are referred to as synaptic connections between neurons in every layer of network architecture are connected to training factors. (Somani et al., 2023) The core function of this weight factor is to highlight, those components that most affect the function of the model and thus the result. Inside the model between the weight matrix and the input value is scalar multiplication. The constant term generally referred to as bias in this context is connected to learning nodes linked to each layer. (Yadav et al., 2019, 19; Goyal et al., 2018, 41-42) The value developed by the activation function is altered by the bias and the bias is equivalent to being constant in the linear activation function. Every node in the network possesses its unique transfer function. This feature of the transfer function integrates multiple input values as one output value which enables input for the upcoming activation function including the following node. This is achieved in all its simplicity of summing the given inputs to the transfer function. The activation function occurs immediately before the node output and this activation function produces nonlinearity to the perceptron's. (Somani et al., 2023, 72)

The process and the results can be modified through the modeling by altering the units of weights, bias, and altering the number of neurons and layers, the way units interact with each other, and how the inputs advance the given set of inputs. This network architecture will learn the modifications applied to the model and the training that affects the accuracy of forecasting. The functioning of the network depends on the process of training the model and learning from the various methods used. (Michelucci, 2018, 32)

2.4 Nonlinear Autoregressive Neural Network

A nonlinear autoregressive neural network (NARNN) model is a type of neural network that is advantageous in forecasting the future developments of values with the use of feedback connections and a deep neural network that contains numerous layers. (Benmouiza and Cheknane, 2013) The NARNN is used in time series and can forecast future values in the series based on past values. (Pereira et al., 2018) According to Ben et al. (2023, 484-498), the NARNN can be expressed in function format to predict different time series:

$$x_t = \varphi(x_{t-1} + x_{t-2} + \cdots x_{t-d}) + \varepsilon_t \tag{3}$$

The function (3) format is explained as where φ represent the non-linear function. x_t is the forecasted value of the data series of x at a discrete time set t, d is earlier values of the series (time delay) and ε_t is the error at the time t. (Ben et al., 2023, 484-498; Merzguioui et al., 2023, 485-486)

This network is appropriate for nonlinear datasets and forecasts future values by employing data from the past via a re-feeding method. The forecasted values can be utilized to generate future forecasts with the help of future-looking points. (Namasudra et al., 2023)

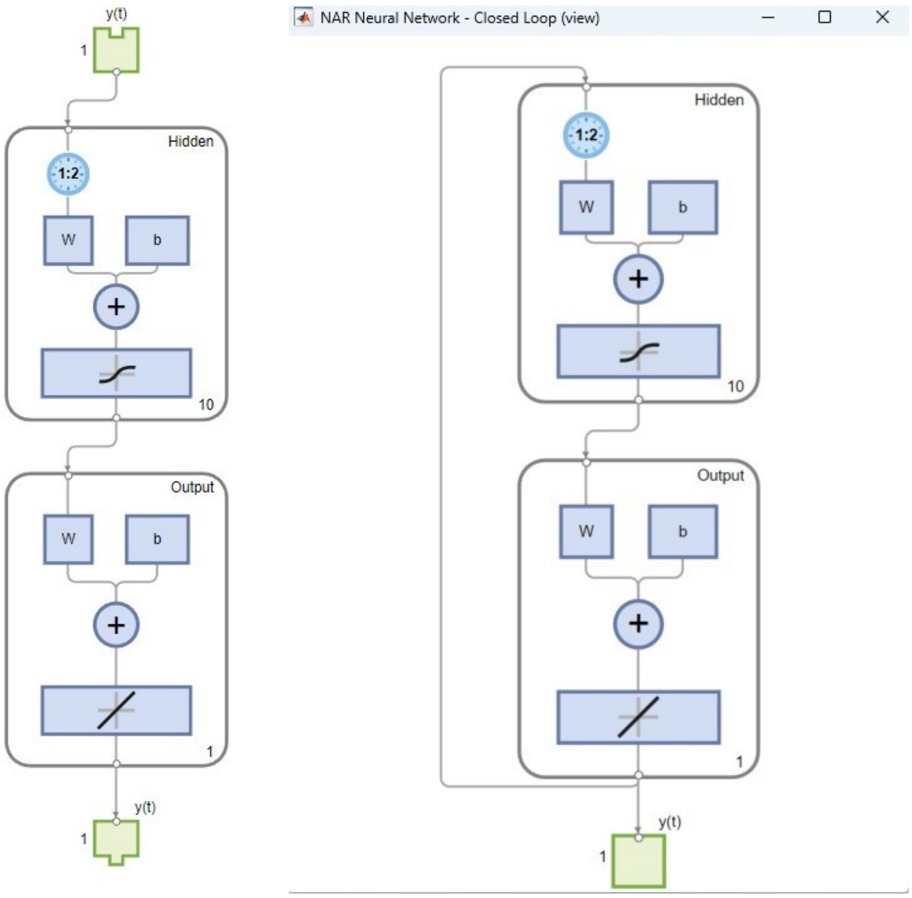

Figure 4: The structure of open loop NARNN is on the left and the structure of closed loop NARNN is on the right. (MATLAB, 2023)

The structure seen in Figure 4 of the NAR network is constructed by identifying settings for network configuration parameters like as feedback delays, hidden layer neuron count, methods of learning, and activation function. This structure of NARNN is a typical structure of a Multilayer Feedforward Neural Network (MFNN) with three or more layers according to Ahmed and Khalid (2017). These variables are only affected by the problem area, and determining the most appropriate values for these variables is a difficult obstacle to overcome. The training process is then completed in an open-loop network using genuine goal values as responses, resulting in a high degree of accuracy. (Namasudra et al., 2023) The new forecasted value is returned as input to the feedback network when the training process is completed, and the model's open loop is changed into a closed loop seen in Figure 4., resulting in the execution of a multistep-ahead forecast, according to Benmouiza and Cheknane (2016) with the following output of closed-loop format:

$$x_{(t+p)} = \varphi(x_{t-1} + x_{t-2} + \cdots x_{t-d}) + \varepsilon_t \quad (4)$$

The equation (4) explained, where the p reflects the predicted data points of the future. According to Abu Al-Haija et al. (2023) the future values of time series are only forecasted from the past values in the series in the NAR model.

2.5 Autoregressive Integrated Moving Average

The model of Autoregressive (AR) Integrated (I) Moving Average (MA) (ARIMA) is a common statistical univariate time series forecasting model and method designed by George EP Box and Gwilym M. Jenkins and it belongs to the class of linear model called (ARMA) according to Myint and Hlaing (2023), and Ampountolas (2023). The ARIMA model can be defined as a linear model with the ability to capture the linear qualities from a time series (Xiao et al., 2014). According to Awe et al. (2022), and Ehsanifar et al. (2022), the ARIMA can be applied to data of time series that are stationary, and using the model involves the assumption that past values can be translated into future values and thus make predictions. ARIMA modeling includes the following three steps that form the model's structure, and these are model identification, coefficient estimation, and model verification (Koutroumanidis et al., 2009).

According to Rhanoui et al. (2019), The ARIMA model with three parameters (p, d, q) can defined as where p stands for the number of non-seasonal autoregressive terms covering the (AR), d stands for the number of non-seasonal differentiations covering the (I), and the last one q stands for the number of non-seasonal moving averages covering the (MA) in the model. The difference between the ARIMA model and the ARMA model can be found in the use of differentiations as the main idea of the whole model is to build a differential autoregressive model (Su, 2021). Financial time series can be found to be stationary or non-stationary and according to Li et al. (2020) the non-stationary time series can be turned into a stationary series by adjusting the values of the difference term d. According to Koutroumanidis et al. (2009), and Hushani, (2019, 767-768), the ARIMA (p,d,g) can expressed generally as the following equation:

$$\phi(B)\nabla_{z_t}^d = \theta(B)a_t \tag{5}$$

With detailed specifications, the above equation is explained as follows:

$$\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots \phi_p B^p \tag{6}$$

In the equation (6), $\phi(B)$ represents the non-seasonal autoregressive term p which is equal to AR in the ARIMA model. ϕ_1, ϕ_2 and ϕ_p are the undetermined coefficients estimated from data.

$$\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots \theta_q B^q \tag{7}$$

In equation (7), $\theta(B)$ represents the non-seasonal moving averages of term q which is equal to MA in the ARIMA model. θ_1, θ_2 and θ_q are the undetermined coefficients estimated from data.

$$B^p z_t = z_{t-p} \tag{8}$$

In equation (8), $B^p z_t$ is defined as the backward shift operator for the term d.

$$\nabla^d = (1 - B)^d \tag{9}$$

In equation (9), ∇^d is defined as the backward shift operator for the term p.

The forecasting method for ARIMA models forms as follows because the use of models in forecasting is often hampered by the subjective nature and complexity of selection processes according to Ampountolas (2023):

$$(1 - \phi_1 B)(1 - \phi_1 B^4)(1 - B)(1 - B^4)x_t = (1 + \theta_1 B)(1 + \Theta_1 B^4)\varepsilon_t \tag{10}$$

In equation (10) the variable of x_t represents the actual value at the *t*th instance. The ε_t represents the error sequence. This is a white noise procedure with Gaussian distribution, with the error sequence having a mean of zero and a constant variance of σ^2, according to Ampountolas (2023).

2.6 Foreign exchange markets

2.6.1 Overview

The foreign exchange market is one of the most significant financial marketplaces in the globe, and this marketplace contains transactions trading over a trillion daily. In the economy and the financial world, the forex market is the most liquid structure across all sectors of markets. There are primarily two categories of currency markets: central bank markets and independent markets. The marketplace for foreign exchange rates is called the OTC market and this comes from the words ”over-the-counter markets”. (Sharpe, 2012, 38) A currency transaction in the foreign exchange marketplace entails the concurrent buying and selling of two currencies. In general, the value of one currency is estimated by evaluating it with a respective currency; these equivalent currencies are collectively referred to as base currency and the counter currency. The outcome of this exchange process is the price between these currencies and the price at which the funds can be changed for one another is referred to as the foreign exchange rate. (Glantz and Kissell, 2014)

The most frequently exchanged pairs of currencies involve the following combinations: EUR/USD, USD/JPY, USD/CHF, and GBP/USD. Among these currencies is the EUR/USD exchange rate, which is the most actively exchanged currency pair in the foreign exchange market. The Forex currency markets can be viewed as a gathering place for numerous parties and entities such as financial institutions, retail dealers outside of the banks and credit unions, brokers, and foreign exchange dealers. These entities are inextricably linked to one another by utilizing an environment of telecommunication infrastructure, electronic devices, and computerized trading platforms. Geographically, the foreign exchange market is divided into three significant sections: Europe, Australasia, and North America. (Kumar, 2014)

2.6.2 Foreign exchange rate forecasting

One of the most significant challenges of our day is the increasing complexity of numerous real-life issues. Among the several affecting variables is the complexity, impacting decision-making across global finance, which has evolved in relevance throughout the previous decade. (Hamid and Habib, 2014) The Forex market has been dramatically affected because of fundamental changes in the global economy and the worldwide financial mechanism. Measures to provide clarification and forecast fluctuating exchange rates have mostly failed. There have been attempts to predict future exchange rate levels among many different researchers, utilizing different time series and structure models, but this has led to the conclusion that exchange rates are exceedingly challenging to predict and the functionality of the model is equivalent to a random walk model. (Ullrich, 2009, 7; Sharpe, 2012, 77)

The interest rate theory is directly connected to the fundamental ideas of informational and speculative market efficiency. If the prices in the financial sector accurately portray any accessible and trustworthy data, the market is considered as (informationally) effective. According to instincts, the market analyzes freshly acquired knowledge instantly, and price fluctuations are solely caused by recent developments. Yet because further developments can’t be forecast, upcoming price fluctuations can’t be foretold either. (Sharpe, 2012, 57)

Available information can be linked to various types of efficiency market hypotheses (EMH), and these types are weak-(any information from examining the security's previous history of trading reflects on the price), mediocre-(all public information reflects on price, but private information offers useful insight to profit), and significant (all known information is immediately included into the price of the security) types of efficiency, this is recognized commonly as the three types of EMH theory (Diamond and Perkins, 2022; Sandubete et al., 2023). According to Vukovic, (2013), technical analysis is considered with the type of mediocre form of EMH, and fundamental analysis is considered a weak form of EMH. In the Forex market, informational effectiveness indicates that the present spot rate must correspond to all currently accessible information. When the prospective currency rate forecast is logical it must all be included in the forward rate. As a result, assuming the theory of an EMH is correct, the forward rate must serve as an "unbiased estimator" of the assumed exchange rate. (Ullrich, 2009, 27)

2.6.3 Foreign exchange risk and hedging

As organizations and businesses evolve more globalized, other than financial institutions are becoming significantly vulnerable to foreign currency fluctuations. Businesses estimate that fluctuating currency exchange rate swings affect approximately almost a third of their profits, expenses, and revenue streams. Because of previous discoveries, the situation is not unexpected that large international enterprises, evaluate the exposure of foreign exchange risk to be one of the costliest categories of risk-facing businesses. Within the deficiency of any decrease in currency volatility, Businesses need to guard their own towards possible damages caused by unanticipated variations in currency rates, given that marketplaces are inefficient in the awareness that the owners of the businesses are unable to hedge the exposure personally. (Ullrich, 2009, 5-6; Deng, 2020)

The typically associated derivative instruments are forward contracts, call options, and put options. Forward options can be defined as an arrangement that exists among two entities that attach them to future transactions. The call option is an arrangement that involves two participants whereby one of the participants has the future opportunity to acquire an underlying asset from the opposite participant. The put option can defined almost as the call option, but the other participant can sell the asset in the future. (Gottesman, 2016)

2.7 Summarizing literature review with previous studies

Academic research on the performance of Neural Networks reveals that the technology holds potential in several disciplines of economics and finance, especially stock market forecasting has been successful according to Hamid and Habib (2014). Several researchers and multiple approaches are utilized to forecast foreign exchange rate movements and future developments of trends between currencies. According to Adewole et al. (2011), Such approaches can be differentiated by the factors they believe will remain constant in the future, and Hidden Markov Models (HMM) for example are too volatile to be effectively exploited in the foreign exchange market as tool for data and trading, as the results are influenced by many different factors. The technical and fundamental data indicators have been utilized as information inputs for the forecasting models in previous studies according to Pornwattanavichai et al. (2022). The research community has been quite active in predicting and understanding the trends that occurred in the forex market using machine-learning models in recent years (Ayitey et al., 2023). The utilization of hybrid techniques categorized as optimization strategies, regression strategies, neural networks, and others have been also explored via different studies in past years and the results have been indicating some proper results for randomly selected currency pairs and time frames according to Fisichella and Garolla (2021). According to Adewole et al. (2011), previous studies have shown that traditional statistical forecasting techniques have met their limits with nonlinear data, such as stock index forecasting, and neural network technology has shown its strength when it comes to nonlinear data related to classification, identification, and prediction.

3 Methodology & data

3.1 Research method

This bachelor's thesis is done utilizing the framework of the quantitative research method. The data used in the study is time series data from the historical currency exchange rate. According to Williams et al. (2021, 3), the quantitative research method can be defined as it is about the measurements and quantities. With the applications of these components, the aim is to find out and explain how long something will happen and what will happen in the future. Implementing this to the context of the research with the focus of forecasting exchange rates and introducing the key components in evaluating the performance of the models.

3.2 Historical exchange rate data

Historical exchange rate data has been utilized to conduct this research and answer research questions. The chosen data from historical exchange rates contains information with the periods from the beginning of 2013 to the end of 2022 to specify this the exact dates are from 1.1.2013 to 31.12.2022. The daily exchange rate consists of the open, highest, lowest, and closed exchange rates of each day. In this study, the close rate from each day beneath the timeframe will be utilized in the models to simplify the research.

The data used for this research has been obtained from the Yahoo Finance live forex rates & currencies website (Yahoo!Finance, 2023), where you can easily select different currency pair rates, order, aggregation methods (i.e., what kind of values to use), date, and desired time accuracy for the data, in this case, day data. Transferring selected currency pairs and exchange rate data to an Excel file for data preparation and editing was relatively straightforward from the Yahoo Finance website.

After the historical exchange rate data from the selected currency pairs is collected and transferred into Excel, the data does not require a lot of adjustment or modification, because the data is a time series data, and the chosen models can adapt and receive the given information in time series as an Excel file.

The selected data includes two currency pairs, and these are the Euro exchange rate ratio to another selected exchange rate ratio, i.e., the exchange rate pairs are EUR/USD, i.e., the Euro ratio to the US dollar, and EUR/GBP, i.e., the Euro ratio to the British pound.

3.3 Research environment

The environment for the research's execution and the main part of the empirical study is the Deep Learning- and Econometrics Toolbox in MATLAB R2023b. The deep learning toolbox is a platform for creating and deploying deep neural networks including different applications, previously trained models, and algorithms. (MathWorks, 2023e) The designer tool in the toolbox helps to construct, evaluate, and train network models graphically. (MathWorks, 2023e) The deep learning toolbox includes different applications of networks and approaches to construct distinct models. The machine- and deep-learning application toolbox includes these programs listed as follows, classification learner, deep network designer, deep network quantizer, neural net clustering, neural net fitting, neural net pattern recognition, neural net time series, regression learner, and reinforcement learning designer. (MATLAB, 2023)

Econometrics Toolbox is a platform for time series data to design and analyze models with different functions and interactive workflows. With the help of the Econometric Modeler app, it is possible to estimate, simulate, and forecast different economic and financial data with several kinds of modeling methods. (Mathworks, 2023a)

3.4 Data preparation

The use of neural networks in this research starts with the selection of what kind of data is wanted to be utilized and processes for the study. After the decision is made the data must be modified to fit in the models of neural networks. The data is acquired to be cleaned from all the unnecessary information and variables before importing it into the network. The data used in this study contain exchange rates with the timeframe of 2013-2022. The data is cleaned, and the null and missing values are removed from both time series in Excel. The data must be divided into training data and testing data. The learning stage of the model utilizes training data to teach the network to produce the desired and optimal solutions when the test data is fed into the network. (MathWorks, 2023b; Yu et al., 2007, 39)

The currency pairs are all evaluated and fed to the neural network and econometric time series model as independent quantities, meaning that there will be two models the NARNN and ARIMA to analyze from two different currency pairs. This is done to prevent currency rates from merging and causing distortions and inaccurate research results.

The neural network development procedure consists of these basic components (MathWorks, 2023b; Chng, 2023a):

1. Gather, prepare/pre-process, and import data to MATLAB.
2. Choose the neural network model in the Neural net time series.
3. Choose the backpropagation algorithm.
4. Select the optimal number of layers and neurons.
5. Divide the data and perform training and testing.
6. Examine the network for the best results.
7. Analyze the results and export session results to MATLAB.
8. Forecast the next times-step for the exchange rate.

The ARIMA model development procedure with the implementation of Box-Jenkins Methodology. (Chng, 2023a; Chng, 2023b; MathWorks, 2023f):

1. Gather, pre-process, and import data to MATLAB.
2. Import Time series data to the Econometric App.
3. Execute exploratory data analysis (Stationary or non-stationary).
4. Fit alternative ARIMA (p, d, q) model
5. Perform and evaluate models with a goodness-of-fit validation test.
6. Choose the best ARIMA model with the best parameters.
7. Conduct the necessary tests, analyze the results, and export them to MATLAB.
8. Conduct the forecasting with the imported variables and generated script.

3.5 Backpropagation algorithm with neural network

3.5.1 Levenberg-Marquardt

The Backpropagation algorithm is a complex mathematical learning technique that is utilized on a multilayer feed-forward neural network. According to Adewole et al. (2011), Bahrami et al. (2023), and Kianpour, et al. (2020) The Backpropagation Algorithm has demonstrated a high potential for financial forecasting. Training and learning are the process of identifying the amount of weight, bias, and variables that result in accurate output.

At the beginning of the 1960s, according to Gavin (2022), and Yadav et al. (2015, 37) the algorithm known as the Levenberg-Marquardt algorithm was created to confront the nonlinear least-squares challenges. Least squares challenges emerge whenever a specified numerical model is fitted to a set of data indicators by lowering a goal defined as the total of the squares of the mistakes between the model function and the set of data indicators. The linearity of the model's parameters affects the goals of the least squares of its parameters. According to Merzguioui et al. (2023, 485-486), the training algorithm can be defined by the following function:

$$m_{t+1} = m_t - [J(m_t)^t J(m_t) + \lambda I] J(m_t) E \tag{11}$$

The equation (11) is explained as where J is the first derivative matrix of network error relative to weight, the error vector of the network is marked by E. The λ is positive constant, and the value is haphazardly set to 0.001.

When a model is linear its goal is to be quadratic in terms of the least square sum of parameters, and the linear matrix equation can be utilized to reduce the model's goal in terms of single-phase parameters. In that scenario, if the model and function are not linear in parameters, an iterative solution algorithm can be used to solve the problem with the smallest square sum. (Abu Al-Haija et al., 2023) Via a series of thoughtfully selected adjustments to model values for parameters, algorithms like this lower the sum of the squares of the mistakes between the data indicators and the model function. (Gavin, 2022)

The Levenberg-Marquardt backpropagation is one of the algorithms utilized in predicting time series. This algorithm is one of the multiple options for algorithms to use in the deep learning toolbox in MATLAB when building neural networks. (MATLAB, 2023) This algorithm is both strongly suggested and quick to operate with tolerable-sized data. (MathWorks, 2023c)

3.6 Performance measures

3.6.1 For NARNN Model

The performance in the NARNN model is measured via two components when building models in a deep learning toolbox with this NAR network. The first one is the mean squared error (MSE), which refers to the average of the squared difference between predicted and actual observed values in practice. (Khan and Gupta, 2020; Subakkar et al., 2023) The lower the value this performance indicator gets, the better and more accurate the prediction of model values will be. According to Adewole et al. (2011), the MSE is presented as the following equation:

$$\text{MSE} = \frac{\sum_{t=1}^{n}(o_t - \hat{p}_t)^2}{n} \tag{12}$$

In equation (12) the $\hat{p}_t$ inside of the equation is the predicted value, o_t is the actual observed value, and n is the number of observations in the data.

The second is the R-value, which refers to the correlation coefficient between the variables calculating the direction and strength in a linear connection. This performance indicator measures the linear relationship between the actual and forecasted values between -1 and 1, and when the value is higher than 0 it is a positive linear relationship. (Abu Al-Haija et al., 2023) The closer the value of this indicator is to 1, the stronger the relationship between the measured variables. According to Namasudra et al. (2023), the R-value is presented as the following equation:

$$R = \frac{n(\Sigma FA) - (\sum F)(\sum A)}{\sqrt{(n\Sigma F^2 - (\Sigma F)[n \sum A^2 - (\sum A)^2]}} \tag{13}$$

The equation (13) explained, where F is the forecasted value and A is the actual value and the number of observations is defined as n.

The last performance measure utilized to evaluate the NARNN model is the root mean square error (RMSE). According to Subakkar et al. (2023), the RMSE is calculated as MSE as the mean squared error between actual and predicted values with square root, but the RMSE equation reduces large errors, provides accurate measurement, and preserves the estimation value. The equation (14) is presented as follows (Guo et al., 2022):

$$\text{RMSE} = \sqrt{\frac{\sum_{t=1}^{n}(o_t - \hat{\rho}_t)^2}{n}} \tag{14}$$

3.6.2 For ARIMA Model

The performance of the ARIMA model will include the above-presented performance measures of MSE and RMSE. The estimation of coefficients for the ARIMA model evaluation of time series reliability, the empirical study of this research will include Akaike's Information Criteria (AIC) and Bayesian Information Criteria (BIC) as criteria measures. The closer to zero the AIC and BIC values proceed, the better the model fits and the model can be considered a real model (Jian et al., 2022). AIC and BIC can be presented in an equation:

$$\text{AIC} = 2 * k - 2 * \ln(L) \tag{15}$$

$$\text{BIC} = k * \ln(n) \cdot 2 * \ln(L) \tag{16}$$

The equations of (15) and (16) are explained, where L is the likelihood function, k is number of parameters in the model, and n is the number of the samples. (Zhang and Meng, 2023)

4 Empirical study

The empirical part of this study will include the explained execution of how the models are constructed and displayed. After explaining and modeling the execution the results of the empirical study will be presented. Following the results, in the last section of this thesis, the conclusion will be drawn based on the research and the results.

4.1 Execution of NARNN model

The execution of the NARNN model will be conducted with the neural net time series application with supervised learning. The data will be evaluated inside the structure of the network with 70% of the training for the years of 2013-2019. The remaining 30% will be divided equally for validation of 15% including the years 2020-2021, and testing of 15% including the years 2021-2022. (Namasudra et al., 2023) The validation data in the network evaluates generalization in the training and ends the training when the generalization is no longer enhancing the performance of the training (Cheng et al., 2019). When training neural network models, the algorithms consist of different hyperparameters such as the number of hidden layers and time delays used for the network according to Dautel et al. (2020)

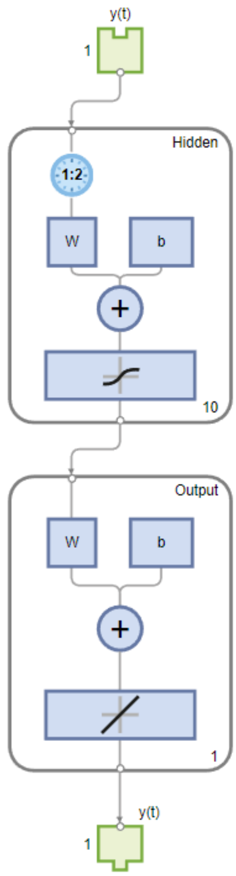

Figure 5: Structure of NARNN model. (MathWorks, 2023d)

Figure 5 shows that the network is constructed with 10 layers and 2-time delays. (MATLAB, 2023). The structure of this network produced satisfactory results per performance measures in the NARNN model for both currency pairs. The algorithm used in this network is the LM backpropagation algorithm to optimize the weights and biases in the network (Kianpour et al., 2020). This algorithm is also suggested by the neural net time series application (MATLAB, 2023).

The data from the currency pairs are divided into training- and testing data in the NARNN model. This action is to train the network to learn the given inputs from the previous movements of rates. The training continues until the performance measures provide adequate results. The additional test data includes values that the network has not seen before and from this, it will make the predicted values based on what the network previously learned from the training process (Adewole et al., 2011). After the session in the Neural Net Time Series app, the variables are exported to the MATLAB workspace and a comprehensive training script is generated. With the command line of code according to MathWorks (2023d) seen in Appendix 6, the multistep forecast can be generated by converting the open-loop network to a closed-loop network and utilizing the closed-loop network. In simple terms, the closed-loop networks remain to forecast by relying on internal feedback because of the absence of external feedback (MathWorks, 2023h).

4.2 Execution of the ARIMA model

The execution of the ARIMA model is done with the Econometrics Toolbox in MATLAB using the Econometric Modeler app. Before the data is imported into the app, it is cleaned from unnecessary observations such as null and missing values.

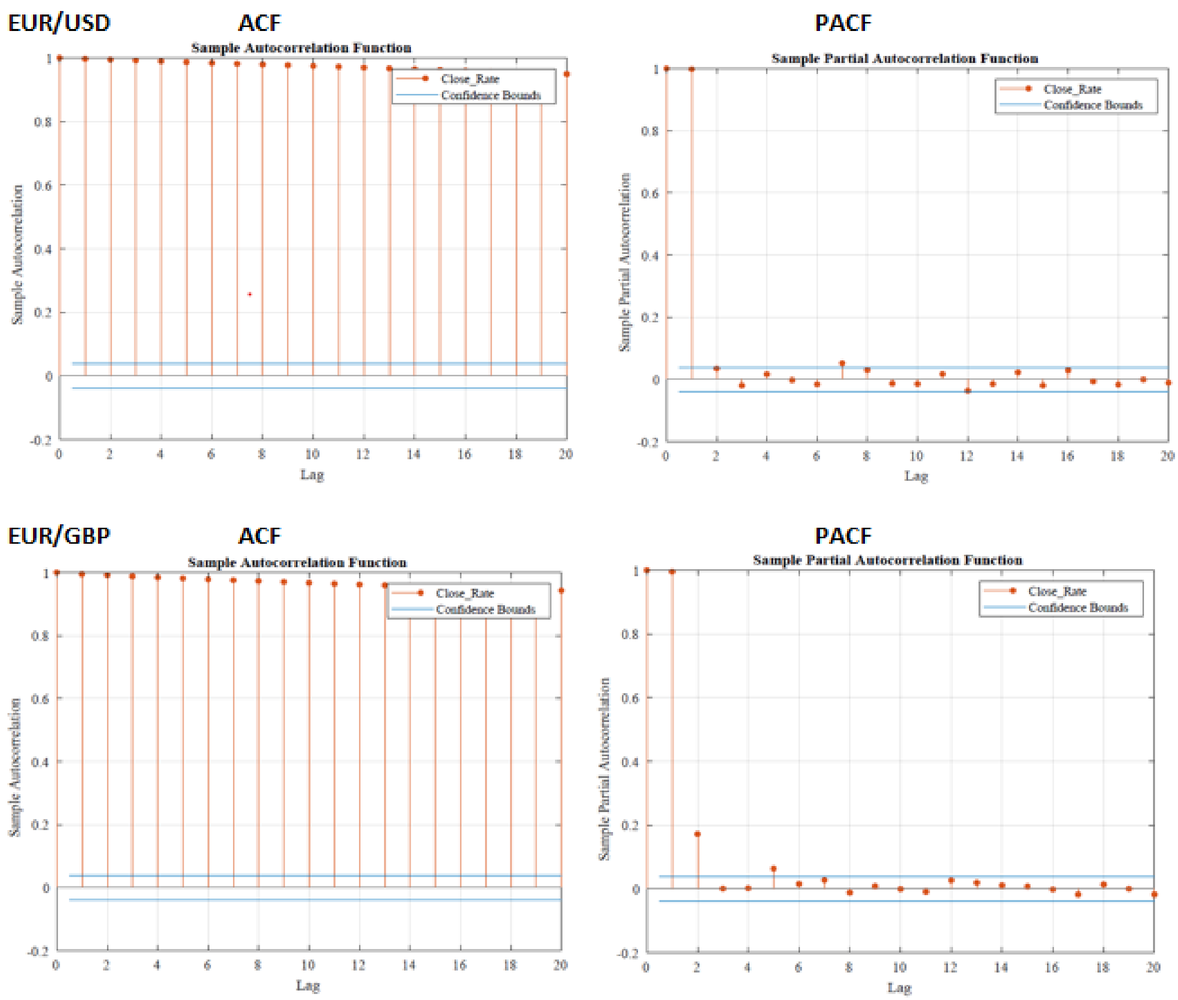

Figure 6: The ACF and PACF correlograms for both currency pairs. (MATLAB, 2023)

The initial action after importing the historical exchange rate data from both currency pairs to the Modeler app is to determine whether the time series is stationary or non-stationary. This is the identification part of the model, and the data needs to be stationary meaning that the properties such as mean are constant over time to properly fit the possible values of p (AR) and q (MA) in the ARIMA model (Gao and Kuruoğlu, 2023). This can be determined by evaluating Figure 6 above of the plots of sample autocorrelation (AFC) and sample partial autocorrelation function (PAFC) drawn based on the historical exchange rate movements from both currency pairs in Appendix 1. Figure 6 shows that the sample ACF implies a non-stationary direction for both currency pairs (MathWorks, 2023f).

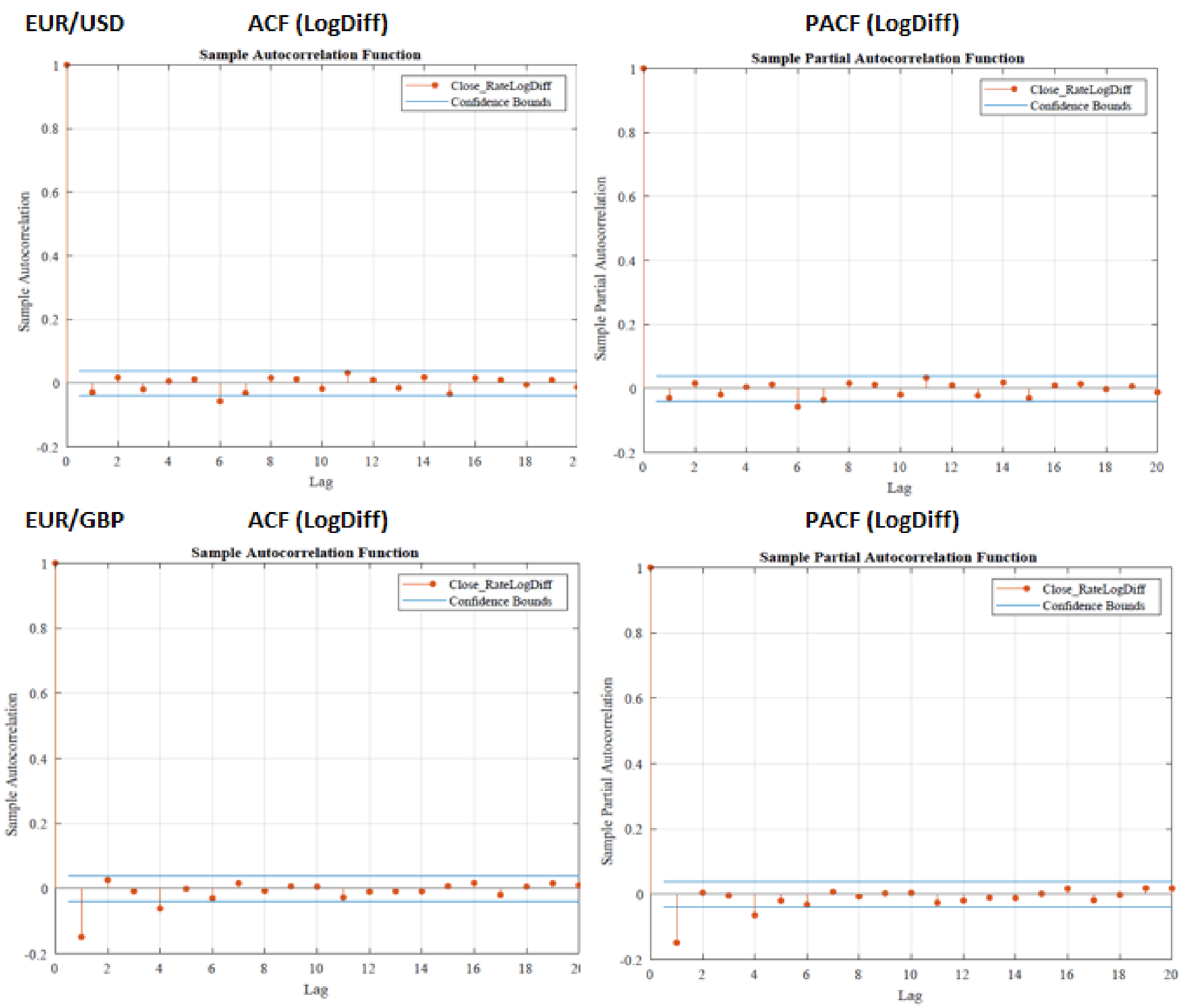

Figure 7: The ACF and PACF LogDiff correlograms (MATLAB, 2023)

To find suitable estimation coefficients for the ARIMA model the data needs to be converted to stationary. This can be achieved by transforming the data to logarithmic (Log) and taking the first difference (Diff) of the time series (Fattah et al., 2018). This removes the time dependence on the variables such as linear trends from the time series. By transforming the data by converting to logarithmic and taking the first difference as in Appendix 5 and by evaluating the sample plots of ACF and PACF in Figure 7 it indicates that the differenced time series breaks down more rapidly making it stationary. To confirm that the time series is stationary the Augmented Dickey-Fuller (ADF) test can be done to verify the findings (Chng, 2023b).

Table 1: The results of the ADF test for EUR/USD and EUR/GBP.

ADF test EUR/USD				
H0: Close_RateLogDiff contains a unit root				
H1: Close_RateLogDiff does not have unit root				
Test Parameters				
Lags	Model	Test	Statistic	Significance Level
1	1	AR	t1	0.05
Test Results				
Null Hypothesis Rejected	P-Value	Test Statistic	Critical Value	
TRUE	0.001	-35.995	-1.9416	
ADF test EUR/GBP				
H0: Close_RateLogDiff contains a unit root				
H1: Close_RateLogDiff does not have unit root				
Test Parameters				
Lags	Model	Test	Statistic	Significance Level
1	1	AR	t1	0.05
Test Results				
Null Hypothesis Rejected	P-Value	Test Statistic	Critical Value	
TRUE	0.001	-38.6467	-1.9416	

The ADF test results are presented for both currency pairs in Table 1. For both currency pairs the null hypothesis of "H0: Close_RateLogDiff contains a unit root" gets rejected with a significance level of 0.05 when the P-value for both currency pairs is 0.001. When the time series contains a unit root it indicates for non-stationary process and when there is no unit root it indicates a stationary process (Fattah et al., 2018). The results indicate a stationary process for both currency pairs.

The estimation results of the coefficients for the ARIMA model selection for both currency pairs will be presented in the results of the ARIMA model. To select the most fitting model for forecasting future values the AIC and BIC model selecting information criteria will be utilized. After the session is done in the Econometric Modeler App the results including variables and generated function script from the session are exported to MATLAB. The forecasting is done in the command line with code using the "forecast" and the residuals are inferred from between the actual and predicted values in the data to calculate the MSE and RMSE between the actual and predicted values from the time series in Excel as seen in Appendix 7. (Chng, 2023b; MathWorks, 2023f; MathWorks, 2023g)

4.3 The results of NARNN model

The evaluation and performance of the NARNN model for both currency pairs including EUR/USD and EUR/GBP starts by investigating the model's performance measures Mean square error and the correlation coefficient R-value. The investigation of results continues after this by observing the model fit between the actual and predicted values of the time series historical exchange rate data for the last 21 days in the series.

Table 2: The performance results in the NARNN model for EUR/USD and EUR/GBP.

Training Results EUR/USD	Observations	MSE	R-value
Training	1823	0.00003549	0.9982
Validation	391	0.0000341	0.9981
Test	391	0.0000774	0.996
Additional Test Results EUR/USD	**Observations**	**MSE**	**R-value**
Test	23	0.00001927	0.778
Training Results EUR/GBP	**Observations**	**MSE**	**R-value**
Training	1823	0.00001621	0.9968
Validation	391	0.00002482	0.9956
Test	391	0.00004362	0.9922
Additional Test Results EUR/GBP	**Observations**	**MSE**	**R-value**
Test	23	0.00001504	0.9246

Table 2 shows the performance measure results of the MSE and R-value in the NARNN model for both currency pairs EUR/USD and EUR/GBP. As the MSE value measures the mean squared error between the actual and the predicted values, the best result is achieved when the value is close to zero (Khan and Gupta, 2020). The MSE values are very low for both currency pairs, and this indicates that the results are advantageous and reliable. The EUR/GBP currency pair has the lowest MSE values at every phase of the model's development including training, validation, testing, and additional testing compared to EUR/USD. The performance of training, validation, and testing for both models and both currency pairs is presented in Appendix 2 measured by MSE. Appendix 2 indicates that there are no significant issues with the training because the test and validation curves are almost identical for both currency pairs. The overfitting problem may occur if the test curve had greatly increased before the validation curve. (MathWorks, 2023i) Appendix 2 shows that the best validation performance for EUR/USD is 0.000034054 at epoch 18 and for EUR/GBP the best validation performance is 0.000024826 at epoch 8.

The correlation coefficient R-values displayed in Table 2 indicate a strong positive linear connection between the actual and predicted values for both currency pairs as all the R-values are close to 1 rather than 0. When the R-value is over 0.7 the connection among the measured variables is considered a strong linear connection (Ratner, 2009). Appendix 3 shows the error autocorrelation for both currency pairs, and this indicates a quite decent model fit for forecasting and prediction performance for both currency pairs because the autocorrelations are inside the confidence level except for EUR/USD when the lag order is -4, 0, and 4. For EUR/GBP when the lag order is -6, 0, and 6. (Cheng et al., 2019)

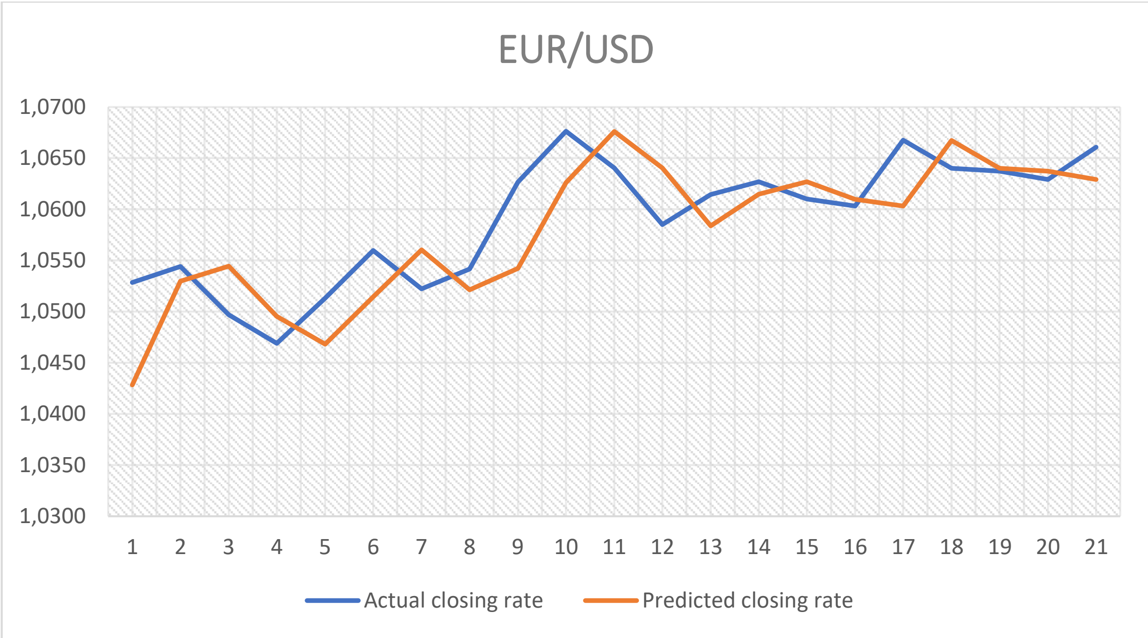

Figure 8: The EUR/USD additional test model fit for actual closing rates and predicted closing rates for the last 21 days inside the research timeframe.

Figure 8 and Figure 9 show the additional test to demonstrate the model fit for EUR/USD and EUR/GBP within the last 21 days of the research timeframe and as can be seen from Figures 8&9, the actual and predicted values of the model differ slightly, although the performance measures indicate good results. The overall response of output is seen in Appendix 4 for both currency pairs as the charts display the outputs, targets, and errors versus time. Appendix 4 additionally specifies which time points were applied for training, testing, and validation. (MathWorks, 2023j)

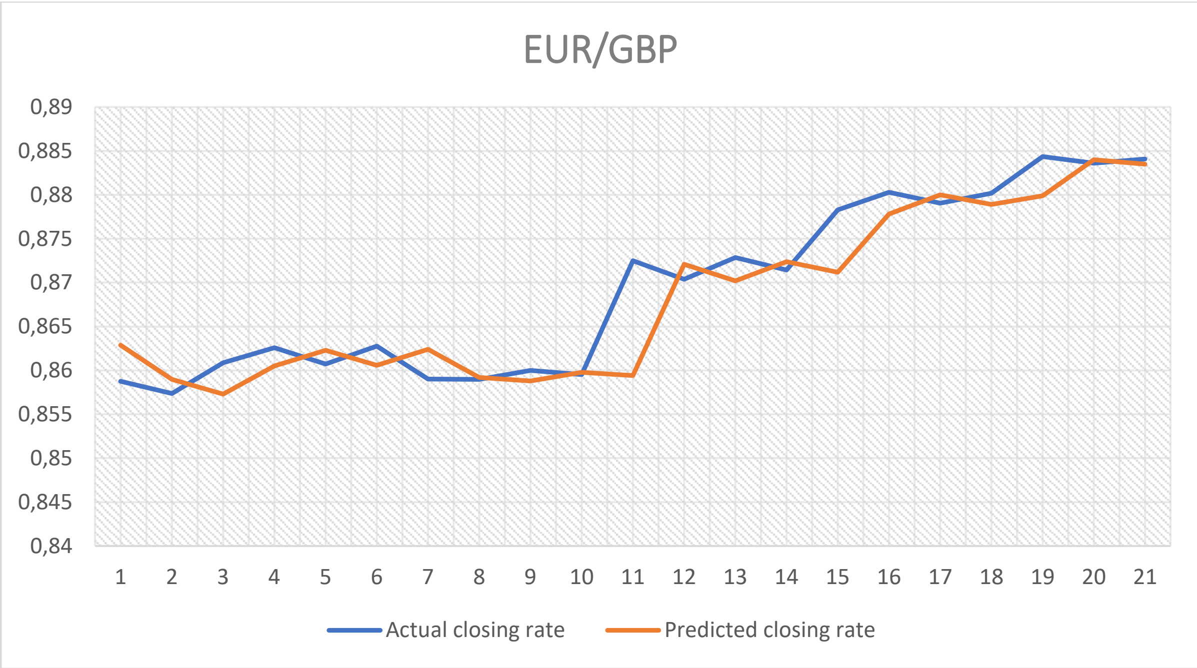

Figure 9: The EUR/GBP additional test model fit for actual closing rates and predicted closing rates for the last 21 days inside the research timeframe.

4.4 The results of ARIMA model

Table 3: The estimation results and goodness of fit with AIC and BIC criteria for EUR/USD. (MATLAB, 2023)

EUR/USD Models(p,d,q)	**AIC**	**BIC**	**Estimation results ARIMA(2,2,2)**				
ARIMA(0,0,0)	-4.6174e+03	-4.6057e+03	Parameter	Value	Standard Error	t Statistic	P-Value
ARIMA(0,1,0)	-1.8883e+04	-1.8871e+04	Constant	3.1627e-06	5.3312e-06	0.59323	0.55303
ARIMA(0,0,1)	-7.9776e+03	-7.9600e+03	AR{1}	-1.0189	0.050008	-20.3743	2.8285e-92
ARIMA(1,0,0)	-1.8884e+04	-1.8866e+04	AR{2}	-0.048814	0.019145	-2.5497	0.010781
ARIMA(1,1,0)	-1.8884e+04	-1.8866e+04	MA{1}	-0.0083246	0.04708	-0.17682	0.85965
ARIMA(1,0,1)	-1.8885e+04	-1.8861e+04	MA{2}	-0.95463	0.046002	-20.7519	1.1776e-95
ARIMA(1,1,1)	-1.8883e+04	-1.8860e+04	Variance	4.2512e-05	2.4196e-07	175.6999	0
ARIMA(2,0,2)	-1.8881e+04	-1.8846e+04	**Equation of ARIMA(2,2,2):**				
ARIMA(2,1,2)	-1.8879e+04	-1.8844e+04	$(1-\phi_1 L-\phi_2 L^2)(1-L)^2 y_t = c + (1+\theta_1 L+\theta_2 L^2)\varepsilon_t$				
ARIMA(2,2,2)	-1.8831e+04	-1.8795e+04					
ARIMA(3,2,3)	-1.8876e+04	-1.8829e+04					

The estimation results for the EUR/USD model are shown in Table 3. The best ARIMA (p, d, q) model can be found and chosen with the lowest goodness of fit measures according to Khan and Gupta (2020), and the ARIMA (2,2,2) model has the best goodness of fit via AIC and BIC criteria. The estimation results for the ARIMA (2,2,2) show that AR {1}, AR {2}, and MA {2} are significant at the significance level of 0.05 (MathWorks, 2023f).

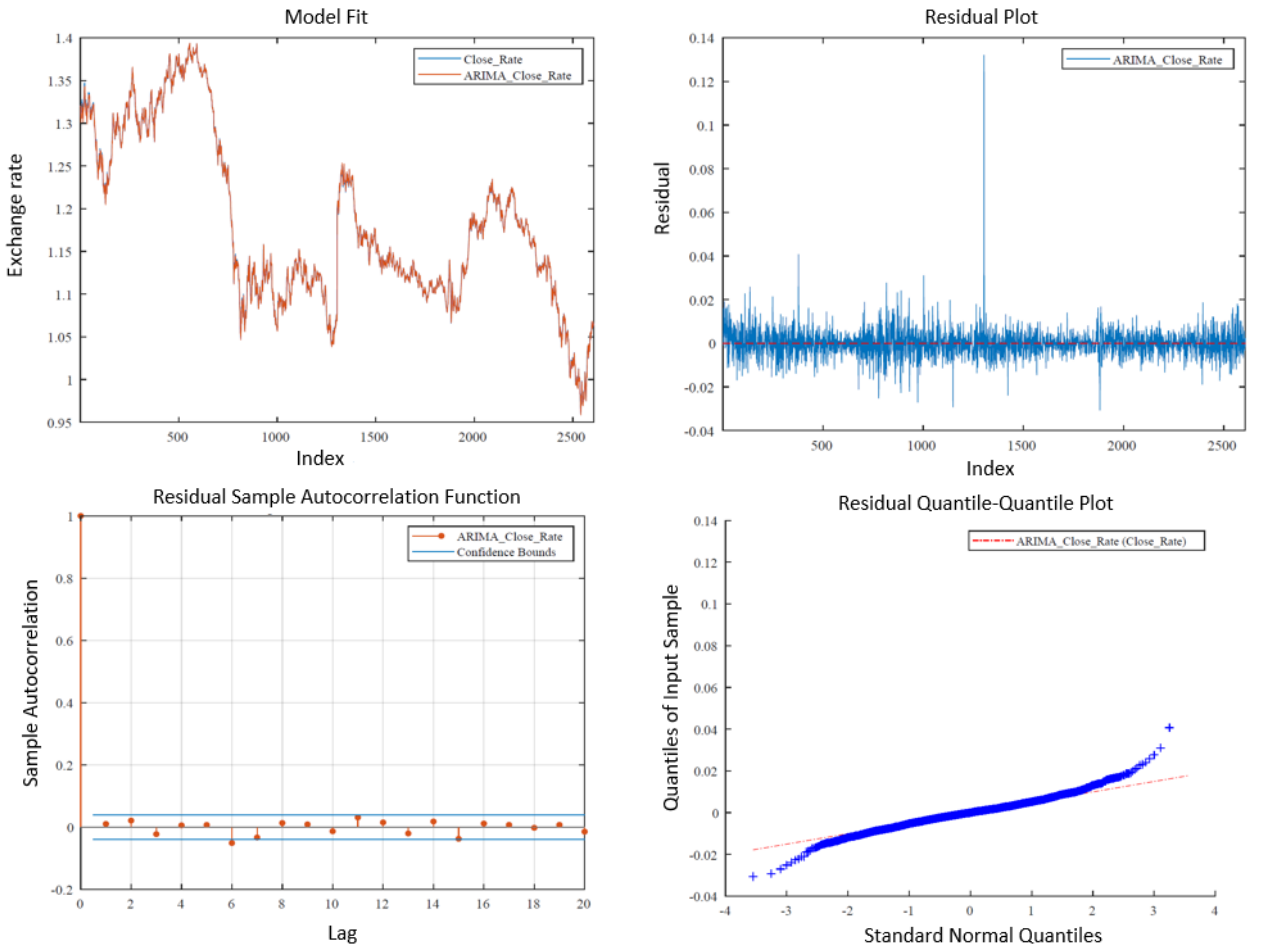

Figure 10: The ARIMA (2,2,2) model fit, residual plot, residual sample ACF, and residuals Quantile-Quantile plot for EUR/USD. (MATLAB, 2023)

Figure 10 displays the model fit for the EUR/USD ARIMA (2,2,2) model and this plot shows that the model fits well to the time series. The residual plots are beneficial to observe if the model has properly captured the details from the data. (Castle et al., 2021) The Residual plot, Residual Sample ACF plot, and Residual Quantile-Quantile plot display in Figure 10 that the residuals are uncorrelated and normally distributed (MathWorks, 2023f).

Table 4: The estimation results and goodness of fit with AIC and BIC criteria for EUR/GBP. (MATLAB, 2023)

EUR/GBP (p,d,q)	**AIC**	**BIC**	**Estimation results ARIMA (0,2,0)**				
ARIMA(0,0,0)	-8.1664e+03	-8.1546e+03	Parameter	Value	Standard Error	t Statistic	P-Value
ARIMA(0,1,0)	-2.0310e+04	-2.0298e+04	Constant	-1.5221e-08	0.00016282	-9.3483e-05	0.99993
ARIMA(1,0,0)	-2.0314e+04	-2.0296e+04	Variance	6.0867e-05	1.7513e-07	347.5483	0
ARIMA(1,1,0)	-2.0389e+04	-2.0371e+04	**Equation of ARIMA(0,2,0):**				
ARIMA(1,0,1)	-2.0389e+04	-2.0366e+04					
ARIMA(1,1,1)	-2.0387e+04	-2.0363e+04					
ARIMA(0,2,0)	-1.8064e+04	-1.8053e+04	$(1-L)^2 y_t = c + \varepsilon_t$				
ARIMA(2,2,2)	-2.0373e+04	-2.0338e+04					
ARIMA(2,1,2)	-2.0382e+04	-2.0347e+04					
ARIMA(3,2,3)	-2.0379e+04	-2.0332e+04					

The estimation results for the EUR/GBP model are shown in Table 4. The best ARIMA (p, d, q) model can be found and chosen with the lowest goodness of fit measures according to Khan and Gupta (2020) and the ARIMA (0,2,0) model has the best goodness of fit via AIC and BIC information criteria.

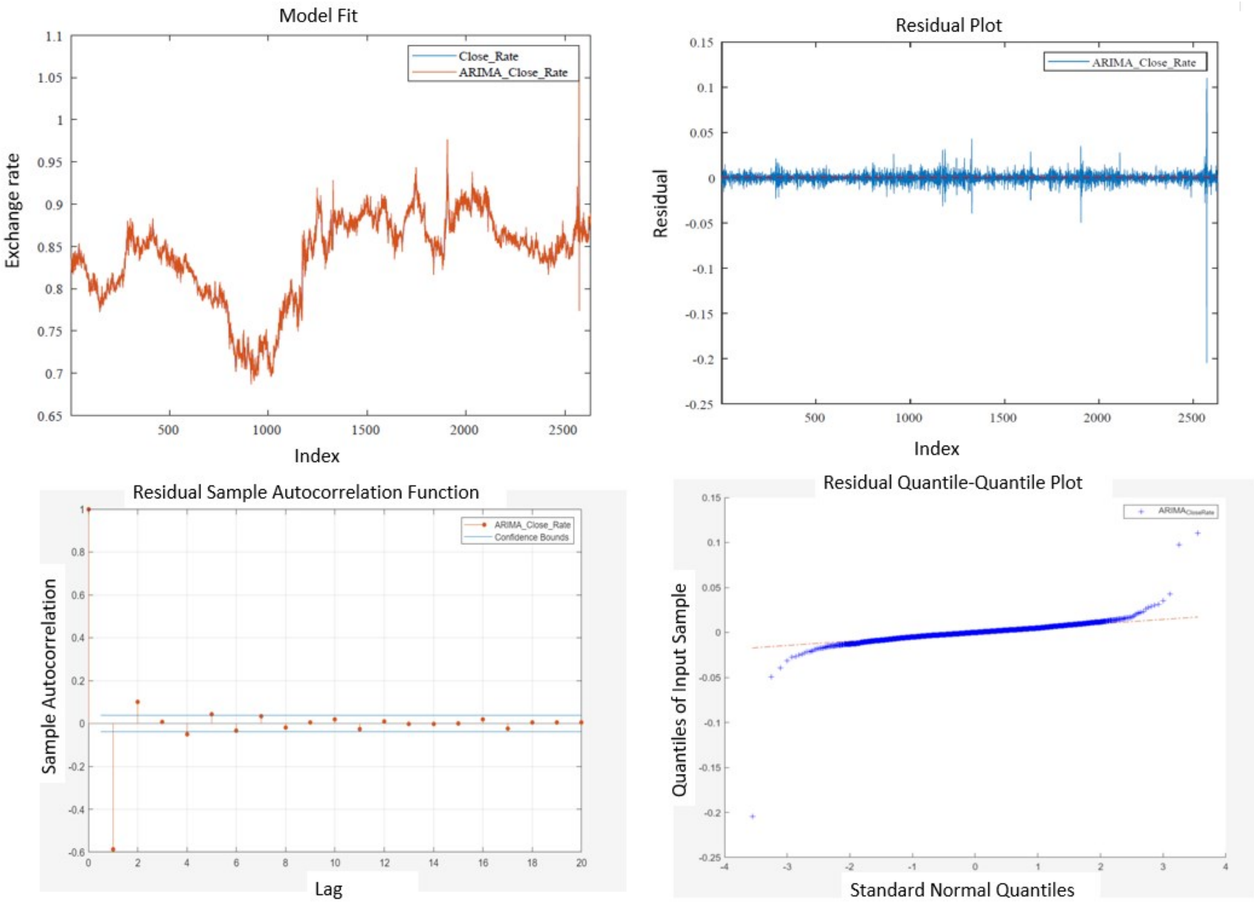

Figure 11: The ARIMA (0,2,0) model fit model fit, residual plot, residual sample ACF, and residuals Quantile-Quantile plot for EUR/GBP. (MATLAB, 2023)

Figure 11 displays the model fit for the EUR/GBP ARIMA (0,2,0) model and this plot shows that the model fits well to the time series. The residual plots are beneficial to observe if the model has properly captured the details from the data. (Castle et al., 2021) The Residual plot, Residual Sample ACF plot, and Residual Quantile-Quantile plot display in Figure 11 that the residuals are uncorrelated and normally distributed (MathWorks, 2023f)

4.5 Comparison of NARNN and ARIMA models

In this part of the empirical study, the overall results from the NARNN model and ARIMA model will be presented and compared for both currency pairs with performance measures of MSE and RMSE. The forecasted future development outside of the research timeframe will be presented as well.

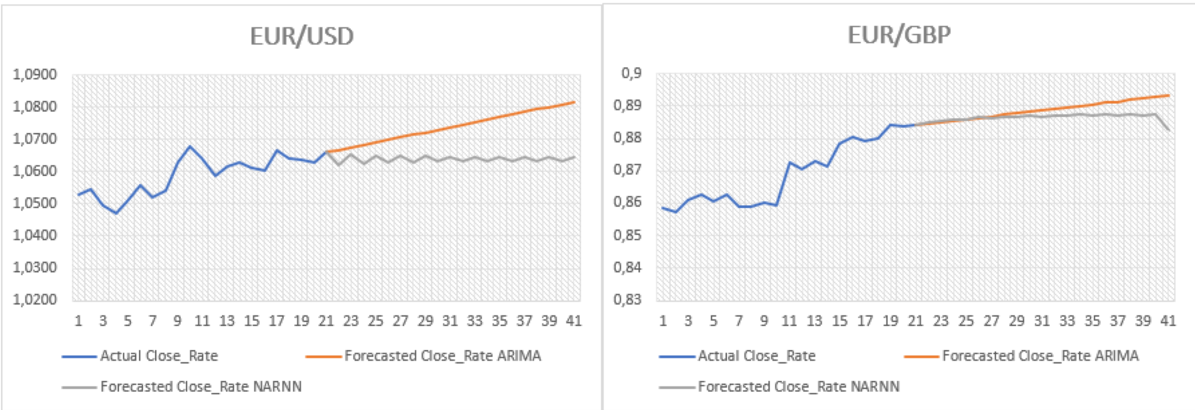

Figure 12: The last 20 days of the actual closing rate and 20-future timestep forecast with the ARIMA and NARNN model for EUR/USD and EUR/GBP.

Figure 12 demonstrates the actual closing rate for the EUR/USD and EUR/GBP currency exchange rate for the last 20 days within the research timeframe, and additionally the future development of the desired exchange rate movement with the ARIMA model and NARNN model.

Table 5: The overall performance of the models for EUR/USD and EUR/GBP.

Model	Currency pair	MSE	RMSE
ARIMA	EUR/USD	0,00004252	0,006521
NARNN	EUR/USD	0,00004154	0,006445
Model	**Currency pair**	**MSE**	**RMSE**
ARIMA	EUR/GBP	0,00006079	0,007797
NARNN	EUR/GBP	0,00002492	0,004992

Table 6 presents the overall performance of the ARIMA model and the NARNN model for the currency pair of EUR/USD. Both models have performed very well based on low MSE value and low RMSE value. According to these performance measures, the NAR model has performed better than the ARIMA model for both the EUR/USD and EUR/GBP currency pairs. The difference between the models in EUR/USD is minimal but the difference between the models in EUR/GBP is striking in this instance.

5 Conclusions

The purpose of this study was to investigate the predictability of currency exchange rates between the selected currency pairs which in this study were selected between EUR/USD and EUR/GBP currency pairs. The NAR and ARIMA models were constructed in MATLAB using the data of the selected currency pairs with the timeframe of the beginning of 2013 to the end of 2022. The selected evaluation variable from both currency pairs to the models was the daily closing rate price.

The main objective of this research was to discover the use and effectiveness of neural networks for forecasting historical exchange rates and compare the performance of the selected neural network model with another traditional statistical time series model. The research is driven by the hypothesis that carefully selected and constructed models (NAR and ARIMA) can be used to form future development and trends from forecasting currency exchange rate movements based on historical exchange rate data. The secondary objective was to examine and investigate the usefulness of the information gained from the models in forecasting the exchange rate movements in the context of the Efficient Market Hypothesis in forex markets. The research questions below were answered by utilizing the literature review and empirical study with the comparison of the NAR and ARIMA models and the performance measured both individually and collectively for comparison. The questions:

1. In what ways can neural networks be effectively employed in forecasting currency exchange rates?

2. How does the chosen NAR neural network model perform compared to the ARIMA model in forecasting currency exchange rates?

3. To what extent the information from currency exchange rate forecasting developed from the NAR and ARIMA models can be useful in the light of EMH theory in the forex market?

As the literature review and empirical study of this research shows the neural networks can be utilized to forecast future developments and trends of currency exchange rate based on the historical exchange rate data. The selected neural network model of the NARNN can adapt and analyze the given exchange rate data. The results gained in this research from the empirical study part of this thesis show that both models NARNN and ARIMA can learn the movements of historical exchange rates and predict future values based on the performance measures used in the models.

The comparison results between the models in the empirical study displayed that the NARNN model performed better for both currency pairs according to performance measures. This result supports the findings from previous research on forecasting exchange rates by utilizing neural networks and comparing their performance with traditional statistical time series models like the ARIMA model according to Babu and Reddy (2015). These results are also consistent with previous studies on how traditional statistical forecasting techniques have met their limits with nonlinear data, such as stock index forecasting, and neural network technology has shown its strength when it comes to nonlinear data related to classification, identification, and prediction according to Adewole et al. (2019)

As the forex market is the most liquid structure across all sectors of markets, this has led to the conclusion that exchange rates are exceedingly challenging to predict and the functionality of the model is equivalent to a random walk model (Ullrich, 2009, 7). Utilizing especially the applications of neural networks and statistical time series models as in this study makes it possible to identify events that have influenced exchange rate movements in history, from which these models could learn similarities and trends as models are fed data and models are learned to recognize data. The information obtained from the forecasted future developments of rates from the models can be considered as a useful alternative tool to reduce risk and maximize return when different entities in the foreign exchange market are trying to make future predictions about foreign exchange rates. Especially when the used models of neural networks and other time series forecasting methods can adapt and fit the historical data almost perfectly. This finding challenges EMH theory with the random walk and technical analysis with the mediocre form of the EMH according to the earlier studies and disagreements among researchers with the correctness of EMH (Diamond and Perkins, 2022; Sandubete et al., 2023; Vukovic, 2013).

The use of Neural Networks and other statistical time series forecasting methods is quite a complex and difficult task for making predictions from the historical exchange rates. Both models require a lot of mathematical-, programming-, and computational skills. Because of these challenging skills, utilities were used in this research, such as a deep learning toolbox and an econometric toolbox with a modeler app to construct the NARNN model and ARIMA model. More accurate and better results can be available from models and forecasts if the models are fully programmed without utilities. The accuracy of the results may be disrupted by the challenging nature of the foreign exchange market and the difficulty of making predictions.

For future research, it is recommended to continue the investigation of foreign exchange rate forecasting. Although the NARNN and ARIMA models managed to build predictions and the models adopted historical exchange rate data, it should be noted that the accuracy of the predictions can be questioned and therefore it is good to do further research on how reliable the predictions are. Further studies could include more variables inside the data so that the results of the models are as accurate as possible. The future investigation should include different methods with Neural networks and traditional forecasting methods for time series for example the applications of recurrent neural networks with long short-term memory (LSTM). The hybrid models with a combination of different methods are fascinating in the field of forecasting exchange rates. This may include both machine learning and deep learning algorithms combined with traditional forecasting methods for example ARIMA-NN or NN-Generalized Auto-Regressive Conditional Heteroskedasticity (GARCH) hybrid model or Support Vector Machines (SVM).

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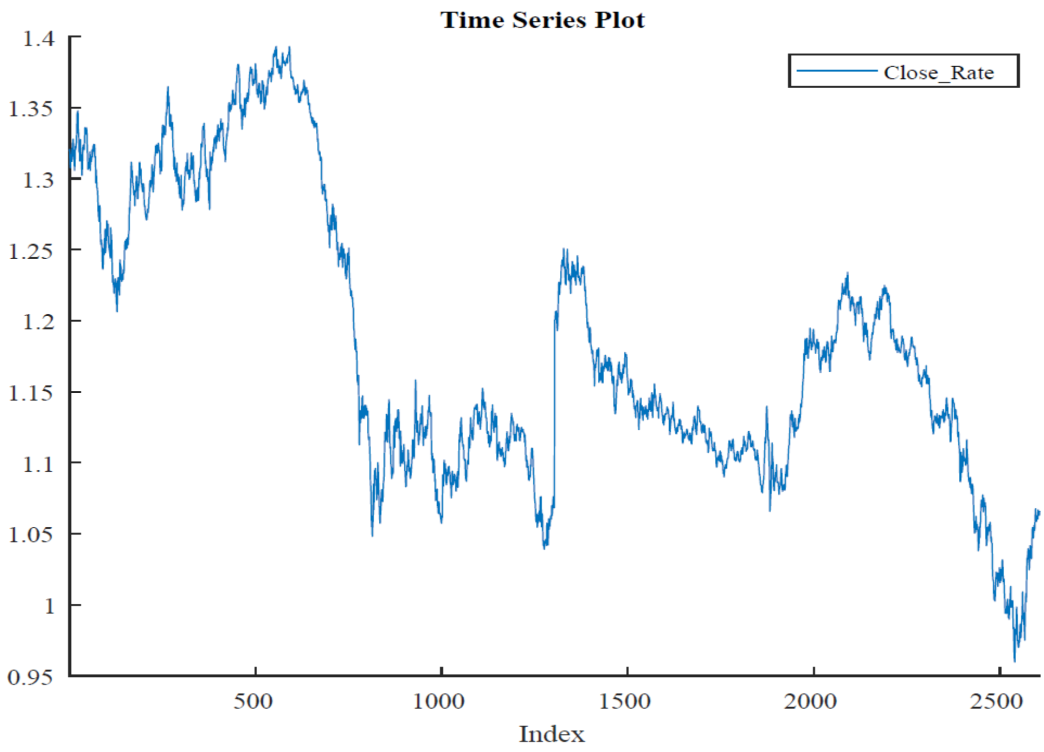
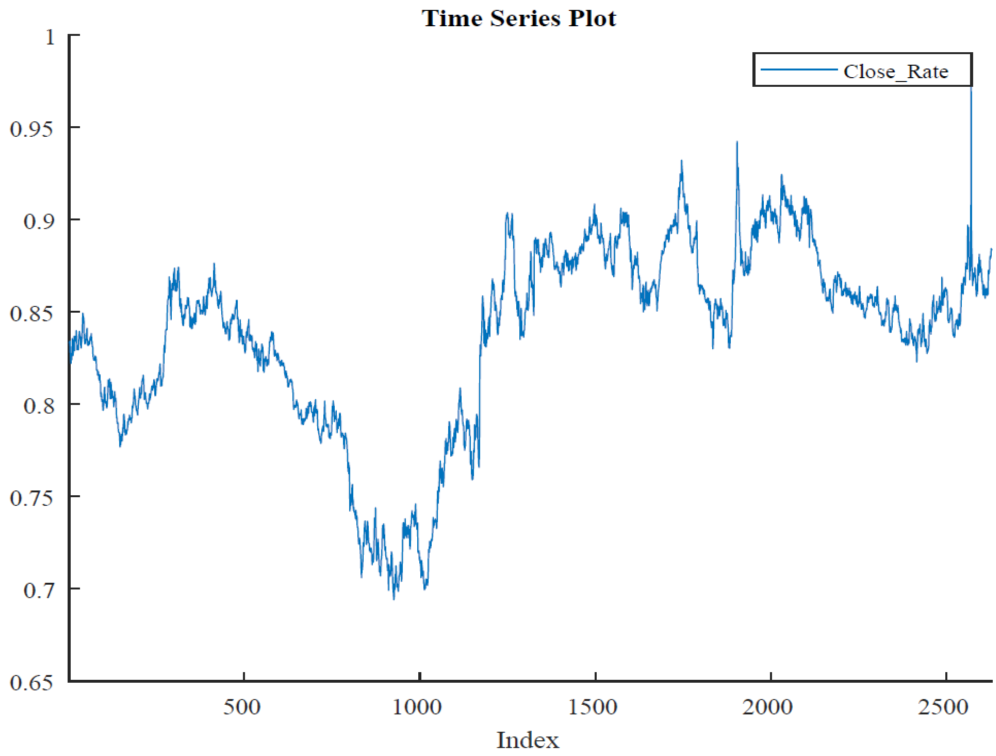
Appendices

Appendix 1. EUR/USD and EUR/GBP historical currency exchange closing rate charts.

EUR/USD.

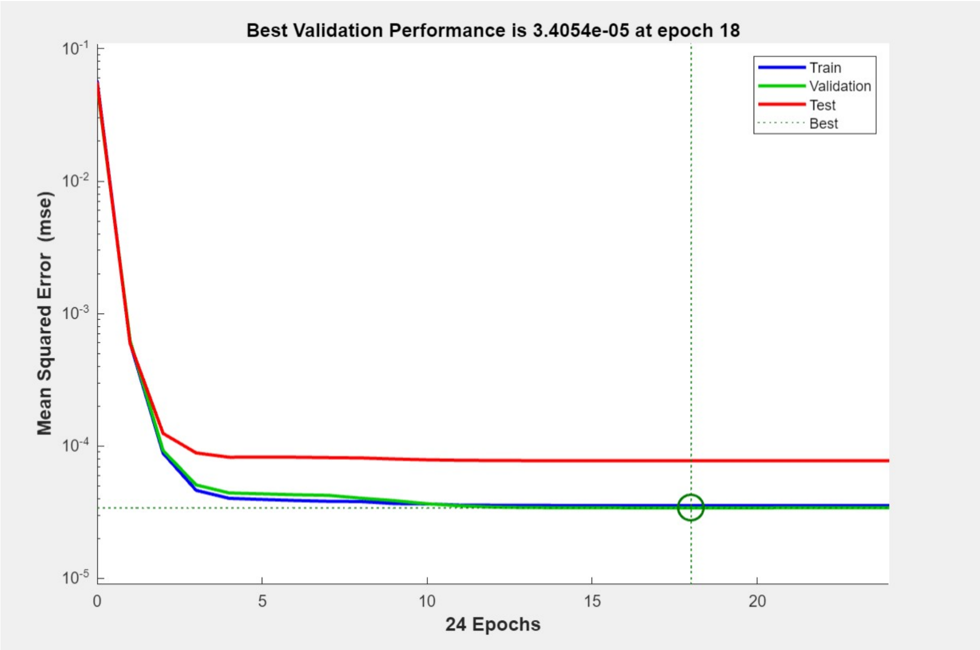


EUR/GBP.

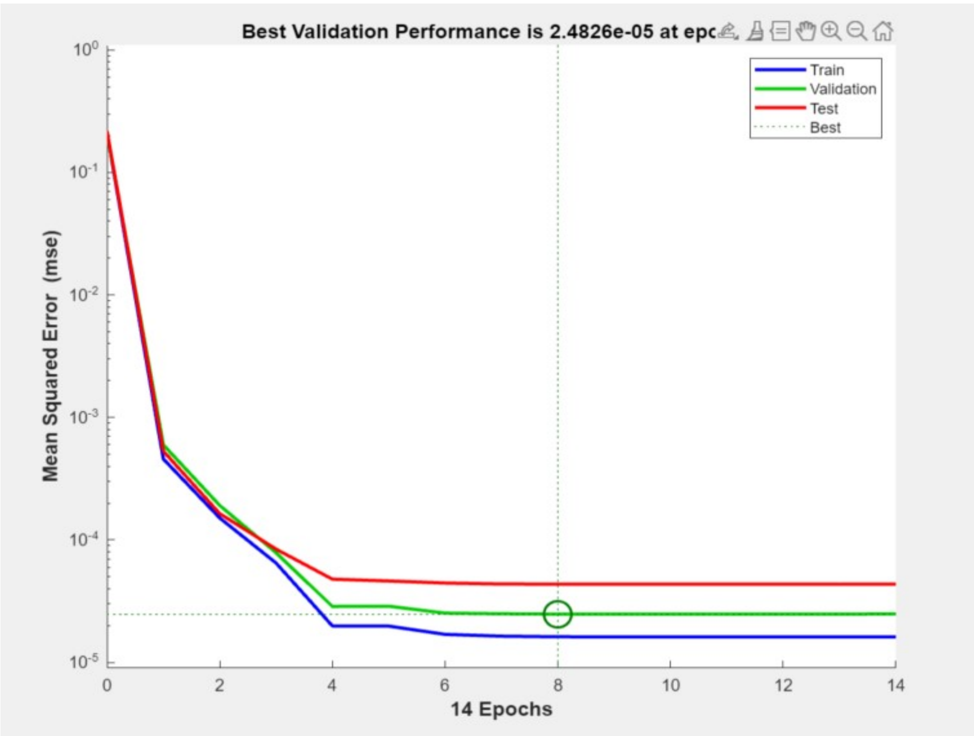

Time Series Plot
Close_Rate
1
0.95
0.9
0.85
0.8
0.75
0.7
0.65
500
1000
1500
2000
2500
Index

Appendix 2. The performance chart for MSE in the NARNN model.

EUR/USD.

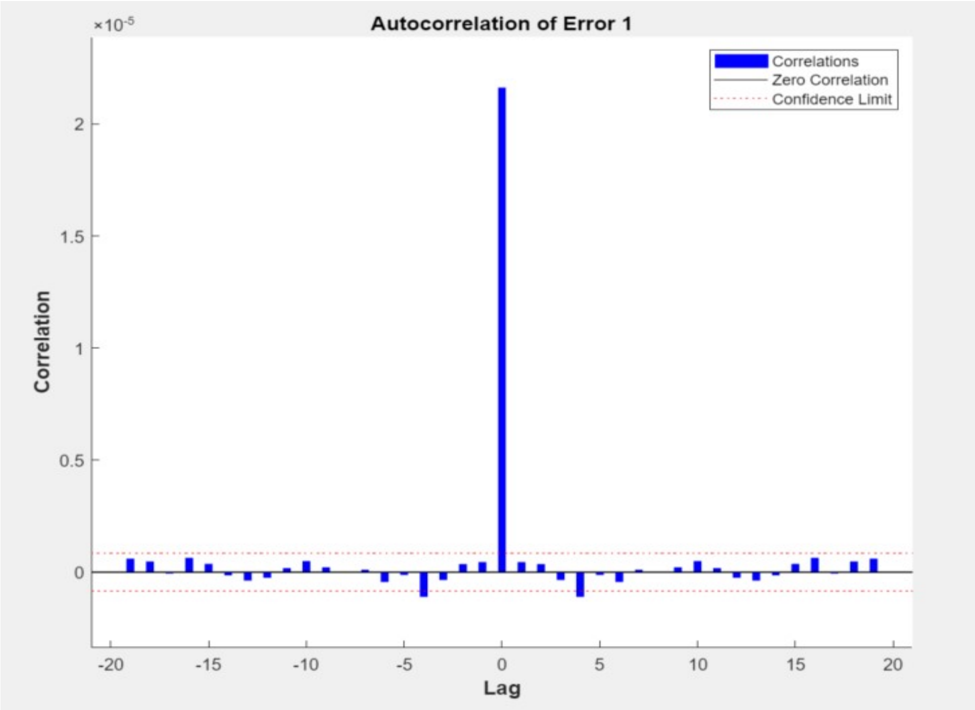


EUR/GBP.

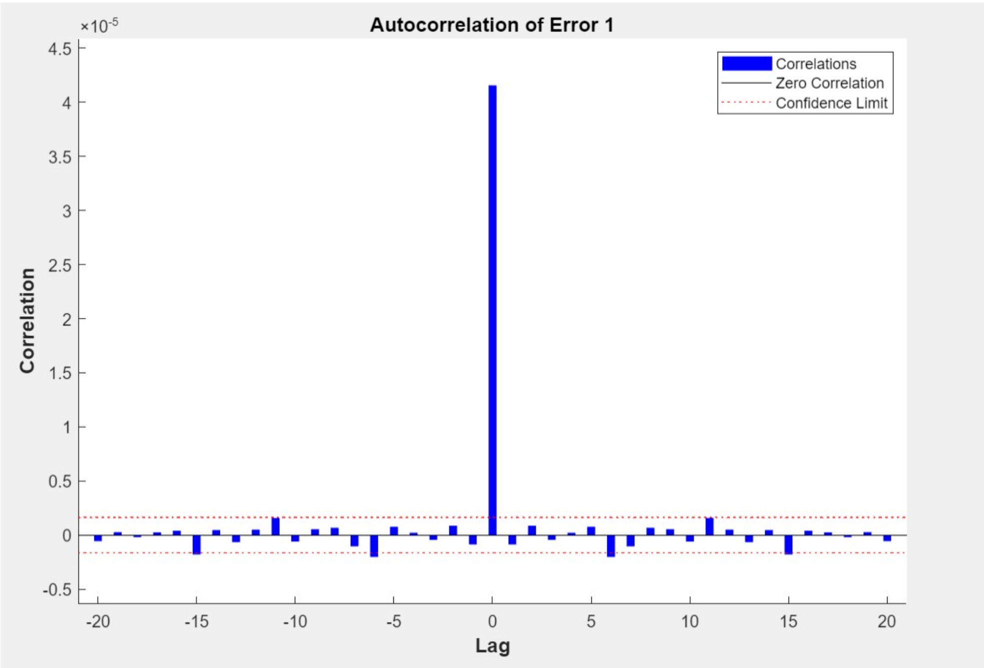


Appendix 3. The error autocorrelation results in the NARNN model.

EUR/USD.



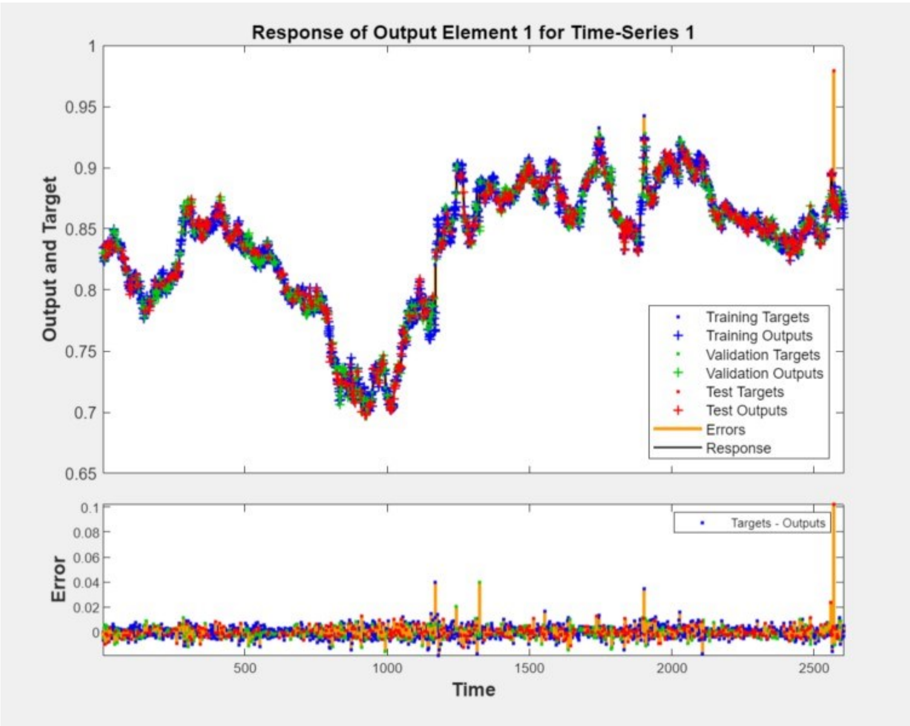
EUR/GBP.



Appendix 4. The response chart of the training, validation, and testing in NARNN.

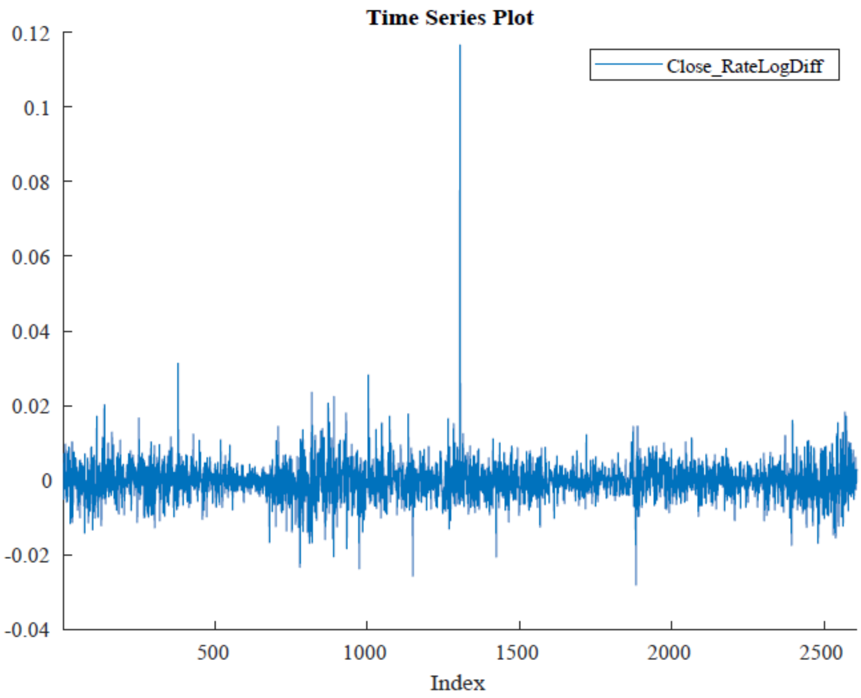
EUR/USD.

EUR/GBP.

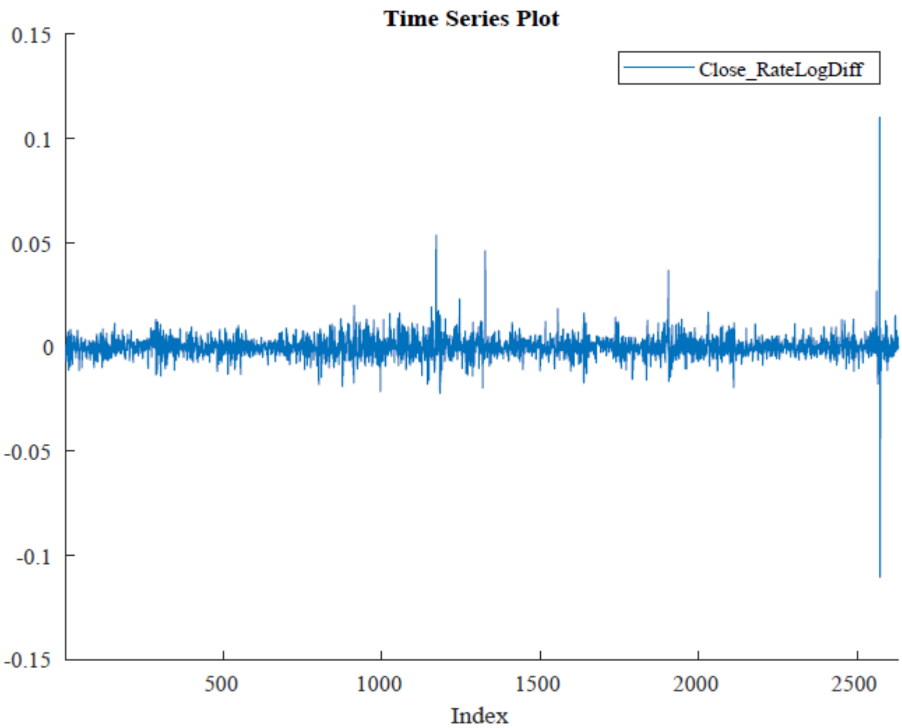


Appendix 5. The logarithmic and first-order difference in ARIMA model time series charts.

EUR/USD.



EUR/GBP.



Appendix 6. The self-written code in rows 148-155 is marked in red for the NARNN model.

```
125 % See the help for each generation function for more information.
126 if (false)
127     % Generate MATLAB function for neural network for application
128     % deployment in MATLAB scripts or with MATLAB Compiler and Builder
129     % tools, or simply to examine the calculations your trained neural
130     % network performs.
131     genFunction(net,'myNeuralNetworkFunction');
132     y = myNeuralNetworkFunction(x,xi,ai);
133 end
134 if (false)
135     % Generate a matrix-only MATLAB function for neural network code
136     % generation with MATLAB Coder tools.
137     genFunction(net,'myNeuralNetworkFunction','MatrixOnly','yes');
138     x1 = cell2mat(x(1,:));
139     xi1 = cell2mat(xi(1,:));
140     y = myNeuralNetworkFunction(x1,xi1);
141 end
142 if (false)
143     % Generate a Simulink diagram for simulation or deployment with.
144     % Simulink Coder tools.
145     gensim(net);
146 end
147
148 [Xs,Xi,Ai,Ts] = preparets(net,{},{},T);
149 net = train(net,Xs,Ts,Xi,Ai);
150 view(net)
151 [Y,Xf,Af] = net(Xs,Xi,Ai);
152 perf = perform(net,Ts,Y)
153 [netc,Xic,Aic] = closeloop(net,Xf,Af);
154 view(netc)
155 Yc = netc(cell(0,20),Xic,Aic)
156
```

Appendix 7. The self-written code in rows 16-24 is marked in red for the ARIMA model.

```
1  function ARIMA_Close_Rate = modelTimeSeries(ARIMAEURGBPDATA)
2  %%Time Series Modeling Using the Econometric Modeler
3  % This code recreates the estimated model produced in the Econometric Modeler app. Use the code below to estimate the same model,
4  %
5  %Input: A table with the same variables as the table imported into the app (ARIMAEURGBPDATA)
6  %
7  %Output: The model containing estimated parameters (ARIMA_Close_Rate)
8  %
9  %Auto-generated by MATLAB (R2023b) and Econometrics Toolbox Version 23.2 on 30-Nov-2023 20:18:12
10 Close_Rate = ARIMAEURGBPDATA.Close_Rate;
11
12 %% Autoregressive Integrated Moving Average Model
13 %Estimate an ARIMA Model of Close_Rate
14 ARIMA_Close_Rate = arima('Constant',NaN,'ARLags',[],'D',2,'MALags',[],'Distribution','Gaussian');
15 ARIMA_Close_Rate = estimate(ARIMA_Close_Rate,Close_Rate,'Display','off');
16
17 %Forecasting data
18 [ARIMA_Close_Rate_Forecast_Future20values] = forecast(ARIMA_Close_Rate,20,'Y0',Close_Rate)
19
20 disp(ARIMA_Close_Rate)
21 %Infer ARIMA_Close_Rate residuals to calculate MSE
22 residuals = infer(ARIMA_Close_Rate, Close_Rate);
23 disp(residuals)
24
25 end
26
```