

Contributions to Finance and Accounting

Musa Gün
Burcu Kartal *Editors*

Machine Learning in Finance

Trends, Developments and Business Practices in the Financial Sector

Springer

Contributions to Finance and Accounting

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ISSN 2730-6038 ISSN 2730-6046 (electronic)
Contributions to Finance and Accounting
ISBN 978-3-031-83265-9 ISBN 978-3-031-83266-6 (eBook)
https://doi.org/10.1007/978-3-031-83266-6

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Preface

The integration of machine learning into the dynamic and rapidly evolving field of finance has ushered in a new era. In this book, we aim to explore the impact of machine learning on financial applications and provide insights into how advanced techniques are transforming the industry.

Machine learning has attracted the financial industry's attention due to its ability to analyze large amounts of data and apply different analyses than traditional methods. Machine learning applications, such as financial transformation, portfolio optimization, digital currencies, and exchange rate forecasting, are vast and constantly expanding.

This book is designed for finance professionals, data scientists, students, and those who want to understand the implications of machine learning algorithms in finance. We provide theoretical foundations and practical insights, making complex concepts accessible to readers with different levels of expertise.

We are extremely grateful to the many individuals and organizations that supported our efforts. We would like to thank our family and friends whose encouragement and feedback helped to shape this work. And, we are especially grateful to our colleagues for sharing their invaluable expertise in finance and machine learning algorithms.

The book is enriched by the contributions of researchers who have integrated machine learning into finance. Their pioneering efforts and innovative ideas have created a rich body of knowledge.

We would also like to thank the first readers and reviewers for their constructive criticisms. Their different perspectives have enriched the content of the book.

Please take a critical and enquiring approach when analyzing the papers. The field of machine learning in finance is still in its infancy, and there is much to explore and discuss. We believe that when those working in this field interact, this field will develop.

It is thought that the book will make a serious contribution to the literature. We dedicate the book to anyone who wants to harness the potential of machine learning in finance. And we wish it to be a valuable resource and source of inspiration.

Rize, Türkiye

Musa Gün
Burcu Kartal

Acknowledgments The authors would like to thank their families for their help and patience during the writing of this book. Their support was instrumental in making this book a reality.

The authors also acknowledge the valuable contribution of the reviewers in improving the quality, consistency, and content presentation of the chapters.

About This Book

The aim of this book is to identify important issues related to the use of machine learning algorithms in finance.

For this purpose, all different perspectives of finance, such as financial transformation, portfolio optimization, digital currencies, and exchange rate forecasting, are analyzed with machine learning algorithms. By focusing on different perspectives, it may be possible to produce more appropriate strategies for the development of finance with machine learning algorithms.

Finance makes a significant contribution to the development of economies. Machine learning algorithms will also contribute to the development of finance and improve economies. The target audience and potential users of this book are defined below.

- Researchers
- Academics
- Policymakers
- Government officials
- Senior executives of companies

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A Comparative Analysis of Artificial Neural Networks and Time Series Models in Exchange Rate Forecasting



Emre Ürkmez

Abstract This study aims to compare the performances in intra-period forecast values of the exchange rate, which is one of the classic linear time series models, ARIMA model, and one of machine learning methods, artificial neural network models. This study uses monthly data for the USD/TRY exchange rates for Turkey over the period from January 2010 to October 2024. Exchange rates are sensitive to unexpected events and political uncertainties in the economy. It is, therefore, highly considerable that the estimation of the future values of exchange rates is important to central banks and companies concerning risk management. ARIMA is a linear univariate time series model that makes in-sample and/or out-of-sample value estimates based on the AR and MA components in the relevant time series data. ARIMA models are models based on a linear component of past data that makes estimates and can yield statistically reliable results. However, all these models are based on the assumption of data having a linear structure and do not give successful results in estimates against nonlinear series. In the literature, it was indicated that the ANN model is more successful than ARIMA models in capturing and predicting the nonlinear structure of the data structure. Since the USD/TRY exchange rate might have a nonlinear structure due to this fact, the use of the ANN model, methods were preferred in this study. According to the empirical findings in the study, the intra-period forecast values obtained with the ANN model on the USD/TRY exchange rate were determined to be more successful than the ARIMA model according to the forecast performance criteria.

Keywords ANN · ARMA · Exchange rate · Finance · Forecasting · Machine learning

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M. Gün and B. Kartal (eds.), *Machine Learning in Finance*, Contributions to Finance and Accounting, https://doi.org/10.1007/978-3-031-83266-6_5

1 Introduction

Since the 1970s, starting from developed countries, a floating exchange rate regime has been adopted and later adopted by developing countries, leading to a rapid growth in world trade volumes, and foreign exchange markets have undergone significant expansion. As the main determinants of international trade, exchange rates play a critical role in shaping the import–export sectors in particular (Kamruzzaman and Sarker 2004). For example, when the US Dollar gains value against the Turkish Lira, firms located in the US can procure Turkish goods and services at a more affordable cost. This increases Turkey's exports to the US and leads to a decrease in its imports. On the other hand, when the US Dollar loses value against the Turkish Lira, goods and services imported from the US become more affordable for firms and households located in Turkey. This increases Turkey's imports to the US and other countries. As a result, an increase or decrease in exchange rates may lead countries to seek alternative trading partners, and this may reflect the profound effects of permanent changes in exchange rates on trade flows and market decisions (McKenzie 2002; Hau and Rey 2005).

International trade relations are inherently dependent on the exchange rate parity of countries' local currencies against other countries' currencies due to the costs associated with exports and imports (Faini and Melo 1990; Lane and Ferretti 2002). Although international trade agreements vary from short-term agreements to long-term commitments, exchange rates fluctuate continuously at all times during the days and hours when foreign exchange markets are open. Therefore, accurate estimation of exchange rates is important for firms, investors, and financial institutions engaged in international trade. Accurate exchange rate estimations contribute to effective risk management by enabling each market participant to make price optimizations (Levich 1985; Papaioannou 2006).

Despite the volatility and uncertainty of exchange rate price movements, exchange rate forecasting has led to the development of a variety of forecasting methods, from classical univariate time series forecasting models to machine learning methods and artificial neural networks. These methods reflect the efforts of researchers and international firms to forecast exchange rate price movements and are important to the critical role of market makers in maintaining international trade and financial stability.

There are some difficulties in making reliable estimates of financial time series. Contrary to the assumptions of traditional econometric methods, financial time series are not normally distributed (Brooks 2019). The distribution of financial time series generally deviates from the normal distribution due to the thickness and extreme sharpness of the tails. The thickness of the tails corresponds to the points where there are extreme, large price movements in the financial time series. In contrast, extreme sharpness indicates that extreme values in the financial time series are expected with a higher probability. Extreme values in financial time series correspond to periods of high volatility (Brooks 1998). Since financial time series have these two properties, they exhibit leptokurtic distribution (Carol 2009; Yavuz 2014). Therefore, the

distribution of financial time series tends to exhibit distribution properties that are more pointed on average and fatter in the tails than the normal distribution. Due to these properties, working with univariate time series models may not be suitable for making accurate and reliable estimates (Clements and Hendry 2000).

The autoregressive integrated moving average (ARIMA) model, which forms the basis of traditional time series analysis, is the most widely used linear forecasting method. The stationarity of ARIMA models depends on the stationarity of the autoregressive part of the model. It is assumed based the assumption on that the time series under study has a linear structure. These assumptions model the series under study through the autoregressive (AR) and moving average (MA) components of the ARMA model and obtain effective estimates (Zhang 2003). If the mean and variance of the time series under study change over time and are not linear, the applicability and effectiveness of the ARMA model are significantly weakened. In the studies conducted in the literature, exchange rate data exhibit a nonlinear and chaotic structure. Deviations from these basic assumptions make it inappropriate to work with the ARMA models (Moosa 2000; Spyros and Nikolas 2016). This situation requires alternative forecasting techniques that can better accommodate the non-linear and chaotic features of volatile financial data sets, especially exchange rates.

Considering this disadvantageous situation of the ARMA models, in recent years' financial time series have been estimated using artificial neural networks (ANN) models with machine learning methods. The ANN models, known for modeling nonlinear structures and adapting to high-frequency series, offer an alternative to the ARMA models, which are traditional forecasting methods. This study aims to compare the performances in intra-period forecast values of the exchange rate, which is one of the traditional linear time series models, the ARMA model, and one of the machine learning methods, artificial neural network (ANN) models. For this purpose, the USD/TRY exchange rate is estimated separately for both models and the forecasting performance criteria are taken into consideration and it is analyzed which model has better forecasting performance.

The remaining part of this study is organized in four parts: the second section summarizes the literature studies and findings about the data on the exchange rate; the third section presents the data of the USD/TRY exchange rate used in the analysis and then explains the traditional time series model of ARMA and the machine learning method of ANN. Second, in the chapter, the forecasting performance measures are briefly summarized to evaluate the effectiveness of two different alternative models used within the study. The findings obtained from both the ARMA and ANN models are presented and interpreted in the fourth section. Lastly, the findings of the study are evaluated and discussed in the fifth section. The limitations are also discussed, and further studies are recommended.

2 Literature Review

The studies in the literature have examined that it is seen that machine learning methods are used less in exchange rate forecasting than traditional time series forecasting models. The ANN models have significant advantages over traditional forecasting methods. ANN models are successful in solving and predicting nonlinear structures where ARIMA models are inadequate. ANN models do not make any assumptions about the statistical distribution of the data. This makes ANN models flexible and powerful models in the presence of missing data and outliers. In addition, ANN models differ from traditional methods by continuously learning from data and improving predictive performance.

This study only includes studies where exchange rates are estimated with the ANN models. Franses and Homelen (1998) aimed to model and forecast four exchange rate returns with respect to the Dutch guilder using ANN models. Simulations showed that neglecting the GARCH effect did not produce successful ANN results and that ANNs would use nonlinear structures other than GARCH to improve forecasts. They found that the forecasting performance of ANNs was not strong in the sample data. These results indicated that the nonlinear structure in exchange rates was most likely due to GARCH and suggested that ANNs could be used to diagnose average nonlinearity. Kamruzzaman and Sarker (2004) examined neural network models based on three learning algorithms: Standard Backpropagation (SBP), Scaled Conjugate Gradient (SCG), and Bayesian Regularized Backpropagation (BPR) for forecasting exchange rates against the Australian dollar. Using five technical indicators, they found that the SCG model outperformed two measures and performed comparably to BPR in the remaining three, demonstrating that effective forecasts can be achieved with basic technical indicators. According to Panda and Narasimhan (2007), the ANN model follows the step forward in predicting the weekly INR/US Dollar exchange rate. In this study, the precision of a neural network was compared against traditional linear autoregressive moving average models. The neural network outperformed other models for both in-sample and out-of-sample predictions based on six different evaluation criteria. These results provide evidence against the efficient market hypothesis and suggest that hidden information in exchange rates can be used in future predictions. Kadılar et al. (2009) suggested using the ANN for the high volatility Turkish Lira/US Dollar exchange rate series in their study and the results showed that the ANN provides the highest forecast accuracy compared to seasonal ARIMA and ARCH time series models. They also provided detailed suggestions on the use of the ANN in Turkish exchange rate forecasting. Pradhan and Kumar (2010) apply the ANN model for the forecast of the foreign exchange for India. The study used on Euro, US Dollar, Japanese yen, and British pound for daily and monthly data. The measures of forecast error are considered while assessing the performance of the forecast such as RMSE, MAE, MAD, and MAPE. Their findings suggest that ANN is a viable option when conducting forecasts of the exchange rate. By using a monthly data set between January 2000 and September 2014, Aydın and Cavdar (2015) estimated the USD/TRY exchange rate, gold price, and the BIST 100

index, some of the key macroeconomic variables. ANN and VAR models were used in this study. The estimated results of the ANN model indicated that the financial crisis in the BIST 100 index and the USD/TRY exchange rate may start in October 2017 excluding gold price. The findings concluded that the ANN model gave better prediction values than the VAR model, even though there were financial crises in the analyzed period. Kristjanpoller and Hernandez (2017) analyzed the series of silver, gold, and copper spot prices between September 7, 1999, and May 20, 2014, using daily data. In the study, they estimated the volatility of the returns of three precious metals using a hybrid neural network and GARCH-type models while analyzing the series. The findings concluded that only the hybrid neural network model successfully estimated the volatility of the returns of the spot prices of three precious metals. Sun et al. (2020) analyzed the time series data of four major currencies, that is, the US Dollar against the Japanese Yen, Chinese Yuan, British Pound, and Euro, using daily data from January 3, 2011 to December 29, 2017. The findings showed that the Bagging-based LSTM (LSTM-B) ensemble deep learning approach made better predictions than alternative models in forecasting exchange rates. Chen et al. (2021) investigated if the economic and technological determinants might serve to generate accurate predictions of Bitcoin exchange rates. They applied ANN and Random Forest methods to judge the importance of those determinants and reviewed Bitcoin exchange rate predictions by using other models like ANFIS, ARIMA, SVR, and LSTM. From their results, it was perceived that economic and technological determinants effectively affected or influenced Bitcoin exchange rate estimations in various periods. Charef (2024) has suggested the use of the ANN-GARCH model to estimate daily exchange rate return volatility. The results showed that the ANN-GARCH model could be an alternative to a conventional linear autoregressive model.

In the literature, the works involving machine learning methods in the prediction of exchange rates against the Turkish Lira are minimal. In the present study, using the monthly data from 2010 through 2024, an in-sample forecast of the exchange rate of the USD/TRY for Turkey was realized. In this study, two different models, which are the ANN model representing machine learning methods and the ARIMA model, a traditional times series model, have been used. In this regard, the current USD/TRY exchange rate data was used to compare the intra-period prediction performances estimated by two different alternative forecast models to reinforce the related studies.

3 The Data and Methodology

3.1 The Data

In this study, intra-period estimates of the USD/TRY exchange rate (ER) were made using a monthly dataset for Turkey over the period from January 2010 to October 2024. The USD Dollar Turkish Lira exchange rate data set used in the study was collected from Trading Economics.

3.2 The Methodology

In this section of the study, firstly the ARIMA model, which is one of the linear time series models, is explained. Then, an alternative forecasting method, machine learning, and the ANN model are given. Finally, for the comparison, the achievements of these two different forecasting methods, the Absolute Error (MAE), Mean Square Error (MSE), and Root Mean Square Error (RMSE) forecasting error performance measures used in the study are briefly summarized.

3.2.1 ARIMA Models for Classical Time Series Model

The autoregressive integrated moving average (ARIMA) model, which is frequently used in classical linear time series models consists of two components: autoregressive AR(p) and moving average MA(q). The AR(p) component models the relationship between a series' lag length and its past values, and the MA(q) component models the relationship between a series' lag length and the error squares. The model could be written as follows (Brooks 2019: 351–352):

$$\phi(L)y_t = \mu + \theta(L)u_t \tag{1}$$

where,

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

$$\phi(L) = 1 + \theta_1 L + \theta_2 L^2 + \cdots + \theta_q L^q \tag{3}$$

or

$$y_t = \mu + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \theta_1 u_{t-1} + \theta_2 u_{t-2} + \cdots + \theta_q u_{t-q} + u_t \tag{4}$$

with

$$E(u_t) = 0;\ E\left(u_t^2\right) = \sigma^2;\ E(u_t u_s) = 0,\ t \neq s \tag{5}$$

Equation 5, assumes that the mean of the error term is randomly distributed around zero, its variance does not change over time, and there is no serial correlation between the error terms in different periods.

In the selection of ARIMA models, the Box-Jenkins approach is the most widely used method. The two criteria suggested by Box and Jenkins (1976) for model selection are that the model has the least parameters and that the translatability feature is realized (Enders 2014: 78). The Box and Jenkins approach consists of three stages: definition, estimation, and diagnostic (Brooks 2019; Box 2013). In the first step,

this determines the lag orders for the AR(p) and MA(q) required to capture the dynamic properties of the data. When determining the lag orders, the coefficients of the ARIMA model must be statistically significant. In the second step, the parameters of the ARIMA (p, q) model defined in step 1 are estimated by an estimation method known as ordinary least squares (OLS) or maximum likelihood (ML). The third step involves model checking, that is, determining whether the model specified and estimated is adequate. The residuals of the estimated ARIMA (p, q) model are checked for serial correlation and heteroscedasticity using the LM and White tests, respectively. If these problems are detected, it indicates that the initially specified model is inadequate to capture the characteristics of the series.

3.2.2 Artificial Neural Networks (ANN) Model for Machine Learning Method

The human brain is an extremely complex and multi-layered system that processes information through the interaction between neurons, which are nerve cells (Tozzi 2019). Despite today's scientific developments, the working mechanism of the human brain has not been fully resolved by scientists. The process of learning information in the human brain is shaped not only by neurons but also by the continuous and multifaceted interactions between these nerve cells (Pessoa 2014). The human brain was taken as a source of inspiration when developing artificial neural network models. The learning processes and data processing of artificial neural networks with the machine learning method have become the basis of this method. Artificial neural network research can be examined under three main headings: (Cheng and Titterington 1994; Allende et al. 2002; Gevrey et al. 2003): The first field includes experimental studies based on the science of biology, physiology, and molecular biology. In this field, attempts are made to understand the basic functioning of artificial neural networks and the interaction processes between artificial nerve cells. The second field includes engineering applications inspired by the human brain structure calculation style. In this area, information is distributed as an analog pattern between the signal neurons and enables the learning process by highlighting their computational capabilities. The third area examines the mathematical basis of neurocalculus, which reveals the basic principles of neuronal cells that have learning capabilities. The field of statistics is particularly closely related to the field of application of artificial neural networks and has led to the development of many application areas such as image recognition and time series analysis. These three areas reveal the multifaceted nature of artificial neural networks and the interaction between different disciplines (Prieto et al. 2016).

The ANN model, a machine learning method, is an alternative prediction method that can explain multivariate and nonlinear relationships. The accurate and successful predictions of the ANN model are based on statistical methods that form the basis of the design of neurocomputers that simulate the behavior of artificial neurons. ANN models provide a theoretical framework for neurocomputers. Therefore, statistical learning is important in improving data analysis and prediction success (Almeida

2002). In addition, these models are effective in addressing a wide range of challenges, including data processing, classification, and nonlinear time series prediction (Baxt 1990; Pirovano and Heringa 2010). ARIMA models are frequently used by econometricians to forecast financial time series. However, the presence of non-linear and chaotic structures in financial time series has led to the increased use of ANN models, one of the machine learning methods, as an alternative to ARIMA models in recent years (Pang et al. 2020).

An artificial neuron consists of five parts: inputs, weights, summation function-activation function, and outputs. Inputs are the data coming to neurons. The data coming from these inputs can process information. Weights are transmitted to the core by multiplying the information coming to the artificial neuron with the weights of the connections they come from before reaching the core via the inputs. The summation function is a function that calculates the net input of that cell by adding the inputs coming to an artificial neuron multiplied by the weights. The activation function is a function that takes the weighted sum of all inputs in the previous layer and then produces an output value and passes it to the next layer. Outputs The value coming out of the activation function is the output value of the cell. These five parts together direct the success of ANN models in data processing, modeling, and prediction tasks (Basheer and Hajmeer 2000).

In this study, a feedforward supervised learning algorithm with two hidden layers was used for estimating the ANN model. The number of hidden layers in the ANN model is determined according to the characteristics of the dataset under study. Nonlinear relationships observed in the structure of the data in the ANN model may affect the learning capacity of this model (Goh 1995). ANN models, also known as Black-Box models, one of the machine learning methods, do not have an assumption that requires prior knowledge about the structural and functional properties of the system under study (Guidotti et al. 2018). Instead, these models learn the relationships between inputs and outputs autonomously by analyzing past data values. Input and output layers are called 'hidden layers' because they contain units that process information but cannot be directly observed. The number of input units usually depends on the characteristics of the data and the requirements of the application at hand (Stathakis 2009). Due to these features, ANN models are preferred in analyses due to their success in revealing complex and non-linear relationships (Ahmad et al. 2017; Pashaei and Pashaei 2021).

In the literature, various artificial neural network strategies have been developed; these strategies include feedforward networks, Hopfield networks, self-organizing maps, and radial basis networks (Barreto and Araujo 2004). Feedforward neural networks stand out as the most common and general type of neural network due to their simple structure and wide usage area; these networks have been effectively used in many problems where nonlinear relationships need to be learned. This study is based on the feedforward neural network structure in the modeling process and the backpropagation algorithm, a popular learning algorithm to optimize the network.

3.2.3 Comparison of Forecasting Performance of Models

This study uses three different criteria, namely Mean Absolute Error (MAE), Mean Square Error (MSE), and Root Mean Square Error (RMSE) to compare the performance efficiency of the ARIMA and the ANN models in forecasting the USD/TRY exchange rate. These performance measures are used to compare alternative forecasting models. Among the alternative models, the model with the smallest performance measures is chosen as the most successful model for prediction. Forecasting performance measures are used to determine how successful the model is in predicting or how small the prediction errors are. The forecasting performance measure errors used in this study are explained as follows (Brooks 2019):

- Mean Absolute Error (MAE): MAE is the average absolute difference between the observed and predicted values. It shows that the model with the smallest MAE value among the alternative models is more successful in predictions. The MAE formula is:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{6}$$

- Mean Square Error (MSE): MSE calculates the difference between predicted and true values. It is a more sensitive measure because it allows for greater penalties for large errors. The formula for MSE is:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{7}$$

- Root Mean Square Error (RMSE): RMSE is calculated by taking the square root of MSE. RMSE is used to understand how much the estimates deviate and provides errors at the same scale as the estimated unit. Smaller RMSE means better performance.

$$RMSE = \sqrt{MSE} \tag{8}$$

4 Empirical Findings

In this study, the natural logarithm of the ER variable is used for analysis. To make reliable predictions in the ARIMA modeling approach, it is a basic requirement that the analyzed time series be stationary. Therefore, the Augmented Dickey-Fuller (ADF 1979) and Phillips-Perron (PP 1988) unit root tests are applied to evaluate the stationarity of the LER variable. Table 1 presents the results of the unit root tests

for the LER variable. The ADF and PP unit root tests test the null hypothesis of the existence of a unit root against the alternative hypothesis that the series is stationary, respectively. According to the results presented in Table 1, it is concluded that the null hypothesis is rejected according to the 1% probability value of the first difference of the LER variable. In other words, the LER variable is determined to be a first difference stationary series.

To convert a non-stationary LER variable, exchange rate returns (DLER) are calculated as follows:

$$DLER = \log(ER_t) - \log(ER_{t-1}) = \log\left(\frac{ER_t}{ER_{t-1}}\right) \tag{9}$$

The most appropriate ARMA (p,q) model for the DLER is estimated and the results are shown in Table 2.

According to the estimation results, the most appropriate model selected by the Akaike information criterion (AIC) is the ARMA (1,2) model. There is no serial correlation problem in the residuals of the ARMA (1,2) model, but the ARCH (1) effect is detected. Since the volatility of the DLER variable will not be modeled in the study and only intra-period forecast values will be obtained, the ARCH (1) effect is not taken into account in the analyses.

Figure 1 shows a graph showing the intra-period forecast values and actual values obtained from the ARIMA model. The closer the observed values and the estimated

Table 1 Unit root tests for the LER variable

Series	ADF test		PP test	
	Level	First difference	Level	First difference
LER	− 1.2290 (2)	− 9.2891 (1)***	− 1.0994 (7)	− 8.4046 (10)***

Note The values in parentheses represent the optimum lag length by the SIC; ***$p < 0.01$, **$p < 0.05$, **$p < 0.10$

Table 2 ARMA (1,2) model estimation results

Dependent variable: DLER	Coefficient	t-statistics/Prob.
Intercept	0.0234	5.3549 (0.0000)***
AR(1)	0.9713	59.7894 (0.0000)***
MA(1)	− 0.4789	− 7.2819 (0.0000)***
MA(2)	− 0.5108	− 7.7616 (0.0000)***
Diagnostic Tests	Test statistics	Prob.
Serial Correlation LM (12) test	8.9976	(0.7031)
ARCH (1)	10.2290	(0.0014)***
$R^2 = 0.2287$		

Note *** $p \leq 0.01$

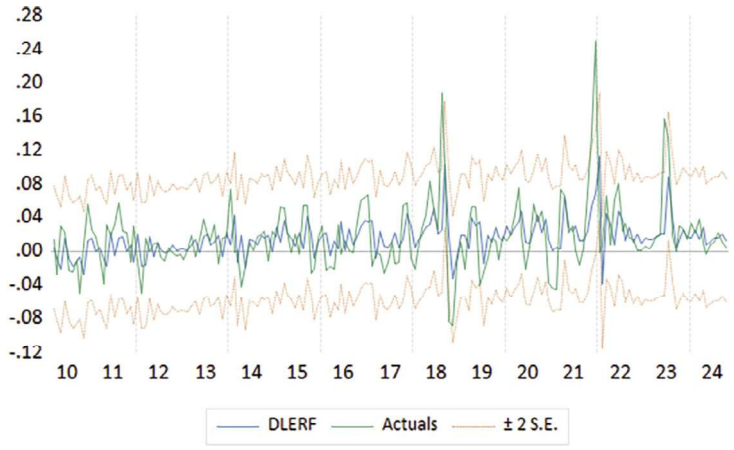


Fig. 1 The DLER forecast (DLERF) and actuals values (DLER)

values are to each other, the model is considered successful. This result indicates that the in-sample prediction values of the ARMA (1,2) model were made successfully and accurately. However, to evaluate whether the in-sample prediction values of the estimated ARMA (1,2) model are successful, it is necessary to compare the prediction error performance measures of the ANN model estimated with machine learning, which is an alternative prediction method.

In this study, the ANN model, being one of the machine learning methods representing an alternative method to linear time series analysis, was estimated using R software. First of all, from the data set of the USD/TRY exchange rate, the minimum and maximum values were obtained. Then, to increase the prediction success and accuracy of the ANN model, all the input and output parameters were normalized and scaled to take values between 0 and 1. These scaled values (SV) are obtained as follows:

$$SV = \frac{DLER_t - DLER_{\min}}{DLER_{\max} - DLER_{\min}} \tag{10}$$

Scaling the input and output parameters of the ANN model allows for standardization and more effective and precise predictions. In the third stage, the observed values were divided into two parts: the training and test data. The first 160 observations in the dataset were assigned to the training data set, while the last 17 were allotted to the test data set. Fourthly, the ANN model was estimated by using the values in the training data set, and intra-term prediction values were obtained. This procedure enables the ANN model to learn from the training data and subsequently make predictions. Then, the performances of the ANN model predictions obtained from the test data and training data were compared with the prediction error criteria. Finally, the prediction error performance criteria of the ANN model, which is a

Table 3 Comparision of the prediction performances of ARIMA and ANN models

Model	MAE	MSE	RMSE
ARIMA	0.027375	0.001624	0.040311
ANN	0.017943	0.000628	0.025069

machine learning method, and the ARIMA model, which is a traditional time series analysis model, are given and shown in Table 3.

According to the results, the ANN model, which is a machine learning method, gave lower MAE, MSE, and RMSE values than the ARIMA model. This result shows that the ANN model, which is a machine learning method, gives more accurate and reliable prediction values for the in-sample prediction performance of the USD/TRY exchange rate.

5 Conclusion

This study aims to obtain the intra-period forecast values of the USD/TRY exchange rate using monthly data for Turkey from January 2010 to October 2024 using two alternative models. For this purpose, the ARIMA model, one of the linear time series analysis methods for the USD/TRY exchange rate, and the ANN model, one of the machine learning methods, were preferred. The performance of these two alternative models was compared with the Mean Absolute Error (MAE), Mean Square Error (MSE), and Root Mean Square Error (RMSE) forecast error measurement values and the model that gives the smallest forecast error measurement value was preferred.

The findings show that the ANN model, one of the machine learning methods, gives a lower forecast error value than the ARIMA model, one of the linear time series analysis methods. This result shows that the ANN model gives more accurate intra-period forecast values of the USD/TRY exchange rate. In addition, it is concluded that the ANN model makes more successful forecasts when exchange rate movements are volatile. In addition, it is concluded that the ANN model makes more successful forecasts when exchange rate movements are volatile. ANN models are successful in capturing nonlinear and chaotic structures in financial time series such as exchange rates. The findings in this study are supported by previous studies such as Panda and Narasimhan (2007), Kadılar et al. (2009), Pradhan and Kumar (2010), Aydın and Cavdar (2015), and Sun et al. (2020). Studies have shown that ANN models provide more reliable results than traditional linear time series models in periods of financial crisis and volatility of exchange rates.

Sudden fluctuations in exchange rates have an immediate impact on financial markets, whereas their macroeconomic effects are often observed over a longer term. Increased volatility in the USD/TRY exchange rate can adversely affect both companies engaged in international trade and domestic investors. For example, an increase in the USD/TRY exchange rate increases costs for companies that depend on raw materials and intermediate goods. Therefore, it is important for companies

that do business with foreign currencies to accurately predict exchange rate price movements. If companies can accurately predict current and future input costs, they can also manage their risks. In addition, exchange rate forecasts play an important role in determining monetary and fiscal policies by central banks and policymakers. Successful exchange rate forecasts contribute to the development of policies that can have an impact on inflation rates and economic growth.

Finally, for new studies on economic time series such as exchange rates, in-sample or out-of-sample predictions can be made with different frequencies such as real-time, daily, weekly, or monthly using machine learning methods. Hybrid ARCH family models can be used as alternative prediction methods to predict volatility movements of financial time series. In addition, alternative prediction models are estimated using various machine learning algorithm methods and prediction error measures can be used to compare the performances of these models. As such, with the use of other methods such as support vector machines, decision trees, random forests, and deep learning models, it is possible not only to forecast different frequency financial time series like daily and weekly but also to measure and compare the effectiveness of alternative methods.

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