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Modelling the Exchange Rates in Türkiye Employing Machine Learning Methods

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Abstract— Exchange rates affect several macroeconomic parameters in open economies. Considering their importance, the USD/TRY and EUR/TRY exchange rates in Türkiye are modelled employing machine learning methods in this study. The exchange rate data are gathered from the official sources for the period of 2003-2023 and then their nonlinearities are inspected in EViews software. As the next step, a machine learning model, namely an autoregressive deep learning model is developed in Python programming language. The developed model is trained separately for the USD/TRY and EUR/TRY exchange rate data. The loss curves regarding the training phases show that the developed model is trained effectively for the exchange rate data. Then, the actual exchange rate data and the results of the developed autoregressive deep learning model are plotted in the same axes showing overlap in a wide range. The performance metrics of the developed model for the USD/TRY and EUR/TRY modelling such as the coefficient of determination, mean absolute error, mean absolute percentage error and the root mean square error are also calculating further verifying the accuracy of the developed autoregressive deep learning model. It is argued that the developed model can also be applied for the modelling of the nonlinear econometric data for other cases.

Keywords— Exchange rate, deep learning, autoregressive modelling, Python programming language, machine learning.

I. INTRODUCTION

Foreign exchange rates play a crucial role in the global economy. These rates determine the value of one country's currency in relation to another, and they have a significant impact on international trade, investment, and financial flows. Foreign exchange rates affect the competitiveness of goods and services in global markets, as well as the cost of imports and exports. They also influence the attractiveness of foreign investments and can impact a country's balance of payments and overall economic growth. As a result, policymakers, investors, and businesses closely monitor foreign exchange rates and make decisions based on their fluctuations. Understanding and predicting foreign exchange rate movements is essential for making informed decisions in the global marketplace.

Foreign exchange rates are constantly fluctuating, and these fluctuations can be affected by a range of factors. Economic indicators such as interest rates, inflation rates, and GDP growth can impact exchange rates, as can political events such as elections or geopolitical tensions. Speculative trading and market sentiment can also influence exchange rate movements. As a result, understanding and predicting exchange rate fluctuations can be challenging, and requires a sophisticated understanding of economic and political factors. To manage exchange rate risk, businesses and investors may use hedging strategies such as forward contracts, options, or currency swaps. Overall, foreign exchange rates are a complex and dynamic aspect of the global economy that requires careful attention from policymakers, businesses, and investors alike.

The foreign exchange market is the largest financial market in the world, with trillions of dollars exchanged daily. It is a decentralized market, with no single exchange or regulator, but rather a network of interconnected markets and participants. The most active participants in the foreign exchange market include banks, central banks, multinational corporations, and hedge funds. The availability of high-speed trading technology and

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advanced financial instruments has made the foreign exchange market accessible to a wider range of investors, including retail traders. As a result, the foreign exchange market is highly liquid and operates around the clock, with trading taking place in different time zones across the globe. The scale and complexity of the foreign exchange market make it a vital component of the global financial system.

The United States dollar (USD) is the most widely used currency in the world, and its importance stems from the dominant role of the United States in the global economy. The USD serves as the primary reserve currency for many countries, which means that central banks hold large amounts of USD in their foreign exchange reserves. The USD is also used as the preferred currency for international trade and financial transactions, particularly for commodities such as oil and gold. As a result, fluctuations in the USD exchange rate can have a significant impact on global financial markets. Moreover, the US Federal Reserve, the central bank of the United States, plays a critical role in global monetary policy, influencing interest rates and financial conditions around the world.

The euro (EUR) is the second most widely used currency in the world, and it is the official currency of 19 out of 27 European Union (EU) member states. The EUR plays a crucial role in the European Union's integration and economic stability. The adoption of the EUR by member states has facilitated cross-border trade and investment within the EU, reducing transaction costs and exchange rate risk. The EUR is also a major reserve currency, held by central banks and investors around the world. Moreover, the European Central Bank (ECB), which is responsible for the monetary policy of the Eurozone, is one of the world's largest central banks, with significant influence on global financial markets. In short, the EUR's importance reflects the economic and political significance of the European Union, as well as its integration and stability efforts.

The Turkish lira (TRY) is the currency of Turkey, a large and strategically located country that acts as a bridge between Europe and Asia. The TRY is an important currency for regional trade and investment, as well as a key indicator of Turkey's economic performance. Turkey has a rapidly growing and dynamic economy, with a young and educated population, a diverse industrial base, and a strategic location at the crossroads of Europe and Asia. The TRY is also used as a proxy for emerging market currencies, as Turkey is one of the largest and most liquid emerging markets in the world. As a result, the TRY's importance reflects both the potential and the risks of investing in emerging markets.

This study employs machine learning methods to model the USD/TRY and EUR/TRY exchange rates in Turkey, given their significant importance. The exchange rate data spanning from 2003-2023 are collected from official sources and examined for nonlinearities using EViews software. An autoregressive deep learning model is then developed separately for the USD/TRY and EUR/TRY exchange rate data using Python programming language. The training loss curves indicate the effectiveness of the developed model for the exchange rate data. The actual exchange rate data and the results of the model are overlapped in a wide range to demonstrate the accuracy of the model. The model's performance metrics, such as the coefficient of determination, mean absolute error, mean absolute percentage error, and the root mean square error are calculated, further verifying the model's accuracy. It is suggested that this model can be applied to model nonlinear econometric data for other cases as well.

II. Literature Survey

There are large number of works regarding the variation and volatility of exchange rates for various countries and time periods in the literature considering the importance of the subject. For example, the exchange rate markets in the Dominican Republic are investigated for the 1989-2001 period and it is shown that the foreign exchange rate volatilities can be modelled accurately using the asymmetric models (Sanches-Fung, 2003). The volatility in the exchange rates in the United States have been studied for the 1980-1985 period considering the USD/DM and USD/GBP parities and it is demonstrated that the generalized autoregressive conditional heteroskedasticity (GARCH) model can be used to accurately represent the foreign exchange rate volatilities (Bollersev, 1987). Similarly, the foreign exchange rates in the United States are shown to be modelled accurately using thr GARCH(1,1) model in another work (Baillie and Bollersev, 1989). In another study, forecasting performances of various models are compared and it is concluded that symmetrical models perform better compared to the asymmetric models (Mapa, 2004). The foreign exchange rate volatility in Türkiye is modelled in another study where GARCH(1,1) and EGARCH(1,1) models are employed and it is found out that various policies have similar effects on the foreign exchange rate volatilities (Ayhan, 2006). In another work, the USD/TRY and USD/DM exchange rates in Türkiye are modelled for the 1988-1995 period uaing GARCH models and it is exposed that foreign exchange rate volatilities increase during the economic crisis periods (Aysoy, 1996). Asymmetric Power ARCH (APARCH) models are utilized to represent the foreign exchange rate volatilities in Türkiye for the period of 1980-2008 and it is exposed that asymmetric models perform better in representing the volatility in the exchange rates (Kiran, 2009). Similarly, the ARCH, GARCH and Switching ARCH (SWARCH) models are utilized to model the foreign exchange rates in Türkiye for the 2001-2007 period and it is found out that SWARCH model provides more accurate results (Guloglu and Akman, 2007). In an extensive study, the foreign exchange rates in OECD countries are modelled using variance models and it is concluded that asymmetric variance models have better accuracy compared to the symmetric variance models (Caglayan and Dayioglu, 2009). The foreign exchange rates in Türkiye for the 2002-2008 period are studied in another work and it is demonstrated that GARCH(1,1), GARCH(1,1) and EGARCH(1,1) models accurately represent the USD/TRY, GBP/TRY and EUR/TRY parities, respectively (Soytas and Unal, 2010).

The exchange rate volatilities in Türkiye for the 1980-2009 period are modelled using the monthly data in another work and it is observed that Threshold ARCH (TARCH) models represent the foreign exchange rate data accurately (Guvenek and Alptekin, 2009). In another work, the USD/TRY exchange rate volatility is modelled in the 2009-2014 period using the ARCH method and it is shown that TGARCH(1,1) model accurately represents the USD/TRY variation (Emec and Ozdemir, 2014). Similarly, the foreign exchange rate volatility in Türkiye for the 2001-2010 period is studied using ARCH, GARCH and SWARCH models and it is concluded that the SWARCH model provides the best accuracy (Gur and Ertugrul, 2012). The daily USD/TRY and EUR/TRY exchange rates are investigated in another work for Türkiye in the 2002-2015 period where it is observed that TARCH(1,1) model accurately represents the foreign exchange rate volatilities (Kayral, 2016). In another extensive study, the USD/TRY exchange rate in Türkiye is modelled using daily data for the period of 2001-2019 and it is demonstrated that TARCH(1,1) model has the highest accuracy (Yaman and Koy, 2019). The volatilities among the first five foreign exchange rates in Türkiye are modelled for the 2005-2019 period in another work where it is concluded that dynamic conditional correlation model can be used to model the exchange rate volatilities (Demirgil and Kesekler, 2019). In another extensive work, the volatilities of the first five foreign exchange rates in the United States are studied using daily data and it is concluded that GARCH(1,5) model is the most accurate model for the modelling of the volatility of the foreign exchange rates (Copeland and Wang, 1994). The WON/USD exchange rate in South Korea is modelled in another work employing GARCH(1,1), EGARCH(1,1), TARCH(1,1) and it is shown that asymmetric models accurately represent the volatility in the foreign exchange rates (Yoon and Lee, 2008). The daily USD/DM data for the period of 1974-1997 is modelled in another study utilizing symmetric and asymmetric models where it is observed that symmetric GARCH model models the USD/DM data better than the symmetric model (Balaban, 2004). In another study, the volatility of the NAIRA/USD exchange rate is modelled employing GARCH(1,1), EGARCH(1,1), GJR-GARCH(1,1), APARCH(1,1), IGARCH(1,1) and TS-GARCH methods where it is shown that TS-GARCH(1,1) and APARCH(1,1) models have high accuracies (Olowe, 2009).

The volatility of the MYR/GBP is modelled employing GARCH, EGARCH, GARCH-M and EGARCH-M models and it is shown that GARCH-M model provides the best goodness of fit metric (Chong et al., 2011). In another work, the USD/TRY and DM/TRY exchange rates are modelled employing ARCH and GARCH models and it is concluded that GARCH(1,1) provides the best accuracy (Aysoy et al., 1996). Similarly, the exchange rate volatility in Türkiye is investigated using ARCH, GARCH and SWARCH methods where it is observed that the SWARCH model has high accuracy (Guloglu and Akman, 2007). The USD/TRY exchange rate for the period of 2002-2006 is analysed employing GARCH(1,1) and EGARCH(1,1) models and the EGARCH(1,1) provides better representation of the data (Ozturk, 2006). In another study, the USD/TRY, EUR/TRY and GBP/TRY exchange rates are modelled employing GARCH(1,1), EGARCH(1,1) and GJRGARCH(1,1) methods and it is shown that according to the root mean square error criterion GJR-GARCH(1,1) has the best accuracy for the USD/TRY and GBP/TRY exchange rates while EGARCH(1,1) has the best accuracy for the EUR/TRY data (Unal, 2009). The daily USD/TRY exchange rate data is modelled in another work for the 1980-2008 period and it is observed that asymmetric models have higher accuracy compared to ARCH/GARCH models (Kiran, 2008). The volatilities of the USD/TRY and EUR/TRY exchange rates in Türkiye are modelled in another study and it is shown that GJR(T)GARCH(1,1) model can be utilized to represent both USD/TRY and EUR/TRY exchange rates (Guven, 2010). Similarly, the USD/TRY, EUR/TRY and GBP/TRY exchange rates are studied employing ARCH, GARCH, EGARCH and TARCH methods and it is observed that EGARCH and TARCH methods provide better accuracy (Saglam and Basar, 2016). Similarly, the foreign exchange rates in Türkiye for the 2004-2008 period are studied and it is concluded that EGARCH model represents the exchange rate data properly (Cicek, 2010). In another study, the dynamic time-series methods are utilized for the modelling of the volatility of the exchange rates in Türkiye for the 2006-2016 period and it is concluded that GARCH and TARCH methods can be used to represent the exchange data accurately (Guler, 2017).

As it can be observed from the literature analysis, there are various methods used to model the exchange rates in different countries and regions considering the importance of the estimation of the exchange rates. An autoregressive deep learning network is developed in this work for the accurate modelling of the exchange rates in Türkiye. The used data and the developed autoregressive deep learning method are explained in the following section.

III.MATERIALS AND METHODS

The foreign exchange rate data namely the USD/TRY and EUR/TRY rates for the 2003-2023 period are taken from the official sources as the first step (EDDS, 2023). The weekly USD/TRY and EUR/TRY exchange rates taken from the EDDS are shown in Figure 1 and Figure 2, respectively.

The histograms and the descriptive data of the USD/TRY and EUR/TRY exchange rates are obtained in EViews software for the further inspection of their behaviour as shown in Figure 3 and Figure 4, respectively.

Figure 1. USD/TRY exchange rate in Türkiye for the 2018W18-2023W17 period

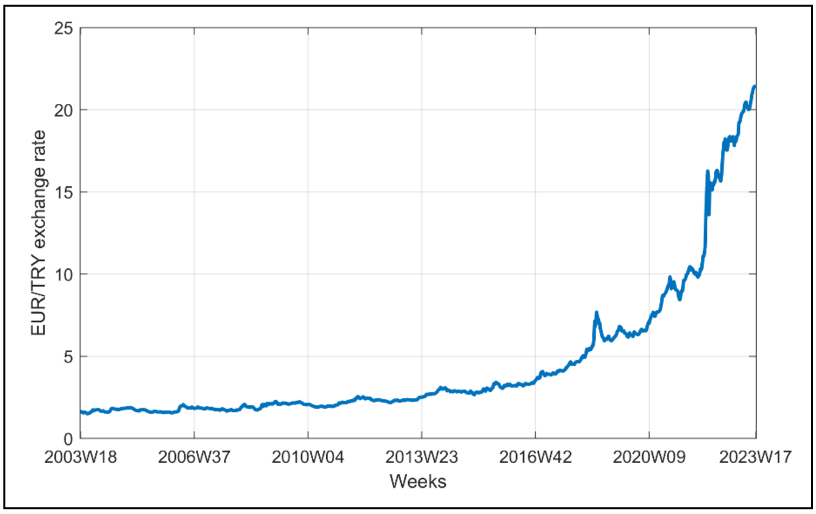

Figure 2. EUR/TRY exchange rate in Türkiye for the 2018W18-2023W17 period

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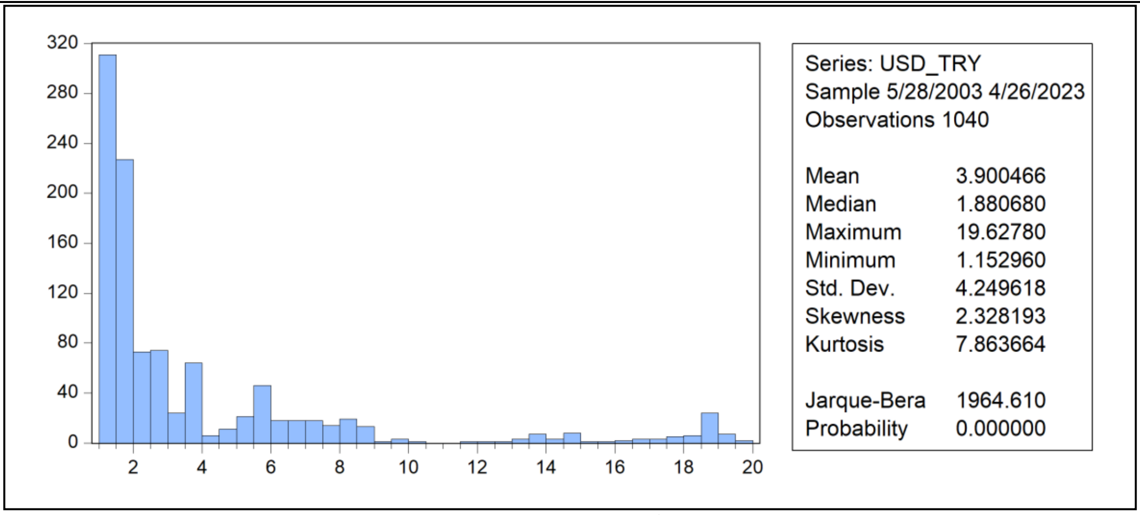

Figure 3. The histogram and the descriptive statistics of the USD/TRY exchange rate data

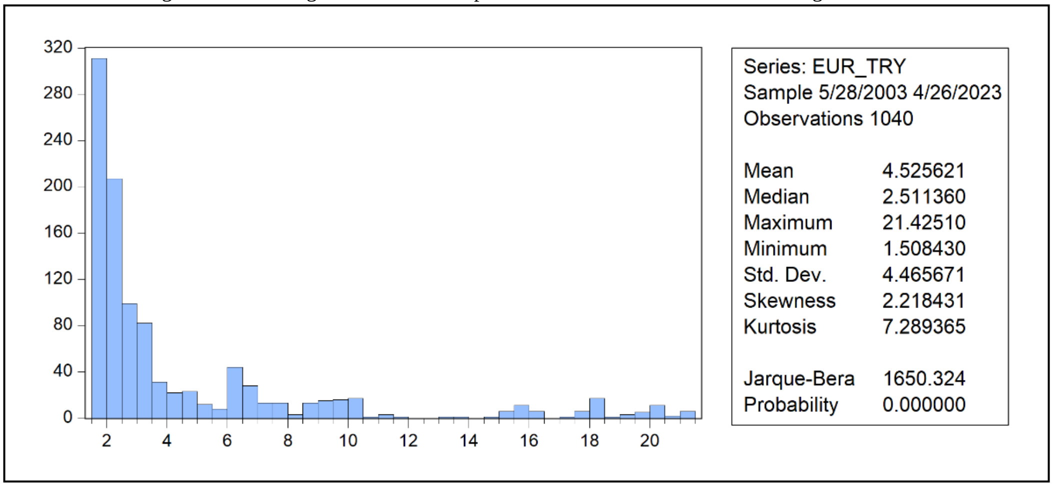

Figure 4. The histogram and the descriptive statistics of the EUR/TRY exchange rate data

As it can be observed from Figure 3 and Figure 4, the USD/TRY and the EUR/TRY rate data have strong nonlinearity therefore it is required to use nonlinear modelling techniques for their representation. Considering this fact, an autoregressive deep learning network is developed in Python programming language for the modelling of the exchange rate data. The structure of the developed deep learning network is given in Figure 5.

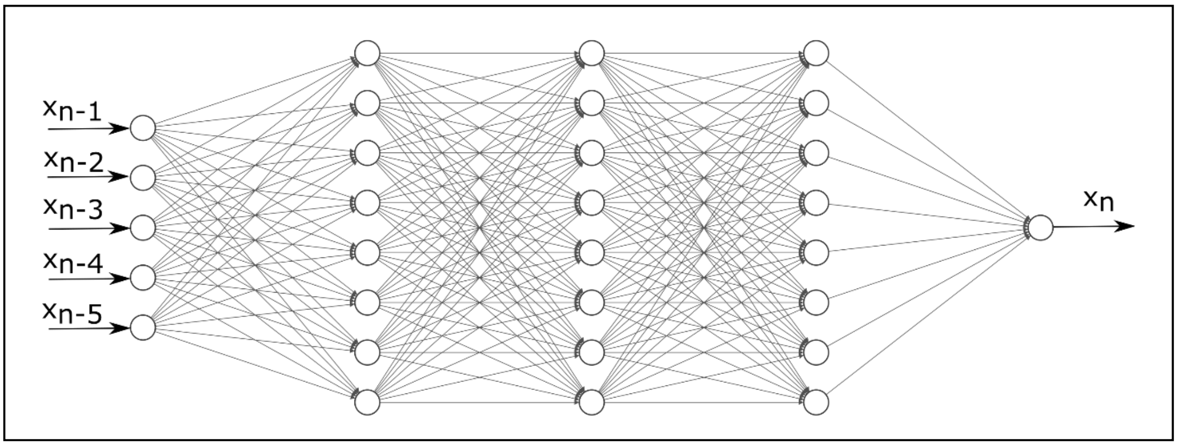

Figure 5. The structure of the developed autoregressive deep learning network

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The developed deep learning network consists of three hidden layers. As the result of the optimization process, the number of neurons in each of these hidden layers are taken as 100. The network accepts five inputs which are the lagged values of the exchange rate data and this makes the deep learning network to be an autoregressive model. The lagged values are generated using a custom function coded in Python programming language. The activation functions of the neurons are selected as the rectified linear unit function which is defined as in Equation 1.

$$f(x) = max(0, x) \quad (1)$$

The rectified linear unit function is shown graphically in Figure 6.

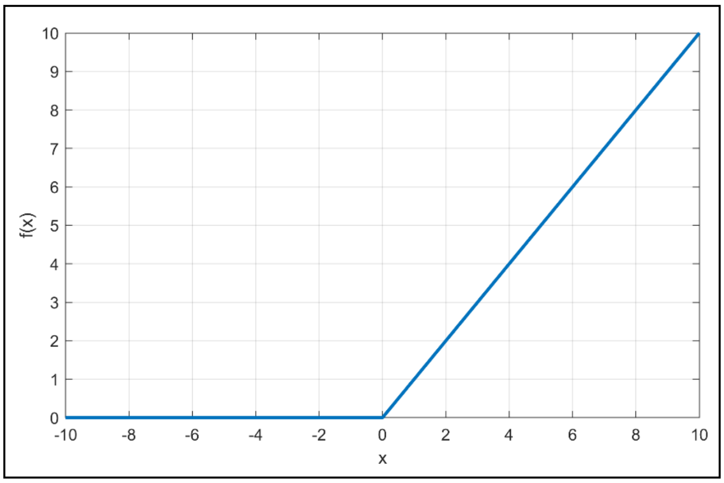

Figure 6. The plot of the rectified linear unit function

The developed autoregressive deep learning network is trained using the 70% of the data and the remaining 30% of the data is utilized as the test data. The details of the training phase and the modelling results are presented in the next section.

IV. RESULTS AND DISCUSSION

The loss function regarding the training phase of the developed autoregressive deep learning network for the USD/TRY and the EUR/TRY data are given in Figure 7 and Figure 8, respectively.

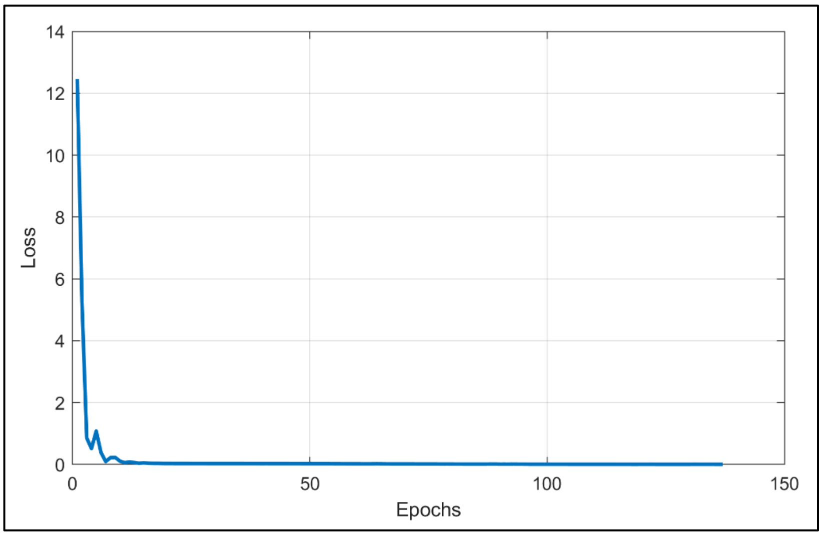

Figure 7. The loss curve regarding the training phase of the network for the USD/TRY data

As it can be observed from Figure 7 and Figure 8, the developed autoregressive deep learning network converges rapidly during the training phase. The training phase is completed in 137 and 138 epochs for the USD/TRY and the EUR/TRY data, respectively. As the next step, the actual USD/TRY and the EUR/TRY data with the result of the autoregressive deep learning model are plotted in Figure 9 and Figure 10, respectively.

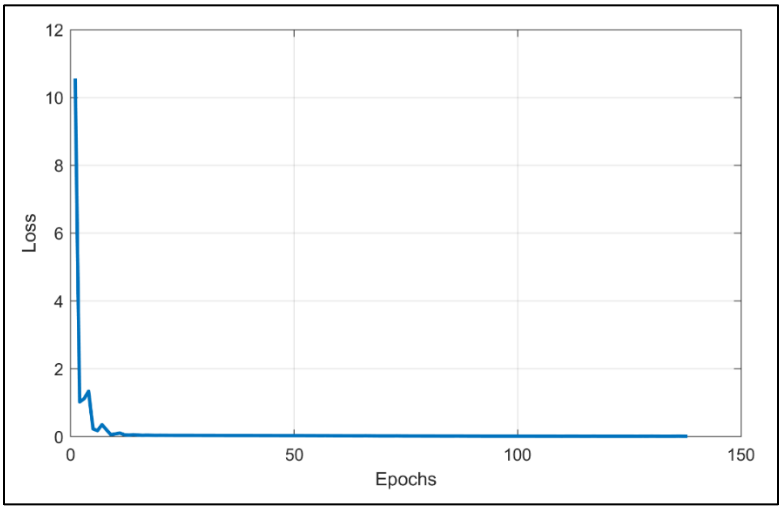

Figure 8. The loss curve regarding the training phase of the network for the EUR/TRY data

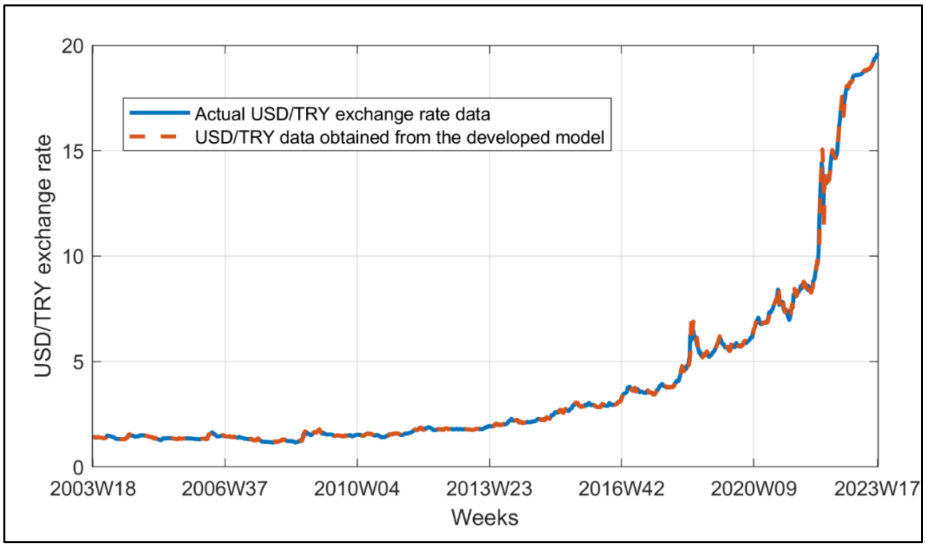

Figure 9. The actual USD/TRY exchange rate data and the result data of the developed model

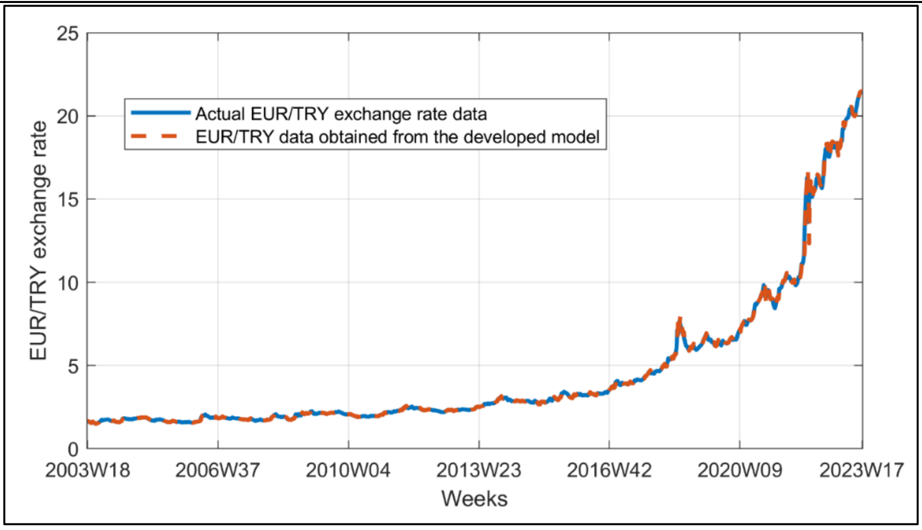

Figure 10. The actual EUR/TRY exchange rate data and the result data of the developed model

The plots of Figure 9 and Figure 10 demonstrate that the developed autoregressive deep learning model accurately represents the USD/TRY and the EUR/TRY exchange rate data. In order to assess the performance of the model, the performance metrics of the model for the USD/TRY and the EUR/TRY data are calculated. The coefficient of determination (R^2), mean absolute error (MAE), mean absolute percentage error (MAPE) and the root mean square error (RMSE) are computed using Equations 2, 3, 4 and 5, respectively (Mombeini and Chamzini, 2015).

$$R^2 = \frac{\sum_1^l (O-avg(O))^2 - \sum_1^l (O-M)^2}{\sum_1^l (O-avg(O))^2} \tag{2}$$

$$MAE = \frac{\sum_1^l |O-M|}{l} \tag{3}$$

$$MAPE = \frac{100}{l} \sum_1^l \left|\frac{O-M}{M}\right| \tag{4}$$

$$RMSE = \sqrt{\frac{\sum_1^l (O-M)^2}{l}} \tag{5}$$

In Equations 2, 3, 4 and 5, *O* represents the actual data, *M* is the model result and *l* is the length of the data. The calculated performance metrics of the developed autoregressive deep learning model for the USD/TRY and the EUR/TRY data are given in Table 1.

Table 1. The performance metrics of the developed autoregressive deep learning model for the USD/TRY and the EUR/TRY data

Model	R^2	MAE	MAPE	RMSE
USD/TRY	0.998	0.046	0.011	0.135
EUR/TRY	0.998	0.059	0.012	0.160

As it can be seen from Table 1, the developed autoregressive deep learning model provides accurate representation of the UST/TRY and the EUR/TRY exchange rate data. The coefficient of determinations are greater than 0.99 and the mean absolute percentage errors are 0.011 and 0.012 for the USD/TRY and the EUR/TRY data which indicate that the developed model provides high accuracy. It can be argued that the developed deep learning network can also be used to model other exchange rate data for other countries and regions.

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V. CONCLUSIONS

Several macroeconomic parameters in open economies are influenced by exchange rates. In this study, machine learning methods are employed to model the USD/TRY and EUR/TRY exchange rates in Türkiye due to their significant impact. The exchange rate data, spanning from 2003 to 2023, is collected from official sources and analysed for nonlinear patterns using EViews software. Subsequently, the Python programming language is utilized to develop a machine learning model known as an autoregressive deep learning model. The model is trained separately using the USD/TRY and EUR/TRY exchange rate data. The loss curves obtained during the training phases indicate that the developed model effectively learns from the exchange rate data and the training phases are completed for 137 and 138 epochs for the USD/TRY and the EUR/TRY data. To demonstrate the performance of the developed model, the actual exchange rate data and the results of the autoregressive deep learning model are plotted on the same axes, revealing a substantial overlap across a wide range. Additionally, performance metrics such as the coefficient of determination, mean absolute error, mean absolute percentage error, and root mean square error are calculated to further validate the accuracy of the developed autoregressive deep learning model for USD/TRY and EUR/TRY modelling. The MAPE parameter of the developed model is found out to be 0.011 and 0.012 for the USD/TRY and the EUR/TRY exchange rate data which indicate high accuracy. It is suggested that this model can also be applied to nonlinear econometric data modelling in other scenarios.

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