AL KUT JOURNAL OF ECONOMIC AND ADMINISTRATIVE SCIENCES
Publisher: College of Economics and Management - Wasit University

Forecasting official and parallel exchange rates in the Iraqi economy for the period (2004-2024)

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Abstract. The purpose of this study is a comparison between classical approaches and machine learning models in forecasting the parallel and official Iraqi dinar exchange rate. The study utilized the creation of models ARIMA and NNAR on monthly bases for the time span (2004-2024). The exchange rate is an essential mechanism connecting the local economy with the global economic system. Through understanding the pattern of the exchange rate and exploring the variables that assume roles in influencing it, it becomes feasible to design future estimations on its movement, which assists economic units in having appropriate decision-making on how to handle potential risks and dangers. The results indicated that the NNAR model with the neural network surpassed the ARIMA model in accurately forecasting exchange rates, particularly in terms of the auction price. The root mean square error (RMSE) in the NNAR auction model decreased from 14.18 in the ARIMA model to 11.15, and the mean absolute percentage error (MAPE) also dropped from 0.2837 in the ARIMA model to 0.2396.

Keywords: Exchange Rate, Iraqi Economy, ARIMA and NNAR Models

1. INTRODUCTION

The contemporary exchange rates are greatly impacted by the nature of the exchange rate system in the global economic order. The gold coin standard, a fixed currency regime, had been one of the world's dominant systems of currency for over forty years prior to 1914, to the extent that this period in history has been characterized as "the age of the classical gold standard." World War I led to the collapse of this order. Since the fall of the classical gold standard, after several decades, the world's leading governments faced challenges in formulating an exchange rate structure in conformity with the evolving global economic order. The inappropriate exchange rate structure was one of the decisive factors in the fall of the global economy in the period charactered as the time between the two global wars, during which this economy experienced fluctuating financial turmoil culminating in its eventual fall. Since World War II, the Western world rebuilt its economy on the basis of the Bretton Woods Monetary System, underpinned by fixed but manageable exchange rates. This structure witnessed truly outstanding success. Nonetheless, since the fall of the Bretton Woods Monetary System, the role of exchange rate policies in global economic management has significantly increased. In today's "age of globalisation," exchange rate policies are playing an integral role in the global economy of almost all countries around the world. For several decades, one of the aims of the European Union has been to provide stability to the currencies of countries within this union, culminating in establishing an unified currency, "the Euro," in 1999. Although the eurozone has experienced significant growth and has encountered substantial obstacles, the euro continues to play an essential role in one of the most ambitious international economic development programs in recent history. Furthermore, currency policy and movements have been heavily discussed both domestically and internationally in developed nations. As is the case with other developing nations, how to determine their exchange rates has created some tough decisions. These REE have decided to either peg their currencies against one of the major currencies (e.g., the dollar, euro, etc.) or float freely, and have utilized many of their REE to promote economic development strategies. The outcome(s) of the development strategies in East Asia—e.g., especially China—has arguably been through policies designed to maintain relatively low exchange rates for export-led development. Other developing areas (e.g., certain African nations) have also experienced continuous periods of currency instability; these occurrences have contributed to subsequent disruptions on an economic, social, and political level. As such, the economic and political drivers of government policies regarding exchange rates have led to the development of models that attempt to explain their behaviours. Therefore, exchange-rate forecasting requires the incorporation of economic and political influences on monetary policy.

Research importance:

The theoretical importance of the study lies in the fact that it expands on the forecasting literature by comparing the performance of models when using two rate regimes in which policy intervention influences one of the series and the market rules the other, and in examining whether nonlinear learning can be effective over the out-of-sample accuracy of models as compared to linear stochastic specifications. It is also applicable as it offers an evidence based forecasting methodology that can be used by monetary authorities, banks and firms in pricing, hedging, cash flow planning and scenario analysis, especially in situations where the parallel market rate has a direct relevance of actual transactions and risk exposure in Iraq.

Research problem

Although the exchange rate is the key element of the macroeconomic stability of Iraq, the design of the policy and the risk management of the private sector, it is difficult to forecast it well when the market environment has structural breakages, administrative intervention, and nonlinear dynamics which are not usually addressed by the traditional linear time series models. The Iraqi situation is also complicated by the fact that there was both an official rate and a parallel market rate which react in a different manner to policy tools, expectations and liquidity environments. This leaves the decision makers with a practical forecasting deficit in terms of dependable and evidence based forecasts that are resistant to volatility and changes in regimes. This paper attempts to fill that gap by the experiment of determining whether machine learning founded neural forecasting is potentially more accurate and stable than classical econometric forecasting when used to make predictions of monthly Iraqi exchange rate data, time period 2004-2024. And Main research question How significant is a neural network autoregression model as compared to an ARIMA model in predicting the official and parallel exchange rates in Iraq using monthly data between 2004 and 2024?

Research hypotheses

H1 NNAR predicts smaller forecast errors than ARIMA on parallel market exchange rate in Iraq during the time of assessment.

H2 NNAR produces less prediction errors than the ARIMA to the official auction exchange rate in Iraq when compared to the evaluation sample.

Research objectives

1-Establish similar ARIMA and NNAR forecasts on the parallel and official exchange rates of Iraq using monthly data in the period 20042024.

2-Measure and analyze predictive accuracy with standard forecasting error measures which include RMSE MAE and MAPE.

3-Determine which model is more effective in capturing nonlinear dynamics and lessening residual dependence on each exchange rate series.

4-Come up with realistic projections that can be utilized to plan and manage risks by the policy makers and the market actors.

Research methodology

It takes a quantitative comparative design that is grounded on time series forecasting. It employs monthly observations of the rate of parallel market and official auction of Iraq between 2004 and 2024 based on the Central Bank of Iraq data utilized in the research. The analysis is conducted within R Studio by means of a structured pipeline which comprises data preparation as time series, estimation of an ARIMA model, order-selection, based on information criteria, and estimation of an NNAR model, using lagged values of the series as inputs, and an automatically tuned network structure. Forecast accuracy indicators (that represent absolute and relative behavior of error) such as RMSE MAE and MAPE are used to estimate model performance which is supported by residual diagnostics to determine whether the remaining autocorrelation is reduced. The last model decision is in accordance with the principle of better out of sample accuracy and stability in both the exchange rate series.

RELATED LITERATURE:

In recent decades, many researchers have tried to find ways to predict exchange rate movement using different types of models and methodologies. According to Jackson and Magkonis (2024), in some cases, exchange rate forecasts can be made more accurately than would have been expected if based solely upon a random walk model, especially when linear models are employed based on Purchasing Power Parity (PPP) theory. They conducted an extensive analysis of forecast accuracy for more than 8,000 error data points. The authors found that increased frequency of data used and longer forecast periods result in better predictive accuracy. Butt et al. (2024) examined the nonlinear effect of petroleum (energy) prices on the nominal exchange rate for Malaysia. They conducted their analysis using a threshold cointegration framework, and their results indicated that monetary factors including interest rates and the money supply, along with energy price fluctuations, are critical in influencing the way in which the nominal exchange rate will adjust over the short term. In addition, Holmes, Iregui, and Otero (2025) provided empirical evidence of psychological barriers to exchange rates as measured through the use of daily observations of the Colombian peso over a period of fifty years. These psychological barriers typically occur around whole figures (e.g., 1,000); the degree of influence that they have on exchange rate behaviour is affected by the exchange rate regime in effect. In focus on the economies of emerging markets, Eniayewu et al. (2024) adopted the MIDAS-GARCH approach to examine the role of monetary fundamentals (specifically interest rates and currency supply) in influencing the volatility of the foreign exchange rates in Nigeria and South Africa. Their results showed an important role of the monetary policies in both countries. Their results confirmed the importance of interest rates in predicting the future values of exchange rates and the importance of the money supply in predicting the currency exchange rate only for South Africa. Gasta (2024) used an approach based on model averaging to develop a framework for predicting nominal exchange rates for nine major currency pairs and found that the approach significantly improves the accuracy of predictions made in the medium and long terms. In a complementary manner, (Wada, 2022) utilized spectral band regression and the LASSO method to forecast out-of-sample predictions, with the conclusion that focusing on cyclic frequencies of the economy improved PPP and Taylor Rule based model predictions. The LASSO analysis also provided assistance in finding relevant predictors of the outcome variables without using pre-defined bands of frequencies. For predictive modeling, (Yuan, 2013) created a Smooth Polynomial Support Vector Machine (BFGS-SVM) model designed to predict the direction of movement of the RMB/USD exchange rate. The BFGS-SVM model used data from the Dow Jones China indices and outperformed the standard predictive models regarding directional accuracy. In addition, (Darvas & Schepp, 2025) forecasted daily GBP/USD exchange rates for a 34-year period based on a rational expectations model of the monetary system. The results demonstrated that the Darvas & Schepp rational expectations model consistently provided superior performance when compared to random walk forecasts across all time periods. The discrepancy in performance provided statistically and economically significant excess returns when compared to traditional trading models.

2. THEORETICAL FRAMEWORK

The exchange rate, described as how much one currency is worth another, is one of the key components in international economics. The exchange rate promotes global trade, investments, and financial transactions. Justification for correct predictions of exchange rate changes has led to numerous developments in macro-econometric models and computing techniques (Jackson & Magkonis, 2024). The exchange rate in international economics can be expressed in two main ways. These techniques involve expressing how much foreign currency is needed for one unit of domestic currency in the domestic market. This is called the direct exchange rate. Theother method involves how much domestic currency is needed for one unit of foreign currency in the foreign market, called the indirect exchange rate (Al-Shammari & Hamza, 2015).

In overseas markets, the indirect quotation system is most prominent. In cases where the direct exchange rate is not available, the cross rate system involves citations with respect to another currency, mostly the U.S. dollar (Marghit, 2019). The U.S. dollar can be considered the premier world currency because it can either be used in official exchanges or in unofficial business (Nower, 2024). They are three main types of exchange rates:

- Nominal Exchange Rate (NER): This rate is based on the current market rate of exchange between currencies, without any consideration for differences in purchasing powers due to differences in rates of inflation. It is applied in real-time transactions but ignores the purchasing power parity (Jabbar, 2016).

- Real Exchange Rate (RER): The RER takes into account both nominal exchange rates and domestic as well as international price levels. It is termed to measure international competitiveness. It can be represented by mathematical equations:

$$REXR_{PPP} = E\frac{PF}{P} \dots\dots\dots..(1)$$

where E is the nominal exchange rate, PF is the foreign price index, and P is the domestic price index (Eichengreen, 2008; Xiangmingli, 2004). A lower RER implies improved competitiveness, and vice versa. Effective Exchange Rate (EER): EER is the weighted average of a currency's value relative to a basket of other currencies, where weights reflect the country's trade shares. If adjusted for inflation, it becomes the real effective exchange rate (REER). It is calculated as:

$$EEXR = \sum W_i \,.\, a_q \dots\dots\dots..(2)$$

Where W_i represents the trade weight of currency i and a_q is the relative change in exchange rate (Marghit, 2019). The exchange rate is determined by supply and demand as a result of trade, capital movements, and economic performance. The exchange rate is a main tool for creating both internal and external balances in the country's economy. Internally, it ensures price stability and employment, while, externally, it ensures that payments and foreign exchange accounts are balanced (Naamah, 2011). The exchange rate also serves as an indicator of a country's competitiveness based on cost differences between countries, including differing levels of development and performance. For instance, a high value of the exchange rate leads to a rise in export prices as well as a fall in import prices, hence reducing a country's competitiveness. Conversely, a country's depreciation decision encourages exports while discouraging imports as a result of higher costs associated with imports (Al-Jaf, 2014). The exchange rate links both domestic and international markets.

The exchange rate has an effect on the three main markets of the economy:

• Goods Market: This determines the price of exported and imported goods.

• Assets Market: This impacts value determination as well as the demand for such assets.

• Labor Market: It has an impact on the wages and employment levels in tradable industries (Al-Mufarji, 2005). The exchange rate plays many roles

Standard Function: It works as a standard by which all domestic or international prices can be compared, facilitating effective decision-making. It shows possible profits that can be realized through trade, which help to ensure income growth. Development Function: The exchange rate policies help to promote export activity or discourage unproductive domestic sectors based on their relative price competitiveness. It thus helps to create an industrial and trade structure (Al-Shammari & Hamza, 2015). Distributive Function: The process of international resource distribution is facilitated by exchange rates, just like domestic price systems. The exchange rate thus affects global income distribution based on international trade patterns and price parity (Marghit, 2019).

3. MATERIALS AND METHODS

The research had used “R Studio” as an integrated environment for the purpose of statistical analysis and modeling, because it provides a flexible way to handle time series data and support libraries for both modeling and machine learning were heavily leveraged. Monthly market exchange rates and auction rates were obtained from the Central Bank of Iraq’s website for 2004 to 2024. These data show what has happened in the foreign exchange market in Iraq, so it was a good introduction to forecasting models. Set of packages were employed for analysis, specifically: readxl for reading data from Excel files, lubridate for time series analysis, forecast for ARIMA and NNAR model construction, ggplot2 for professional graph visualization, tseries for statistical analysis of time series data, and writexl for storing analysis outcomes into exportable files. The employed software enables the construction of precise models for forecast, analysis of time series attributes, exploitation of descriptive indicators, and determination of relationships. The data were transformed into the time series format ts in R, characterized by monthly patterns, facilitating precise execution of statistical computations and forecast models. The analysis framework made possible the assessment of the predictive capabilities of both the classical ARIMA model and the neural model NNAR, along with the evaluation of these models’ accuracy utilizing specific measures of performance.

3.1 Autoregressive Moving Average (ARIMA) Model:

ARIMA, which stands for Autoregressive Integrated Moving Average, is a popular statistical tool for making forecasts for times series forecasts. In this paper, the ARIMA model was employed using the "Auto ARIMA" function, which determines the optimal values for the parameters (p, q, d) for the model. The ARIMA model is defined as per the following equation (Ma, 2024; Taiba et al., 2022):

$$\left(1-\phi_1 B-\phi_2 B^2-\cdots-\phi_p B^p\right)(1-B)^d y_t=c+\left(1+\theta_1 B+\theta_2 B^2+\cdots+\theta_q B^q\right)\epsilon_t \quad (3)$$

where y_t is the current value of the series at time t. B is the back-shift operator: By_t=y_(t-1), and *ϕ_1, ϕ_2,. ϕ_p* are the AR coefficients, while θ_1, θ_2,. θ_q are the MA coefficients. d is an integer representing the degree of differencing, while "c" is a constant that is usually 0. ϵ_t is a function of error at time t. The "Auto ARIMA" function chooses a combination of parameters p, q, and d to achieve the smallest Akaike Information Criterian (AIC).

3.2 Autoregressive Recurrent Neural Network (NNAR) Model:

A recurrent neural network (NN) model is an artificial neural network designed to work with sequential data. This allows the model to be effectively used in the task of time series forecasting. The math equation representing an NN model can be understood as follows:

The hidden state, h_t, computed using an NN model at any given time, t, using an input sequence, x_t, can be calculated using the following equation, as stated in (Bharadiya, 2023) and (Yang et al., 2023):

$$h_t = \sigma(W_h h_{t-1} + W_x x_t + b_h) \quad (4)$$

Where W_h is the weight matrix for the hidden state. W_x is the weight matrix for the input. b_h is the bias term. σ is the activation function, which is a nonlinear function used in this study, and DeepRNN. The output y_t is calculated at time step t as follows:

$$y_t = W_y h_t + b_y \quad (5)$$

where W_y is the weight matrix for the output. b_y is the bias term for the output. The model is known for having the capability to learn from the "temporal" features in the data. The Hybrid model "NNAR" uses the strengths of the "ARIMA" model to learn the linear patterns in the data. It uses the "NN" model to learn the "Nonlinear" patterns in the data. The Hybrid model combines the outputs from both models. It uses the "ARIMA" model to learn the "linear" patterns from the data. It uses the "NN" model to learn the "Nonlinear" patterns from the data. The Hybrid model can mathematically be represented as shown in equation 6 (Zhu et al., 2024):

$$y_t^{\text{Hybrid}} = y_t^{ARIMA} + y_t^{NN} \quad (6)$$

where y_t^{ARIMA} is the forecast value of the ARIMA model for time t. y_t^{NN} represents the forecast value of the NN model during the same time step t. Equations in the ARIMA module are represented as:

$$\left(1 - \phi_1 B - \cdots - \phi_p B^p\right)(1 - B)^d y_t^{ARIMA} = c + \left(1 + \theta_1 B + \cdots + \theta_q B^q\right)\epsilon_t \quad (7)$$

While the RNN component follows the standard formula for a recurrent neural network:

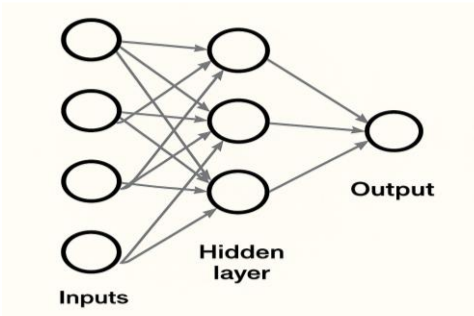
$$h_t = \sigma(W_h h_{t-1} + W_x x_t + b_h),\ y_t^{NN} = W_y h_t + b_y \quad (8)$$

With this approach, we aim to combine the capabilities of neural network layers to use them as time-delayed differentiators, i.e., to integrate features into the model and not just for predictions, according to the following equation:

$$Y_t = f(Y_{t-1}, Y_{t-2}, \dots, Y_{t-p}) + \varepsilon_t \quad (9)$$

Where the value we want to predict depends on Y_t relies on a nonlinear activation function f approximated by neural networks with deep learning layers and autoregressive delays p. This approach enhances model accuracy by leveraging ARIMA's ability to explain linear patterns and NN's ability to handle nonlinear complexity in data. As shown below:

Figure 1. Architecture of a multi-layer artificial neural network (MLP)



In this research, forecasting systems will be analyzed based on a number of metrics of performance: mean error (ME), root mean square error (RMSE), mean absolute error (MAE), mean percentage error (MPE), mean percentage absolute error (MAPE), and mean absolute standard error (MASE). All these metrics will be very important in measuring how accurately and reliably a forecasting system performs. The mean error (ME) is calculated based on average differences between predicted and actual values of a function or process and is described in detail by a relationship given by Ahmadi et al. (2019):

$$ME = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i) \quad (10)$$

“N”is the total number of data points. This measure helps in determining if the classifier has a tendency to underestimate or overestimate the actual outcomes. The root mean square error (RMSE) can be calculated using the following equation (Chai & Draxler, 2014):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (11)$$

It calculates the square root of the average squared errors, with emphasis on large deviations, which makes it a very good indicator for the general accuracy of the model.

The mean absolute error is computed using the equation below (Chai & Draxler, 2014):

$$MAE = \frac{1}{n}\sum_{i=1}^{n} \mid y_i - \hat{y}_i \mid \qquad (12)$$

It is defined as the average size of errors irrespective of their signs, making it relatively insensitive to outliers when compared with RMSE. Errors in terms of percentage are measured by mean percentage error and mean absolute percentage error, which will be defined as follows: Mean Percentage Error (MPE).The mean percentage error is defined by the equation:

$$MPE = \frac{1}{n}\sum_{i=1}^{n} \left(\frac{y_i - \hat{y}_i}{y_i}\right) \times 100 \qquad (13)$$

It shows the direction of forecast errors (overprediction or underprediction), while the mean absolute percentage error (MAPE) is given by the formula below (Wen et al., 2022):

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} \mid \frac{y_i - \hat{y}_i}{y_i} \mid \times 100 \qquad (14)$$

It calculates the average size of the errors, which ensures easy comparison between datasets of different sizes. Finally, in calculating the mean absolute standard error (MASE), the following formula is used (Wen et al., 2022):

$$MASE = \frac{\sum_{i=2}^{n+1} \mid y_i - y_{i-1} \mid}{\sum_{i=2}^{n+1} \mid e_{naive,i} \mid} \qquad (15)$$

It allows for scale independence because it uses the values of error predictions in comparison to those of another model, such as combined random walk, which is represented by ∑_(i=2)^(n+1)▒〖|e_(naive,i)|〗This gives information about how to measure forecasts.

RESULTS AND DISCUSSION

Table (1) includes summary descriptive statistics listing for both the market exchange rate and Auction Market Exchange Rate during the time period that this study has taken place. This table highlights some of the fundamental differences between these two market exchange rate series.

The lowest market price ever was 1,178 Dinar, while the lowest auction price was 1,166 Dinar. Therefore, at the lowest market prices, there is a small disparity between these two market exchange rate types; however, as we move along the scale of each indicator, the gap between market and auction price increases significantly. The market price's average price (mean) was 1,310 Dinar and the auction price's average price (mean) was 1,265 Dinar, suggesting that the market price always has a higher average price than the auction price.

The median value of the market price is 1,248 Dinar, while the median value of the auction price is 1,190 Dinar. The fact that the median of the market price is greater than the median of the auction price is indicative of the fact that the market price has an upward bias. In addition, upon examining the 3rd quartile (the 75th percentile), 75% of all values within the market price are lower than 1,467 Dinar; on the other hand, only 1,311 Dinar were below the auction price. This indicates a wider range of market price values and a narrower range of auction price values.

Finally, observing the upper limits of these two markets reveals another difference between them. The maximum market exchange rate was 1,603 Dinar, whereas the maximum auction exchange rate was only 1,487 Dinar. Overall, the statistical indicators above demonstrate that the market has a greater degree of variability and instability when compared to auction exchange rates. These two markets exhibit different behaviours in terms of price behaviour, revealing a broad divergence, as a result of the impact of Central Bank actions on these two markets.

Table 1. Descriptive statistics for market and auction prices

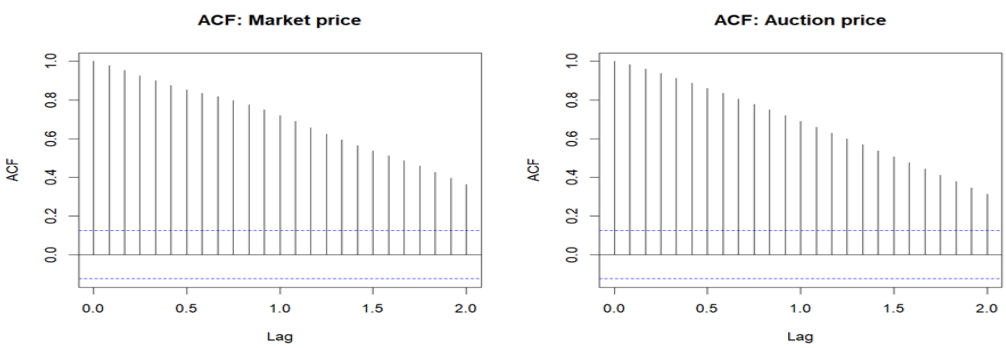
Statistic	Market Price	Auction Price
Minimum	1178	1166
1st Quartile	1204	1177
Median	1248	1190
Mean	1310	1265

3rd Quartile	1467	1311
Maximum	1603	1487

Source: Prepared by the researcher based on R Studio

The descriptive statistics above provide a summary of the behaviour of both series over time (Table 1). Although both series showed convergence at their minimum, the distance between the two series was greater as each successive indicator was used to calculate the standard deviation of market values. Thus, the average value of the market in the third quarter was 1,310 Dinars compared to 1,265 Dinars for the auction series, indicating a continuing price differential in favour of the market price. The median number for the market was also higher than for the auction (1,248 Dinars for the market and 1,190 Dinars for the auction), reflecting the upward skew of market values. In addition, when looking at the 75th percentile (the third quartile) of both data sets, we see that 75 per cent of all market values fell below 1,467 Dinars, while at the auction, this figure reached only 1,311 Dinars. This indicates not only the range of market values but also the relative restriction of auction value relative to market value. At the highest end of the market, however, there was a clear difference between the maximum price of the market (1,603 Dinars) and the maximum price at the auction (1,487 Dinars). In conclusion, the data supports the theory that while both markets operate under the Iraqi monetary system, their behaviours differ greatly from one another.

Figure 2. Autocorrelation Function (ACF) of Market Price and Auction Price



Source: Prepared by the researcher based on R Studio

Figure 2 above shows the autocorrelation function for the market price series and auction price series. As can be observed in the above two graphs, the series start with very high values for autocorrelation at lag (lag = 0), steadily becoming low as the lag number progresses. The trend depicted by the above graphs portrays the autoreliance depicted in the time series constructure of the economic variables.

Analysis of the above graphs indicates that the series start with very high values but steadily reduce as the lag number progresses. For the Market price series: The graphs for the series show that the values reduce steadily but very slowly, meaning that the series has a trend component that could qualify it for mean instability, meaning the series needs to be differenced to create stationarity for the ARIMA model. For the auction price series: The graphs for the series show that the values reduce steadily but much faster compared to the previous series, hence the series could qualify for transition to stationarity after once differentiation.

The graphs above illustrate the need to interpret the series using the eigenvectors for prediction models and the viability of using temporal models such as ARIMA and NNAR for analysis and prediction.

Table 2. Summary of the coefficients of the ARIMA and NNAR neural network models for market and auction exchange rates

Series	Model	Coefficients	Std. Errors	Sigma²	Log Likelihood	AIC	AICc	BIC
Market Price	ARIMA(3,1,0)	ar1 = 0.2170, ar2 = 0.1088, ar3 = -0.1517	0.0635, 0.0648, 0.0638	402.4	-1107.38	2222.76	2222.92	2236.86
Auction Price	ARIMA(1,1,1)	ar1 = 0.1151, ma1 = 0.5344	0.1061, 0.0899	203.8	-1022.67	2051.33	2051.43	2061.91

NAR Model Summary						
Series	Observations	Lags	Size	Model Class	Residuals Length	Fitted Length
Market Price	252	4	1	nnetarmodels	252	252
Auction Price	252	3	1	nnetarmodels	252	252

Source: Prepared by the researcher based on R Studio

ARIMA and NNAR models were applied to analyze and compare predictive market and auction price series, and compare price metrics. A summary of the predictive models used in both series is shown in Table (2). For the market price series, the optimal model identified was the ARIMA(3,1,0) model, and was characterized as having three autoregressive coefficients: ar1=0.2170, ar2=0.1088, and ar3=-0.1517, with smaller than average standard deviation values corresponding to the three coefficients, suggesting the stability of these values. The Sigma² for the market ARIMA(3,1,0) model was found to be 402.4, Log Likelihood value of -1107.38 indicated that the ARIMA(3,1,0) model has acceptable fit, with the AIC and BIC indices having comparative values of 2222.76 and 2236.86, respectively. Conversely, for the auction price series, the best performing predictive model identified was the ARIMA(1,1,1) model, which was represented by an autoregressive coefficient ar1=0.1151, and a moving average coefficient ma1=0.5344. These coefficients also provide evidence of moderate standard deviation values, and the lower Sigma² (203.8) indicates less dispersion of the model residuals compared to the ARIMA(3,1,0) model. The Log Likelihood value of -1022.67 was also substantially higher than that of the market ARIMA(3,1,0) model, indicating a better fit between the model and the auction price series. For the NNAR neural network models, the number of lagged time series variable inputs was set to four for the market price series and three for the auction series, with an internal number of nodes equal to 1 in both neural networks. The model that was developed was based on the nnetarmodels class, which provides a means of hierarchy that is available to apply a neural network approach to time series data. A total of 252 observations were input into both neural network models, and fitted values were generated from the same 252 observations, thereby providing the models with full coverage of the available data without exclusion. The findings presented in this report demonstrate the ability of both ARIMA and

NNAR to capture linear relationships (as shown through ARIMA) and alternative relationships between the input variables within the models that were tested.

Table 3. Performance metrics of ARIMA and NNAR models

Series	Model	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Market Price	ARIMA	0.1364	19.8994	10.5745	0.0009	0.7851	0.2159	-0.0149
Auction Price	ARIMA	-0.3956	14.1898	3.8663	-0.0301	0.2837	0.0983	-0.0597
Market Price	NNAR	0.0949	16.8677	10.2066	-0.0099	0.7630	0.2084	0.0693
Auction Price	NNAR	0.0246	11.1551	3.1721	-0.0062	0.2396	0.0807	0.0290

Source: Prepared by the researcher based on R Studio

Table 3. Quantitative evaluation of the performance of the ARIMA and NNAR models on market and auction price predictions. It is worth noting from these statistical metrics for assessing accuracy and quality that the NNAR model outperformed the ARIMA model for most of these metrics in both series, proving its efficiency in handling nonlinear patterns within the series. In terms of the market price, in this model, NNAR attained an RMSE value of 16.86, corresponding to 19.90 in the ARIMA model, while the mean squared deviation of the forecasts from their actual values was smaller. On the other hand, the MAE was equal to 10.21 for the NNAR model compared with 10.57 for the ARIMA model; a clear improvement in accuracy was shown. Another important finding is the slight decrease in the MAPE from a value of 0.7851 to 0.7630, reflecting the ability of the NNAR model to reduce the relative error. The second case is that of the auction price, where the difference turned out to be more remarkable: the value of the RMSE dropped from 14.19 in ARIMA to 11.16 in NNAR. Besides, the MAE in NNAR was equal to only 3.17 when compared to 3.87 in ARIMA, which reflects high accuracy. In this sense, the MASE index, which means the error relative to a simple reference model, was lower in NNAR (0.0807) when compared with 0.0983 in ARIMA; further support for preference can be found in the neural model. Furthermore, the ACF1 value of the residuals of the NNAR was closer to zero than that of

the ARIMA model, which suggested fewer residual correlations in the series after forecasting-a quality indicator of the model. These findings confirm that the NNAR provides better performance, especially in using auction data, and presents more stable and reliable predictions than the ARIMA model, which therefore makes it more efficient for this application context. This paper selected a neural network model known as NNAR because it can achieve high skills in capturing nonlinear and complex patterns in time series, which is difficult to achieve using traditional statistic models such as ARIMA. Neural networks take advantage of learning internal relations between inputs and outputs through many layers of processing, which gives them the ability to accurately model nonlinear interactions within data. Technically, neural networks provide a flexible tool that enables them to learn from data without imposing strict assumptions about the structure of the time series or the error distribution. This is to their advantage in economic environments characterized by instability and sudden fluctuations, such as the Iraqi exchange market. As for the overfitting and underfitting problems of the models, the NNAR model addresses these in the following ways:

- Controlling the number of lag inputs: The model has only a few input values that are taken from the previous points.

- Employing a simple neural network (commonly a single-layer structure): In R programming, the NNAR model employs a simpler structure that captures complexity and generalization ability. - Automatic cross-validation: During the fitting of the model, the number of hidden units is determined based on the performance of the model. Therefore, the NNAR model achieves a good balance between model generalization capabilities and modeling flexibility to capture complicated patterns, ensuring that it is the most appropriate technique to employ when handling real and volatile time series phenomena like exchange rates. The forecast outcome for the remaining months up to the year 2025 is presented below

Table 4. Market and auction price forecasts for the months from January to December 2025 with 95% confidence intervals using the best model (NNAR)

Month	Market Price Forecast	95% CI (Lower - Upper)	Auction Price Forecast	95% CI (Lower - Upper)

Jan 2025	1506.389	1503.889 – 1508.889	1306.821	1304.321 – 1309.321
Feb 2025	1506.186	1503.686 – 1508.686	1308.895	1306.395 – 1311.395
Mar 2025	1505.239	1502.739 – 1507.739	1310.387	1307.887 – 1312.887
Apr 2025	1504.643	1502.143 – 1507.143	1311.064	1308.564 – 1313.564
May 2025	1503.863	1501.363 – 1506.363	1311.095	1308.595 – 1313.595
Jun 2025	1503.335	1500.835 – 1505.835	1310.801	1308.301 – 1313.301
Jul 2025	1503.328	1500.828 – 1505.828	1310.460	1307.960 – 1312.960
Aug 2025	1503.567	1501.067 – 1506.067	1310.220	1307.720 – 1312.720
Sep 2025	1503.970	1501.470 – 1506.470	1310.114	1307.614 – 1312.614
Oct 2025	1504.825	1502.325 – 1507.325	1310.111	1307.611 – 1312.611
Nov 2025	1505.410	1502.910 – 1507.910	1310.157	1307.657 – 1312.657
Dec 2025	1505.967	1503.467 – 1508.467	1310.209	1307.709 – 1312.709

Source: Prepared by the researcher based on R Studio

In Table (4) the NNAR Model has been used for monthly Price Forecasting till 2025 in Iraq based on the NNAR Training Results already discussed to show the viability of the NNAR Model for monthly Price Forecasting.

The monthly Price Forecast Estimates indicate a relatively stable Price of the Market, which is expected to range from approximately 1,503 to 1,506 Dinar each month; along with an approximate Auction Price Range of approximately 1,306 to 1,311 Dinar for Auction in Iraq. The Price Gap between Market & Auction is likely to continue throughout the coming 12 months based on the Estimated Forecast. Along with the Monthly Price Forecasts are the 95% Confidence Intervals for each month, which establish the expected limits of volatility that would occur around the estimated central mean price forecast. This confidence interval adds further dimension to understanding the level of uncertainty associated with the estimated Monthly Forecasts. In the vast majority of months, the Confidence Intervals appear to be somewhat narrow, typically from about ±2 to ±3 Dinar, indicating relatively stable Price Estimates and high levels of confidence in the NNAR

Model used. The NNAR Model provides accurate Price Forecasts as well as realistic Estimated Volatility Margins. This provides a key benefit for decision-makers regarding Monetary Policy as well as Forecasting Currency Flows in the marketplace. The NNAR's Reliability also allows Stakeholders to effectively conduct a financial Planning Process in a manner that provides measurable Quantitative Indicators in the financial planning process.

CONCLUSIONS

1. NNAR had superior out of sample accuracy as compared to ARIMA in the two exchange rate series. The difference was more pronounced in the official auction rate where RMSE dropped to 11.16 and MAPE dropped to 0.2396 as compared to the 14.19 and 0.2837 respectively. This reflects the opinion that the dynamics of exchange rate conduct in Iraq has nonlinear dynamics which are not well reflected in linear specifications.

2. The dispersion of the parallel market rate was higher when compared to the dispersions of the auction rate across the entire sample. The average and upper tail in parallel market was higher and this indicates a continued premium associated with expectation, liquidity strain and transaction impediments. This superiority renders the parallel rate for more realistic to the risk exposures of the private sector and cash flows planning.

3. The chosen ARIMA shapes that needed differencing still had to face patterns that were better reduced by the neural approach. The NNAR case residual behavior was brought near to white noise which provides better extraction of time dependence. This makes the argument of using learning based models even more robust as the regimes change and administrative intervention moves the data generating process.

4. The 2025 forecasts indicated that the various series will remain stable within a thin range but with the persistent disparity between the market and the auction rates. Small confidence bands refer to short horizon predictability despite a volatile environment. The existence of the gap alone indicates that the policy and market channels convey differently between the two regimes.

5. Statistical fit is not the only practical value of forecasting. It has direct improvements in pricing, hedging, inventory import planning and budget scenarios of banks and firms. Better forecasts are also beneficial in policy communication in that they convert uncertainty into quantifiable ranges which can be implemented by decision makers. **Recommendations:**

1- The Central Bank of Iraq is advised to make a monthly exchange-rate forecasting organization where NNAR is a standard tool that is used in conjunction with ARIMA standards, where re-estimates roll and backtesting reports are mandatory to facilitate policy tuning and reporting.

2- The Ministry of Finance and the Central Bank ought to release more indicators in a timely manner, which forms the expectations of the exchange-rate, such as auction volume and other important liquidity indicators where possible, to minimize uncertainty and thus the information gap that contributes towards the premium in the parallel-market.

3- Auction rate and parallel rate commercial banks are supposed to develop two risk dashboards and utilize forecast intervals to establish FX liquidity reserves, pricing margin, and stress-test situations of trade finance and settlement of imports.

4- Note - the bank risk committees and financial regulators must mandate model-governance rules of FX forecasting which include validation, break-detection triggers when major policy changes occur, documentation of how the forecast converts into limits, hedging policy, and capital planning.

5- Iraq After more needs to be done on the applied forecasting by universities and research centers: combining exchange-rate models with macro-financial as well as market microstructure variables and generating open, repeatable evaluation protocols to permit consistent comparison across methods and times.

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