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Original Article

Hybrid Method of Forecasting Central Bank Sales of Dollars

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Abstract: *By fusing the most effective aspects of machine learning and statistics, hybrid approaches hold the potential to enhance time series forecasting. The basic notion is that by merging Artificial Neural Networks (ANN) and the Autoregressive Integrated Moving Average (ARIMA) model, this combination makes up for the shortcomings of one strategy with the advantages of the other. The linear model, which can only model linear relationships, and the nonlinear model, which can only model nonlinear relationships, are the two types of time series that the hybrid model can handle. Time series data of the Central Bank of Iraq's sales of US dollars during the period from 2003 to 2024 were used. The accuracy measures, Mean Square Error (MSE) and Mean Absolute Percentage Error (MAPE) of the hybrid combination were also compared with ARIMA and ANN methods. The results showed a significant improvement in the MSE and MAPE values of the hybrid model.*

Keywords: *Central bank sales, ARIMA, ANN, Hybrid Models.*

I. INTRODUCTION

Iraq relies on a platform for selling foreign currency (the dollar) directly to local banks and companies, which was previously known as the daily dollar auction, as one of the mechanisms for maintaining the value of the Iraqi dinar against the US dollar and combating speculative operations in the parallel market. Forecasting financial variables is particularly important due to its influence on the method of decision-making that governs the administration of macroeconomic policy, particularly monetary policy (Odah,2021).

Based on the Central Bank's goals of meeting the strong demand for foreign currency in regional markets and achieving stability in the overall level of prices and exchange rates. The foreign currency (auction) window was established in October 2003. That window played a dual role in the work of the Central Bank of Iraq's monetary policy, both in controlling local liquidity, Which requires exchanging the dinar for the dollar for external transfer related to financing domestic trade, in addition to achieving the goal of controlling the stability of the Iraqi dinar exchange rate at the same time.

During the past periods, many economic and social phenomena have been studied through time series characterized by their fluctuations, which are characterized by instability or uncertainty. When plotting time series data, it turns out that the series is unstable(Odah M. H,2021). The use of various forecasting models to reach future results and in order to make appropriate decisions regarding the phenomenon under study among these studies are: Making the appropriate decisions to address the issue of unemployment might be aided by using the Markov chain technique to predict the unemployment rate for the upcoming years (Odah,2021).

Models were used to predict the Central Bank's sales of the dollar, and the most common of these models were the exponential smoothing model and the ARIMA models. In previous literature, there are a small number of studies on time series forecasting using hybrid models, from researchers in diverse fields of economics, statistics, engineering, and science (Song et al., 2018). The emission of pollution sources is taken into account as an independent variable in the construction of a prediction model that uses a combination of ARIMA and SVM to forecast the daily mean value of PM2.5 concentration for various meteorological types. (Chatfield, 2016) forecasted monthly gold price data using an ARIMA & ANN combination. The study's findings suggest that the hybrid ARIMA-ANN model can perform more predictively than either model alone. (Al Anazi etal, 2022) The hybrid ARIMA-ANN model was applied instead of using a single ARIMA model to forecast natural rubber price time series data. The results of the study indicate that using the hybrid ARIMA-ANN model can give predictive accuracy. Linear models are often inefficient in predicting complex time series, so it is necessary to review nonlinear models to fill the shortcomings of the exponential smoothing model. As for ARIMA models, they have been successfully used in forecasting and analyzing linear time series, but they are less efficient in the field of complex non-linear time series (Montgomery et al., 2015).

Recently, intelligent neural network models (ANN) have been applied, and they are known for their ability to identify non-linear features present in financial time series data. Accordingly, ANN models have been widely used in the field of time series forecasting (Mitchell et al., 2013).

These series have both a linear model and a non-linear model at the same time. Therefore, it is not appropriate to use non-linear models to predict complex time series because these models may not take into account the linear characteristics available in the time series. In some cases, it is found appropriate to use a model. A hybrid that addresses linear and non-linear characteristics because neural network models and ARIMA models are integrated models. During this study, a hybrid model of ARIMA models and neural networks was reached.

II. FORECASTING MODELS - DATASET AND MODEL EVALUATION

In this research, it includes a time series that contains a linear model and a non-linear model at the same time. Because forecasting is difficult to predict complex time series that do not take into account linear properties, it is appropriate to use a hybrid model consisting of neural network models that address non-linear properties, ARIMA. A model that deals with linear properties. During this study, a hybrid model of ARIMA models and neural networks was developed to achieve the desired results. In the following subsections, the ARIMA, ANN and hybrid models are described.

A) ARIMA Models

This approach, which is based on a combining of the autoregressive and shifting average models, is one of the most well-known ways to forecast Autoregressive Integrated Moving Average Models (ARIMA).

Represent models (ARMA) integrate observations and random errors can be expressed (Shumway and Stoffer, 2017):

$$ARMA(p,q) = \alpha + \eta_1 Y_{t-1} + \eta_2 Y_{t-2} + \cdots + \eta_p Y_{t-p} + b_t - \delta_1 b_{t-1} - \delta_2 b_{t-2} - \cdots - \delta_q b_{t-q} \quad \dots\dots(1)$$

Where:
α: Constant
$\eta_1, \dots, \eta_p$ &$\delta_1, \dots, \delta_q$: Parameters of the model
t: Time

Models ARIMA time series are widely used models that make up these models from the above step, where AR (p), MA(q) & (d) represent the differences by time series to be stable, then the model turns into (p,d,q).

B) Artificial Neural Networks (ANN) Method

Neural networks are a mathematical technology designed to carry out various tasks and duties. There have been many studies in the field of neural networks over the past decades, but they appeared clearly starting in the year 1980.

ANN is characterized by some characteristics that help them reach distinctive solutions through their applications in areas whose goal is to identify linear and non-linear models. One of these qualities is the learning ability, generalization, parallel processing, and error endurance; as stated in (Venkatesh & Bind, 2020), these characteristics help neural networks in solving complex problems with high accuracy and sufficient flexibility.

This can be expressed by, (Dongare et al., 2012):

$$y_t = \alpha + \sum_{j=1}^{n} \alpha_j f\left(\sum_{i=1}^{m} \beta ij\; y_{t-i} + \beta_j\right) + \varepsilon_t \quad \dots\dots(2)$$

Where:
m: Number of input nodes
n: Number of hidden nodes
f: Sigmoid transfer function
(β_j, α): Weights specific to the bias term and have a value equal to one.
$\{\alpha_j, j, = 0,1, \dots, n\}$: A vector of weights starting from the hidden nodes and ending with the output nodes.
$\{\beta_{ij}, i, = 1,2, \dots, m, j = 1,2, \dots, n\}$: Weights starting from the input nodes and ending with the hidden nodes.

$$\log f(x) = \frac{1}{1 + \exp\,(\alpha - x)} \quad \dots\dots(3)$$

Equation (3) indicates the use of a linear transfer function with respect to the output nodes for forecasting purposes.

C) Hybrid Model

The ARIMA model addresses the linear characteristics of the time series, while neural networks address the non-linear characteristics of the time series. To reach an efficient method of forecasting, the hybrid method was used by integrating neural networks with ARIMA models, as follows:

$$Y_t = F_1 + F_2 \quad \dots\dots(4)$$

Where:
F_1: The linear part of the time series.
F_2: The non-linear part of the time series.

The merging process takes place in two stages. During the first stage, ARIMA models are used to estimate the central bank's sales of the dollar. In the second stage, the neural network model is fed with the outputs of the ARIMA models for the first stage so that the outputs are the predicted values of the central bank's sales of the US dollar.

The second stage is merging using the linear regression analysis method to determine the merging weights for the above methods, as follows:

$$Y = a + w_1 F_{\text{ARIMA}} + w_1 F_{\text{ANN}} \quad \ldots\ldots (5)$$

Where:
a: Real data
w_1: The first weight is the first linear regression coefficient.
w_2: The second weight is the second linear regression coefficient.
F_{ARIMA}: Forecasting ARIMA method.
F_{ANN}: Forecasting ANN method.

We assume that $a = 0$. The original data for the regression model will be the dependent variable for central bank sales, the prediction results of the ARIMA models will be the first independent variable, and the prediction results of the ANN model will be the second independent variable.

D) Dataset and Model Evaluation

The data utilized for this investigation are shown in this section. Furthermore, we give the standard evaluation criteria used in this research. The study's dataset is derived from the dollar sales made by the central bank. Obtained from https://cbiraq.org/ from October 2003 to June 2024, with 249 observations. Figure 1 shows central bank dollar sales on the y-axis versus time periods (i.e. months) on the x-axis.

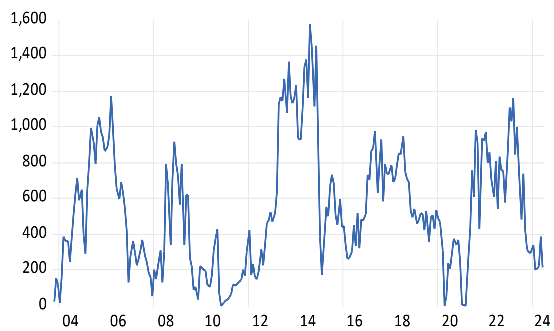

Fig. 1 Time Series Plot of the central bank dollar sales.

E) Model Evaluation

The model will be evaluated according to the accuracy performance results by selecting the appropriate method, hyperparameter optimization, etc. until the most suitable model is obtained. In this study, we used two well-known error metrics to evaluate the performance of the applied models.

The Mean Squared Error (MSE) is as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(\beta_i - \hat{\beta}_i\right)^2 \quad \ldots\ldots (6)$$

Mean Absolute Percentage Error (MAPE) is as follows:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|\beta_i - \hat{\beta}_i\right|}{\beta_i} \times 100, \;\; \beta_i \neq 0 \quad \ldots\ldots (7)$$

Where n is the number of test data; β_i is the actual value and $\hat{\beta}_i$ is the forecasted value.

III. RESULTS AND DISCUSSION

A) Application Determines the Appropriate Model

a. Apply Fitting ARIMA Model

In this section, we use the ARIMA model to forecast central bank dollar sales. The R programming language's "auto_arima" function assisted us in selecting the ideal ARIMA model. By examining the potential models for time series, you select the model that reduces the AIC. The following formula is used to determine the model's AIC values:

$$AIC = 2m - 2ln(\hat{K}) \quad \ldots\ldots (8)$$

Where $\hat{K}$ denotes the maximum value of the likelihood function of the model, and m is the number of parameters estimated by the model. The best model with a smaller AIC, given the number of parameters, is the smallest. The different models associated with the accuracy criterion are listed in Table 1.

Table 1. The Values of AIC for Different ARIMA Models.

Model	AIC
ARIMA (0,1,0)	1804.15
ARIMA (0,1,1)	1772.67
ARIMA (1,1,0)	1762.73
ARIMA (1,1,1)	1766.83
ARIMA (2,1,0)	1766.81
ARIMA (2,1,1)	1766.13

Based on the "auto_arima" function, the appropriate model for the central bank dollar sales is ARIMA (1,1,0). After selecting the best ARIMA model, the "predict" function built into the R programming language is used to forecast central bank dollar sales.

Since the ARIMA (1, 1, 0) model is fitted to central bank dollar sales, we can use this model directly to predict central bank dollar sales for the testing data study data. Table 2 indicates the predicted and actual values for the last 20 observations as follows.

Table 2. Actual Values and Forecasted Values Using the ARIMA Model.

Date	Actual	Forecast	Date	Actual	Forecast
Nov-22	577	596	Sep-23	420	640
Dec-22	860	915	Oct-23	312	524
Jan-23	1106	1211	Nov-23	293	471
Feb-23	1030	1253	Dec-23	297	385
Mar-23	1163	1279	Jan-24	335	513
Apr-23	844	953	Feb-24	199	270
May-23	998	1080	Mar-24	207	390
Jun-23	673	780	Apr-24	217	382
Jul-23	479	591	May-24	383	494
Aug-23	738	882	Jun-24	210	331

b. Apply Fitting ANN Model

Nonlinear autoregressive network models forecast future values based on only several past values. The neural network has a great fitting ability for nonlinear time series. The nonlinear auto-regressive network contains three layers (input, hidden, and output). The nonlinear auto-regressive network was used to forecast central bank dollar sales. The input variable includes previous monthly central bank dollar sales. This variable is fed as a data string to the network. The R programming language is then initialized to forecast central bank dollar sales.

In this study, we implemented time steps to validate the model and to test the model. The nonlinear autoregressive network suitable for central bank dollar sales consists of three layers: the input layer is the values of the monthly sales, a hidden layer consists of 10 processing elements, and finally, the output layer is the current index values; therefore, the network model (1:10:1). Table 3 indicates the predicted and actual values for the last 20 observations as following.

Table 3. Actual Values and Forecasted Values Using the ANN Model

Date	Actual	Forecast	Date	Actual	Forecast
Nov-22	577	591	Sep-23	420	398
Dec-22	860	889	Oct-23	312	273
Jan-23	1106	1160	Nov-23	293	270
Feb-23	1030	1081	Dec-23	297	246
Mar-23	1163	1192	Jan-24	335	284
Apr-23	844	894	Feb-24	199	168
May-23	998	1071	Mar-24	207	244
Jun-23	673	702	Apr-24	217	253
Jul-23	479	490	May-24	383	407
Aug-23	738	769	Jun-24	210	239

c. Apply Fitting Hybrid model

The section focuses on using the Hybrid ARIMA-ANN model, as described in Section 3, to forecast monthly central bank dollar sales. After selecting the appropriate ARIMA model, the "auto_arima" function was taught using the residuals that were received by fitting it using ARIMA; as a result, the network that is utilized has three layers. The three layers are the input layer, the concealed layer, and the output layer.

In this model, we do not place the bank's monthly sales data in the grid because it is included in ARIMA as a linear part. Therefore, ANN was used to model the residuals of the ARIMA model as a nonlinear part.

Within this portion, there is one delay and ten hidden levels. Various numbers are tried, and how they perform is compared to determine this model. The best fit for this model is ARIMA-ANN (1,1,0) (1:10:1). Table 4 indicates the predicted and actual values for the last 20 observations as follows.

Table 4. Actual Values and Forecasted Values Using the Hybrid Model.

Date	Actual	Forecast	Date	Actual	Forecast
Nov-22	577	586	Sep-23	420	463
Dec-22	860	869	Oct-23	312	352
Jan-23	1106	1120	Nov-23	293	330
Feb-23	1030	1043	Dec-23	297	344
Mar-23	1163	1174	Jan-24	335	353
Apr-23	844	851	Feb-24	199	221
May-23	998	1032	Mar-24	207	239
Jun-23	673	682	Apr-24	217	238
Jul-23	479	489	May-24	383	401
Aug-23	738	759	Jun-24	210	245

B) Compare models

To evaluate the predictive ability of the predictive models, the predictive models are applied to central bank dollar sales. The forecasting performance metrics applied in this study consist of two metrics: Mean Square Error (MSE) and mean absolute error (MAPE).

Table 5. Forecast performance results for models

Model	MSE	MAPE
ARIMA-ANN	**912.36**	**12.86**
ANN	1160.40	19.41
ARIMA	6079.43	43.47

The prediction performance outcomes for ARIMA, ANN, and hybrid models in terms of MSE and MAPE are displayed in Table 5. The hybrid model outperformed the other models in terms of mistakes, as can be seen in the table above. This may indicate that the ARIMA or ANN model does not capture all the patterns in the data.

Figure 2 also shows the comparison of the predicted and actual values of the monthly central bank dollar sales for the test data. It was found that the hybrid model forecasts values closer to the actual value and has a similar pattern to the actual data.

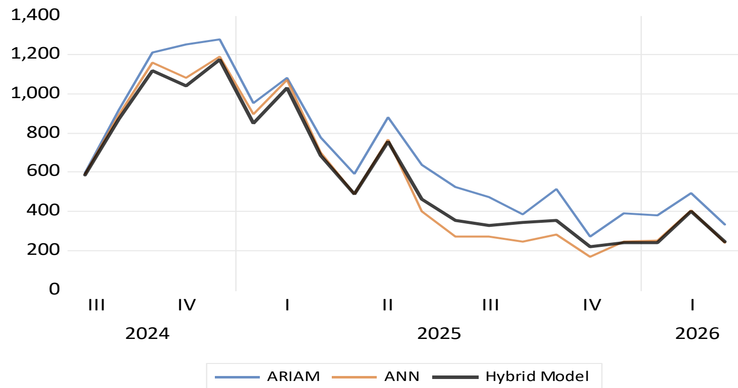

Fig. 2. Forecasting the central bank dollar sales.

IV. CONCLUSION

The study aimed to compare ARIMA, ANN and hybrid models for forecasting the Central Bank of Iraq's sales of US dollars. Through the results of (MSE and MAPE), the outcomes of the applied ARIMA, ANN, and hybrid models were contrasted. The study's findings suggest that the hybrid model outperformed the ARIMA and ANN models in forecasting monthly central bank dollar sales, based on the hybrid model's outcomes showing less error and greater accuracy.

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