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Research Article

US Dollar/IQ Dinar Currency Exchange Rates Time Series Forecasting Using ARIMA Model

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ABSTRACT

The use of currency exchange estimation as a tool for economic planning is being researched as a technique for gaining economic stability. The main purpose of this study is to use the Autoregressive Integrated Moving Average (ARIMA) model to forecast monthly US dollar against IQ dinar exchange rates. The information was gathered from January 2010 to December 2020. We got the information from the website (sa.investing.com). The minimum value of root means square error and the Mean Absolute Error are used to select the optimal model. ARIMA (2, 1, 0) was found to be the best model for the US Dollar/IQ Dinar series. This is the forecasted meaning for the future of this exchange rate time series, which indicates a perpetual increase continuously in the next two years. Statgraphics version 15 was the statistical software package utilized to complete this project.

Keywords: Exchange rate forecasting, US Dollar/IQ Dinar, time-series analysis, autoregressive integrated moving average model

INTRODUCTION

Time series analysis is used in a wide variety of fields. In economics, time series are used to represent the economy's recorded history. The consumer price index, gross national product, and unemployment, as well as the population, products, and output, are all measured in the same time series. The statistical theory of time series has sparked a lot of interest in recent years.

It is generally believed that the degree of financial transactions in and out of a country depends on several factors prevailing in that country. Since the advent of money, the world has always experienced the movement of money from one country to another due to economic, cultural, social, political, and other reasons. The Central Bank in every country usually keeps a record of such money transactions through various financial intermediaries. Every country has its own money, which can only be accepted for use within its territory. Hence, the establishment of foreign money became necessary. Foreign money is the money of other countries of the world which serves as money in the foreign exchange market.

The researcher's study time-series data to attempt to establish a strong statistical way for forecasting a future rate of exchange of the US dollar over the Iraqi dinar basis on previous data here on the exchange rate of the US dollar and the Iraq dinar. Using the historic date of the exchange rate of the local currency against the foreign currency, this statistical tool can be used to forecast the rate of exchange of any foreign currency.

The most common technique in time series is Box-Jenkins modeling. The other name of it is Autoregressive Integrated Moving Average (ARIMA) modeling. Recent work on ARIMA forecasting has revealed an apparent accuracy for forecasting. ARIMA models have been applied for US Dollar/IQ Dinar Currency Exchange Rates time series forecasting. In this work, the original dataset has 132 observations. ARIMA modeling was used to forecast two years ahead of data. The rest of the paper is structured as the following: Section 2 describes the methodology of Box Jenkins and provides a brief introduction to the theory of ARIMA model building. Section 3 introduces the data used in this study and follows the ARIMA procedure for building an adequate model for the forecasting exercise and discusses the results. Finally, section 4 is devoted to conclusions.[1-5]

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METHODOLOGY

This section introduces some basic definitions and concepts.

Time Series

A time series is a collection of correlated observations made in a specific order across time. A discrete-time series is one in which the set T_0 of times at which observations are taken is discrete, such as when they are conducted at fixed intervals. When observations are recorded continuously across a time interval, such as when $T_0 = [0, 1]$, a continuous-time series is obtained. If we want to emphasize that observations are recorded continuously, we'll use the notation (t) rather than X.[6,7]

Stationary Time Series

The first and second moments of a stochastic process X_t are deemed stationary although they are time-invariant. To put it another way, if the first criterion is met, X_t is stationary, meaning that all members of a stationary stochastic process have the same constant mean. For example, a time series generated by a stationary stochastic process must vary around a constant mean and not show a trend. The variances are often time-invariant due to the second requirement. The variance $\sigma^2{}_x = [E(X_t - \mu_x)^2] = \gamma_0$ is independent of t when k = 0. Furthermore, the covariance E $[(X_t - \mu_x)\ (X_{t-k} - \mu_x)] = \gamma_k$ depends only on the distance in time k between the two members of the process, not on t.[8,9]

Time Series Models

A time series model for observed data X_t is a description of the joint distributions (or, in some cases, just the means, and covariance) of a set of random variables X_t, where X_t is supposed to represent a realization.[10]

Autoregressive (AR) Model

A process $\{X_t\}$ is said to be an AR model of an order p, abbreviated AR (p), is of the form.

$$X_t = \varnothing_1 X_{t-1} + \varnothing_2 X_{t-2} + \ldots + \varnothing_p X_{t-p} + \epsilon_t \quad (1)$$

Where it X_t is stationary, $\varnothing_1, \varnothing_2, \ldots, \varnothing_p$, are constants $(\varnothing_p \neq 0)$.[11]

Moving Average (MA) Model

A process $\{X_t\}$ is called to be the MA model of order q, or MA (q) model, is identified to be

$$X_t = \epsilon_t - \theta_1 \epsilon_{t-1} - \theta_2 \epsilon_{t-2} - \ldots - \theta_q \epsilon_{t-q} \quad (2)$$

Where there are q lags in the MA and $\theta_1, \theta_2, \ldots \theta_p$ $(\theta_p \neq 0)$ are parameters.[11]

ARMA Model

The process $\{X_t, t = 0, \pm 1, \pm 2.,\}$is said to be an ARMA(p, q) process if $\{X_t\}$ is stationary and if for all the t,

$$X_t - \varnothing_1 X_{t-1} - \ - \varnothing_p X_{t-p} = \varepsilon_t + \theta_1 \varepsilon_{t-1} + \ + \theta_q \varepsilon_{t-q} \quad (3)$$

where $\{\epsilon_t\} \sim N(0, \sigma^2)$. We say that $\{X_t\}$ is an ARMA (p, q) process with mean μ. If $X_t - \mu\}$ is an ARMA (p, q) process.[7]

ARIMA Model

If the d^{th} difference $Z_t = \nabla^d X_t$ is a stationary ARMA process, a time series $\{X_t\}$ is said to follow an integrated ARMA model. We state that $\{X_t\}$ is an ARIMA (p, d, q) process if $\{Z_t\}$ follows an ARMA (p, q) model. Fortunately, we can typically take d=1 or 0 greater than for practical purposes.[9]

Consider an ARIMA (p, 1, q) process. With $Z_t = X_t - X_{t-1}$, we have

$$Z_t = \varnothing_1 Z_{t-1} + \varnothing_2 Z_{t-2} + \ldots + \varnothing_p Z_{t-p} + \epsilon_t - \theta_1 \epsilon_{t-1} - \theta_2 \epsilon_{t-2} \ldots - \theta_q \epsilon_{t-q} \quad (4)$$

Stages of Time -Series Model Building

The process of a three-step adaptive approach is used to build an ARIMA model. First, previous data analysis helps to identify a probable model of a time series model class. Second, the model's unknown parameters are approximated. Finally, diagnostics checks are carried out through residue left models to analyze the model's appropriateness or to predict possible developments. Then, we will go through each of these processes in any further context.[12]

Identification

To make the data stable, it may have to be pre-processed. Some of the other four stages below must be followed to achieve stationarity:

1- Start by looking at it.
2- Rescale it using a logarithmic or exponential transform, for example.
3- Take out the deterministic elements.
4- And that is the distinction. To put it another way, take $\nabla(B)^d X$ until you reach a stop. In most cases, d = 1,2 will enough. The autocorrelations decline to zero exponentially fast, indicating that the system is stationary. We can try to fit an ARMA (p, q) model when the series is stationary. The correlogram $r_k = \hat{\gamma}_k / \hat{\gamma}_0$ and partial autocorrelations $\hat{\varnothing}_{kk}$ are considered. The following observations have previously been made.

Both the sample ACF and PACF, as previously mentioned, have a standard deviation of around 1/N, where N is the length of the series. A good rule of thumb is that ACF and PACF values between $\pm 2/\sqrt{N}$ are inconsequential. for k > max (p, q), the k^{th} order sample ACF and PACF decay geometrically in an ARMA (p, q) process, as shown in Table 1.[13,14]

Estimations of parameters

Various methods, such as the moment method, least squares, maximum likelihood, and Yule-Walker estimate, can also

Table 1: Theoretical ACF and PACF properties for stationary processes

Process	ACF	PACF
AR (p)	Tails off as exponential decay or damped sine wave	Cuts off after lag p
MA (q)	Cuts off after lag q	Tails off as exponential decay or damped sine wave
ARMA (p, q)	Tails off after lag (q-p)	Tail off after lag (q-p)

be used to predict the values as in the tentatively defined model.[12]

Verification of the model

The box-Jenkins methodology's confirmation procedure is rather extensive. The predicted model's compliance with the examined data must be confirmed using various diagnostic tests.[15]

Forecasting[12]

Once a suitable time series model has been fitted, it may be used to create forecasts of observations in the future. If the current time will be is denoted by T, the forecast for $X_{T+\tau}$ is named the τ-period-ahead forecast, then denoted by $\hat{X}_{T+\tau}(\mathrm{T})$. The mean squared error, which is the averaged value of the squares prediction error, is the conventional criterion to use in getting the best forecast, $\mathrm{E}[(X_{T+\tau}-\hat{X}_{T+\tau}(\mathrm{T}))^2]=\mathrm{E}\,[e_T(\tau)^2]$ is minimized. It can be seen that the best forecast in the mean square sense is the conditional expectation of $X_{T+\tau}$ given current and previous observations, that is, $X_T, X_{T-1}, \ldots$.

$$\hat{X}_{T+\tau}(\mathrm{T})=\mathrm{E}(X_{T+\tau}\mid X_T, X_{T-1},\ldots) \quad (5)$$

Consider, for example, an ARIMA (p, d, q) process at time T+τ (i.e., τ a period in The future):

$$X_{t+\tau}=\delta+\sum_{i=1}^{p+d}\varnothing_i X_{t+\tau-i}+\epsilon_{T+\tau}-\sum_{i=1}^{q}\theta_i\epsilon_{T+\tau} \quad (6)$$

And Box Jenkins described the flow chart shown in Figure 1.[16]

The Dependable Statistical Standards to Test Forecasting Model

Mean absolute error (MAE)

$$MAE=\frac{\sum_{t=1}^{N}|e_t|}{N}=\frac{\sum_{t=1}^{N}\left|\frac{(Y_t-\hat{Y}_t)}{N}\right|}{N}=\frac{1}{N}\sum_{t=1}^{N}\left|(Y_t-\hat{Y}_t)\right| \quad (7)$$

Where t = time period, N = total number of observations, and e_t = (observed value - forecasted value) at time t.[17]

Root mean square error (RMSE)[1]

This is simply the square root of MSE:

$$RMSE=\sqrt{MSE}=\sqrt{\frac{\sum_{t=1}^{n}(Y_t-\hat{Y}_t)^2}{n}} \quad (8)$$

APPLICATION ON REALDATA

Data Description

The dataset used in this analysis is monthly US Dollar/IQ Dinar Currency Exchange rates time series forecasting using the ARIMA model. All the data were collected from the website (sa.investing.com).data were collected for the period January 2010 to December 2020. There were overall 132 observations. The statistical analysis was computationally implemented in the Stat graphics 15 software, as shown in Table 2.

Time Series Plots

The monthly exchange rate between the US Dollar/IQ Dinar is depicted in the data set's time series plot. Because the variation in the size of the fluctuations with time is referred to as non-stationary in the variance, the plot reveals that the data is clear of being non-stationary in the mean and variance, seasonal, and trend patterns with an increasing variety of variance, as shown in Figure 2.

Randomness Test

First of all, the randomness test of the one series should be made using the Box-Pierce test. The null hypotheses are the time series are random, versus the alternative hypotheses of non-randomness, to know that the data has a certain behavior than having a random behavior. As explained in Table 3 for the series; as $P < 0.05$ to every series, therefore null hypotheses were rejected, meaning that the one-time series are not random series.

The hypothesis was as follows for the exchange rate US dollar/IQ dinar the series.

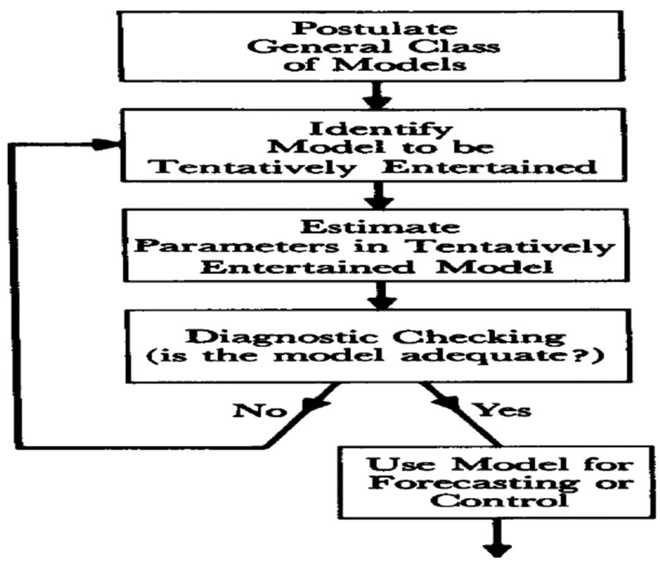

Figure 1: Depicts the Box-Jenkins model-building methodology

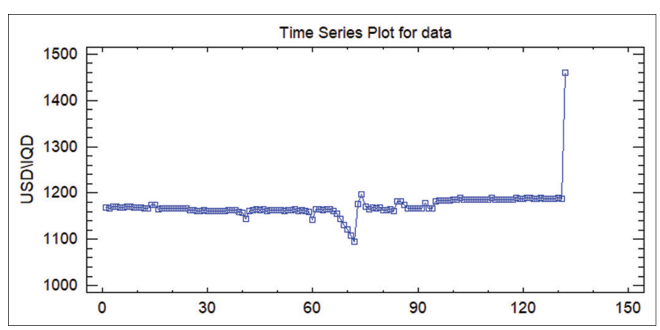

Figure 2: Time series plot of the original monthly exchange rate USD/IQD data from 1 January 2010 to 31 December 2020

Table 2: Monthly average US Dollar/IQ Dinar Currency Exchange Rates data for the period 1 January 2010–31 December 2020

Years	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
January	1169.00	1166	1163.5	1163.25	1163.8	1164	1175.9	1181	1184.05	1186.43	1189.4
February	1165.9	1175	1163	1163	1163	1165	1196.44	1175	1184.05	1186.43	1189
March	1170	1175	1160.9	1160	1163.55	1163	1170	1166	1184	1189	1187.62
April	1170.1	1165	1160.9	1157	1162	1164	1165.7	1166	1185.24	1186.43	1187.62
May	1168	1166	1162.25	1145	1162.5	1165	1169.4	1167	1186.43	1186.43	1189
June	1168	1166	1162	1160.5	1162.9	1162	1167.2	1166	1190	1186.4	1187.62
July	1170.03	1166.05	1162.05	1162.5	1164.2	1156	1168	1167	1186.43	1186.43	1187.62
August	1171	1166	1162	1164	1161.3	1145	1162.7	1177.73	1186.43	1186.2	1187.62
September	1169.2	1166	1162	1163.8	1163.05	1131	1162.7	1166.1	1186.43	1186.43	1187.62
October	1169.05	1167	1162	1164	1162	1122	1164	1166	1186.43	1189	1189
November	1169.47	1167	1162	1160.8	1160	1108	1160.3	1182.8	1186.43	1187.62	1187.62
December	1166.5	1166.3	1163	1163.8	1142	1095	1181	1184	1186.43	1187.62	1459

H_0: The series is random
H_1: The series is not random

Data Transformation

After proving the non-randomness of the exchange rate US Dollar/IQ Dinar time series, it can be concluded that all the data series have a certain behavior, so to overcome this behavior we will try to transform the data series, each according to its behavior. Then, the data were transformed, for instance, a non-seasonal difference of order one for the variable. Then, the series was tested again to test the existence of randomness. The hypotheses were accepted when $P > 0.05$ as shown in Table 4.

The hypothesis for the exchange rate USD/IQD series was as follows.
H_0: The series is random
H_1: The series is not random.

It can be noticed that all the data series were accepted to be random after the transformations made on the series.

Stationary

The series under consideration must satisfy the condition of being stationary; that is, the mean and variance are independent of time throughout the series. The original series needs to be differentiated to make the series stationary around meaning and to get stationary around variance for the series, we make transformations The rest original series exchange rate US dollar/IQ dinar is needed non-seasonal differencing of order one transform to achieve stationary, Figure 3 show the differenced series.

To identify the entire order of the models for the series, we investigate the Autocorrelation Function (ACF) and Partial ACF (PACF) for the original data. The ACF and PACF plots are displayed in the Figure 4 series.

The estimated autocorrelations and PACF between corrected data values at various lags are shown in this table. The auto-correlation coefficient lag k determines between the residuals at time t-k and time t is related and The partial autocorrelation coefficient measures the correlation between the residuals at time t and time t+k having accounted for the correlations at all lower lags 95.0% probability bounds around 0 are also indicated. There is a statistically significant association at the 95.0% confidence level if the probability bounds for a certain lag do not contain the calculated coefficient. The 95.0% probability bounds around 0 are also indicated. There is a statistically significant association at the 95.0% confidence level if the probability bounds for a certain lag do not contain the calculated coefficient. At the 95.0% confidence level, none of the 24 partial autocorrelation coefficients are statistically significant.

The same procedure was conducted for the series; Table 5 through Table 6 contain that.

Table 3: Hypothesis of randomness test and *P*-value for data

Series	Box-pierce test *P*-value	Decision
Exchange rate USD/IQD	0.000	(SNR)

Table 4: Hypothesis of randomness test and *P*-value for transformed data

Series	Box-Pierce test *P*-value	Decision
Exchange rate USD/IQD	1	(SR)

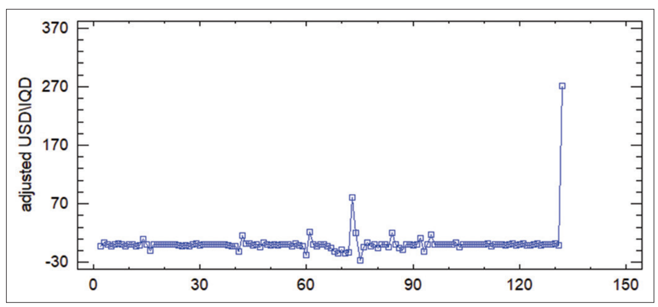

Figure 3: Exchange rate USD/IQD series plot after non-seasonal differencing of orders one

Table 5: Estimated Autocorrelations for adjusted exchange rate USD/IQD

Lag	Autocorrelation	Standard Error.	Lower 95.0%Probability. Limit	Upper 95.0%Probability. Limit
1	0.260945	0.087038	-0.170593	0.170593
2	0.211871	0.092776	-0.181839	0.181839
3	0.189218	0.096372	-0.188886	0.188886
4	0.174333	0.099146	-0.194324	0.194324
5	0.16255	0.101442	-0.198824	0.198824
6	0.160989	0.103397	-0.202654	0.202654
7	0.16544	0.105279	-0.206343	0.206343
8	0.16592	0.10723	-0.210168	0.210168
9	0.167997	0.109158	-0.213946	0.213946
10	0.178883	0.111099	-0.217751	0.217751
11	0.187412	0.11326	-0.221986	0.221986
12	0.170011	0.115586	-0.226544	0.226544
13	0.140489	0.117465	-0.230227	0.230227
14	0.1297	0.118731	-0.232709	0.232709
15	0.127231	0.119799	-0.234803	0.234803
16	0.128438	0.120819	-0.236801	0.236801
17	0.127931	0.121849	-0.23882	0.23882
18	0.132377	0.122862	-0.240806	0.240806
19	0.131391	0.123938	-0.242914	0.242914
20	0.119234	0.124989	-0.244974	0.244974
21	0.126591	0.125847	-0.246657	0.246657
22	0.120522	0.126808	-0.24854	0.24854
23	0.10901	0.127673	-0.250235	0.250235
24	0.0940275	0.128376	-0.251614	0.251614

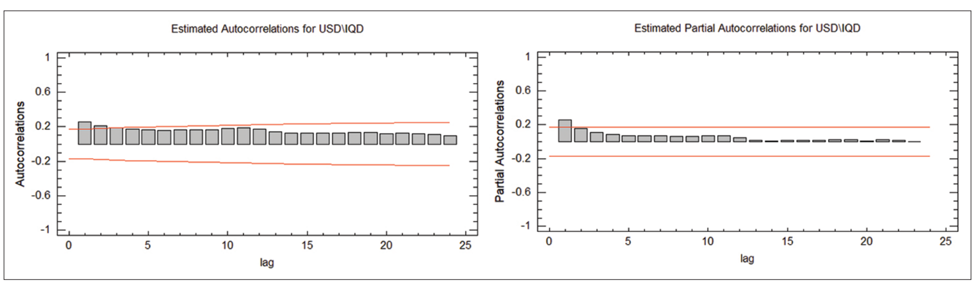

Figure 4: The original monthly ACF and PACF for the US Dollar/IQ Dinar exchange rate data

After we take the differenced series for the exchange rate, which is transformed into a stationary series of the mean and the variance, the ACF and PACF plots of the differenced series show that all the lags are within the confidence limits as shown in the mentioned Figure 5.

Choosing Appropriate Model

After checking for stationary of the time series' mean and variance, the model identification process is used to determine the adequate model given the ACF and PACF. The appropriate model for the series is shown in Table 7. At least the RMSE and MAE are used to determine the best models.

Model Identification

After getting on the stationary for the time series study, the ACF and PACF are shown in the table accordingly for stationary data. We will examine the data in ACF and PACF. The ARIMA model for the exchange rate variable is obtained $(2,1,0)_{12}$.

Estimation

It was found that the best model describing the exchange rate US Dollar/IQ Dinar series mentioned above, the parameters were estimated, as shown in Table 8.

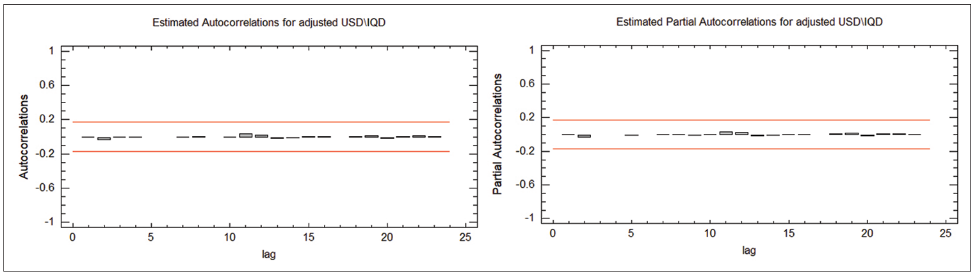

Figure 5: ACF and PACF of exchange rate time series after non-seasonal differencing of order one

Table 6: Estimated Partial Autocorrelations for adjusted exchange rate USD/IQD

Lag	Partial autocorrelation	Standard. Error	Lower 95.0%Probability. Limit	Upper 95.0%Probability. Limit
1	0.260945	0.0870388	-0.170593	0.170593
2	0.154285	0.0870388	-0.170593	0.170593
3	0.112343	0.0870388	-0.170593	0.170593
4	0.0880657	0.0870388	-0.170593	0.170593
5	0.0712356	0.0870388	-0.170593	0.170593
6	0.0682761	0.0870388	-0.170593	0.170593
7	0.0702673	0.0870388	-0.170593	0.170593
8	0.0654201	0.0870388	-0.170593	0.170593
9	0.0633015	0.0870388	-0.170593	0.170593
10	0.0712627	0.0870388	-0.170593	0.170593
11	0.073625	0.0870388	-0.170593	0.170593
12	0.0458525	0.0870388	-0.170593	0.170593
13	0.0129112	0.0870388	-0.170593	0.170593
14	0.00989309	0.0870388	-0.170593	0.170593
15	0.0141497	0.0870388	-0.170593	0.170593
16	0.0192469	0.0870388	-0.170593	0.170593
17	0.0192278	0.0870388	-0.170593	0.170593
18	0.0242387	0.0870388	-0.170593	0.170593
19	0.0214791	0.0870388	-0.170593	0.170593
20	0.00718463	0.0870388	-0.170593	0.170593
21	0.0199373	0.0870388	-0.170593	0.170593
22	0.0126535	0.0870388	-0.170593	0.170593
23	0.00311673	0.0870388	-0.170593	0.170593
24	-0.00737107	0.0870388	-0.170593	0.170593

Table 7: Evaluation of ARIMA models

No.	Model	RMSE	MAE
1	ARIMA (1,1,0) $(2,1,2)_{12}$	27.219	7.557
2	ARIMA (1,1,1) $(1,0,1)_{12}$	25.798	5.959
3	ARIMA (1,1,2) $(2,0,1)_{12}$	25.717	6.122
4	ARIMA (1,1,2) $(1,0,1)_{12}$	25.615	6.121
5	ARIMA (2,1,2) $(2,0,1)_{12}$	25.845	6.020
6	ARIMA (0,1,1) $(1,0,1)_{12}$	25.698	5.965
7	ARIMA $(0,1,1)_{12}$	25.549	5.733
8	ARIMA $(1,1,1)_{12}$	25.648	5.736
9	ARIMA $(2,1,0)_{12}$	25.494	5.664
10	ARIMA $(1,1,0)_{12}$	25.549	5.729

Model Diagnostic Checking

The residuals for the fitted model should be just white noise for forecasting a good model; in other words, the chosen model has exhausted the whole behavior of the series. As a result, we compute and plot the ACF and PACF of the residuals; we want to find no significant ACF or PACF. Furthermore, the fitted model should accurately predict the future.

Autocorrelation and partial autocorrelation of residual test

The residual ACF and PACF of the models that we develop will be checked. Also, the model needs to pass the test for randomness of the residuals to prove that the model chosen has exhausted the data and that there are no significant remaining to be explained in the data. After the model diagnostics

Table 8: Function Model, Parameter Estimate for Series Model

Series	Model	Function Model	Parameter Estimate							
			θ_1	θ_2	$\varnothing_1$	$\varnothing_2$	Θ_1	Θ_2	Φ_1	Φ_2
Exchange rate	ARIMA $(2,1,0)_{12}$	$\Delta Z_t = \varnothing_1 \Delta Z_{t-1} + \varnothing_2 \Delta Z_{t-1} + e_t$			-0.28	-0.01				

Table 9: Hypothesis and *P*-value for the residual series model

Series	Model	Hypothesis	***P*-value**
Exchange Rate	ARIMA $(2,1,0)_{12}$	Null hypothesis (H0): Adequate Model Alternative hypothesis(H1): not Adequate Model	0.241

Table 10: Forecasting monthly average exchange rate USD/IQD Series for the 24 Months using ARIMA $(2,1,0)_{12}$ model

Years	Months	Forecast	LCL	UCL
2021	January	1456.25	1405.81	1506.69
	February	1379.31	1308.39	1450.24
	March	1380.98	1301.65	1460.32
	April	1402.79	1315.71	1489.86
	May	1402.06	1306.26	1497.86
	June	1395.88	1292.15	1499.62
	July	1396.16	1285.46	1506.87
	August	1397.91	1280.63	1515.19
	September	1397.81	1274.21	1521.41
	October	1397.32	1267.71	1526.93
	November	1397.35	1262.02	1532.68
	December	1397.49	1256.67	1538.31
2022	January	1397.48	1251.38	1543.58
	February	1397.44	1246.23	1548.65
	March	1397.44	1241.3	1553.58
	April	1397.45	1236.53	1558.38
	May	1397.45	1231.88	1563.02
	June	1397.45	1227.36	1567.54
	July	1397.45	1222.96	1571.94
	August	1397.45	1218.67	1576.24
	September	1397.45	1214.48	1580.43
	October	1397.45	1210.38	1584.53
	November	1397.45	1206.37	1588.54
	December	1397.45	1202.44	1592.46

process, we can do further forecasts. Plots are displayed in the Figure 6 series.

Goodness of fit test

It is possible to know the adequate model ARIMA (2,1,0) for the exchange rate USD/IQD time series repeatedly using the Box and Pierce test. The null hypothesis is not rejected because the *P*-value is more than 0.05 and the model above is acceptable, implying that the residuals are also random and that the forecast will be adequate and dependable, as shown in Table 9.

Forecasting

After diagnosing the fitted model and selected as the best one, the final step comes forward forecasting. It is time to use the specified model for forecasting future values starting from January 2021 until December 2022, as shown in Table 10 and Figure 7.

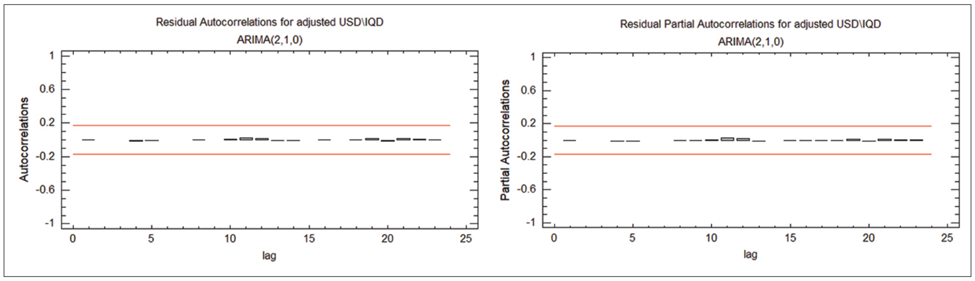

Figure 6: ACF and PACF of residuals model

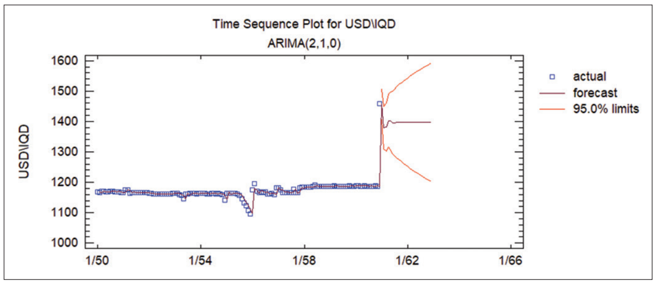

Figure 7: Original USD/IQD series, forecasted values, and confidence limits using ARIMA $(2,1,0)_{12}$ model for the Period January 2021–December 2022, Forecast (24 Months)

CONCLUSION

The results of the analysis show that the time series data was not stationary around the mean and the variance. This means that almost all data of this kind should be different to remove any sort of trend influence on the data. Because such series deal with metrology, fluctuations in the data for monthly US Dollar/IQ Dinar currency exchange rates are to be expected. The RMSE and MAE are being used to select the best model. The ARIMA model was found to be the better model for the series data ARIMA $(2,1,0)_{12}$. This is the forecasted means for the future of this US Dollar against IQ Dinar time series which indicates a perpetual increase in the exchange rate.

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