



Comparison Between the Simulated Prediction Methods of the Markov and Mixed Models

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Article's Information	Abstract
<p>Received: 06.04.2024 Accepted: 13.06.2024 Published: 03.10.2024</p> <hr/> <p>Keywords: Iraqi dinar US dollar Markov model Mixed model</p>	<p>The aim of this study is to make a comparison between the Markov model and the mixed model to predict future values, based on monthly data of the exchange rates of the US dollar against the Iraqi dinar for the period from January 2017 to December 2022. By comparing the two models using MAD, RMSE, and MAPE prediction accuracy measures to find the most appropriate model for analyzing the data of interest, the study concluded that the mixed model (ARIMA) (0,2,1) with the lowest values of the prediction accuracy measures is the most suitable and appropriate model for analyzing the study data, in order to predict the future exchange rates of the US dollar against the Iraqi dinar compared to the Markov model. Based on this model, the exchange rates of the US dollar against the Iraqi dinar were predicted until the end of June 2023 AD, and the predictive values were consistent with the original values of the series, which indicates the efficiency of the model. Two statistical models were used: the Markov model, the autoregressive model, and ARIMA. The two models were applied to the data under study in order to compare them with the exchange rates of the dollar against the Iraqi dinar the importance of studying.</p>
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1. Introduction

Statistics is one of the important and vital sciences in scientific research, which has grown and developed in the current century, as this science has become of great importance in this era, so a large part of this science is focused on studying and analyzing time series that are used in describing the phenomenon to know the nature of changes that occur in the time period. There is no doubt that one of the basic tasks of statistical sciences is reading the future. Interest in studying the future is one of the most important matters in various fields of life.

And that the stochastic processes (random phenomena) are the processes that change randomly with time and include a wide range of models. Among the most used models are the usual Markov models that belong to statistical models. Markov processes occupy a great importance in the analysis of stochastic processes. This position is reinforced by the multiplicity of practical applications in our daily lives, in addition to its multiple applications in

many statistical and engineering models and in reliability theory, have become titles for prominent books in statistics and mathematics, which indicates the interest of many institutions and researchers in this subject because the mathematical procedures in the analysis of time series have become important functions for estimation as well as other very important points in making decisions in many important topics, and it helps to fit some models. Mathematical and statistical for the problem to be studied [1].

2. Markov chains

A random process that enjoys that its state in the future does not depend on its state in the past and that knowing its state in the future depends on knowing its state in the present. This type of random process is called Markov processes. Markov chains [2] in the study of population movement, production planning, inventory, queue models, machinery maintenance ...etc. A random process $\{X$

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n is called $\in T$ [3]. This process achieves the Markov property:

$$P(X_{n+1} = j | x_n = i, x_{n-1}, \dots, x_1 = i_1, x_0 = i_0) = p(x_{n+1} = j | x_n = i) \quad \dots (1)$$

then Markov operations are called Markov chains, relative to the mathematician (Andrei Markov) when he used this The method to study the movement of gas molecules in a closed container and then predict the movement of these molecules in the future [3].

3. The use of the Markov model in forecasting

The Markov model formula is based on the following procedures [4].

3.1. Defining descriptive statistical measures and Markov model parameters

$$\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i \quad \dots (2)$$

deviation standard the calculate To

$$s = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2} \quad \dots (3)$$

modulus torsion the calculate To

$$g = \frac{n \sum_{i=1}^n (x_i - \bar{x})^3}{(n-1)(n-2)s} \quad \dots (4)$$

and calculate correlation:

$$r_k = \frac{n \sum_{i=1}^{n-k} (x_i - \bar{x})(x_{i+k} - \bar{x})}{(n-k)s^2}; k = 1 \quad \dots (5)$$

3.2. Learn about the distribution of data

($q_i = \frac{x_i - 1}{\lambda}$) distribution: By imposing several values λ of (1,-1) for each month separately, to obtain new values whose skewness coefficient is close to zero[5][6].

3.3. Markov model for prediction

The general formula for the Markov model is as follows:

$$x_i = \bar{x} + r_i(x_{i-1} - \bar{x}) + st_i \sqrt{(1 - r_i^2)} \quad \dots \dots \dots (6)$$

where:

x_i : value in i -th time.

\bar{x} : the arithmetic mean of the data.

r_i : linear correlation coefficient.

s : standard deviation of the data.

t_i The random number generated from the data generation and follows the standard normal distribution. As for the monthly Markov model developed by Thomas and Fiering , it takes the following formula [7].

$$q_{ij} = \bar{q}_j + b_j(q_{i-1,j-1} - \bar{q}_{j-1}) + t_{ij}s_j(1 - r_j^2)^{\frac{1}{2}} \quad \dots (7)$$

i : month code for the generated time series and takes values from 1 to the length of the series.

j : month code in the string (from January to December).

q_j : the arithmetic mean of values in month j th (January-December)

b_j : regression coefficient for the values in the two months.

\bar{q}_{j-1} : the arithmetic mean of the values of the month preceding

s_j : standard deviation of values for month j th (January-December).

t_{ij} : the derived random number and follows the standard normal distribution.

4. Prediction Accuracy Measure

The process of evaluating the models is intended to assess the suitability of the model for the pattern in which the series data goes, or the accuracy of the model in predicting the current and future values of the series. Certain and the value of the series that the model expects at that time [8] , we will rely in this study on these tests in order to compare the two models used in the research, which one is more accurate in prediction, and these tests are

I. Root mean square errors (RMSE)

It is defined as follows:

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^n e_t^2} = \sqrt{\frac{1}{n} \sum_{t=1}^n (y_t - \hat{y}_t)^2} \quad \dots (8)$$

where this criterion is considered one of the most important measures of the prediction accuracy of the models, and in general this criterion is easily distinguished from others by its statistical characteristics.

II. Mean relative absolute error (MAPE)

positive values, does not amplify the error by squaring as the sum of squares of the error does and

models can be compared across different series, it is called Mean Absolute Percentage Error (MAPE) As shown by the following formula:

$$MAPE = \frac{1}{n} \sum_{t=1}^n \frac{|y_t - \hat{y}_t|}{y_t} \times 100 \quad \dots (9)$$

III. MAE mean absolute error

This scale can be expressed in the following form:

$$MAE = \frac{1}{n} \sum_{t=1}^n |y_t - \hat{y}_t| = \frac{1}{n} \sum_{t=1}^n |e_t| \quad \dots (10)$$

where e_t represent residuals the y_t the of values real the series \hat{y}_t , estimated are values The n number the represents of observation. The lower the value of these measures, the closer the predicted values are to the real values of the phenomenon series data.

5. Mixed Models (ARIMA)

- a. In most branches of science, engineering and commerce, there are variables measured successively in time and such variables are called the time series [9]. A time series is defined as a sequence of observed values for a particular phenomenon arranged with time. Usually, these values are not independent, that is, dependent on each other. Non-independence is used to reach reliable predictions Miljanovic [10].
- b. Types of time series: Series data are classified according to the method of monitoring series values over time, and time series are divided into two types [11]. If the values of the phenomenon are measured in intermittent periods of time, such as an hour, day, month, season, or year, then it is called the intermittent time series, and if it is measured in continuous periods of time such as temperature or humidity, then it is called the continuous time series. The most common time series in the applied field are time series Intermittent, in which the time period between one observation and another is equal, and this can be obtained either by recording the values of the phenomenon at fixed times, or by collecting the values of the phenomenon for a fixed period of time [12, 13].
- c. Detection of time series compounds: Detecting time series components The presence of time series components can be detected by analyzing the information graphically according to the

general trend in that component that pushes the development curve of the series over time up or down according to the Kreskas-Wallis test to detect the quarterly component [14, 15].

- d. Stages of application of ARIMA models in forecasting. There are several conditions that must be met to apply the (ARIMA models) which are [16].
 - i. Series should not be than 40 views of than studies time.
 - ii. These models are suitable for time series with unexpected observations, in the sense that they are not suitable for series with inevitable or intuitive observations, whose present and future are just an extension of their past.
 - iii. ARIMA models assume that the series is not static or weakly static, so work must be done to convert it into a static series by achieving the stability of the average and the stability of the variance over time.
 - iv. These models assume equal time intervals, which indicates that ARIMA models do not fit series with missing data..

6. ARIMA Time Series Models are Built Through a Set of the Following Stages

6.1. Data preparation stage

The data initialization stage is the first stage for building ARIMA models for time series [17].

6.2. Recognition stage

The two tools used to determine the model and its score are the ACF and correlation functions Partial autonomy, PACF and then the autocorrelation coefficients and partial autonomy are matched with the behavior Theoretical function of autocorrelation and partial autocorrelation, if it is:[18][19].

6.3. Appreciation stage

Linear time series models are non-linear in features, and as a consequence the estimation stage Difficult stage, which means estimating the model to determine its parameters, ie obtaining numerical values for the model's parameters which was selected in the renewal phase The model is based on the string values observed using one of the methods The following assessments [20] [21].

- a. Yule -Walker method, which depends on the autocorrelation of the model, is called the method of moments MM.
- b. The Maximum Likelihood Method (ML) depends on The function is maximized to make the squares of errors $S(\hat{\theta})$ as small as

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possible, which is the most common method in the application.

- c. **Nonlinear Least Squares Method** This method is based on the principle of reducing the sum of squares estimation error e .

At this stage, several close models are usually estimated to be compared, and the parameters of a good model estimated are usually significant and can also be compared through a group of squares of residuals as a measure of the quality of the model [22, 23].

6.4. Sleep analysis

It is known in the alphabets and literature of modern analysis of time series the importance of stillness. And he comes. This is done by examining the estimates of the autoregressive parameters that are adopted for the chosen model. Obtaining it at the estimation stage - to ensure that it fulfills the theoretical conditions for dormancy, which is that the roots of Characteristic equation $\phi(B) = 0$. They all lie outside the unit circle, so that if the absolute value of each One of these roots is greater than the correct one, which indicates the rest of the random process that generated it. The observed series, and if the absolute value of one of the roots is close to the correct one, it may indicate. This is based on the need to take other differences [24]. In terms of observations without the need to fulfill certain conditions. On the other hand, there is a type of chains model. It is known as moving average models, it is not always reversible, but it needs to fulfill certain conditions even becomes reflexive, and the inversion conditions for the q - order moving averages model are to be. The absolute roots of the equation $\theta q(B) = 0$ are greater than 1, which indicates an inversion of the model. The original

must all lie outside the unit circle, and if the absolute value of one of the roots is close. From the correct one, this may indicate the use of unnecessary distinctions [25]. Stages of application of the Markov model in forecasting.

7. Results and Discussion

Defining descriptive statistical measures and Markov model parameters.

Table 1. Descriptive statistical measures of the US dollar exchange rates index

Statistics	Value
Number of values	125
Minimum value	3.27
The middle value	4.81
Mediator	4.73
Highest value	5.42
Standard deviation	0.79
Torsion Modulus	0.09

We note from table 1 above that the lowest value of the exchange rate is equivalent to 3.27, as well as the highest value recorded 5.42. We also note that the value of the arithmetic mean is equivalent to 4.81, very close to the median value of 4.73, and this is an indication of the moderation of the data distribution. Based on the theoretical aspect that dealt with the developed Markov model of Thomas-Firing, which was based on the following formula (7). And to find Markov parameters for the monthly data from January 2017 to December 2022 which are defined by 200 observations, and this is illustrated by the following table 2.

Table 2. Parameters of the Markov model

I	\bar{q}_j	s_j	r_j^2	r_j	b_j
Jan	2,544	0.276	0.1341	0.888	0.1760
Feb	2.3449	0.236	0.1457	0.436	1,1018
Mar	2.7561	0.091	0.1563	0.060	1,0123
Apr	2.5423	0.548	0.0432	0.6716	0.5866
May	2.5980	0.245	0.0602	0.318	0.8534
Jun	2.4446	0.229	0.1526	0.577	0.6008
Jul	2.6788	0.194	0.177	0.222	0.1802
Aug	2.7712	0.166	0.027	0.659	0.0160
Sep	2.0265	0.150	0.0227	0.308	0.9300
Oct	2.4981	0.131	0.010	0.451	0.9680
Nov	2.4451	0.949	0.124	0.619	0.8089
Dec	2.8712	0.681	0.082	0.399	1,0810

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Table 3. Culmegrove test results – Smirnov

KS	N	Sig
0.066	200	0.15 >

Table 3 shows the results of the Klum grove test – Semenov. Also, from the following figure (1), most of the data are located on the straight line and very close to it, and this in turn is consistent with the results of the previous test, which confirms the nature of the data.

The stage of building a Markov model for prediction. The monthly Markov prediction model is arrived at according to formula (7) as shown in Table 4. In the same context, we can predict the exchange rate of the US dollar against the Iraqi dinar for the year 2023, as shown in the following table (5).

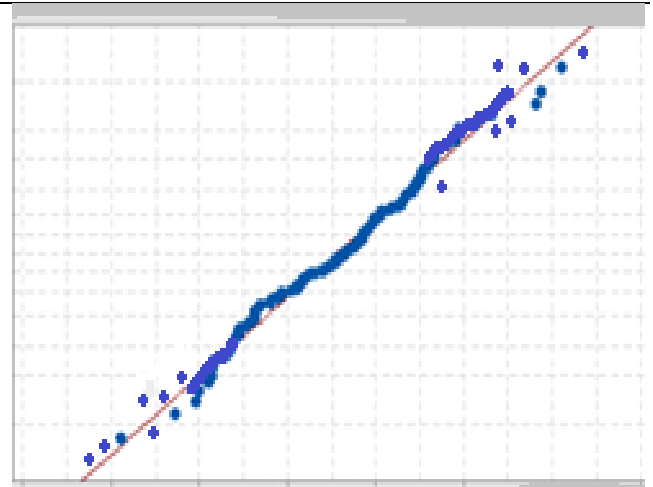


Figure 1. Normal Probability Plot of series data. 1

Table 4. The stage of building a Markov model for prediction in year 2022

I	Random Component		Deterministic Component		Model flow
	$q_{i-1,j-1}$	$\bar{q}_j + b_j(q_{i-1,j-1} - \bar{q}_{j-1})$	t_{ij}	$t_{ij}S_j(1 - r_j^2)^{\frac{1}{2}}$	q_{ij}
Jan	2.3412	2.2640	1.523379	0.283818	3.31809
Feb	2.8792	2.7834	0.886483	0.6123	2.11143
Mar	2.3109	2,9100	0.49313	0.030580	3.02189
Apr	2.6570	2.6194	0.234657	0.013554	2.01289
May	2.3353	2.8280	0.280915	0.033538	3.0079
Jun	2.7519	2.9208	0.929536	0.050106	3.61222
Jul	2.8058	2.5002	3.041859	0.230124	2.1870
Aug	2.8194	2.5577	1.083163	0.055202	3.9160
Sep	2.8755	2.8332	-0.29772	0.09650	3.4507
Oct	2.7473	2.7657	-0.63136	0.05612	3.7091
Nov	2.8348	2.8689	3.021362	0.191231	2.7002
Dec	2.8920	2.4959	0.766834	0.059053	3.6194

Table 5. Building a Markov model to predict the exchange rate for the year 2023.

I	Random Component		Deterministic Component		Model flow
	$q_{i-1,j-1}$	$\bar{q}_j + b_j(q_{i-1,j-1} - \bar{q}_{j-1})$	t_{ij}	$t_{ij}S_j(1 - r_j^2)^{\frac{1}{2}}$	q_{ij}
Jan	2.45	2.9929	1.912000	0.056199	3.3835
Feb	2,334	2.9680	0.9123688	0.9255488	2.79872
Mar	2,655	2.5697	0.409310	0.0363555	2.12900
Apr	2.7306	2.8839	0.203657	0.044427	2.81845
May	2,7723	2.6444	0.912344	0.091273	2.99994
Jun	2.8792	2.5476	0.929536	0.059906	2.712098
Jul	2.532	2.500	3.041859	0.030124	2.78863
Aug	2.4989	2.9277	1.6512163	0.055658	2.67120
Sep	2.5612	2.5406	0.294572	0.015350	2.95041
Oct	2,589	2.6344	0.6612336	0.005581	2.78199
Nov	2.5001	2.0839	2.024312	0.0375531	2.95236
Dec	2.4876	2.4571	0.761204	0.0059953	2.91007

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Table 6. Predictive values of the Markov model

Date	Y _t	\hat{y}_t	e _t
Jan/2023	2.6796	3.0547	-0.3751
Feb/2023	2.4960	2.4712	0.0284
Mar/2023	2.4835	2.9361	-0.4526
Apr/2023	2.7664	2.6975	0.0689
May/2023	2.9205	2.3220	0.5985
Jun/2023	2.9860	2.7216	0.2644

The RMSE, MAPE, and MAE prediction measures are considered an indicator to determine the success of the model in prediction. This is evident from the following table 7. Stages of application of ARIMA models in forecasting In this part, we will discuss the stages of applying ARIMA models, as follows :

1. Data preparation stage

The data preparation stage is the first stage for building ARIMA models for time series The stage is to prepare the data by drawing the scattering shape to identify its initial characteristics In examining the stability of the time series and apply the necessary transformations to make it stable if it is not in order to describe the time series under study, its observations are drawn to identify the rest and its general trend. Figure (2) represents the time series drawing of the US dollar exchange rate against the Iraqi dinar.

Table 7. Measures of prediction accuracy for the Markov model

standard	RMSE	MAPE	MAE
Markov model	0.37613	5.9126	0.3510

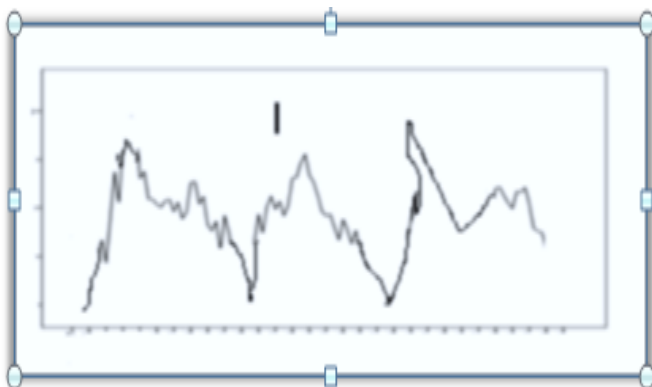


Figure 2. Drawing the time series of the exchange rate of the dollar against the Iraqi dinar

This is evident through the graphic representation of the time series under study with its actual values shown in In the figure above, we notice that the variance tends to be stable, but we also notice an increasing general trend And a time Others are decreasing with time, which indicates the instability of the series data on average. In this case it is preferable to take the differences for smoothing out where the differences were taken The first is to smooth, and then redraw the series, so it becomes the graph of the string after taking the first differences filter of the string as appears in doubt to 3.

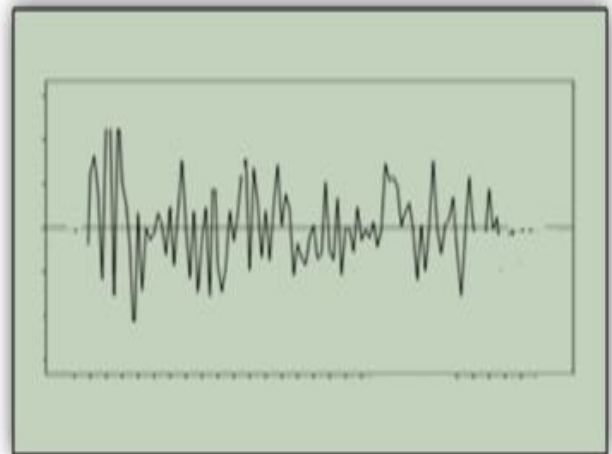


Figure 3 Drawing the time series of the exchange rate after taking the first difference.

We notice from the above figure that there is still a slight general trend, so the second difference will be taken as And then re-draw the series, so it becomes the graph of the series after taking the

second difference filter for the series Shown in Figure 4.

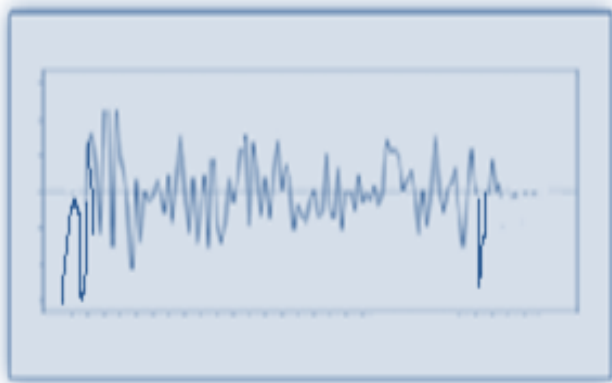


Figure 4. Drawing the time series of the exchange rate after taking the second difference

2. Recognition and appreciation

The main goal at this stage is to identify the appropriate prototype for the description The series under study is based on the autocorrelation and partial autocorrelation functions to determine mixed models (p,2,q) to identify the model by determining the rank of MA and AR This is done through Examining the autocorrelation function ACF of the first difference series leading to the proposal of the MA(1) model Known by the symbol (q) , the examination of the partial autocorrelation function PACF leads to the proposal of a model AR(1) , known by the symbol (p) and fig (5) Shows the behavior of the autocorrelation and partial

autocorrelation functions of the ARIMA (p,2,q) models.

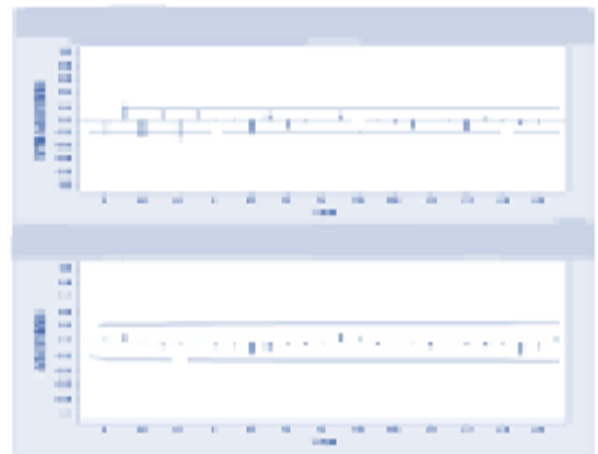


Figure 5. The autocorrelation and autocorrelation functions after taking the second difference of the time series

After careful examination of the autocorrelation function ACF and the partial autocorrelation function PACF We note that the autocorrelation function is interrupted after the first time gap, which draws attention to the existence of a parameter for the moving averages model, and therefore the ARIMA (0,2,1) initial model can be nominated . The candidate model is taken as a prototype that can be modified later

Table 8. Comparison of the candidate model with clicks directly above and below it.

models	ARIMA (1,2,0)	ARIMA (0,2,1)	ARIMA (0,2,2)	ARIMA (1,2,1)	ARIMA (1,2,2)	ARIMA (2,2,0)	ARIMA (2,2,1)
BIC	-3.813	3,612	-3,214	-3,480	-3,681	-3,651	-3,688

We note from table 8 above that the best model is the ARIMA(0,2,1) model because it has the lowest value for the BIC evaluation criterion . Thus, the final model that can be used in Prediction is the model ARIMA(0,2,1). After selecting the proposed model ARIMA(0,2,1), the model parameters will be estimated And by applying Using the usual least squares method, on series data, estimates of parameters were obtained The above model is shown in the following table 9.

Table 9. Estimators parameters ARIMA(0,2,1)

models	standard error	t value	P-value
MA(1)	0.0817	36.58	0.000

Therefore, the form will be according to the conversion of the second difference in the following form

$$\phi(B)\nabla^d y_t = \theta(B)\epsilon_t$$

$$\nabla^d y_t = (1 - B)^d y_t, d > 0$$

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$$\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_p B^p$$

$$\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \dots - \theta_q B^q$$

Accordingly, the equation of the ARIMA (0,2,1) model is:

$$\phi(B)\nabla^d y_t = \theta(B)\varepsilon_t$$

$$(1 - B)^2 y_t = (1 - \theta_1 B)\varepsilon_t \Rightarrow (1 - 2B + B^2)y_t = (1 - \theta_1 B)\varepsilon_t$$

$$\Rightarrow y_t - 2By_t + B^2y_t = \varepsilon_t - \theta_1 B\varepsilon_t$$

$$\Rightarrow y_t - 2y_{t-1} + y_{t-2} = \varepsilon_t - \theta_1 \varepsilon_{t-1}$$

$$\Rightarrow y_t = 2y_{t-1} - y_{t-2} - \theta_1 \varepsilon_{t-1} + \varepsilon_t$$

$$y_t = 2y_{t-1} - y_{t-2} - \theta_1 \varepsilon_{t-1} + \varepsilon_t$$

$$y_t = 2y_{t-1} - y_{t-2} - 0.9985\varepsilon_{t-1} + \varepsilon_t$$

It is the appropriate model for the exchange rate of the US dollar against the Iraqi dinar prediction stage. Forecasting is one of the primary goals of any time series analysis study. Move to this stage only after completion and make sure that all examinations and statistical tests are performed. Necessary to diagnose the model that was chosen in the previous stages. It was concluded that it can be used. The model is a candidate for prediction because it passes most of the operations. Examination and diagnosis were statistically good. Other models and using the ARIMA (0,2,1) model, the exchange rates of the US dollar against the Iraqi dinar were predicted during the first six months of 2023.

Through the above table, the original values will be compared with the predicted values from January until June 2023, these values showed some agreement with the original values. Compare Markov model and ARIMA (0,2,1). RMSE and MAE were used and MAPE started. It is useful in developing a real vision of future estimates to predict the behavior of the phenomenon in order to take the appropriate decision as shown in tables 11.

Table 10. ARIMA(0,2,1) predictive values

months of the year	y t	\hat{y}_t	e t
Jan/2023	2.4996	2.9176	-0.418

Feb/2023	2.6769	2.7125	-0.0358
Mar/2023	2.2305	2.8155	-0.0356
Apr/2023	2.8268	2,8320	-0.0052
May/2023	2.7165	2.9191	-02026
Jun/2023	2.5893	2.9707	-0.3814

Table 11. Comparison between the Markov and the ARIMA(0,2,1) model

Sample	RMSE	MAPE	MAE
Markov	0.387	5,988	0.953
ARIMA(0,2,1)	0.066	1,023	0.095

8. Conclusions

After examining several models and through evaluation criteria among the proposed ARIMA models, it was found that the ARIMA model (0,2,1) is the best and most suitable for application to the study data for the series of exchange rates of the dollar against the Iraq dinar and the study concluded that the time series of the exchange rates of the dollar against the Iraqi dinar represents a time series that is not static in relation to the available original data. In addition to Adopting the ARIMA model (0,2,1) to predict the time series of the exchange rates of the dollar against the Iraqi dinar and A comparison was made according to the criteria of prediction accuracy (RMSE, MAPE, MAE) between the Markov model and the ARIMA model (0,2,1), and the results showed the superiority of the ARIMA (0,2,1) model over the Markov model.

References

- [1] Song, L.J.; Meng, F.R; Yuan, G.; " Moving object location prediction algorithm based on Markov model and trajectory similarity".J. Comput. Appl.,36(1): 39–43, 2016.
- [2] El-Eraqi, M.B.; Mohammed, A.; Mohammed, S.; "The Urban Sprawl on Agricultural Lands in Giardia Governorate". J. Agric. Sci., 27(3): 1771-1781, 2019.
- [3] Shana, M.; Hong, H.; Sajjad, H.; "Analyzing urban spatial patterns and trend of urban growth using urban sprawl matrix: A study on Kolkata urban agglomeration India". Sci. Total Environ., 62(8): 1557-1566, 2018.
- [4] Baig, M.; "Assessment of land use land cover changes and future predictions using CA-ANN

Al-Nahrain Journal of Science

ANJS, Vol. 27 (4), Special Issue – October, 2024, pp. 12 – 20

- simulation for Selangor”, *Water*, 14(3): 402, 2022.
- [5] Erkan, U.; Gökrem, L.; “Levant. A new method based on pixel density in salt and pepper noise removal”. *Turk. J. Elec. Eng. Comp. Sci.*, 26(1): 162-171, 2018.
- [6] Samat, N.; Mohammed, N.A.; Maghsoodi, M.J.; “Modeling land cover changes in peri-urban areas A case study of George town conurbation, Malaysia”. *Land*, 9(10): 373-380. 2020.
- [7] Wang, S.; Zheng.; Xi.; “Dominant transition probability: Combining CA-Markov model to simulate land use change”. *Environ. Develop. Sustain.*, 25(7): 6829-6847. 2023,
- [8] Sadek, M.; Mostafa, X.L.; Freeshan.; M.; “Low-cost solutions for assessment of flash flood impacts using Sentinel-1/2 data fusion and hydrologic/hydraulic modeling” *Egypt. Adv. Civ. Eng.*, 20(20): 1-21. 2020.
- [9] Sadek, M.; Xuxiang, I.; “Low-cost solution for assessment of urban flash flood impacts using sentinel-2 satellite images and fuzzy analytic hierarchy process: a case study of ras ghareb city, Egypt”. *Water*, 20(19): 1-15, 2019.
- [10] Mostafa, E.; Sadek.; M.; Dosou.; Monitoring and forecasting of urban expansion using machine learning-based techniques and remotely sensed data: A case study of gharbia governorate, Egypt”. *Rem. Sens.*, 13(22): 4498,. 2021.
- [11] Pal, S.; Ziaul, S.K.; “Detection of land use and land cover change and land surface temperature in English Bazar urban center”. *J. Remote Sens. Space Sci.*, 20(1): 125-145, 2017.
- [12] Sadek, M.; Mustafa, L.E.; Dosou.; F.; “Monitoring flash flood hazard using modeling-based techniques and multi-source remotely sensed data: the case study of Ras Ghareb City, Egypt”. *Arab. J. Geosci.*, 23(14): 1-16, 2021.
- [13] Subasinghe, S.; Estoque, R.C.; Murayama, Y.; “Spatiotemporal analysis of urban growth using GIS and remote sensing: A case study of the Colombo Metropolitan Area, Sri Lanka”. *Int. J. Geo-Inf.*, 5(11): 197, 2016.
- [14] Rousta, I.; Sarif, M.; Gupta, R.D.; Olafson., H.; “Spatiotemporal analysis of land use/land cover and its effects on surface urban heat island using Landsat data: A case study of Metropolitan City Tehran (1988–2018)”. *Sustainability*, 10(12):4433-4439. 2018.
- [15] Hamdy, O.; Zhao, S.; Sallhen, M.A.; “Analyses the driving forces for urban growth by using idrisi Selva models Abouelreesh-Aswan as a case study”. *Int. J. Eng. Sci. Technol.*, 9(3):.216 - 226, 2017.
- [16] Wang, Y.; Yuan, N.J.; Lian, D.; “Regularity and conformity Location prediction using heterogeneous mobility data”. *Int. Conference Knowledge*, 1275-1284, 2015.
- [17] Wang X.; Jiang, X.H.; Lin, J.; “Xiong JB. Prediction of moving object trajectory based on probabilistic suffix tree”. *J. Comp. Appl.* 33(11): 3119–3122, 2013.
- [18] Qiao, Y.S.; Zhang, Y.; Abdesslem, F.B.; Zhang, X.; Yang, J.; “A hybrid Markov-based model for human mobility prediction”. *Neurocomputing*, (278): 99–109, 2018.
- [19] Subasinghe, S.; Estoque, R.C.; Murayama, Y.; “Spatiotemporal analysis of urban growth using GIS and remote sensing: A case study of the Colombo Metropolitan Area, Sri Lanka”. *Int. J. Geo-Inf.*, 5(11): 197, 2016.
- [20] Kore, N.B.; Ravi, K.; Patil, S.B.; “A simplified description of fuzzy TOPSIS method for multi criteria decision making”. *Int. Res. J. Eng. Technol.*, 4(5): 2047-2050, 2017.
- [21] Zhang, C.; Liang, H.; Wang, K.; Sun, J.; “Personalized trip recommendation with poi availability and uncertain traveling time”. *Int. Manag.*: 911-920, 2015.
- [22] Zhenhui, L.I.; “Where Did You Go: Personalized Annotation of Mobility Records”, *Int. Manag.*: 589–598, 2016.
- [23] Lian, D.; Zheng, V.W.; Yuan, N.J.; Zhang, F.; “CEPR; A collaborative exploration and periodically returning model for location prediction”. *Acmt. Intel. Sys. Tech.*, 6(1): 1-27, 2015,
- [24] Aburas, M.M.; Ramli, M.F.; Ashaarri, H.; Improving the capability of an integrated CA-Markov model to simulate spatio-temporal urban growth trends using an Analytical Hierarchy Process and Frequency Ratio”. *J. App. Earth Obs. Geoinf.*, 59(2):.65-78, 2017.
- [25] Sánchez, M.J.; Galve, J.M.; Gonzalez, J.; “Monitoring 10-m LST from the Combination MODIS/Sentinel-2, validation in a high contrast semi-arid agro ecosystem”. *Remote Sens.* 12(9): p.1453-1465. 2020.