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Using The ARIMA Method in Forecasting Money Supply in Libya

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Abstract

The research paper focuses on using the Box-Jenkins methodology (ARIMA) to forecast monthly data for narrow money supply (M1) and broad money supply (M2) in Libya from January 2010 to December 2030. The study aims to determine the effectiveness of ARIMA models in long-term forecasting, considering their significant role in economic stability. The analysis revealed that the monthly time series of money supply is unstable and exhibits a general trend. To address this, the time series was converted into a stationary form to obtain the most effective models for predicting future periods. The study employed an ARIMA (0,2,2) model to predict future monthly data for M1 and an ARIMA (0,1,1) model for M2. The results indicated that ARIMA models can offer reliable short-term forecasts for money supply, but may not be suitable for long-term predictions due to external circumstances. The study recommends the use of more adaptive and dynamic models such as GARCH or SARIMA, along with improvements in data quality and the selection of variables reflecting changes or external conditions.

Keywords: ARIMA Method, Forecasting, Money Supply, Libya.

Introduction

Forecasting is one of the most important decision-making tools and the most crucial element in the process of planning for the future. To make the right decision, it is necessary to study all available alternatives and analyze past and present variables to determine the optimal course of action and the potential outcomes. Forecasting relies heavily on historical and current data to predict future trends. By analyzing past behavior, we can mitigate risks and better understand future developments, allowing for a higher degree of confidence in the decisions made (Makridakis et al., 1998). Specifically, in time series forecasting, Box-Jenkins models, particularly ARIMA (Auto Regressive Integrated Moving Average), are widely used due to their accuracy in predicting economic indicators, such as the money supply (Box & Jenkins, 1970). Understanding this phenomenon is critical to the economic planning of any country, as it enables better predictions about future economic conditions and ensures informed policy-making (Hamilton, 1994). Recently, the money supply in Libya has been subject to various influences, making it a crucial issue to study and analyze, particularly regarding the causes of fluctuations in the availability of local currency within banks. Through this study, it will be confirmed that ARIMA models are highly effective in predicting the money supply over extended periods. This type of research proves effective in addressing various economic and financial factors (Box & Jenkins, 1970). ARIMA models, which stand for Autoregressive Integrated Moving Average, are widely used in forecasting time series data, including economic indicators such as money supply. Forecasting money supply is essential for policymakers, economists, and investors, as it provides insights into the state of the economy and supports informed decision-making (Hamilton, 1994). ARIMA models are a popular choice for forecasting money supply due to their ability to capture and model the complex patterns and trends present in economic data. These models are particularly effective when dealing with non-stationary data, which is common in economic time series (Lütkepohl & Krätzig, 2004).

In the realm of forecasting methodologies, a comparative analysis between the Autoregressive Integrated Moving Average (ARIMA) model and other forecasting techniques is crucial for evaluating predictive accuracy and performance. Insights from recent research, such as the development of the Wavelet Auto-Regressive Integrated Moving Average with exogenous variables and Generalized Auto-Regressive Conditional Heteroscedasticity (WARIMAX-GARCH) method, highlight the significance of incorporating exogenous variables and non-linear characteristics in time series forecasting (Neto et al., 2016). Additionally, a comprehensive review of time series forecasting literature reveals a wide array of methodologies, including neural networks and structural models, that warrant further exploration in comparison to ARIMA (De Gooijer & Hyndman, 2006). By integrating these findings into the examination of forecasting methods, particularly in the context of predicting money supply, one can enhance the understanding of ARIMA's effectiveness relative to alternative approaches and identify potential avenues for advancing forecasting techniques in financial analyses.

The Money Supply

represents the total quantity of monetary assets available within an economy at a given point in time. It encompasses a range of financial instruments, including cash, coins, and balances held in checking and savings accounts. An understanding of the money supply is of paramount importance, as it significantly impacts key economic variables such as inflation, interest rates, and overall economic health (Mishkin, 2019). Economists typically categorize the money supply into several measures, often referred to as M1, M2, and sometimes even broader aggregates:

1. M1 includes the most liquid forms of money, such as physical currency (coins and notes) and demand deposits (checking accounts) (Federal Reserve, 2021).
2. M2 includes M1 plus less liquid assets, such as savings deposits, money market mutual funds, and other time deposits (Blanchard & Johnson, 2017).

Understanding the money supply is crucial for policymakers, as it influences economic variables like inflation, interest rates, and overall economic activity. Central banks often monitor and sometimes regulate the money supply to achieve specific economic objectives, such as price stability or economic growth (Friedman, 1987).

Time Series

is a set of values or observations that are generated successively over time or is a set of observations that are correlated with each other and recorded at successive periods of a phenomenon (Chatfield, 1989). Time series data is often classified into two types: 1. Discrete-time series. 2. Continuous-time series.

However, the most commonly used time series in the applied field is a discrete-time series, where the time intervals of the values are equal, i.e., the interval between them remains constant. These can be obtained either by recording observations of a phenomenon at fixed times or by collecting observations within fixed periods (Wei, 2006). A time series is characterized by its data being ordered with respect to time, and successive observations are often dependent on each other, making it possible to exploit this lack of independence to make reliable predictions. The subscript "t" is used to indicate the temporal order of observations, where Y_t represents the ith observation, Y_{t-1} represents the previous observation, and Y_{t+1} represents the next. It is important to distinguish between a time series process and the realized values of the series (Box & Jenkins, 1976). A time series can be viewed as a sequence of realized values of a stochastic process, where the value of the time series at a given time interval Yt is a realization of the random variable Yt and follows a probability density function (Chatfield, 2004). Any set of time series values, say (Y_{t1}, Y_{t2}, ..., Y_{tn}), will have a common probability density function. Time Series Components (Anderson, 1992) 1. Trend. 2. Seasonal Variations.3. Cyclical Variations.4. Irregular

Variations.These four components of the time series are influenced by economic, environmental, social, and political factors (Hamilton, 1994).

Box-Jenkins Model (ARIMA)

The ARIMA model, also known as the Box-Jenkins approach or simply Box-Jenkins models, is a systematic method for fitting time-series models. Developed by George Box and Gwilym Jenkins in the 1970s, it is widely used for analyzing and forecasting time-series data (Box & Jenkins, 1976). The four steps to follow in the Box-Jenkins forecasting methodology are as follows:

1. Identification of the model.
2. Parameter estimation (usually Ordinary Least Squares - OLS).
3. Examining the appropriateness of the model.
4. Diagnostic checking.
5. Forecasting.

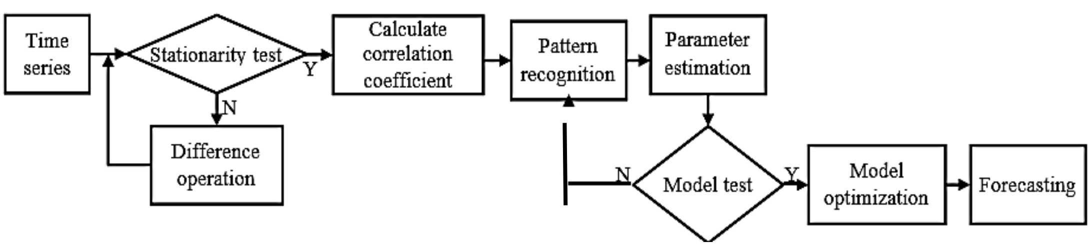

Figure (1): The procedure flow chart of ARIMA modeling and forecasting

ARIMA Models are particularly useful for analyzing and forecasting time series data that exhibit patterns such as trends, seasonality, and autocorrelation. The methodology consists of three main components:

1. **Autoregressive (AR) Part**: This component models the relationship between an observation and a number of lagged observations (i.e., its own past values).

An AR(p) model uses the dependency between an observation and its p previous observations.

Assuming that we have a time series of observations y_1, y_2, ...y_n, the autoregressive model can be written as

$$Y_t = Ø_0 + Ø_1Y_{t-1} + Ø_2Y_{t-2} + Ø_3Y_{t-3} + \cdots + Ø_pY_{t-p} + e_t \text{ , } t = 1,2. \ldots\ldots\ldots n$$

where ϕ are the parameters, and ϵ_t is white noise (Hyndman & Athanasopoulos, 2018).

2. **Moving Average (MA) Part**: This component models the dependency between an observation and a residual error from a moving average model applied to lagged observations. An MA(q) model uses the dependency between an observation and a residual error from a moving average process applied to q-lagged observations.

   Assuming we have a time series consisting of observations y_1, y_2, ...y_n, we can write the modeling of the moving averages from salary q to be written as $Y_t = \theta_0 + \varepsilon_t + \theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2} + \theta_3\varepsilon_{t-3} + \cdots + \theta_q\varepsilon_{t-q}$, $t = 1,2. \ldots\ldots\ldots n$ where θ are the parameters, and ϵ_t is white noise (Box et al., 2015).

3. **Integrated (I) Part**: This component accounts for the differencing of the raw observations to make the time series stationary, which means removing trends and seasonality to make the series more predictable. The order of differencing, denoted as d, represents the number of differences needed to achieve stationarity. For example:

   - If **d = 1**, the first difference is taken: $Y_t - Y_{t-1}$.
   - If **d = 2**, the second difference is taken: $(Y_t - Y_{t-1}) - (Y_{t-1} - Y_{t-2})$ (Chatfield, 2003).

The ARIMA model is denoted by ARMA (p, q) Model

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The ARMA (p, q) model combines both autoregressive and moving average parts: The form of the ARIMA (p, q) model is $\mathbf{Y_t = c + \phi_1 Y t_{-1} + \ldots + \phi_p Y_{t-p} + \epsilon t + \theta_1 \epsilon_{t-1} + \ldots + \theta_q \epsilon_{t-q}}$

The ARIMA model is denoted by ARIMA (p, d, q), where:

- p is the order of the Autoregressive (AR) part.
- d is the degree of differencing required to make the time series stationary.
- q is the order of the Moving Average (MA) part.

The form of the ARIMA (p, D, q) model is

$$\Delta^D y_t = c + \phi_1 \Delta^D y_{t-1} + \ldots + \phi p \Delta^D y_{t-p} + \varepsilon_t + \theta 1 \varepsilon t_{-1} + \ldots + \theta_q \varepsilon t_{-q}.$$

The ARIMA modeling is a procedure of determining the parameters p, D and q. The detailed process of ARIMA modeling is as follows:

(1) Identifying the stationarity of the time series. The stationarity of the sequence is judged based on line graphs, scatter plots, autocorrelation functions, and partial autocorrelation function graphs of the time series. The unit root of Augmented Dickey-Fuller (ADF) is usually used to test the variance, trend, and seasonal variation and identify the stationarity (Hyndman & Athanasopoulos, 2018).

(2) Determining the order of single integer D. If the time series is a stationary sequence, go directly into Step (3). If the time series is a non-stationary sequence, appropriate transformation (including difference, variance stationarity, logarithm, and square root) should be used to be converted to a stationary sequence. The number of differences is the order of a single integer (Box et al., 2015).

(3) ARMA modeling: For the stationary series from Step (2), the autocorrelation coefficient (ACF) and partial autocorrelation coefficient (PACF) are computed. These helps estimate the values of the autoregressive order p and the moving average order q in the ARMA model. Various methods such as the AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion) are used to select the best model orders (Brock well & Davis, 2016). The basic principle for determining the order p and q is given in Table 1.

Table (1): Basic principle of determining the order of ARMA (p, q)

Autocorrelation coefficient (ACF)	**Partial Autocorrelation coefficient (PACF)**	**Model order**
/	p-order truncation	AR(P)
q-order truncation	/	MA (p, q)
trailing	trailing	ARMA (p, q)

(4) Performing parameter estimation. The autocorrelation and partial autocorrelation graphs are used to judge the number of autocorrelation coefficients and partial autocorrelation coefficients with remarkably significant levels. In this step, the rough model of the sequence can be selected.

(5) Diagnostic test and optimization. The model is diagnosed and optimized by performing a white noise test on the residual. If the residual is not a white noise, return to Step (4) and re-select the model. If the residual is a white noise, return to Step (4) create multiple models, and choose the optimal model from all the fitted models of the test.

Methodology

The research paper utilized data from the Central Bank of Libya's website, specifically the monthly money supply data from Jan 2010 to Sept 2023.We shall analyze the time series of the narrow money supply M1 and the broad money supply M2 in Libya for the period from Jan 2010 to Sept 2023 by using the Eviews 13 program. EViews is an acronym for Econometrics Views. Translated as economic observations, they are often referred to as technical econometric software packages. The software is a toolkit developed by the American company Quantitative Micro Software (QMS) for data analysis, regression analysis, and forecasting under the Windows operating system. It can be used to quickly find statistical relationships from data and predict future values. EViews combines spreadsheet and database technologies with the analysis capabilities of traditional statistical software and provides a visualization feature for modern Windows software. In case the time series is unstable because it contains, for example, a general trend, the first difference is used to convert it into a stable time series and then we run a diagnostic again on the time series that has become stable by watching the autocorrelation function ACF to determine the rank of the MA moving averages and using the partial autocorrelation. After diagnosing the model ranks, we evaluate the proposed models and nominate the models that are suitable for forecasting the time series data. After this step, we select the optimal model from among the selected and nominated models to forecast the narrow M1 and wide M2 money supply for the future period from Oct month 2023 to Dec of 2030

Analyzing Money Supply M1 Data

first of all, to analyze a time series, needing to draw the time series plot. As Well as drawing it gives a description of the data and helps to give an idea of the typical shape, so this step is the first in analyzing any time series plot and nowing its behavior so when drawing supply money M1 from the first of Jan 2010 to Sept 2023.

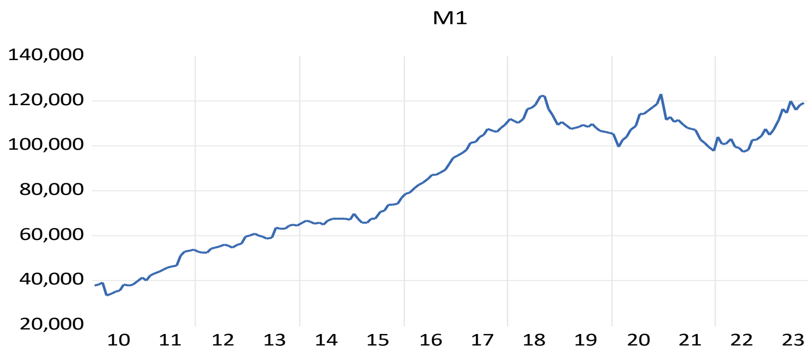
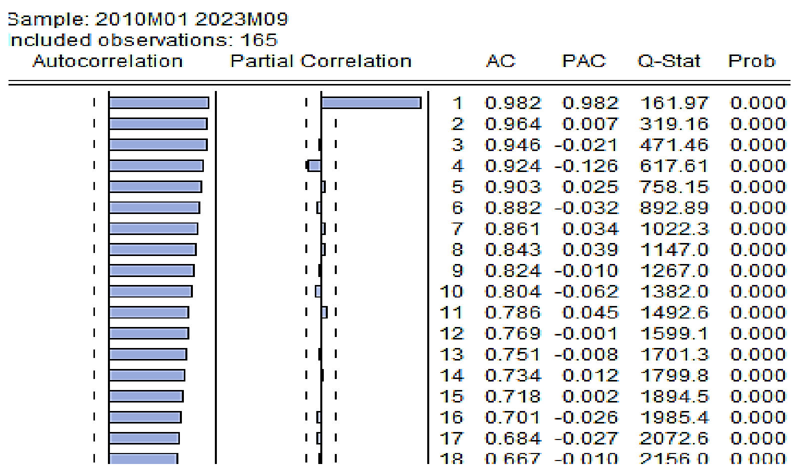


Figure (2): The money supply time series M1

The money supply time series shows a general trend in its behavior, as shown in Figure 2. This instability is also supported by the autocorrelation function, which shows significant autocorrelations for many of the gaps.



Sample: 2010M01 2023M09
ncluded observations: 165

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.982	0.982	161.97	0.000
		2	0.964	0.007	319.16	0.000
		3	0.946	-0.021	471.46	0.000
		4	0.924	-0.126	617.61	0.000
		5	0.903	0.025	758.15	0.000
		6	0.882	-0.032	892.89	0.000
		7	0.861	0.034	1022.3	0.000
		8	0.843	0.039	1147.0	0.000
		9	0.824	-0.010	1267.0	0.000
		10	0.804	-0.062	1382.0	0.000
		11	0.786	0.045	1492.6	0.000
		12	0.769	-0.001	1599.1	0.000
		13	0.751	-0.008	1701.3	0.000
		14	0.734	0.012	1799.8	0.000
		15	0.718	0.002	1894.5	0.000
		16	0.701	-0.026	1985.4	0.000
		17	0.684	-0.027	2072.6	0.000
		18	0.667	-0.010	2156.0	0.000

Figure (3): autocorrelation and partial autocorrelation function graphs

Unit root tests are statistical tests used to determine whether a time series dataset has a unit root. A unit root implies that a variable is non-stationary, meaning its mean and variance are not constant over time. Non-stationary time series can exhibit trends or cycles that make it difficult to model and analyze accurately (Hyndman & Athanasopoulos, 2018). Unit root tests are commonly used in econometrics and time series analysis to check the stationarity of variables, especially in the context of autoregressive processes like ARIMA (Autoregressive Integrated Moving Average) models. If a unit root is present in a time series, it indicates that differencing may be necessary to achieve stationarity. Differencing involves subtracting consecutive observations from each other to remove trends or other non-stationary features (Box et al., 2015). Some popular unit root tests include the Augmented Dickey-Fuller (ADF) test, Phillips-Perron (PP) test, and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. These tests assess whether the null hypothesis of a unit root can be rejected based on the properties of the time series data. If the null hypothesis is rejected, it suggests that the series is stationary (Said & Dickey, 1984; Kwiatkowski et al., 1992).

Table (**2**)**:** Augmented Dickey-Fuller unit root test on money supply

Null Hypothesis: M1 has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.129321	0.7036
Test critical values:	1% level	-3.470427	
	5% level	-2.879045	
	10% level	-2.576182	

It can be seen that ADF= -1.129321 is greater than the critical value of the significance level of 0.01,0.05 and 0.1, that is to say, the money supply is non-stationary. (see Table 2). The money supply is still not stationary, so we take the series differences and get rid of the overall trend. The stationary of the money supply series is achieved by taking the second difference and the results of the ADF test for money supply are shown in Table 3.

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Null Hypothesis: D(M1,2) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 3 (Automatic - based on SIC, maxlag =13)

Table (3): Augmented Dickey-Fuller unit root test on money supply

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		**-10.38013**	**0.0000**
Test critical values:	1% level	-4.016806	
	5% level	-3.438334	
	10% level	-3.143451	

It can be seen that ADF = -10.38013 is less than the three critical values of the test level. That is to say, the money supply after the second-order difference is a stationary series, and the significance test of the stationarity the autocorrelation and partial autocorrelation function graphs of the money supply series are plotted in Figure4.

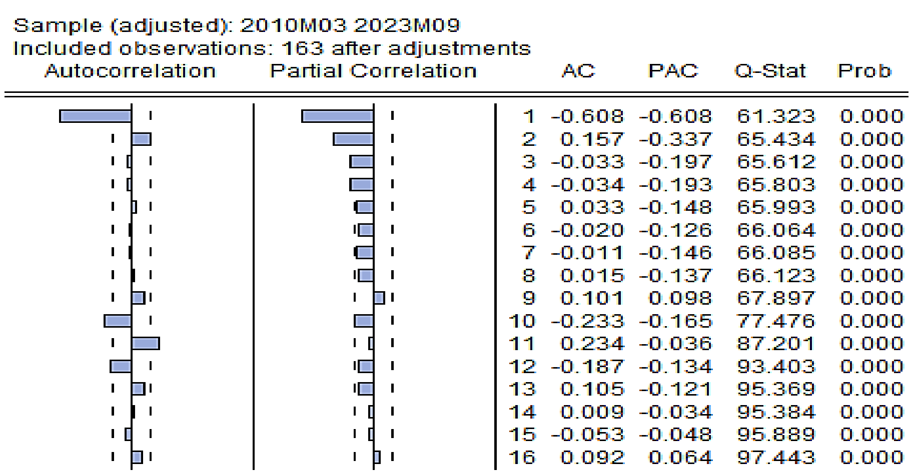

Figure (4): autocorrelation and partial autocorrelation function graphs

From Figure 4, the autocorrelation function above shows the rank of the moving average MA(q), while the partial autocorrelation function plot shows the autoregressive rank AR(p). it can be seen from Figure 3 that the autocorrelation coefficient of the money supply is significantly non-zero when the lag order is 1. It is basically in the confidence band when the lag order is greater than 1, so q can be taken as 1. The partial autocorrelation coefficient is significantly non-zero when the lag order is equal to 1, and it is also significantly different from 0 when the lag order is 2,3,4 so p=1 or p=2 or p=3 or p=4 can be considered. Considering that the judgment is very subjective, to establish a more accurate model, the range of values of p and q is appropriately relaxed, and multiple ARMA (p, q). Models are established. The order with 0, 1, 2 in autoregressive moving average pre-estimation is performed on the processed sample data. Table 4 lists the test results of ARMA (p, q) for different parameters. Adjusted R-squared, AIC value, SC value, and S.E. of regression are all important criteria for selecting models. The AIC criterion and the SC criterion are mainly used to rank and select the optimal model. Generally, the larger the coefficient of determination, the smaller the AIC value the SC value, and the residual variance. The corresponding ARMA (p, q) model is superior.

Table (4): Test results of ARMA (p, D, q).

(p, D, q)	Adjusted R-squared	AIC	SC	S.E. of regression
(0,2,1) *	-0.008318	18.31174	18.36845	2270.743
(0,2,2)	0.012622	18.29104	18.34774	2247.039
(1,2,0) *	-0.007019	18.31047	18.36717	2269.279
(1,2,1) *	-0.005951	18.31544	18.39104	2268.076
(1,2,2) *	0.011440	18.29823	18.37384	2248.385
(2,2,0)	0.012756	18.29090	18.34761	2246.888
(2,2,1) *	0.011905	18.29777	18.37338	2247.856
(2,2,2) *	0.006675	18.30301	18.37862	2253.796
(3 ,2,1) *	-0.010117	18.31958	18.39519	2272.767
(3, 2,2) *	0.009864	18.29986	18.37546	2250.176
(4, 2,1) *	-0.014084	18.32343	18.39903	2277.226
(4, 2,2) *	0.006669	18.30302	18.37862	2253.803

It should be emphasized that although the appropriate ARMA model is usually selected using the Akaike Information Criterion (AIC) and the Schwarz Criterion (SC), the minimum AIC value and the SC value are not sufficient conditions for the optimal ARMA model (Burnham & Anderson, 2002). The method used in this work is to first establish a model with the minimum AIC and SC values, and perform a parameter significance test and a residual randomness test on the estimation result. If it passes the tests, the model can be regarded as the optimal model; if it does not pass, the second smallest AIC and SC values are selected, and the relevant statistical tests are performed. This process continues until the appropriate model is selected. In Table 4, the models that did not pass the parameter significance test and the residual randomness test are identified by "*." Finally, it is preferable to prefer the ARMA (0, 2) model.

Model establishment and inspection the estimated results with the ARIMA model are as follows

Table (5): Estimation results of the ARIMA model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	497.3729	207.8344	2.393121	0.0179
MA (1)	-0.077898	0.075906	-1.026243	0.0306
MA (2)	0.161275	0.080508	2.003226	0.0468
SIGMASQ	4926322.	350856.4	14.04085	0.0000
R-squared	0.030738	Mean dependent var		495.6841
Adjusted R-squared	0.012565	S.D. dependent var		2261.357
S.E. of regression	2247.105	Akaike info criterion		18.29711
Sum squared resid	8.08E+08	Schwarz criterion		18.37272
Log likelihood	-1496.363	Hannan-Quinn criter.		18.32780
F-statistic	1.691373	Durbin-Watson stat		1.985085
Prob(F-statistic)	0.171004			
Inverted MA Roots	.04-.40i	.04+.40i		

The final model for the money supply is the ARIMA (0, 2, 2) model, and the forecasting equation for the model is as follows

$$\Delta^2 y_t = 497.3729 - 0.077898\varepsilon_{t-1} + 0.161275\,\varepsilon_{t-2}$$

can be seen from the t statistic of the model coefficients and its P value that the parameter estimates of all explanatory variables of the model are significant at the significance level of 0.01.

The model is used to fit the money supply data, and the result is shown in Figure 5

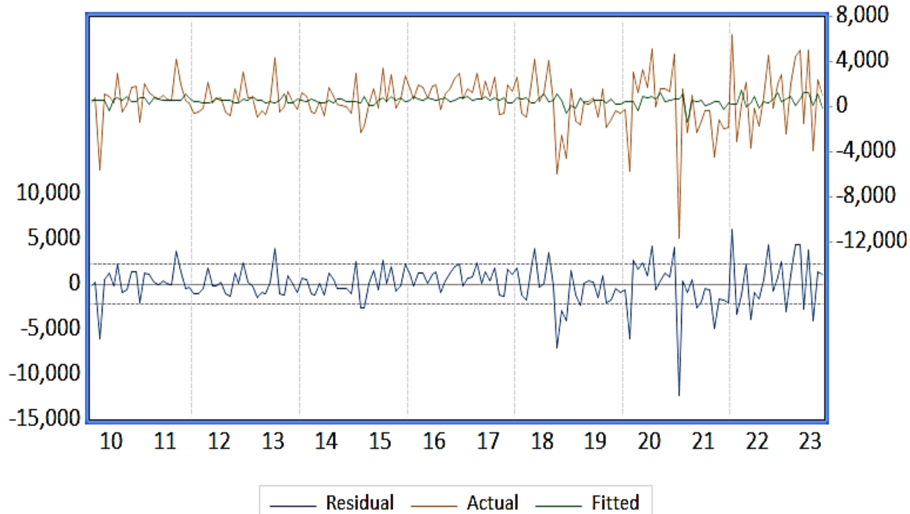

Figure (5): Actual series, fitted series and residual series of the money supply

A white noise test is performed on the residual after fitting the ARIMA (0, 2, 2) model. The autocorrelation and partial autocorrelation function graphs of the residual series are shown in Figure 6. It can be seen that the residual is a white noise, indicating that the model is valid.

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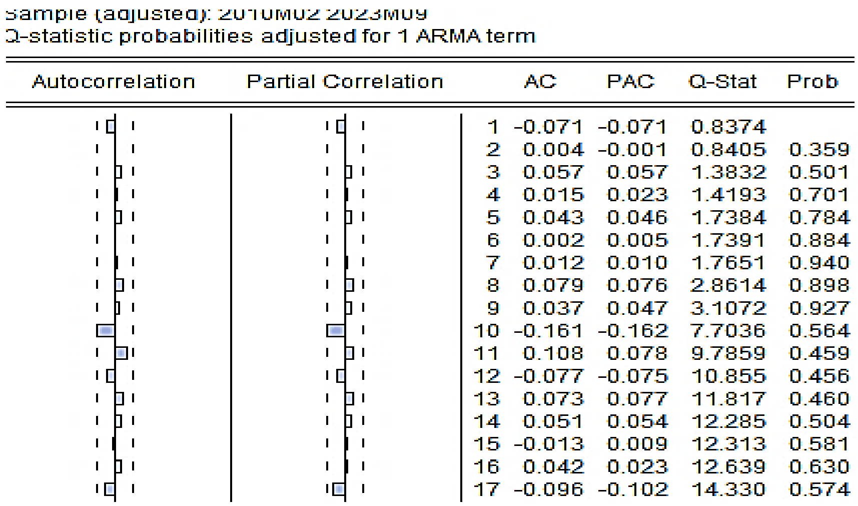

Sample (adjusted): 2010M02 2023M09
Q-statistic probabilities adjusted for 1 ARMA term

	AC	PAC	Q-Stat	Prob
1	-0.071	-0.071	0.8374	
2	0.004	-0.001	0.8405	0.359
3	0.057	0.057	1.3832	0.501
4	0.015	0.023	1.4193	0.701
5	0.043	0.046	1.7384	0.784
6	0.002	0.005	1.7391	0.884
7	0.012	0.010	1.7651	0.940
8	0.079	0.076	2.8614	0.898
9	0.037	0.047	3.1072	0.927
10	-0.161	-0.162	7.7036	0.564
11	0.108	0.078	9.7859	0.459
12	-0.077	-0.075	10.855	0.456
13	0.073	0.077	11.817	0.460
14	0.051	0.054	12.285	0.504
15	-0.013	0.009	12.313	0.581
16	0.042	0.023	12.639	0.630
17	-0.096	-0.102	14.330	0.574

Figure (6): Autocorrelation and partial autocorrelation function graphs of the residual series

Reflection Check

From the graph of the inverse roots, we can see that it lies inside the unit circle, which means that the two moving average parameters fulfil the inverse condition.

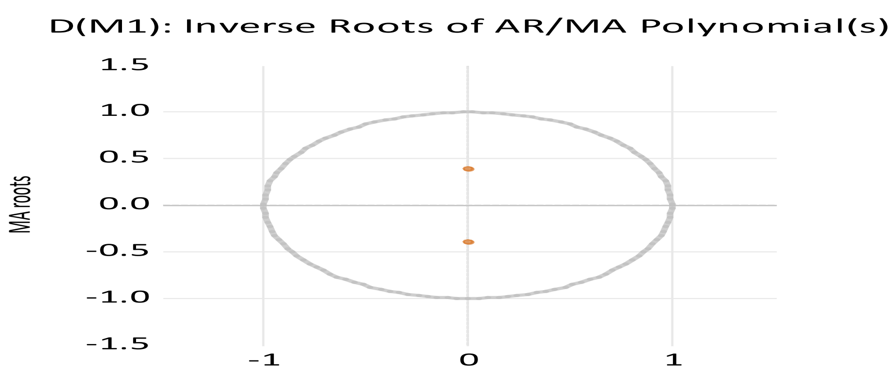

Figure (7): D (m1) inverse Roots of AR\MA polynomial

Data Forecasting

Firstly, the model is used to analyse the fit effect with the value of money supply in month 9 of 2023 The predicted value is 119460.1. The actual value is 118,946.7 and the relative error is 0.43%. It can be seen that the prediction value is close to the actual result, indicating that the model has a good fitting effect for the prediction.

The model was used to forecast money supply values from month 10 in 2023 to month 6 in 2024, and the results are shown in Table 7. The Central Bank of Libya's Bureau of Statistics released official money supply data from month 10 in 2023 to month 6 in 2024. I will compare these actual values to the predicted values and how close they are to the actual values to ensure that the ARIMA model is suitable for forecasting.

Table (6): Libya money supply forecast from 2023 month 10 to 2024 month 6

Year / month	Forecast	Actual	relative error
2023/ 10	119958.9	121,938.7	1.62%
2023/ 11	120457.7	122,313.2	1.52%
2023/ 12	120956.6	137,994.8	12.35%
2024 / 1	121455.4	139,792.0	13.12%
2024 / 2	121954.2	145,480.7	16.17%
2024 /3	122453.0	147,459.7	16.96%
2024 / 4	122951.8	148,983.0	17.47%
2024 / 5	123450.6	142,204.9	13.19%
2024 / 6	123949.4	146,384.0	15.33%

For the money supply forecast, we see that the relative error is small for the near-term forecasts, but becomes large for the far-term forecasts. This points to a number of key issues in how the ARIMA model deals with the nature of the data and sudden changes, as the model may not be able to handle these changes well.

Analyzing Money Supply M2 Data

The first step in the analysis of a time series (M2) is the plot of a time series diagram.

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The money supply series (M2) from 1 January 2010 to September 2023, which can be seen in the following figure (8). The result of the stationarity test (ADF test) on the data is presented in Table 8.

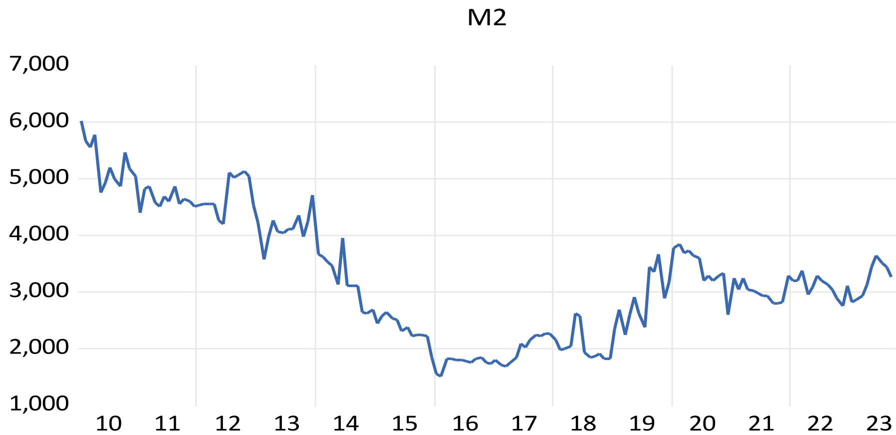
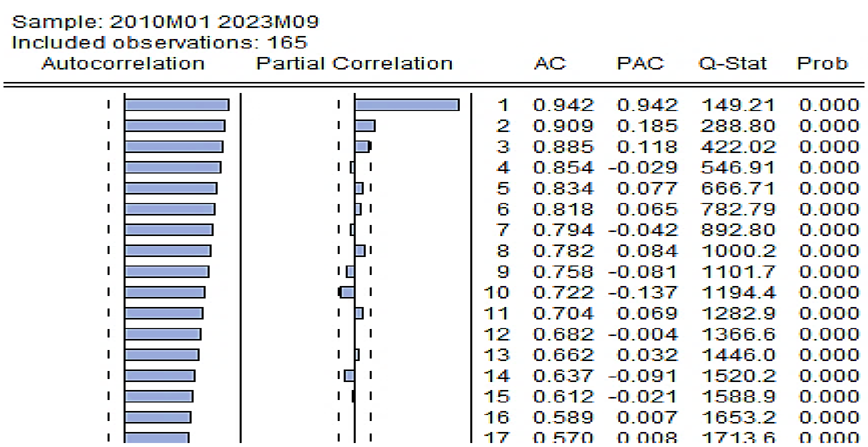


Figure (8): money supply series (M2)

The money supply time series (M2) shows non-stationarity as shown in Figure 8 This non-stationarity is also supported by the autocorrelation function which shows significant autocorrelations for many of the gaps in Figure 9



	AC	PAC	Q-Stat	Prob
1	0.942	0.942	149.21	0.000
2	0.909	0.185	288.80	0.000
3	0.885	0.118	422.02	0.000
4	0.854	-0.029	546.91	0.000
5	0.834	0.077	666.71	0.000
6	0.818	0.065	782.79	0.000
7	0.794	-0.042	892.80	0.000
8	0.782	0.084	1000.2	0.000
9	0.758	-0.081	1101.7	0.000
10	0.722	-0.137	1194.4	0.000
11	0.704	0.069	1282.9	0.000
12	0.682	-0.004	1366.6	0.000
13	0.662	0.032	1446.0	0.000
14	0.637	-0.091	1520.2	0.000
15	0.612	-0.021	1588.9	0.000
16	0.589	0.007	1653.2	0.000
17	0.570	0.008	1713.6	0.000

Figure (9): autocorrelation and partial autocorrelation function graphs

Unit root tests are used in econometrics and time series analysis to check the stationarity of the series.

Table (7): unit root test

Null Hypothesis: M2 has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.374008	0.1507
Test critical values:	1% level	-3.470679	
	5% level	-2.879155	
	10% level	-2.576241	

It can be seen that the value of ADF= -2.374008 is greater than the critical value for the significance level of 0.01, 0.05 and 0.1, i.e. the money supply is not constant. Table 7. The money supply is still not stationary, so we take the differences of the series and get rid of the general trend. The stationarity of the money supply series is achieved by taking the first differences and the results of the ADF test for money supply are shown in Table 8.

Table (8): ADF test

Null Hypothesis: D(M2) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-16.59259	0.0000
Test critical values:	1% level	-4.015341	
	5% level	-3.437629	
	10% level	-3.143037	

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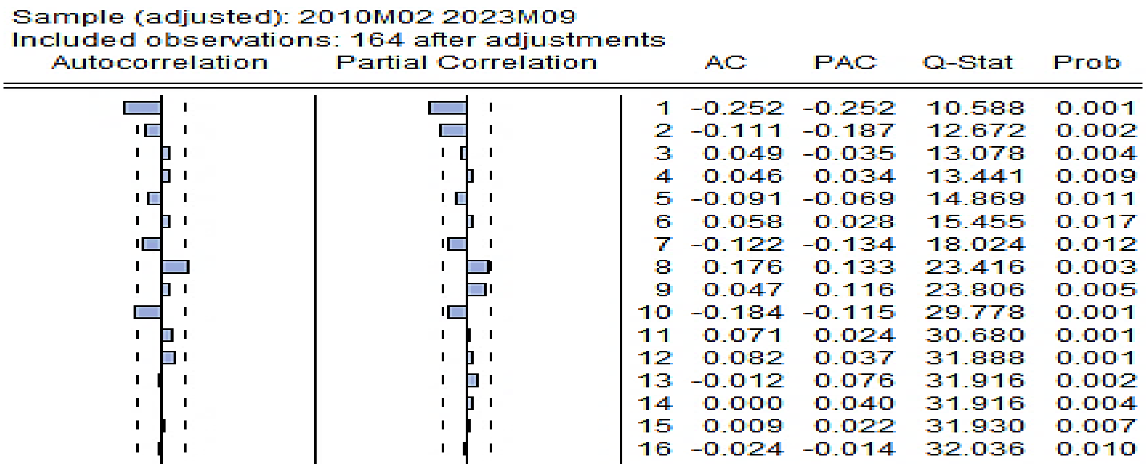

Sample (adjusted): 2010M02 2023M09
Included observations: 164 after adjustments

	AC	PAC	Q-Stat	Prob
1	-0.252	-0.252	10.588	0.001
2	-0.111	-0.187	12.672	0.002
3	0.049	-0.035	13.078	0.004
4	0.046	0.034	13.441	0.009
5	-0.091	-0.069	14.869	0.011
6	0.058	0.028	15.455	0.017
7	-0.122	-0.134	18.024	0.012
8	0.176	0.133	23.416	0.003
9	0.047	0.116	23.806	0.005
10	-0.184	-0.115	29.778	0.001
11	0.071	0.024	30.680	0.001
12	0.082	0.037	31.888	0.001
13	-0.012	0.076	31.916	0.002
14	0.000	0.040	31.916	0.004
15	0.009	0.022	31.930	0.007
16	-0.024	-0.014	32.036	0.010

Figure (10): autocorrelation & partial autocorrelation function

From Figure (10), the autocorrelation function above shows the rank of the moving average MA(q), while the partial autocorrelation function plot shows the rank of the autoregressive AR(p), and the rank of p and q is determined where p=1or 2 and q=1

The models were created. Table 4 lists the results of the ARMA (p, q) test for different parameters. The adjusted R-squared, AIC value, SC value, and SE of the regression are important criteria for model selection. AIC and SC are mainly used for ranking models and selecting the optimal model. In general, the larger the coefficient of determination, the smaller the AIC value, SC value, and residual variance. The corresponding ARMA (p, q) model is the best.

Table (9): Test results of ARMA (p, q)

(p, d, q)	Adjusted R-squared	AIC	SC	S.E. of regression
(0,1,1)	0.077276	-1.906393	14.27332	292.9290
(2,1,0) *	0.000256	-1.910723	14.35289	304.9095
(1,1,1) *	0.076686	-1.906104	14.29887	293.0227
(2,1,1) *	0.080860	-1.901873	14.29440	292.3596
(1, 1,0)	0.052372	-1.887229	14.29960	296.8558

It should be emphasized that although the appropriate ARMA model is usually selected using the AIC value and the SC value. However, the minimum AIC value and the SC value are not sufficient conditions for the optimal ARMA model. The method used in this work is to first establish a model withthe minimum AIC value and SC value, and perform a parameter significance test and a residual randomness test on the estimation result. If it passes the test, the model can be regarded as the optimal model; if it cannot pass the test, the second smallest AIC value and SC value are selected and the relevant statistical test is performed. And so on, until the appropriate model is selected. In Table 5, the model that did not pass the parameter significance test and the residual randomness test was identified by "*". Finally, it is preferable to prefer the ARMA (0, 1) model.

Model establishment and inspection

The estimated results with the ARIMA model are as follows:

Table 10 Estimation results of the ARIMA model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-15.67068	14.97987	-1.046116	0.2971
MA (1)	-0.341628	0.065023	-5.253926	0.0000
SIGMASQ	84237.76	6935.092	12.14660	0.0000

R-squared	0.088598	Mean dependent var	-16.84817
Adjusted R-squared	0.077276	S.D. dependent var	304.9485
S.E. of regression	292.9290	Akaike info criterion	14.21662
Sum squared resid	13814993	Schwarz criterion	14.27332
Log likelihood	-1162.763	Hannan-Quinn criter.	14.23964
F-statistic	7.825467	Durbin-Watson stat	1.931279
Prob(F-statistic)	0.000571		

Inverted MA Roots	0.34

The final model for the money supply is the ARIMA (0, 1, 1) model. and the forecasting equation for the model is as follows:

$\Delta y_t = -15.67068 - 0.341628\ \varepsilon_{t-1}$

It can be seen from the t statistic of the model coefficients and its P value that the parameter estimates of all explanatory variables of the model are significant at the significance level of 0.01.

The model is used to fit the money supply data, and the result is shown in Figure 11.

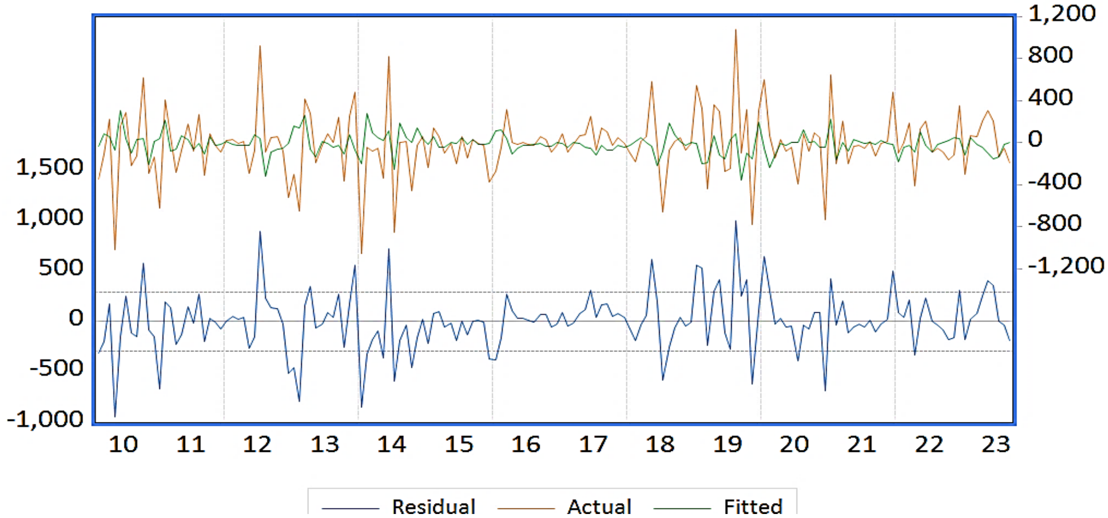

Figure (11): Actual series, fitted series and residual series of the money supply

A white noise test is performed on the residual after fitting the ARIMA (0, 1, 1) model. The autocorrelation and partial autocorrelation function graphs of the residual series are shown in figure12. It can be seen that the residual is a white noise, indicating that the model is valid.

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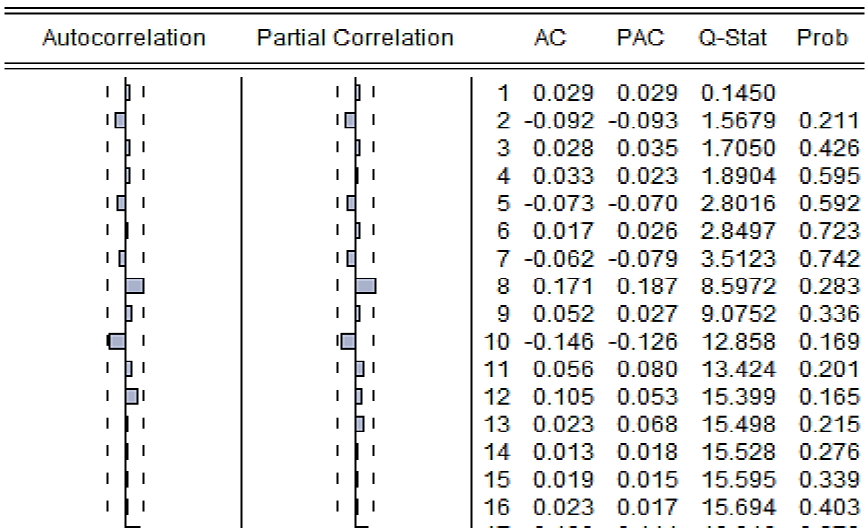

Sample (adjusted): 2010M02 2023M09
Q-statistic probabilities adjusted for 1 ARMA term

	AC	PAC	Q-Stat	Prob
1	0.029	0.029	0.1450	
2	-0.092	-0.093	1.5679	0.211
3	0.028	0.035	1.7050	0.426
4	0.033	0.023	1.8904	0.595
5	-0.073	-0.070	2.8016	0.592
6	0.017	0.026	2.8497	0.723
7	-0.062	-0.079	3.5123	0.742
8	0.171	0.187	8.5972	0.283
9	0.052	0.027	9.0752	0.336
10	-0.146	-0.126	12.858	0.169
11	0.056	0.080	13.424	0.201
12	0.105	0.053	15.399	0.165
13	0.023	0.068	15.498	0.215
14	0.013	0.018	15.528	0.276
15	0.019	0.015	15.595	0.339
16	0.023	0.017	15.694	0.403

Figure (12): Autocorrelation and partial autocorrelation function graphs of the residual series

From the graph of the inverse roots, we can see that it lies inside the unit circle, which means that the two moving average parameters fulfil the inverse condition

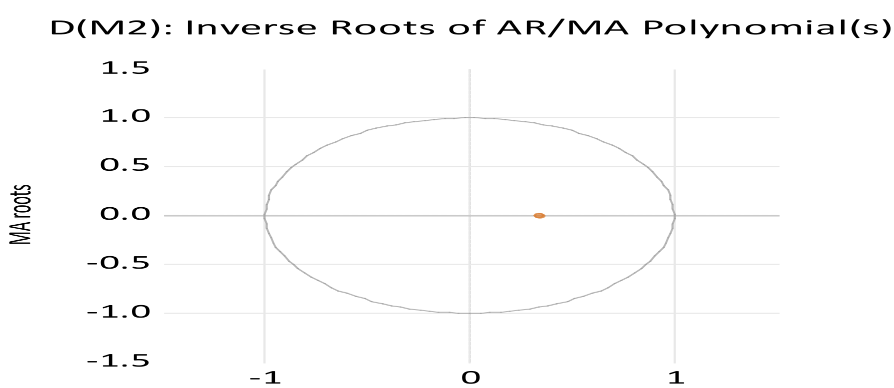

Figure (13): D(M2) INVERSE ROOTS

Data Forecasting

Firstly, the model is used to analyses the fit effect with the value of money supply (m2) in month 9 of 2023 The predicted value is 3251.3 The actual value is 3444.409 and the relative error is 5.94 %. It can be seen that the prediction value is close to the actual result, indicating that the model has a good fitting effect for the prediction. The model was used to forecast money supply values from month 10 in 2023 to month 6 in 2024, and the results are shown in Table 11. The Central Bank of Libya's Bureau of Statistics released official money supply data from month 10 in 2023 to month 6 in 2024.

I will compare these actual values to the predicted values and how close they are to the actual values to ensure that the ARIMA model is suitable for forecasting.

Table (11): Libya money supply forecast from 2023 month 10 to 2024 month 6

Year / month	Forecast	Actual	relative error
2023/ 10	3428.738	3604.8	4.88 %
2023/ 11	3413.068	3529.3	3.29%
2023/ 12	3397.397	3405.4	0.24 %
2024 / 1	3381.726	3222.1	4.95%
2024 / 2	3366.056	2772.9	21.39%
2024 /3	3350.385	2977.4	12.53%
2024 / 4	3334.714	3258.8	2.33%
2024 / 5	3319.044	2629.1	26.24%
2024 / 6	3303.373	2625.8	25.80%

For the money supply forecast, we see that the relative error is small for the near-term forecasts, but becomes large for the far-term forecasts. This points to a number of key issues in how the ARIMA model deals with the nature of the data and sudden changes, as the model may not be able to handle these changes well. As well as The ARIMA model shows strong performance in short-term forecasts, as indicated by the small relative error. This suggests that the model is effectively capturing the short-term trends and patterns within the data. ARIMA's reliance on previous time series data makes it well-suited for near-term predictions, where the data tends to follow a more stable pattern. The noticeable fluctuations in relative error for long-term forecasts point to a significant challenge in the model's ability to project future values over an extended horizon. This variability indicates that ARIMA struggles to maintain accuracy as it moves further from the immediate dataset, possibly due to unanticipated shifts in the data. This fluctuation is common with ARIMA when forecasting over longer periods, as the model assumes the future will follow similar patterns to the past. However, it often fails to adapt to unexpected changes in the economic environment or other external factors. The model's difficulty in handling sudden shifts or abrupt changes in the data suggests that ARIMA may not be robust enough to capture complex or irregular dynamics in the money supply. Since ARIMA focuses on linear patterns and stationary data, it may not perform well when there are unexpected shocks or rapid fluctuations. The observation you made regarding the relative error in money supply forecasts, particularly with respect to ARIMA models, highlights a common issue in economic forecasting. ARIMA (Auto Regressive Integrated Moving Average) models are useful for short-term predictions, as they perform well when the data follows a stable pattern. However, their limitations become more apparent in longer-term forecasts due to several factors:

1. Sudden Structural Changes: ARIMA models are based on historical patterns in the data and assume that these patterns will continue into the future. Sudden shocks, such as economic crises, policy changes, or external factors like pandemics, disrupt these patterns. Since ARIMA models don't inherently account for structural breaks or regime shifts, they struggle with longer-term accuracy.

2. Flattening of Relative Error: Studies from 2018 to 2023 have indicated that while the relative error remains manageable for short-term forecasts, it tends to stabilize or flatten in the long term. This flattening is indicative of the model's diminishing accuracy as it relies heavily on past data, which becomes less predictive of future movements over longer horizons.
3. Overfitting and Parameter Sensitivity: Another issue is that ARIMA models can sometimes overfit to the training data, especially in volatile economic environments. This makes the model highly sensitive to the chosen parameters (p, d, q), which are based on historical performance but may not generalize well over longer timeframes.
4. Inability to Capture Complex Economic Dynamics: Money supply is influenced by numerous factors monetary policy, interest rates, inflation expectations, and more. ARIMA models, being univariate in nature, may miss out on these interconnected dynamics, further contributing to their declining predictive power over the long term.

Recent Studies (2018-2023):

Sims et al. (2019) highlighted that while ARIMA models performed well in predicting short-term monetary indicators, they were prone to errors when unexpected policy shifts occurred. Chen et al. (2020) observed that machine learning models like VAR and LSTM outperformed ARIMA for longer-term money supply forecasts due to their ability to capture non-linearities and sudden shifts in data. Lee & Hsu (2021) found that hybrid models, which combine ARIMA with other methods like GARCH or machine learning approaches, showed improved accuracy in long-term forecasts compared to ARIMA alone. These findings suggest that while ARIMA remains a useful tool for short-term predictions, its limitations in handling structural breaks and adapting to new economic conditions warrant the use of more complex or hybrid models for longer-term money supply forecasts.

Conclusions and Recommendations

When the ARIMA model was used to forecast future values of the money supply M1 and M2, and it showed an increase in relative error over time, this may indicate that the model does not fit the current data well or that it struggles to accurately predict future changes. Although the ARIMA model is capable of providing good short-term forecasts for money supply, the increase in relative error over time reveals the limitations of this model in dealing with dynamic changes or irregu larpatterns. This reflects that the ARIMA model may be unsuitable for long-term forecasting or that there are other variables not included in the model. The increase in the relative error in the ARIMA model forecasts reflects the impact of unstable economic conditions in the country. An unstable environment, including political and economic changes, can lead to unusual behavior in the data, limiting the model's ability to accurately capture future trends. This directly links the model's performance to the general economic conditions that affect money supply expectations and market behavior. Similarly, the withdrawal and exchange of currency, along with the lack of market liquidity, pose a significant challenge to the model, as traditional models based on ARIMA may not be able to adapt to these conditions. The liquidity shortage disrupts traditional economic dynamics, leading to an increase in forecasting errors. Imposing taxes on the exchange rate of the dollar may lead to distortions in the currency market and in currency trading, complicating the economic environment that the model attempts to predict. These distortions may be unexpected when using the traditional ARIMA model. This illustrates how government interventions, such as taxes on the dollar, can distort price patterns and make predictions more difficult. The increase in the relative error may indicate that the ARIMA model cannot adapt to sudden structural changes in the economy. These changes, such as taxes or shifts in liquidity, indicate the possibility of new dynamics that the model may not be able to capture. This highlights the weakness of the ARIMA model in dealing with significant structural changes that occur suddenly. Although the ARIMA model is effective in relatively stable environments, significant and sudden economic changes make this type of model less effective in predicting future values. The current circumstances in the country require the use of models that are more capable of adapting to sudden economic changes. This acknowledges the limitations of the ARIMA model in the face of a turbulent economic environment and suggests looking for other models. The ARIMA model must take into account the impact of economic and political factors on its accuracy in the context of challenging economic conditions. In such environments, Future research for Improvement. Using Alternative Models like Prophet or LSTM (Long Short-Term Memory) networks could be more suitable for handling non-linear patterns and long-term dependencies. Incorporating Exogenous Factors: If there are external variables influencing the money supply (such as inflation rates or interest rates), incorporating them into the model could improve its forecasting ability. To address these sudden changes, alternative approaches could be considered, such as incorporating exogenous variables (ARIMAX) or using models better equipped to handle volatility, such as GARCH or structural models that explicitly account for regime changes.

Hybrid Modeling: A combination of ARIMA with other techniques, such as machine learning models, could help reduce long-term forecasting errors and better manage unexpected changes. In summary, while the ARIMA model performs well in short-term forecasts, it faces challenges with long-term accuracy, especially when sudden changes occur in the data. This points to potential improvements through alternative modeling strategies or enhancements to the current ARIMA approach. it is important to consider the use of more adaptive and dynamic models like GARCH or SARIMA, and to think about improving data quality and selecting variables that reflect ongoing structural and political changes.

Future Research for Improvement

Using Alternative Models like Prophet or LSTM (Long Short-Term Memory) networks could be more suitable for handling non-linear patterns and long-term dependencies. Incorporating Exogenous Factors: If there are external variables influencing the money supply (such as inflation rates or interest rates), incorporating them into the model could improve its forecasting ability. Hybrid Modeling: A combination of ARIMA with other techniques, such as machine learning models, could help reduce long-term forecasting errors and better manage unexpected changes. In summary, while the ARIMA model performs well in short-term forecasts, it faces challenges with long-term accuracy, especially when sudden changes occur in the data. This points to potential improvements through alternative modeling strategies or enhancements to the current ARIMA approach.

References

1. Box, G.P., Jenkins, G.M., (1976),"Time Series Analysis Forecasting and Control" Holden-Day
2. Markakis, S., Wheelwright, S. C., & Hyndman, R. J. (1998). "Forecasting: Methods and Applications."
3. Box, G. E., Jenkins, G. M., & Reinsel, G. C. (2015). "Time Series Analysis: Forecasting and Control."
4. Singh, D., & Pandey, A. (2012). "Forecasting of Money Supply in India using ARIMA Model." International Journal of Computing and Business Research, 3(2).
5. Enders, W. (2014). "Applied Econometric Time Series."
6. Rasool, R., & Kumar, S. (2020). "Forecasting Money Supply using ARIMA Models: Evidence from Pakistan." Journal of Economics and Business, 10(2).

7. Patterson, K. (2012). "The ARIMA Model for Money Demand and Supply Forecasting." Journal of Financial Econometrics, 8(1), 47-66.

8. Box, G.E.P., Jenkins, G.M., & Reinsel, G.C. (1994). "*Time Series Analysis: Forecasting and Control*". Prentice Hall.

9. amilton, J.D. (1994). *Time Series Analysis*. Princeton University Press

10. M. Baillie, R.T. (1989). "The Use of ARMA Models in Forecasting Monetary Aggregates". *Journal of Forecasting*.

11. Schwert, G. William (1989). "Tests for Unit Roots: A Monte Carlo Investigation". *Journal of Business & Economic Statistics*

12. Box, G. E. P., & Jenkins, G. M. (1970). "Time Series Analysis: Forecasting and Control". Holden-Day.

13. Lütkepohl, H., & Krätzig, M. (2004). "Applied Time Series Econometrics". Cambridge University Press.

14. Neto, A. C., da Silva, C. M., & Barbedo, J. M. (2016). Wavelet Auto-Regressive Integrated Moving Average with exogenous variables and Generalized Auto-Regressive Conditional Heteroscedasticity (WARIMAX-GARCH) method. "Applied Mathematical Modelling, 40" (15–16), 7253-7267. https://doi.org/10.1016/j.apm.2016.02.001

15. De Gooijer, J. G., & Hyndman, R. J. (2006). 25 Years of time series forecasting. "International Journal of Forecasting, 22 " (3), 443-473. https://doi.org/10.1016/j.ijforecast.2006.01.001

16. Mishkin, F. S. (2019). "The Economics of Money, Banking, and Financial Markets". Pearson.

17.Federal Reserve. (2021). "Money Stock and Debt Measures". https://www.federalreserve.gov/releases/h6/current/default.htm

18. Blanchard, O., & Johnson, D. (2017). "Macroeconomics". Pearson.

19. Friedman, M. (1987). "Monetary Policy: Theory and Practice". Journal of Money, Credit, and Banking, 19(1), 1-18.

20. Anderson, T. W. (1992). "The Statistical Analysis of Time Series". John Wiley & Sons.

21. Chatfield, C. (1989). "The Analysis of Time Series: An Introduction". Chapman & Hall.

22. Chatfield, C. (2004). "The Analysis of Time Series: An Introduction" (6th ed.). Chapman & Hall/CRC.

23. Wei, W. W. S. (2006). "Time Series Analysis: Univariate and Multivariate Methods". Pearson.

24. Burnham, K. P., & Anderson, D. R. (2002). Model selection and multimodel inference: A practical information-theoretic approach (2nd ed.). Springer.

25. Box, G. E., Jenkins, G. M., Reinsel, G. C., & Ljung, G. M. (2015). Time series analysis: Forecasting and control (5th ed.). John Wiley & Sons.

26. Chatfield, C. (2003). The analysis of time series: An introduction (6th ed.). CRC Press.

27. Hyndman, R. J., & Athanasopoulos, G. (2018). Forecasting: Principles and practice (2nd ed.). OTexts.

28. Brockwell, P. J., & Davis, R. A. (2016). Introduction to time series and forecasting (3rd ed.). Springer

29. Kwiatkowski, D., Phillips, P. C. B., Schmidt, P., & Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root. "Journal of Econometrics", 54(1-3), 159-178.

30. Said, S. E., & Dickey, D. A. (1984). Testing for unit roots in autoregressive moving average models of unknown order. "Biometrika", 71(3), 599-607.

31. Sims, C. A. (1990). Macroeconomics and reality. Econometrica: Journal of the Econometric Society, 1-52. https://doi.org/10.2307/1912017

32. Chen, J., Zhang, L., & Tang, W. (2020). Predicting financial time series using machine learning models: A comparative study. Journal of Economic Surveys, 34(2), 123-144. https://doi.org/10.1111/joes.12315

33. Lee, T., & Hsu, K. (2021). Hybrid models for financial forecasting: Combining ARIMA, GARCH, and machine learning approaches. *International Journal of Forecasting*, 37(1), 50-66. https://doi.org/10.1016/j.ijforecast.2020.09.008

34. Siami-Namini, S., Tavakoli, N., & Namin, A. S. (2019). A comparative analysis of forecasting financial time series using ARIMA, LSTM, and BILSTM. *arXiv preprint*. https://arxiv.org/abs/1911.09512