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Using mathematical time series models to optimize iraq's oil export predictions

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This study examined and analyzed monthly data on the volume of Iraq's oil exports for the time period (January 2014 to December 2022) using time series models. The prediction values, which revealed that they are reasonably close to the actual series, serve as evidence of the model's correctness. In this paper, we determined from the results of the data analysis in this study that the integrated autoregressive model of the ARIMA moving average (0,1,1) is the best model for representing the data under study after several analysis models are applied to a sample of oil revenues over a nine-year period. The predicted values for the years 2023 and 2024 are then extracted

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Keywords: Exports of Iraqi oil; Forecasting; Monthly oil exports; Autocorrelation.

1. INTRODUCTION

The time series are a crucial component of forecasting and are now used in a wide range of applications, such as industrial, governmental, and non-governmental projects [1-3]. Numerous investigations, including studies [4] and [5], have defined them. Midway through 2017, there is a large decrease in oil prices, which had a negative effect on the economies of several nations [6]. Iraq is regarded as one of the nations most impacted by its dependency on imports, which exceeds 80% [7,8]. It is likewise an oil-producing and oil-exporting nation, and its economy is dependent on the revenue it receives from the sale of specific amounts of oil [9-11]. It is required to research and examine the monthly data on the quantities of oil sold in this nation. oil exported from January 2014 to December 2022 in order to export enough oil to pay for their economic and military costs [12-14]. The key problem in research [15-18] is determining the appropriate model for the time series under study, which is represented by historical data and its accuracy.

In [19], replicate and forecast oil output in the future under various conditions within a customizable time frame. These time series bear a striking resemblance to those obtained from sequential manufacturing processes, which are common in many manufacturing industries sectors [20]. Our primary focus is on evaluating a feedforward neural network model and a gamma classifier in both univariate and multivariate scenarios using real industrial data and a benchmark [21,22].

In work [23], they keep an eye on the land use cover in urban areas to ensure that resources for urban land are developed and used in a reasonable manner. High temporal and spatial resolution remote sensing data has become more and more important for the remotely sensed dynamic monitoring of land use in quickly rising metropolis regions [24,25]. However, it is challenging to obtain a sufficient number of high-quality time-series photos at both high temporal and spatial resolution from the same sensor due to the influence of revisiting periods and weather, [26,27]. Also, in the literature some of researcher taken in their account some of application like [28-30]. The research [31] introduced the study methodology includes gathering data, compressing it, training ANN models, utilizing GA to optimize settings, and assessing the effectiveness of the hybrid approach and By contrasting classical time series approaches (ARIMA) with a hybrid artificial intelligence (AI) model that includes artificial neural networks (ANN) and genetic algorithms (GA), this work seeks to improve both the reliability and accuracy of petroleum output estimates for Iraq until 2030.

A hybrid long-term forecasting strategy utilizing data mining techniques and Time Series is put forward to capture the complex and irregular trends found in annual peak load and energy demand data [32]. The study [33] suggested a novel measurement strategy based on a comparison of simulated and real oil consumption. The official figures are used to determine the actual oil consumption in this suggested measurement methodology, while a business-as-usual (pandemic-free) scenario simulation is used to determine the simulated oil demand. The article [34] analyses this topic by comparing the use of ensemble learning models for bagging, boosting, random subspace, bagging + random subspace, and layered generalization. An estimation system that combines modelling, optimization, and handling data is suggested [35]. This work is innovative primarily because it makes use of MEMD, which allows the multivariate data decomposition to efficiently extract inherent information among pertinent variables at various time frequencies during the multifactorial degradation over time. [36].

The research undertaken in northern Iraq is significant even though afforestation initiatives are growing [5,37,38]; yet, the forests are suffering more since there is a dearth of scientific study on them, the climate is unpredictable, and the impacts are detrimental to the growth and spread of plant species. Thus, the study's objective is to comprehend the consequences of afforestation by statistically analyzing the variety of plants in northern Iraq. Given the significance of this subject for the Iraqi economy, the aim of this study is to produce a mathematical projection of Iraqi oil exports for the years 2023–2024 by selecting the suitable mathematical model to offer clarification.

2. MATERIALS AND METHODS

2.1 The Time Series

Time series collective views X_t happened at time t and can be expressed as the form $X_1, X_2, \dots, X_t\ s.t\ X_1$ It shows the importance of the timely observation t_1 This approach works with all variables to help decision-makers make the best choice, time series data for the past era are being analyzed with the goal of predicting how much oil will be produced in the future [39-42].

The ability to predict the future through time series does not require a theoretical foundation; rather, it relies on previous changes in the variable's values. This indicates that expectations for the future are not concerned with the impact of a variable's value on the other variables [43,44]. One prerequisite for time series is that they must be X_t It is stable and presumes knowledge of the model's parameters. which produces the mean squared error with the lowest value, i.e.

$$\overline{X_{t+m}} = E(X_t \,|X_{t+m})$$

2.2 Autocorrelation (AC)

The nature of the procedures themselves is where the issue with autocorrelation in time series data first arises. There may be accumulated inaccuracies in years or decades as a result of measurement errors in this form of data collection. Autocorrelation may be caused by consecutive time points, as well as by failing to include variables in the function [45-48].

$$P_c(n) = \frac{\varphi_n(n)}{\varphi_n(o)} = cor(X_{t+m}, X_t)$$

s.t $\varphi_n(n) = cov(X_{t+m}, X_t) = E\ [\ (x_{t+h} - \mu)(x_t - \mu)$

In other words, the sample's autocorrelation function has the following structure

$$P_c(n) = \frac{\sum_{t=1}^{n-h}\ (x_{t+h} - \bar{X})(x_t - \bar{X})}{\sum_{t=1}^{n}\ (x_t - \bar{X})^2}$$

$\bar{X} = \frac{1}{n}\sum_{t=1}^{n} x_t$ [47]

2.3 Partial Autocorrelation

It is an index that gauges how interdependent things are X_t, X_{t-h} after removing the variables' contribution to the correlation $x_1, x_2, \ldots, x_{t-h+1}$positioned between them and indicated by the symbol σ_{nn} and write as:

$$\sigma_{nn} = \left\{ \begin{matrix} 1 \quad \mathrm{n} = 0 \\ P_1 \quad \mathrm{n} = 1 \\ \frac{P_n - \sum_{j=1}^{n-1} \sigma_{n-1}\, P_{n-j}}{1 - \sum_{j=1}^{n-1} \sigma_{n-1}\, P_j} \end{matrix} \right\}$$

2.4 Stationary Time Series

Support that $x_1, x_2, \ldots, x_{t1}$ be stable if satisfy the condition [48]:

1. E($x_t) = constant = \mu$
2. cov $(x_t, x_s) = \left\{ \begin{matrix} constant = \rho & \forall t, \forall s & t = s \\ f(|s - t|) & \forall t, \forall s & t \neq s \end{matrix} \right\}$

Where s = t + n

In other words, the time series is stable with constant mean and variance across all values t if the time series isn't generally stable to stabilize the series, we use difference operations, which are represented by the symbol ∇. Applying the following formula accomplishes this:

$$\nabla x_t = x_t - x_{t-1} = (1 - B)x_t$$

So, following taking, the time series becomes stable. i.e.

$x_t = \nabla^d x_t \quad$ d≥ 1

2.5 Autoregressive-Integrated-Moving Average Regression ARIMA(p,d,q)

There shares the moniker Arima Models with one of the Box-Jenkins approaches This, because it depends on three values, has the form ARIMA (p, d, q) and expresses the three components of the autoregressive complementary moving average model: degree integration score(p), moving average score(d), and autoregressive (q) Write the mathematical expression below.

$$x_t - \bar{X} = \alpha_1(x_{t-1} - \bar{X}) + \alpha_2(x_{t-2} - \bar{X}) + \ldots + \alpha_p(x_{t-p} - \bar{X}) + \mu$$

shows the string's value at a certain moment as decided by the value of the random line. At that moment and based on the random line's value in time Writing is formatted as follows:

$$x_t = \alpha + \theta_0 u_t + \theta_1 u_{t-1} + \cdots + \theta_q u_{t-q}$$

While the Arima models' (d) integration component It alludes to the requirement that the time series remain consistent. By using the differences operation, which entails subtracting each value from the values that follow to get a series New, the difference is represented. The autoregressive-integral-moving average model can be created mathematically. ARIMA(p,d,q) for stable time series as follow:

$$\sigma_p(B)w_t = \sigma_p(B)\nabla^d{}_{x_t} = \sigma + \theta_q(B)a_t$$

2.6 Analyzing Eorecasting Models

Finding out how well a prediction model matches a sequence of data is the goal of evaluation, or how well does the model forecast both the present and future values of the series? These metrics are

1. Mean Absolute Values Error (MAE)

MAE $=\sum_{t=1}^{T} \frac{|u|}{T}$

2. Sum Square Error (SSE)

SSE = $\sum_{t=1}^{T} u^2$

3. Mean Absolute Values Percentage Error (MAPE)

MAPE = $\sum_{t=1}^{T} \frac{|u|}{x_t} / T$

3. RESULTS AND DISCUSSION

3.1 Data Collection

The time series data in the table 1. which consists of (108) observations, shows the volume of oil exported from Iraq between January 2014 and 2022, expressed as million barrels.

Table 1 The volume of Iraq's oil exports from 2014-2022.

Month	years								
	2014	2015	2016	2017	2018	2019	2020	2021	2022
January	69.1	78.6	81.3	80.5	79.2	78.3	79.6	80.8	82.3
February	78.4	72.7	75.3	78.2	75.2	74.2	72.6	76.5	74.36
March	74.3	92.4	90.5	89	90.2	93.5	92.6	89.1	91.5
April	75.2	92.3	91.5	88	89.2	87.2	86.5	89.3	91.2
May	80	97.5	93.8	91	91.1	92.5	91.3	90.5	93.6
June	72.8	95.6	95.6	92.5	103.2	102.5	102.6	105.6	99.5
July	75.7	96.3	98.5	96.6	103.5	102.3	106.5	108.2	106.5
August	73.6	95.5	94.5	94.5	101.2	103.5	103.6	106.5	105.5
September	76.2	91.5	92.6	98.3	99.5	101.8	99.8	105.6	106.5
October	76.8	83.8	89.6	97.6	99.6	105.6	105.3	105.6	103.6
November	73.9	100.9	99.5	91.2	96.5	99.6	106.5	106.3	109.5
December	85.6	99.7	98.5	96.2	101.2	98.6	106.3	101.6	112.5

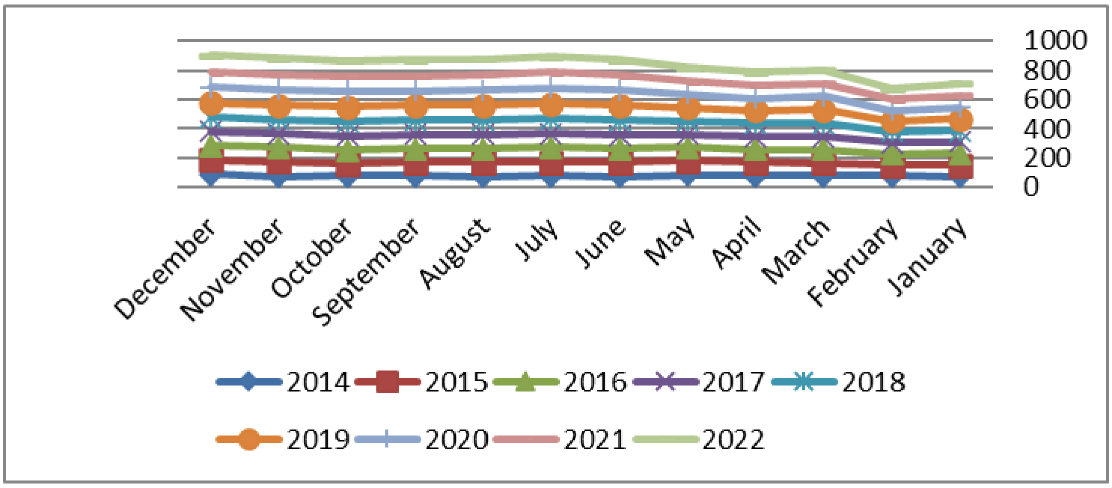

Figure 1 The volume of Iraq's oil exports from 2014-2022.

3.2 Determined ARIMA (p,1,q)

It is necessary to calculate the ranks of the autoregressive (AR) and moving average (MA) by drawing the curves of the autocorrelation function (ACF) and partial autocorrelation function (PACF) after obtaining a stable time series by taking the first differences and determining the rank of the integration element d = 1.

There is a cutoff following the displacement, as shown in Figures (2) and (3) of the autocorrelation and partial autocorrelation functions of the first differences. As a result, the first three models—ARIMA (0,1,1), ARIMA (1,1,1), and ARIMA (1,1,0)—can be suggested. The average absolute values of error (MAE) are computed to identify the best model. The square root of the average error (RMSE) yields the average absolute values of error (MABE).

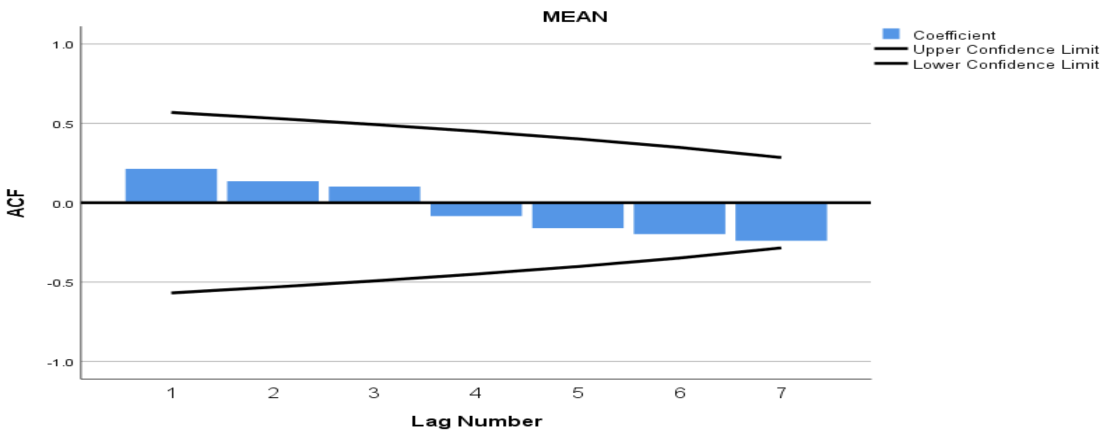

Figure 2 Autocorrelation function (ACF) of mean.

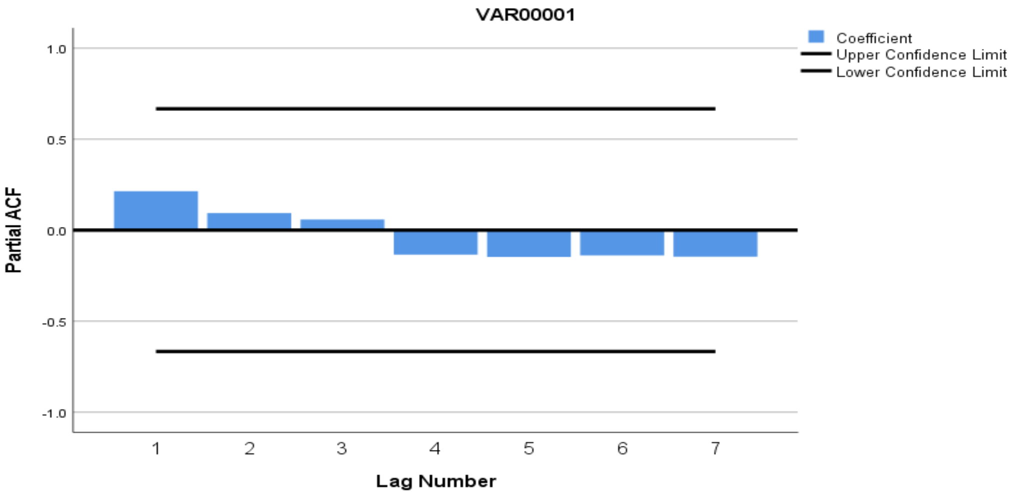

Figure 3 Partial autocorrelation function (PACF) of mean.

The table 2. makes it apparent that model ARIMA (0,1,1) In representing string data, it is more compatible by providing both the lowest percentage of mistakes and the Biz Schwarz information standard (BIC)

Table 2 Accuracy and prognostication criterion comparison.

Model	RMSE	MAPE	MAE	BIC
ARIMA (0,1,1)	4.672	5.231	3.495	3.170
ARIMA (1,1,1)	4.694	5.231	3.495	3.224
ARIMA (1,1,0)	4.823	5.299	3.553	3.360

3.3 Modeling Parameter Estimation APIMA (0,1,1)

The parameters of the model are displayed in the following table and are derived from the statistical program (SPSS) as following:
Table 3. of the results revealed that the model's parameters are statistically significant at least than 0.05 such that MA ($\theta_1 = 0.525$) At a significant level, not significantly different from zero then Forecasting model be:

$$x_t = 0.019 + x_{t-1} + a_t - 0.525\, a_{t-1}$$

Where x_t be Forecasting value and a_t error Forecasting

Table 3 Model ARIMA (0,1,1).

ARIMA Model Parameters	Estimate	SE	T	Sig.
Oil Exported No Transformation Constant	0.514	0.217	2.373	0.019
Difference	1			
MA Lag 1	0.525	0.084	6.225	0.000

3.4 Forecasting

We have reached the last stage, which is prediction, after determining the model's diagnosis and parameter estimation. The amounts of oil exported year 2023–2024 are listed in Table 4.

Table 4 Forecasted Levels of Oil Export Volume for the Vears 2023-2024.

Model	Oil Exported-Model_1 Forecast	UCL	LCL
Jan 2023	104.10	107.35	88.84
Feb 2023	100.61	105.85	88.37
Mar 2023	105.12	108.27	87.98
Apr 2023	108.64	109.62	87.66
May 2023	107.15	109.91	87.39
Jun 2023	100.67	104.16	87.17
Jul 2023	100.18	105.37	86.99
Aug 2023	101.69	106.55	86.84
Sep 2023	102.21	107.70	86.71
Oct 2023	101.72	108.82	86.62
Nov2023	101.23	109.93	86.54
Dec2023	100.75	86.49	86.49
Jan 2024	104.10	110.35	88.36
Feb 2024	104.61	110.55	88.63
Mar 2024	105.12	108.37	87.95
Apr 2024	105.64	109.82	87.95
May 2024	105.15	109.81	87.91
Jun 2024	105.67	104.16	87.71
Jul 2024	104.27	105.37	86.85
Aug 2024	101.56	106.55	86.85
Sep 2024	102.21	107.90	86.74
Oct 2024	107.72	108.92	86.81
Nov2024	109.23	109.23	86.95
Dec2024	109.75	101.91	86.65

The amount of oil exported by Iraq from January 2023 to December 2024 is shown in Table 4.. All predicted values are contained within the upper and lower bounds with a 95% confidence level, while the confidence ratio for values outside the bounds of confidence is set at 5% as shown in Figures (4) and (5).

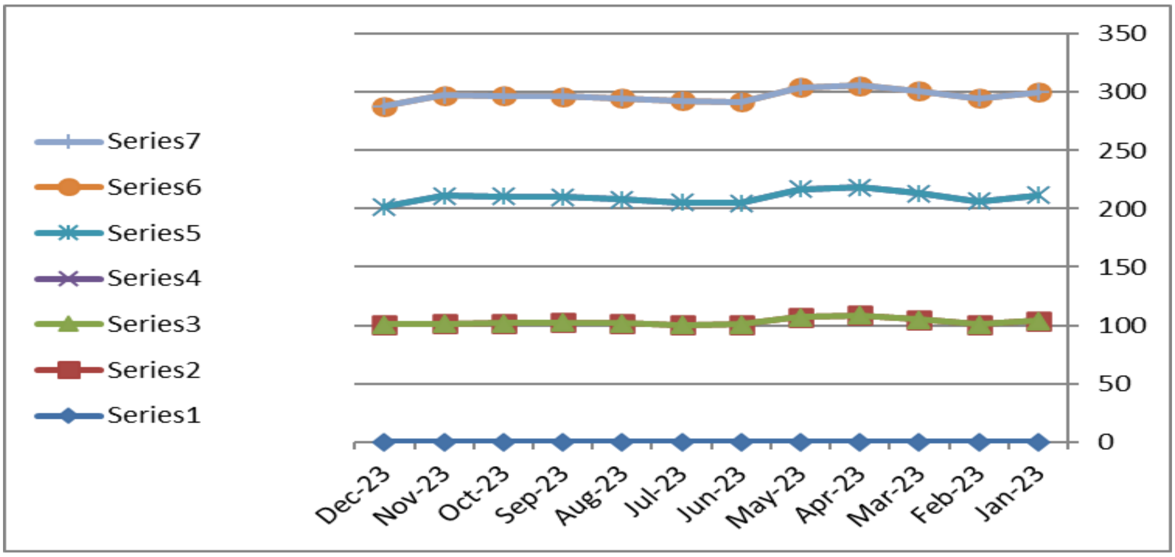

Figure 4 Forecasted levels of oil export volume for the years 2023.

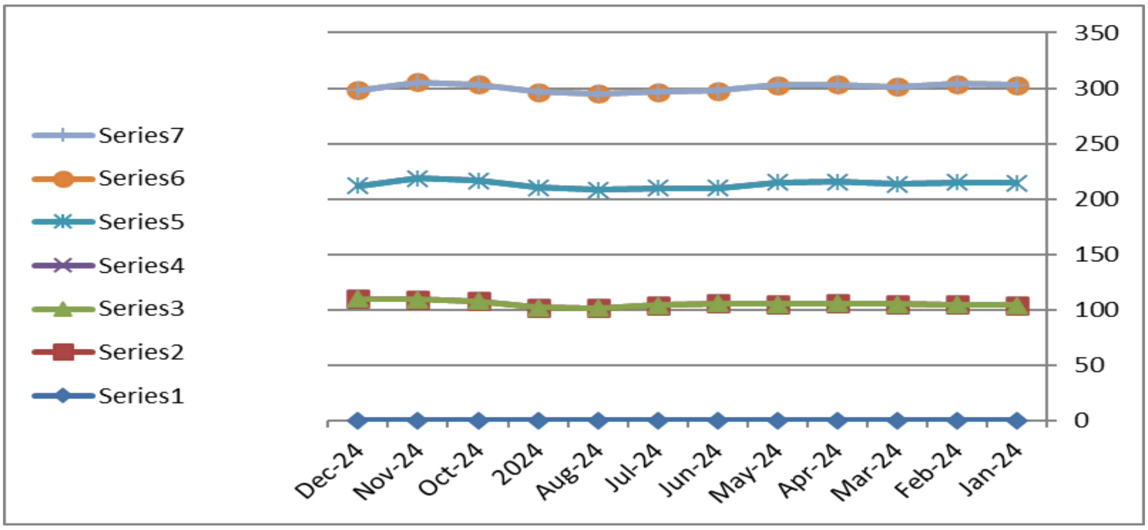

Figure 5 Forecasted levels of oil export volume for the years 2024.

4. CONCLUSIONS

After analyzing the time series data, it was discovered that the time series under study had an overall upward trend, meaning that when oil prices fell, more oil was exported to cover costs. Because the time series under study were generally unstable, statistical analysis (using the SPSS program) was used to create the initial difference that would stabilize the series. Generally speaking, this means employing mathematical models to stabilize the time series so that we can forecast the years 2023 and 2024. We observe that the time series utilized in these two years is unstable, particularly in the initial months of 2023; nevertheless, the time series used at the start of 2024 is more stable. When November and December become unstable.

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