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RESEARCH ARTICLE

"Forecasting Mining Revenues in Saudi Arabia: A SARIMA Approach for Economic Diversification under Vision 2030"

Abu Elgasim Abbas Abow Mohammed[1], Dalia Kamal Alnagar[2], Amin M. A. Haleeb[3], Yousef S. Alharbi[4], Atif Ali. Yassin[5], Elfarazdag M. M. Hussein [6]

[1,4]Department of Management Information System, College of Business and Economics, Qassim University, Qassim, Saudi Arabia
[2,3, 5,6] Department of Statistics, College of Sciences, University of Tabuk, Tabuk, Saudi Arabia

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***Corresponding Author:**

haneenn@hebron.edu

ABSTRACT

This academic investigation intends to analyze mining revenue projections in the Kingdom of Saudi Arabia for the years 2010 to 2023 by utilizing sophisticated time series modeling techniques, notably the SARIMA methodology. In alignment with Saudi Arabia's Vision 2030 initiative, the nation has undertaken considerable initiatives to diversify its economic framework, wherein the mining sector is recognized as a fundamental component for fostering non-oil economic advancement. The investigation employs historical data pertaining to mining revenues to construct models and forecast prospective trends within this domain, which is pivotal in the Kingdom's strategy for economic diversification. Following comprehensive analyses, the SARIMA (0,2,1)(0,0,1)[12] model emerged as the most efficacious for encapsulating both seasonal and non-seasonal characteristics inherent in the data, thereby yielding precise and dependable forecasts. The model exhibits robust predictive proficiency, with a projection horizon extending over the subsequent 36 months, signifying a consistent escalation in mining revenues. The results emphasize the significance of precise revenue forecasting for strategic decision-making, resource distribution, and policy formulation. Furthermore, the study advocates for enhancements in infrastructure and productivity within the mining sector to leverage the anticipated revenue growth, thereby augmenting public revenues and fostering sustainable economic progress. The research makes a noteworthy contribution to the existing literature by addressing the apparent scarcity of studies focused on mining revenue forecasting in Saudi Arabia, providing a comprehensive instrument for stakeholders engaged in economic planning and sectoral development. While the model yields credible predictions, subsequent research endeavors might investigate alternative forecasting methodologies or the influences of external variables, such as fluctuations in global commodity prices, on revenue anticipations. The practical ramifications of this investigation are considerable, as it presents actionable recommendations for policymakers to synchronize the growth of the mining sector with Saudi Arabia's overarching economic objectives. Socially, this research bolsters the establishment of employment opportunities and infrastructure advancement in remote regions, thereby contributing to the broader aims delineated in Vision 2030.

INTRODUCTION

Renowned for its extensive oil reserves, Saudi Arabia boasts significant mineral resources. The Kingdom's Vision 2030 program aims to diversify its economy and reduce dependence on oil by developing non-oil sectors, including mining. Recognizing the potential of its mineral wealth, the Saudi government has initiated significant reforms and investments in the mining sector, positioning it as a key pillar for economic growth.

Interest in the Kingdom's mining sector dates back to the 1960s. A comprehensive evaluation conducted in 2016 assessed its mineral potential, revealing deposits of gold, copper, zinc, lead, silver, and other minerals. The Saudi government's unwavering commitment to the sector, evident in its significant investments and international partnerships, is a testament to its substantial importance after oil and gas. Vision 2030's goal for mining to become a major driver of economic growth, surpassing even oil and gas, is a promising sign of stability. The aim to increase the sector's contribution to the gross domestic product to $64 billion by 2030, according to (Mohammed, 2024), further solidifies this commitment. This initiative is also expected to create new job opportunities and develop remote areas.

Domestic demand currently exceeds production, which motivates further sector development and aims to reduce imports. As part of its economic diversification strategy, there has been a focused increase in mining investment, leading to higher exploration spending. Additionally, the Kingdom has introduced a program offering incentives for mineral exploration, including a reduction in taxes from 45% to 20%, to bolster global competitiveness.

This study presents a time series analysis to forecast mining revenues in the Kingdom of Saudi Arabia using data from January 2010 to June 2023. The importance of this study lies in applying time series analysis to actual data on mining revenues, providing valuable insights for specialists, decision-makers, and workers in the sector. The study is limited to data only on the mining revenues in Saudi Arabia over the period (2010 – 2023). Forecasting mining revenues in Saudi Arabia is crucial for several reasons. This study provides valuable insights into the potential economic contributions of the mining sector, aiding in the strategic planning and policy-making necessary for sustainable growth. Accurate revenue forecasts help the government and stakeholders in resource allocation, investment decisions, and risk management. Additionally, understanding the trends and patterns in mining revenues supports the broader goals of Vision 2030 by highlighting the sector's role in diversifying and strengthening the Saudi economy beyond its traditional reliance on oil. This analysis is essential for ensuring the long-term economic stability and prosperity of the Kingdom.

The objectives of this study are threefold: to provide a concise description of the mining revenue time series process, to construct a model that explains the behavior of mining revenues over time, and to use the results of the time series analysis to forecast future mining revenues. The study proposes two hypotheses: that the series of mining revenues is non-stationary, and that mining revenues increase over time.

The results of this paper will be especially beneficial in light of Saudi Arabia's economic changes as it transitions towards a non-oil-dependent economy. Mining is considered one of the Saudi economy's most essential pillars after oil.

The research addresses two key questions: Are mining revenues showing a significant upward trend over time? And, to what extent can these revenues be expected to increase?

2. LITERATURE REVIEW

The paper utilized time series analysis to identify the most effective predictive models. Accordingly, the following literature is reviewed:

1: (Box and Jenkins,1970) introduced mixed autoregressive-moving average models (nonstationary hybrid models) for analyzing various types of time series, both stationary and nonstationary and seasonal and nonseasonal. They also developed an integrated method for using these models in analyzing and forecasting time series, known as the Box and Jenkins Method.

2: (Jobbery, 2009) examined a time series with binary variables to predict the exchange rate of the dinar against the U.S. dollar from January 2004 to December 2008. It concluded that the direction of the exchange rate follows a second-order autoregressive binary variables model, ARIMA (2,1,0).

3 : (Tomah, 2012) applied the Box and Jenkins method to determine the best forecasting model for the number of patients with malignant tumors in Anbar Province using monthly data from 2006 to 2010. The analysis indicated that the most suitable model is an integrated autoregressive model of order (2), ARIM (2,1,0).

4 : (Abow ,2018) conducted a time series analysis using quarterly data from 2007 to 2016 to predict the number of tuberculosis (T.B.) patients in Khartoum State. The study concluded that the best model was ARIMA (2,1,0), and the most important outcome was estimating the number of T.B. patients over the next four years.

5: .(Moshashai, D., Leber, A. M., & Savage, J. D. ,2020) According to reports, in response to a fast drop in global oil prices, Saudi Crown Prince Mohammed Bin Salman unveiled a new economic blueprint known as Saudi Vision 2030, which is supported by the National Transformation Plan. This strategy seeks to diversify the Kingdom's primarily oil-dependent income source, decrease its mounting budget deficits, balance its budgets, and foster long-term economic growth. The article examines the Vision's aims and the strategies intended to accomplish them, which include considerable revisions to the Kingdom's economic and budgetary systems. The report also explores the political and institutional issues confronting the Saudi Vision and rates its chances of achievement

6 : (Derendinger, M., & Frank, B. , 2023) Since the release of its ambitious Vision 2030 plan in 2016, the Kingdom of Saudi Arabia (KSA) has risen in worldwide growth rankings. Vision 2030 aims to transform the social, political, and economic landscape of Saudi Arabia. Economically, the plan seeks to diversify and strengthen the Saudi economy, which has historically relied on profitable oil output. This study aims to examine the economic developments in Saudi Arabia by reviewing Vision 2030 across eight economic sectors: petrochemical, tourism and hospitality, mining, healthcare, manufacturing, retail, construction, and finance. We will assess recent successes, growth trends, complications, and risks, and provide recommendations for the future of Saudi economic growth and diversification. If Saudi Arabia intends to expand non-oil industries to balance its economy, this report identifies the key sectors critical to achieving Vision 2030's goals. Given Saudi Arabia's significant oil wealth and centralized control, designing a future beyond oil is essential for both regional and global economies.

7:(Manigandan, P., Alam, M. S., Alharthi, M., Khan, U., (2021). The study forecasts seasonal trends and growth in U.S. natural gas (NG) production and consumption, comparing various models, including SARIMA-X, which is used here for the first time. Results indicate that SARIMA-X outperforms SARIMA in predicting NG trends, with RMSE and MAPE confirming model accuracy, providing valuable insights for energy planning and policy development.

8: (Alshammari, F., Aljojo, N., Tashkandi, A., Alghoson, A., Banjar, A., & El Abbadi, N. K. (2023). This study developed an urban growth forecasting model for Riyadh, Saudi Arabia's most populous city, using a hybrid approach with Linear Regression (LR), SARIMAX, and ARIMA. By analyzing satellite images from 1992 to 2022, the model projects future population growth in the expanding Riyadh metropolitan area. Model accuracy was evaluated using Mean Absolute Percentage Error (MAPE). The forecasts suggest that the city's expansion trends are well-aligned with the model's projections.

9: (Almanjahie, I. M., Chikr-Elmezouar, Z., & Bachir, A. (2019). This study addresses the rising water demand in Saudi Arabia due to factors like population growth, urbanization, industrialization, and agricultural expansion. To support water management, the research aimed to identify the best forecasting model for water consumption. Analyzing data from January 2010 to July 2017, the study found that the optimal model is SARIMA (1,0,1) x $(1,1,2)_{12}$, providing a reliable approach for predicting future water demand in the kingdom.

The literature review covers foundational time series models, such as ARIMA and SARIMA, which are widely used for economic and environmental forecasting. It highlights applications in various fields, including exchange rates, healthcare, and natural gas production, emphasizing their relevance to seasonal data. For Saudi Arabia, accurate forecasting supports Vision 2030's focus on economic diversification, particularly in the mining sector. While numerous studies have applied time-series models such as ARIMA and SARIMA to forecast economic indicators in various sectors globally, research focused on forecasting mining revenues in Saudi Arabia remains scarce. A review of the existing literature found no studies specifically addressing the use of time-series models to predict mining revenues in Saudi Arabia from 2010 to 2023. This study aims to bridge this gap by applying advanced forecasting techniques to the mining sector, contributing valuable information to support Saudi Arabia’s Vision 2030 objectives.

3. METHODOLOGY

The study was based on Box-Jenkins's time series analysis method, which was applied to the data on mining revenues in Saudi Arabia. The study discusses a time series and introduces some of the time series analysis procedures and the Box-Jenkins approach for analyzing time series data.

The (study used) ARIMA model was selected for forecasting mining revenues due to its effectiveness with non-stationary data, its ability to capture seasonal patterns through the SARIMA structure, and its reliable accuracy as demonstrated by low error metrics (RMSE and MAPE). Additionally, its proven track record in economic forecasting, along with diagnostic tools like Akaike Information Criterion (AIC) for model selection, confirmed ARIMA as the most suitable model for this study. The paper used R and Excel for analysis and data presentation

3.1Time series analysis

A time series is a series of observations taken sequentially over time (Harrison,1994). A time series is a sequence of data points recorded chronologically over time. A key characteristic of time series data is that they are ordered in time, and each successive observation is typically dependent on previous ones. This temporal dependence is critical for making accurate forecasts; we denote by z_t the observation of the time series. The preceding observation is denoted by $z_{t-1}$and the next observation as z_{t+1}. This notation helps analyze the relationships and dynamics within the data over time.

It's important to distinguish between a time series process and a time series realization. The time series process refers to the underlying theoretical mechanism that generates the data, while a time series realization is the actual set of observations recorded from this process. A realization includes a sequence of data points, not just a single point. Time series analysis seeks to accurately model this theoretical process, creating an observable model that closely mirrors the characteristics of the original process. (Vandael,1983).

A fundamental assumption in many time series analyses is that the data must be stationary. This means the statistical properties such as mean, variance, and autocorrelation of the process do not vary with time. In more practical terms, a stationary time series exhibits no long-term trends or seasonal patterns. It appears flat with a consistent mean, maintains uniform variance throughout, and displays a stable autocorrelation structure.

3.2Seasonal ARIMA (SARIMA) Model

This study addresses the Seasonal ARIMA (SARIMA) model, which better accounts for cyclical revenue patterns and offers improved predictive accuracy. Aligning with Saudi Arabia's Vision 2030, which emphasizes economic diversification through sectors like mining, accurate revenue forecasting is vital for strategic planning and investment (Moshashai et al., 2020). This study's use of SARIMA with robust accuracy metrics such as Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE), demonstrates the model's reliability and value for economic forecasting (Abow & Alnagar, 2024). Through this approach, the study contributes to the literature on revenue forecasting in transforming economies, offering a valuable tool for strategic planning in Saudi Arabia's mining sector

The Seasonal Autoregressive Integrated Moving Average (SARIMA) model, also known as the seasonal ARIMA model, is an extension of the ARIMA model designed to handle time series data with seasonality. SARIMA is particularly useful when the data show seasonal patterns or periodic fluctuations in addition to non-seasonal trends. SARIMA incorporates both non-seasonal and seasonal factors in a single framework, making it suitable for applications where data exhibit recurring seasonal behaviors, such as quarterly revenue or monthly sales.

Structure of the SARIMA Model

The SARIMA model is denoted as ARIMA (p, d, q) (P, D, Q) [m], where:

- **p, d, q** are the parameters of the non-seasonal part of the model:
  - **p**: Order of the non-seasonal autoregressive (AR) term.
  - **d**: Degree of non-seasonal differencing.
  - **q**: Order of the non-seasonal moving average (MA) term.
- **P, D, Q** are the parameters of the seasonal part of the model:
  - **P**: Order of the seasonal autoregressive (SAR) term.
  - **D**: Degree of seasonal differencing.
  - **Q**: Order of the seasonal moving average (SMA) term.
- **m** represents the length of the seasonal cycle (e.g., m = 12 for monthly data with yearly seasonality).

The SARIMA model combines the effects of seasonal differencing (to remove seasonal patterns) and non-seasonal differencing (to stabilize the series), which improves the model's ability to accurately capture both types of fluctuations in the data.

Steps in Building SARIMA

1. **Data Analysis**: Visualize data to detect trends and seasonality.
2. **Stationarity Check**: Use differencing if necessary to stabilize the series.
3. **Parameter Selection**: Use ACF and PACF plots to identify model orders.
4. **Model Fitting and Diagnostics**: Choose the model with the lowest AIC and check residuals to ensure accuracy.
5. **Forecasting**: Use the model to forecast future seasonal trends.

3.3 Model Diagnostic Checks

Model diagnostic checks are crucial to ensure that the selected model adequately fits the time series data and meets the assumptions required for accurate forecasting. **Residual Analysis**: After fitting the model, examine the residuals (differences between actual and predicted values) to ensure they are randomly distributed around zero. Residuals should show no discernible patterns, indicating that the model has captured all underlying structure in the data. Apply the Box-Ljung test to check for autocorrelation in residuals. A high p-value (> 0.05) suggests no significant autocorrelation, indicating a good model fit.

3.4 Forecasting

Despite the growing importance of the mining sector within Saudi Arabia's Vision 2030 economic diversification plan, limited research exists on forecasting mining revenues specifically for the Saudi context. A thorough literature search revealed no studies that forecast mining revenues in Saudi Arabia using time-series models over the period from 2010 to 2023.Time series analysis shows data changes over time and good forecasting can identify the direction in which the data is changing, it is the last step of time series analysis and it is basic goal of the study after determining, a fitted model used to generate forecasts for future period L, and the prediction of the number L steps can be calculated according to the formula (Abow&Alnagar 2024)

$$\hat{Z}_{t+1} = E[Z_{t+1}|Z_{t-1}, Z_{t-2}, \ldots] \quad for\ L \geq 1 \qquad (3)$$

If the model is AR (1), then the best prediction for the number of steps L is

$$\hat{Z}_{t+1} = \Phi_1{}^{\mathrm{L}} Z_{t-1+\mathrm{L}} \qquad for\ L \geq 1 \qquad (4)$$

If the model is AR (2), then the best prediction for the number of steps L is

$$\hat{Z}_{t+1} = \Phi_1{}^{\mathrm{L}} Z_{t-1+\mathrm{L}} + \Phi_2{}^{\mathrm{L}} Z_{t-2+\mathrm{L}} \quad for\ L \geq 1 \quad (5)$$

If the model is MA (q), then the best prediction for the number of steps L is

$$\hat{Z}_{t+1} = a_{t+1} - \theta_1{}^{\mathrm{L}} a_{t-1+\mathrm{L}} - \theta_2{}^{\mathrm{L}} a_{t-2+\mathrm{L}} - \ldots\ \theta_q{}^{\mathrm{L}} a_{t-q+\mathrm{L}} \; for\ L \geq 1 \quad (6)$$

If the model is AR MA (p, q), then the best prediction for the number of steps L is

$$\hat{Z}_{t+1} = \Phi_1{}^{\mathrm{L}} Z_{t-1+\mathrm{L}} + \Phi_2{}^{\mathrm{L}} Z_{t-2+\mathrm{L}} \quad for\ L \geq 1 \quad (7)$$

4. Application

In this section, the application is made using models that allow us to model several stationary time series. Researchers referred in previous studies to three models:

According to the study methodology, autoregressive and mixed moving average models, and autoregressive integrated moving average models.

The data consist of 162 observations covering the period from January 2010 to June 2023; the data are the Saudi Arabia Mining Revenues Rates (M.R.) and are in current Riyal millions

4.1Time series analysis

The first step in any time series analysis should be to plot the available observation against time, and here, we plot the time series of mining revenue data. Figure 1 contains a plot of the M.R. Saudi Arabia Series from January 2010 to June 2023 with observation 149.

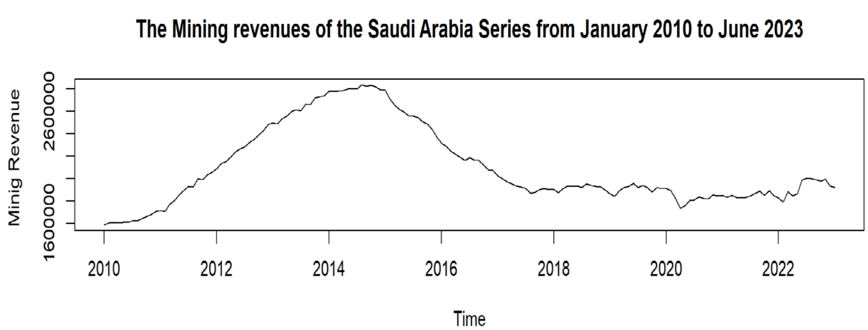

Figure (1). The Mining revenues of the Saudi Arabia Series from January 2010 to June 2023

The plot shows that Saudi Arabia's mining revenues rose significantly from 2010 to a peak around 2015, followed by a steady decline until 2018. After 2018, revenues stabilized with minor fluctuations, suggesting a mature phase in the mining sector. This trend reflects growth, decline, and stabilization phases, which are crucial for forecasting future revenues..
The decomposition reveals a repeating seasonal pattern with a period of 12 months, indicating annual seasonality in the data.
The data demonstrate evident nonstationarity accompanied by some seasonal patterns. In order to rectify this, we initially implement a seasonal differencing technique. The seasonally differenced data, as represented in Figures 1 and 2, continue to exhibit nonstationary characteristics. Consequently, we proceed with an additional second differencing, as illustrated in Figure 3. To ascertain the stationarity of the monthly M.R. time series, we performed an Augmented Dickey-Fuller (A.D.F.) test. The outcomes of the test revealed a statistic of -2.319 and a p-value of 0.4433. Given that the null hypothesis posits that the series is nonstationary while the alternative hypothesis asserts its stationarity, we fail to reject the null hypothesis based on the test outcomes, thereby confirming the nonstationary nature of the series.

Following the first difference, the outcomes of the A.D.F. test reveal Dickey-Fuller, and the p-value of 3.7778 exceeds 0.05. Consequently, we deduce that the time series exhibited non-stationarity post the application of the first difference 0.02055. Variations in certain determinants have played a role in this enduring trend. Nevertheless, first-order differencing proves insufficient to eliminate the trend component, thereby necessitating further analytical procedures. In Figure 2, we have illustrated the transformations of the natural logarithm alongside the first and second differences. It is evident that a trend is no longer apparent.

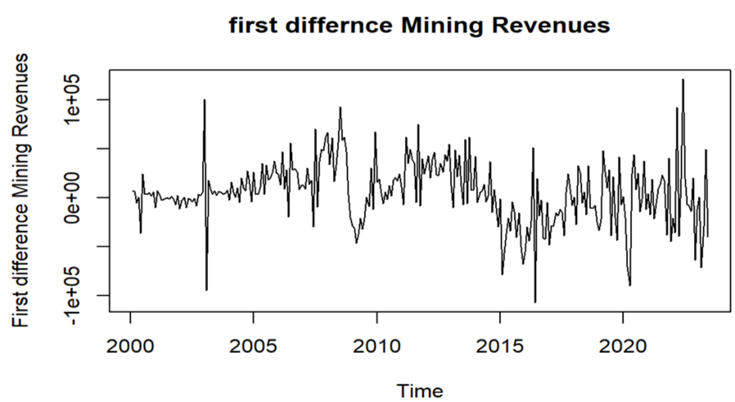

Figure (2): The transforms natural log and first differences

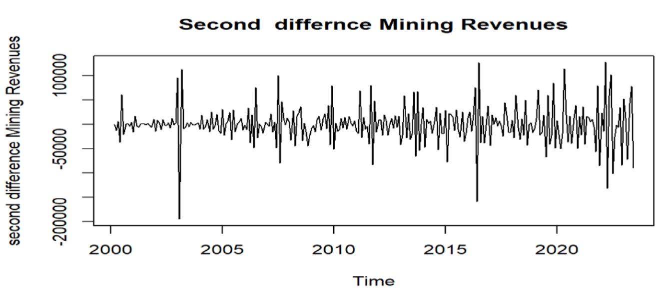

Figure (3): The transforms natural log and second differences

After the second difference, the results of the A.D.F. test are Dickey-Fuller = - 9.531; the p-value is 0.01, less than 0.05. Hence, we conclude that the time series was stationary after the second differences were taken. To identify the appropriate Seasonal ARIMA models adding more seasonal components to the ARIMA models, we have seen that a seasonal ARIMA model has been created.

This is how it is written:
ARIMA (p, d, q)(P, D, Q)[m]

Where: (p, d, q) nonseasonal part of the model and (P, D, Q)Seasonal part of the model

m= number of observations per year.

After the stationarity of the time series of monthly M.R. of study was determined, the next step is to identify and list the candidate models. Using the characteristics of the autocorrelation function (A.C.F.) and partial autocorrelation function (PACF), the potential models are identified and listed once the stationarity of the time series of the monthly M.R. of the research has been established. Several models for each period according to the A.C.F. and PACF of the data, were examined to determine the best model. The model that gives the minimum Akaike Information Criterion (A.I.C.) is selected as the best-fit model.

4.2 The best ARIMA model monthly MR:

Figure 3 shows the A.C.F. and PACF for the monthly MR. after the first difference is taken.

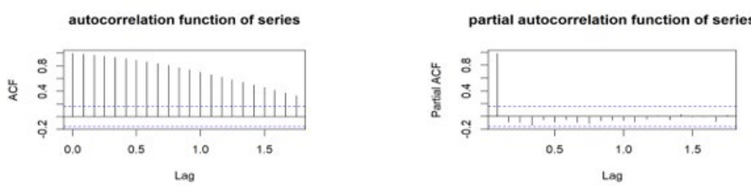

Figure (4). A.C.F. and PACF for time series

According to the analyzed ACF and PACF visual representations, the ACF plot exhibits a gradual, exponential decline, which is characteristic of an autoregressive (AR) model. The PACF demonstrates a sharp cutoff subsequent to lag 1, indicating the presence of an AR (1) component.

4.3 Building SARIMA model

Based on the analysis of the ACF and PACF plots, a suitable SARIMA model can be determined as follows: For the non-seasonal component, the partial autocorrelation function (PACF) plot shows a cutoff after lag 1, indicating an autoregressive component of order p=1. Since second differencing was applied to achieve stationarity, the non-seasonal differencing order is d=2. The autocorrelation function (ACF) shows an exponential decay pattern, suggesting no significant moving average component, so q=0. For the seasonal component, if seasonality is present in the data, a seasonal differencing order D=1 is assumed, with no strong indications of seasonal autoregressive or moving average terms, so both P and Q are set to 0. Assuming monthly data with yearly seasonality, the seasonal period mmm is set to 12. Therefore, the suggested SARIMA model for this data is **SARIMA (1, 2, 0) (0, 1, 0) [12]**
Therefore, we start with a SARIMA (1, 2, 0) (0, 1, 0) [12] model, which incorporates both a first and seasonal difference, along with nonseasonal and seasonal MA (1) components.

Table (1) presents various candidate ARIMA models for the time series of mining revenues, along with their corresponding Akaike Information Criterion (AIC) values. The AIC is a measure used to compare different models, with lower values indicating a better fit to the data. Among these models, the SARIMA (2,2,1) (1,2,1) [12], has the lowest AIC value of 3160.72, indicating it is the best fit for the time series of mining revenues. This model effectively captures both the non-seasonal and seasonal components, making it a strong candidate for further analysis and forecasting.

Table (1) Candidate ARIMA Models with corresponding AIC. for time series Mining Revenues.

Model	**A.I.C.**	**Model**	**AIC**
ARIMA (1,2,1) (0,0,1) [12]	3632.36	ARIMA (0,2,1) (0,0,1) [12]	3630.38
ARIMA (2,2,1) (0,0,1) [12]	3634.36	ARIMA (2,2,1) (1,1,1) [12]	3383.5
ARIMA (2,2,1) (1,0,1)[12]	3636.14	ARIMA (2,2,1) (1,2,1) [12]	**3160.72**

Source: Own calculation based on R package

4.4Diagnostic checking

To determine if the model is adequate, residual analysis is performed. Figure 4 displays the plot of residuals versus time for ARIMA (0,1,1) (1,1,0) [12] model and it is observed that there are no strong patterns which indicates that the residuals are not time-dependent.

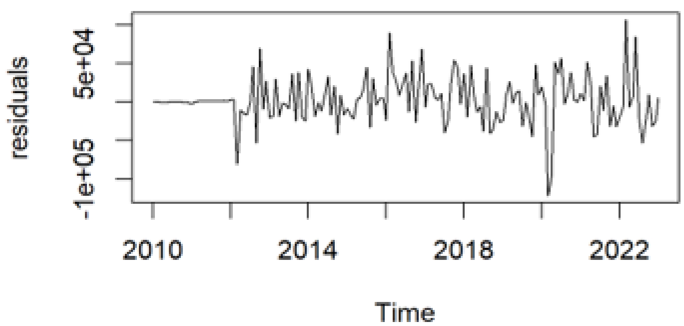

Figure (4) Residuals versus time for the ARIMA (2,2,1) (1,2,1) [12]

Table (2) represented the high p-value (0.9401), indicating that we do not reject the null hypothesis at any reasonable significance level. This suggests that there is no significant autocorrelation in the residuals of the ARIMA (2,2,1) (1,2,1) [12] model. Therefore, the residuals can be considered independently distributed, implying that the model is a good fit for the time series data.

Table (2) The Box-Ljung test of the residuals for the ARIMA (0,1,1) (1,1,0) [12]

Test statistic	**Df**	**p-value**
4.1554	10	0.9401

Source: Own calculation based on R package

4.5 Forecasting

The ARIMA (0,1,1) (1,1,0) [12] used to obtain the forecasted values of the Mining Revenues in K.S.A. from January 2010 to June 2023. Table 3 gives the forecasted, the Mining Revenues actual cases and the error, while Figure 5 displays the actual versus forecasted values and shows that the forecasted values are consistently close to the actual revenues, with most errors being minor, typically under 500 units. This indicates a high level of precision in the model's predictions. Positive errors, where the actual revenue exceeds the forecasted amount, are the norm, except for a single instance in December 2010 where the forecast slightly overestimated the actual revenue. The small magnitude of these errors underscores the model's accuracy and reliability. The observed and forecasted Mining

Revenues, and use the model to forecast the Mining Revenues for the next 36 months show in appendix bellow.

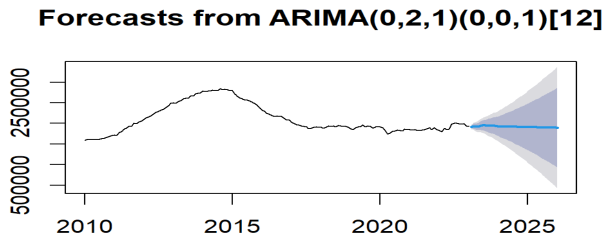

Figure (5) The observed and forecasted Mining Revenues.

Figure (5) shows the ARIMA (0,2,1) (0,0,1) [12] model forecasts stable mining revenues in the upcoming years, with no major shifts expected. The confidence interval suggests that while small variations are possible, a major trend change is not anticipated based on past patterns.

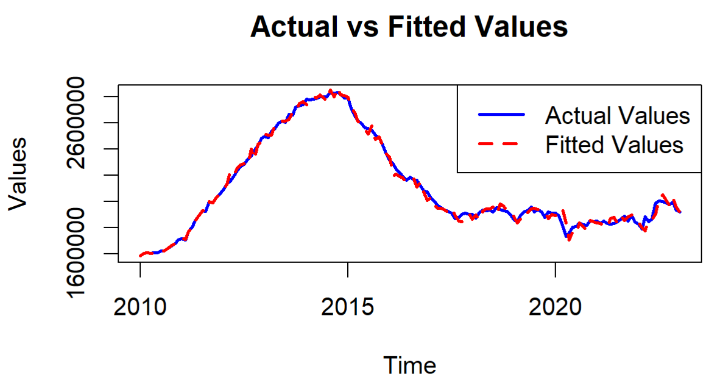

Figure (6) the actual and forecasted Mining Revenues

The plot suggests that the model used to generate the fitted values provides a good fit to the actual data, capturing the major trends and fluctuations. This indicates that the model is (reliable for forecasting future values, as it accurately reflects the historical behavior of the data.

Figure (6) plot shows that the model used to generate the fitted values provides a good fit to the actual data, capturing the major trends and fluctuations. This indicates that the model is likely (so) reliable for forecasting future values, as it accurately reflects the historical behavior of the data.

Table(3): The forecasted Mining Revenues, the actual values and the error

Date	Actual	Forecast	Error	Date	Actual	Forecast	Error
Jan 2010	1586694	1585778	916	Jul. 2010	1621838	1621707	131
Feb. 2010	1605130	1604706	424	Aug. 2010	1623985	1623869	116
Mar. 2010	1605617	1605339	278	Seb.2010	1642247	1642126	121
April 2010	1609464	1609253	211	Oct. 2010	1663137	1663009	128
May 2010	1610701	1610532	169	Nov. 2010	1680751	1680617	134

June 2010	1621838	1621707	141	Dec. 2010	1705389	1706137	-748

Source: Own calculation based on Excel

This study applied the ARIMA (0,2,1) (0,0,1) [12] model to forecast mining revenues in Saudi Arabia and evaluated its accuracy and reliability through statistical measures. The model demonstrated a high level of precision, with the Root Mean Square Error (RMSE) calculated at 219.73, indicating that, on average, the forecasted values deviated by about 219.73 units from the actual values. Additionally, the Mean Absolute Percentage Error (MAPE) was found to be 2%, suggesting that the model's predictions differed from the actual revenues by only about 2% on average. This low error margin highlights the model's accuracy and reliability, making it a suitable tool for predicting mining revenues and aiding in strategic planning for the sector

The Root Mean Square Error and the Mean Absolute Percentage Error for the ARIMA (0,2,1) (0,0,1) [12]) are as follows

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(x_t - \hat{x}_t)^2} = \sqrt{\frac{1}{12}(579385)} = 219.73$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{x_t - \hat{x}_t}{x_t}\right| \times 100 = \frac{1}{12}(0.00214) \times 100 = 60.93$$

5. Conclusion

As a final point, this examination effectively harnessed the Seasonal Autoregressive Integrated Moving Average (SARIMA) model to analyze mining revenue trends in Saudi Arabia from 2010 to 2023, thus offering meaningful insights for those involved in policy and industry. When it comes to prediction capabilities, the SARIMA (0,2,1) (0,0,1) [12] model emerged as a leader, marked by its minimal RMSE and MAPE figures. These findings emphasize the model's robustness in projecting forthcoming trends in mining revenues, which constitute a vital element of Saudi Arabia's Vision 2030 initiative aimed at economic diversification.

The results illuminate a persistent upward trajectory in mining revenues, indicative of the increasing significance of this sector within the Kingdom's economic framework. As Saudi Arabia endeavors to lessen its reliance on oil and broaden its non-oil sectors, particularly mining, this study offers critical forecasts that can inform strategic planning, investment strategies, and policy development within the mining domain.

Notwithstanding the model's accomplishments, subsequent research could investigate alternative forecasting methodologies or assess the influence of external variables, such as fluctuations in global commodity prices or advancements in mining technology, on revenue estimates. Furthermore, broadening the focus to encompass additional economic sectors would further augment the forecasting framework established in this research. By addressing these dimensions, future investigations can enhance the predictive precision and flexibility of economic forecasting models, thereby bolstering Saudi Arabia's ambitions to realize its long-term economic objectives under Vision 2030.

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Appendix

The Mining Revenues Forecasting from July 2023 to Jun 2026

No.	Month	Forecast Mining Revenues	No.	Month	Forecast Mining Revenues
1	Jul-23	1960457	19	Jan-25	1804226
2	Aug-23	1968880	20	Feb-25	1815297
3	Sep-23	1973488	21	Mar-25	1834530
4	Oct-23	1980943	22	Apr-25	1855103
5	Nov-23	1983365	23	May-25	1903247
6	Dec-23	1989707	24	Jun-25	1906955
7	Jan-24	1812183	25	Jul-25	1944747
8	Feb-24	1823360	26	Aug-25	1953199
9	Mar-24	1842586	27	Sep-25	1957822
10	Apr-24	1863153	28	Oct-25	1965229
11	May-24	1911174	29	Nov-25	1967586
12	Jun-24	1915081	30	Dec-25	1973945
13	Jul-24	1952897	31	Jan-26	1796101
14	Aug-24	1961351	32	Feb-26	1807179
15	Sep-24	1965975	33	Mar-26	1826412
16	Oct-24	1973379	34	Apr-26	1846985
17	Nov-24	1975731	35	May-26	1895121
18	Dec-24	1982092	36	Jun-26	1898841

Source: Prepared by researchers