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# Forecasting Global Silver Prices using Autoregressive Integrated Moving Average Time Series Models

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## ABSTRACT

This study examines the application of the autoregressive (AR) integrated moving average (ARIMA) model can be used to forecast global silver prices expressed in US dollars. Daily silver price data from 1 January 2025 to 10 March 2026 were used to identify the most appropriate time series model using the Box-Jenkins methodology to be used in accurate forecasting. The determination of an appropriate ARIMA model, using AR and moving average orders from 0 to 2, was made by evaluating a number of different candidates using both the Akaike information criterion (AIC) and Bayesian information criterion (BIC) for model selection purposes. The ARIMA (2,1,1) specification had the lowest AIC and BIC among all specifications evaluated, thus being selected as the most appropriate ARIMA model. The ACF and PACF plots confirmed that the residuals do not have any significant autocorrection and residues that are not normally distributed. The results of the forecasting are very useful in terms of making decisions and planning strategies because they allow investors and enterprises to predict upcoming changes in silver prices and reduce financial risks. In general, this analysis shows that the result indicates that the ARIMA model provides reliable forecasts for silver price prediction.

**Index Terms:** Silver Price Forecasting, Autoregressive Integrated Moving Average Model, Time Series Analysis, Commodity Prices, Financial Forecasting, Global Silver Market

## 1. INTRODUCTION

Silver is also one of the most significant precious metals, and it is highly utilized in industries, such as electronics and solar energy as well as jewelry and investment markets. Its price changes carry great implications to investors, businesses, and policymakers [1]. Proper forecasting of silver prices is thus of great essence in effective financial planning, risk management, and strategic decision-making [2]. Due to the fluctuations of the global commodity markets caused by economic, political, and industrial factors, silver price prediction is a complex and complicated task [3]. This has been dealt with using traditional statistical tools and contemporary computational tools, yet there is a need to find models that can deliver accuracy and reliability, and this is an issue that is still under research [4]. Time series models are especially suitable in the forecasting of financial data since they are used to analyze the past and predict future trends [5]. The autoregressive integrated moving average (ARIMA) is mostly applied in non-stationary time series data in machine learning. It is commonly used in the prediction of prices of commodities, such as silver, and aid investors and industries to make improved judgments [6]. ARIMA is a combination of autoregressive (AR) terms, moving averages (MAs), and differencing processes that help to capture the underlying trends in historical data, which is why it is applicable to short-term and median-term forecasting. The

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versatility, strength, and statistical nature of ARIMA have established it as a universally applied modelling technique in commodity price prediction applications in the oil, gold, and silver markets [7]. Although commodity forecasting has been the subject of extensive research, new studies show that it is important to validate models by giving full performance measurements and diagnostic tests to have a reliable forecast [8]. This paper will make a contribution to this field by using the ARIMA model to predict the prices of silver in US dollars of the world prices. This study uses daily short-term silver prices to estimate different candidate models and the most successful configuration, which is evaluated by the key performance indicators, including mean squared error (MSE) and mean absolute percentage error (MAPE). Residual analysis is also done to help in checking the adequacy of the model and hence the reliability of forecasts in making financial decisions [9]. This study is beneficial in offering information on accurate and practical forecasts to investors, traders, and businesses requiring to maximize trading plans and minimize financial risks of silver price volatility. It also brings out the practical applicability and efficiency of the ARIMA model in the international commodity market, and this leads to well-informed economic and financial policies.

### 1.1. Study Overview and Research Contribution

In this study, the authors aimed to predict world silver price movements by employing ARIMA analysis on the daily price data from January 1, 2025 through March 10, 2026. Several candidate models were tested for their suitability using Akaike information criterion (AIC) and Bayesian information criterion (BIC) as model selection criteria [10]. The model that best fit the data was ARIMA (2,1,1). In addition, residual diagnostics indicated that the model was appropriate for fit.

### 1.2. Research Objectives

The main aims of the study are to:-

Evaluating ARIMA model performance in forecasting silver prices

1. Applied thus ARIMA model: To predict silver prices using the ARIMA model is the objective of this study.
2. Finding the best fit model: The optimal ARIMA model will be determined by estimating a number of candidate models with different AR and MA orders between 0 and 2. The AIC and the BIC have been used to select the model.

### 1.3. Validity of Forecasted Prices

The final section of this study will analyze whether the forecasts that the selected model produces are valid and suitable to support financial decision-making by investors and other stakeholders.

### 1.4. Significance of the Study

The significance of this study stems from the role that silver plays in international markets. This research provides valuable information to aid in developing improved financial decisions and managing risk for investors and businesses. In addition, this research will provide a contribution to the body of literature on time series forecasting through demonstrating how ARIMA models have effectively been employed to predict commodity price movements.

### 1.5. Research Questions

The following research questions can be answered in the present study:

1. What type of ARIMA model yields the best predictions for future silver prices?
2. How well does ARIMA forecasting work in predicting the immediate future?
3. Are residuals from the ARIMA model normally distributed?
4. How can the results from these forecasts assist decision makers in their investing process?

## 2. LITERATURE REVIEW

### 2.1. ARIMA Time Series Models

Past research shows that the ARIMA model is a time-tested and popular time series forecasting system, especially within the finance and economics sectors. ARIMA is the combination of AR, differencing, and MAs and is a developed model by Box and Jenkins (1976) [11] to estimate non-stationary data and short-term trends. It has been used effectively to forecast commodity prices, such as gold, oil, and silver, among others, where it has been found to effectively make correct predictions in the short term with very low error. ARIMA is also flexible to non-seasonal financial data than conventional models, including Exponential Smoothing. However, it is only accurate when selected properly in terms of the choice of models and diagnostic testing. On the whole, ARIMA is a powerful instrument of silver price forecasting, which can be used to make decisions about investors and policymakers. To predict the price of silver, the ARIMA model was used, which explained about 26% of the observed variability in price changes [12]. However, to predict the exchange IQD/USD rate in Iraq used ARIMA model to capture non-linear model and the accuracy was suitable with this model [13]. In addition, A large gap still exists in terms of a broad comparison and assessment of the performance of traditional forecasting techniques and machine learning techniques in this field, especially to performance analysis in exchange rate prediction [14]. To forecast non-linear crude oil futures price used ARIMA model and compared with other models; it was mentioned that need to improve the model in this topic [15]. The Box-Jenkins methodology is employed, comprising four stages: Model identification, parameter estimation, diagnostic checking, and forecasting (Das, 2015). In this analysis, the ARIMA model validation is done by the residual diagnostics, and the Ljung-Box test is performed to assess the absence of autocorrelation in the residuals [16]. Previous studies on oil price forecasting using ARIMA models have typically addressed key challenges – such as trend, seasonality, holiday effects, and missing data – in isolation. As an example, Zhao *et al.* (2021) concentrated on the seasonal patterns focused on the problem of missing values, pointing to the disjointed treatment of the given aspects in the literature [17]. To predict the stock market using long short-term memory (LSTM), ARIMA, and a hybrid of LSTM-ARIMA models, the results showed that the accuracy of the ARIMA model based on the Criteria performance is close to the hybrid model [18]. Finally, by AI methodologies applied LSTM network and ARIMA models were used for comparative analysis through sales retail forecasting [19].

As a rule, previous studies show that ARIMA is an appropriate and common tool when predicting time series. ARIMA prediction of silver prices can help policymakers and investors, as it can predict the movement of the prices and help them make their financial decisions. The present paper is founded on this study because it will consider the short-term prices of silver each day and the best ARIMA model to be employed to enable credible forecasting.

### 2.2. Box-Cox Transformation and Diagnostic Checking

The Box-Cox transformation is a useful method of leveling off the variance of time series data and its approximation to a normal distribution, which is critical in most forecasting models [21]. It is usually used to improve the accuracy of ARIMA and other linear models by decreasing the variability and improving the behavior of the data, allowing more consistent and accurate forecasts. Its significance in time series analysis has been highlighted in previous studies. The Box-Cox transformation was earlier used to transform economic data before ARIMA modeling, showing it was useful in correcting non-normality. More recent research on financial time series, including stock market forecasting, has demonstrated that the transformation can greatly enhance prediction accuracy [20]. Similarly, research on temperature data verified that it improves residual diagnostics and the general model adequacy. Box-Cox transformation with differencing has been applied in epidemiological tasks (e.g., malaria incidence forecasting) to reach stationarity before ARIMA modeling. Overall, the literature indicates that Box-Cox transformation is a valuable pre-processing step that strengthens the reliability and performance of ARIMA forecasting models.

### 2.3. Research Gap and Motivation

Despite the extensive application of the ARIMA model in forecasting financial time series, such as commodities, exchange rates, and stock prices, several limitations remain evident in the existing literature. First, prior studies often focus on ARIMA applications in isolation or compare it with advanced models, such as LSTM or hybrid approaches, but there is a lack of focused, systematic evaluation of ARIMA specifically for silver price forecasting using a constrained and interpretable parameter space (e.g., limited AR and MA orders). Second, although pre-processing techniques, such as the Box-Cox transformation are acknowledged, their integrated impact on model selection, residual behavior, and forecast validity is not consistently analyzed in a unified framework. Third, many studies emphasize prediction accuracy but provide limited attention to diagnostic validation, particularly in ensuring residual normality, independence, and overall model adequacy using statistical tests, such as Ljung-Box and Shapiro–Wilk. Moreover, there is a noticeable gap in linking forecasting results to practical decision-making contexts, especially in terms of how short-term forecasts can support investors and policymakers. Therefore, this study addresses these gaps by systematically evaluating ARIMA model performance for silver price forecasting, identifying the optimal model using AIC and BIC criteria within a defined parameter range, and rigorously validating forecast reliability through diagnostic checking, with a clear emphasis on its applicability for financial decision-making [22].

## 3. METHODOLOGY: RESEARCH DESIGN

The research design employed in this study is a quantitative research study in an effort to predict the price of silver on a daily basis in US dollars. The primary objective is to determine the most valid time series model that can be used to produce short-term predictions.

### 3.1. Data Collection

The data of this analysis consisted of the daily prices of silver in January 01, 2025–March 10, 2026, obtained via reputable financial sources. The official publications and verified market reports have provided accurate and up-to-date information, and the dataset obtained is reliable and allows forecasting.

### 3.2. Data Pre-processing

The data collected were initially cleansed by eliminating rows that had empty or erroneous values. The column of Silver Price was changed to a number format by excluding any commas, and the column of date was changed into a date type to be consistent in the time series analysis. The dataset was made ready to be analyzed by removing any remaining missing values.

### 3.3. Time Series Analysis

The clean dataset produced a time series object starting in January 2025, in which the daily observations were made. The first step in exploratory analysis is by plotting the original series to make sense of trends and patterns. To examine stationarity, the Augmented Dickey–Fuller (ADF) test was used, and differentiation was done when required to put the series into a stationary form that could be used in modeling.

### 3.4. Model Selection and Fitting

A number of time series were tested, among them being ARIMA, exponential smoothing, and trend models. The Box-Cox transformation was used to stabilize the variance. ARIMA model showed the best performance in terms of measures used to evaluate its performance, including AIC, BIC, and MSE [23]. R was used to automatically estimate the best ARIMA model and estimate its parameters with the auto. Arima () function.

#### *3.4.1. ARIMA (p, d, q)*

A general ARIMA model, which is abbreviated as ARIMA (p,d,q), is a very popular statistical method of time series modeling and prediction. It is a mixture of three main elements:

$$y_t = C + \theta_1 y_{t-1} + \theta_2 y_{t-2} + \ldots + \theta_p y_{t-p} + \epsilon_t + \phi_1 \epsilon_{t-1} + \phi_2 \epsilon_{t-2} + \ldots + \phi_q \epsilon_{t-q}$$

$$\epsilon_t \sim N(0, \sigma^2)$$

With parameters of the MAs $\phi_i$, AR parameters are $\theta_i$, the white noise error term is $\epsilon_t$, and the differenced series is $y_t$ (if d > 0, so c attains to zero or not significant).

### 3.5. Diagnostic Checking

The fitted ARIMA model was tested through residual analysis to test its suitability. The autocorrelation of the residues was discussed by the autocorrelation function (ACF) and partial ACF (PACF) plot. The Shapiro-Wilk test was used to test the normality of the residuals. Furthermore, diagnostic plots, such as plots of residuals over time, ACF/PACF of residuals, and Q-Q plots, were plotted to validate the model and the expectation of the residuals as white noises, which confirmed the validity of the forecasts.

### 3.6. Forecasting Model

A one-step-ahead forecast was made of future 3 months using the chosen ARIMA model. Confidence intervals of 80% and 95% were calculated to give a precinct of values that might occur in the future. The confidence intervals and the values of the forecasted variables were plotted and provided a useful insight to inform the strategical planning and financial decision-making.

### 3.7. Model Selection Criteria

To choose the best ARIMA model, the AIC and BIC are some of the information criteria that are usually adopted. These criteria are used to evaluate the performance of a model by balancing between the model fit and the model complexity.

The AIC is defined as:

$$AIC = -2\ln(L) + 2k \tag{1}$$

Where L is the likelihood of the model and k is the number of estimated parameters.

The BIC is defined as:

$$BIC = -2\ln(L) + k\ln(n) \tag{2}$$

Where $n$ is the number of observations.

AIC and BIC both punish overfitting by penalizing models with high numbers of parameters. Lower values of AIC and BIC indicate a better model. In practice, the best model is chosen as the one with the smallest values of AIC and BIC.

### 3.8. Statistical Analysis

In this study, statistical analysis was done in various steps to guarantee the accuracy and reliability of the time series forecasting model.

First, exploratory data analysis (EDA): To analyze the main features of the data on the silver price rates, their trends, patterns, and possible anomalies, first, EDA was conducted.

Second, stationarity testing: The ADF test was conducted to verify that the series was stationary, which is necessary to make an effective ARIMA model. When it was found that the mean was non-stationary, a difference was used to ensure stationarity. Furthermore, Box-Cox transformation was employed to stabilize the variance across the series, which took care of the possible non-stationarity of variance.

Third, model identification: The plots of ACF and PACF were analyzed to derive preliminary values of the ARIMA model parameters. These plots were used to give information on the probable sequences of the AR and MA terms. Key measures, such as MSE, AIC, and Mean, were then used to measure the accuracy and the accuracy of the model in its forecasting.

Finally, diagnostic checks: Once the ARIMA model was fitted, diagnostic checks were conducted to verify that the model was satisfactory. Box-Pierce test was done to ensure that there was no significant autocorrelation in the residuals. The Shapiro-Wilk test was used to ensure that the residues followed a normal distribution. The residual ACF and PACF plots were also explored to ensure that no residual patterns existed. These tests showed that the model met the requirements of correct predictions and hence the predictions were credible in decision-making.

### 3.9. Software and Tools

The data analysis was conducted in R, which is a statistical computing software. Various tasks were performed with the help of a number of R packages, such as time series modeling, data visualization, and diagnostic checks. These tools were used to construct and confirm the ARIMA model and come up with dependable forecasts. The analysis was done using several R packages:

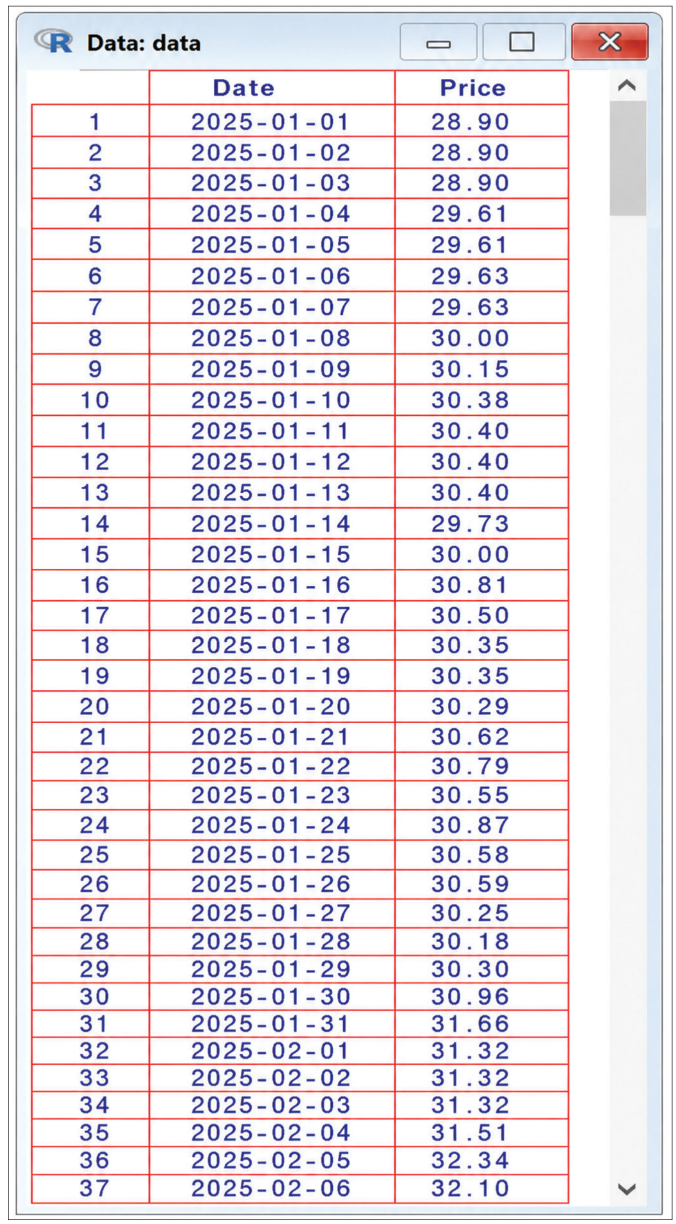
- readr: To read and manipulate CSV files of data
- Tseries: When working with the ADF test, and other time series operations
- forecast: The forecast package is used to fit ARIMA models, forecast, and model diagnostics
- TSA: More tools of time series analysis
- lmtest: To test the model residuals statistically
- ggplot2: To design sophisticated and custom plotting engines to visualize results and data.
- BoxCox: Box-Cox transformation model to level off variance.

All these tools gave an end-to-end time series analysis framework, comprising of model fitting, diagnostic checking, and forecasting. R and its packages were used to obtain strong and reproducible results and thus provide the possibility to study the silver price rate time series data in a comprehensive manner.

## 4. RESULT AND ANALYSIS

### 4.1. Description of the Data

This chapter shows the findings and discussion of the results of daily silver rate prices. The data collection was carried out online using the marketing publications in the Kurdistan region of Iraq. The data were gathered online through marketing publications in the Kurdistan region of Iraq. Fig. 1 illustrates a sample of Data in Program R by the Function view (data) before applying ARIMA, and Table 1 shows the summary statistics of the silver price rates.



Data: data

| | Date | Price |
|---|---|---|
| 1 | 2025-01-01 | 28.90 |
| 2 | 2025-01-02 | 28.90 |
| 3 | 2025-01-03 | 28.90 |
| 4 | 2025-01-04 | 29.61 |
| 5 | 2025-01-05 | 29.61 |
| 6 | 2025-01-06 | 29.63 |
| 7 | 2025-01-07 | 29.63 |
| 8 | 2025-01-08 | 30.00 |
| 9 | 2025-01-09 | 30.15 |
| 10 | 2025-01-10 | 30.38 |
| 11 | 2025-01-11 | 30.40 |
| 12 | 2025-01-12 | 30.40 |
| 13 | 2025-01-13 | 30.40 |
| 14 | 2025-01-14 | 29.73 |
| 15 | 2025-01-15 | 30.00 |
| 16 | 2025-01-16 | 30.81 |
| 17 | 2025-01-17 | 30.50 |
| 18 | 2025-01-18 | 30.35 |
| 19 | 2025-01-19 | 30.35 |
| 20 | 2025-01-20 | 30.29 |
| 21 | 2025-01-21 | 30.62 |
| 22 | 2025-01-22 | 30.79 |
| 23 | 2025-01-23 | 30.55 |
| 24 | 2025-01-24 | 30.87 |
| 25 | 2025-01-25 | 30.58 |
| 26 | 2025-01-26 | 30.59 |
| 27 | 2025-01-27 | 30.25 |
| 28 | 2025-01-28 | 30.18 |
| 29 | 2025-01-29 | 30.30 |
| 30 | 2025-01-30 | 30.96 |
| 31 | 2025-01-31 | 31.66 |
| 32 | 2025-02-01 | 31.32 |
| 33 | 2025-02-02 | 31.32 |
| 34 | 2025-02-03 | 31.32 |
| 35 | 2025-02-04 | 31.51 |
| 36 | 2025-02-05 | 32.34 |
| 37 | 2025-02-06 | 32.10 |

**Fig. 1.** Sample of data in program R by the function view (data) before apply autoregressive integrated moving average.

**TABLE 1: Summary statistics of daily silver prices**

| Statistic | Value |
|---|---|
| Mean | 40.1773 |
| Minimum | 28.9 |
| Maximum | 79.31 |
| Mode | 33 |
| Median | 36.52 |
| Standard deviation | 10.4122 |
| Skewness | 1.4702 |
| Kurtosis | 1.7926 |

Several time series techniques, such as ARIMA, were used to predict the future rates of silver price. Analysis will consist of a description of data, model fitting and forecasting, and then residual analysis and testing of the coefficients will be taken to ensure that the model chosen is sufficient. The rates of data, which will be applied in this analysis, include daily of silver prices.

## 4.2. Model Fitting and Forecasting

### *4.2.1. Time series plots and stationarity*

The time series plot (Fig. 2) of the silver price series indicates that the time series is not stationary since the mean and variance seem to vary with time. To verify this observation, the ADF test was applied. The *P*-value obtained was larger than 0.05, which means it was not possible to reject the null hypothesis of a unit root. This finding presents statistical proof that the series of silver prices is not stationary. Fig. 3 shows the dataset of daily silver prices after change to a time series dataset by R program.

The first test to test the stationarity of the silver price series was the ADF test. These findings also showed that the initial series was not a stationary series because the *P*-value was greater than the 5% level of significance ($P = 0.55$). To overcome this problem, a first-order differencing transformation was done to the series. The ADF test was once more done on the differenced data, and the $P = 0.01$, which is less than the 0.05 significance level. This finding supports that the differenced series is only stationary and thus can be used in future time series modeling. Figs. 4 and 5 demonstrate the silver price series with BoxCox transformation, and then it was tested with the ADF test to test the stationarity on the transformed silver price series.

## 4.3. ACF and PACF Plots

According to the ACF plot (Fig. 6) of the original series, some of the lag values are not at all equal to zero. The gradual and slow negative changes in the coefficients of autocorrelation indicate that there exists a trend element in the data.

**TABLE 2: Test Dickey–Fuller and *P*-value for original dataset**

| Dataset | Dickey-Fuller | *P*-value |
|---|---|---|
| Original series dataset | −2.0626 | 0.5512 |
| First-order differencing | −8.2052 | 0.01 |

**TABLE 3: Model performance metrics**

| Model | MSE | ACF1 | BIC |
|---|---|---|---|
| ARIMA (1,1,1) | 0.2787 | −0.0231 | 2566.434 |
| ARIMA (1,1,2) | 0.2914 | −0.0314 | 2587.521 |
| ARIMA (2,1,2) | 0.2951 | −0.0354 | 2487.328 |
| ARIMA (0,1,2) | 0.2143 | −0.0154 | 2247.101 |
| ARIMA (2,1,1) | 0.1973 | −0.0083 | 2087.335 |

ARIMA: Autoregressive integrated moving average, MSE: Mean squared error, ACF: Autocorrelation function, BIC: Bayesian information criterion

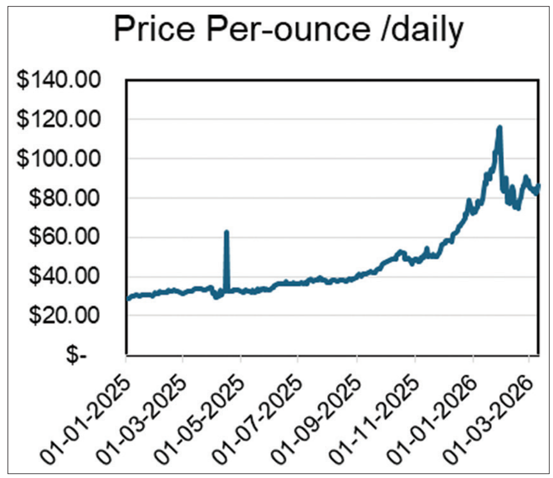



**Fig. 2.** Time series plot of daily silver prices.

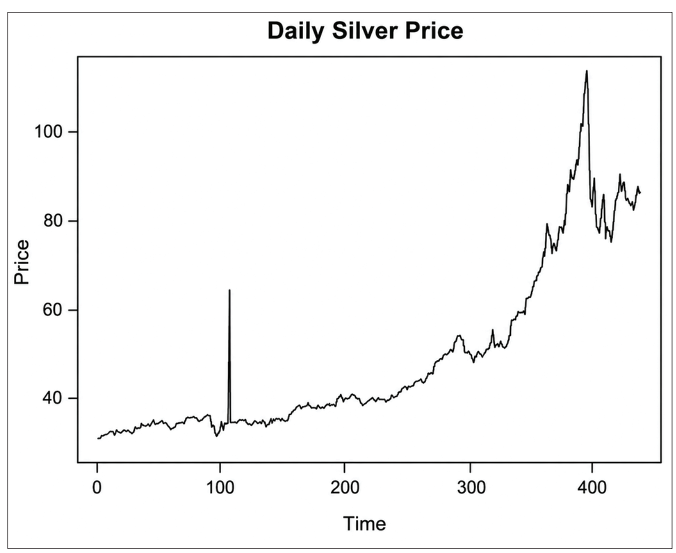



**Fig. 3.** Change dataset to time series data by program R.

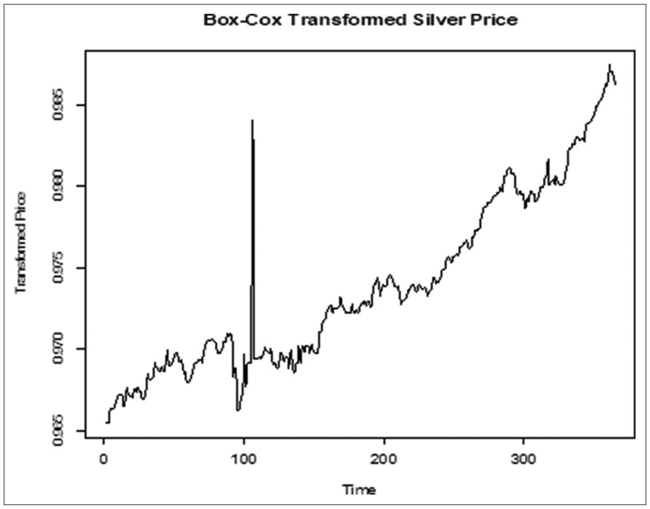



**Fig. 4.** As illustrated, the data were transformed using the Box-Cox method to stabilize variance.

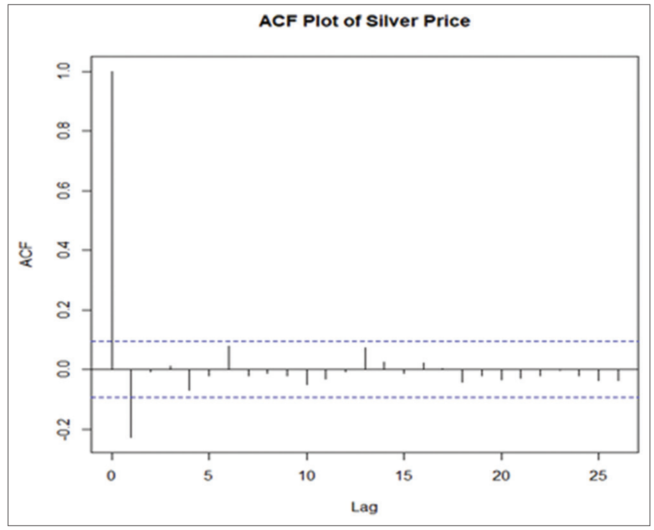



**Fig. 6.** Autocorrelation function of the differenced silver price series (USD).

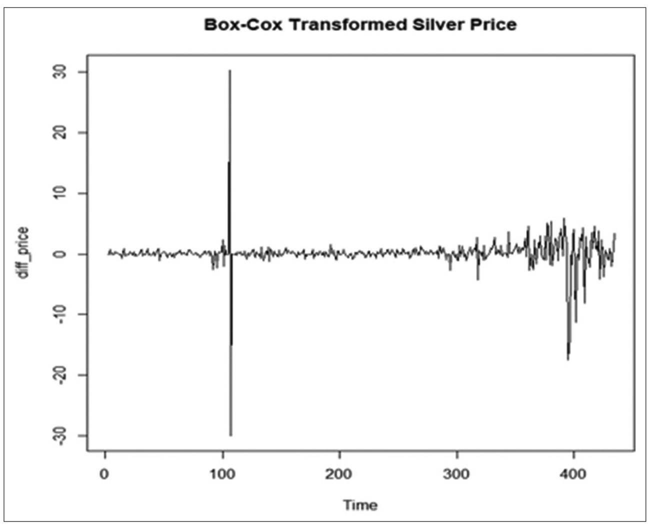



**Fig. 5.** illustrates the silver price series after applying the Box-Cox with augmented dickey-fuller-test.

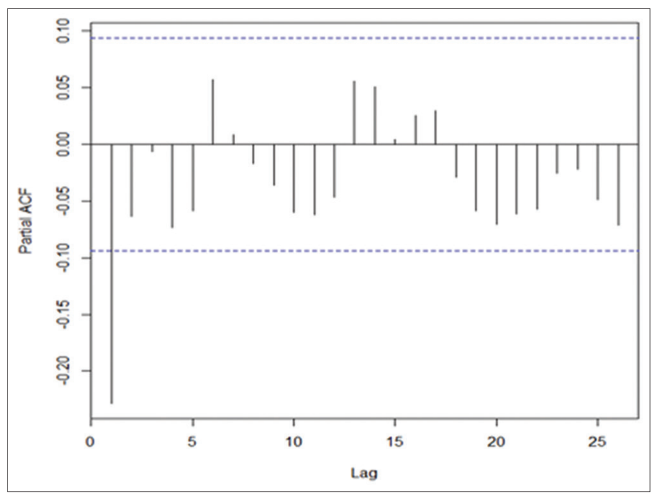



**Fig. 7.** Partial autocorrelation function of the differenced silver price series (USD).

The PACF plot indicated in Fig. 7 depicts that at the first and second lags, there exist significant partial autocorrelations and therefore, an AR (2) model would be appropriate to the series.

## 4.4. Test of Stationarity

The results of the silver price series application of the ADF test are provided in Table 2. The results indicate that the original series is not stationary. The transformed series is also stationary, as shown by the significant test results, after first-order differencing.

## 4.5. Performance Model Fitting and Forecasting

A number of models were estimated on both the original and differenced series. Table 3 shows the performance metrics of every model. The ARIMA (2,1,1) model was the best-performing model according to the lowest MSE, BIC, and AIC for evaluation criteria.

## 4.6. Residual Analysis

The residual analysis was conducted to evaluate the suitability of the fitted ARIMA model. The ACF and PACF plots confirmed that the residuals do not have any significant autocorrelation. The Shapiro–Wilk test of normality showed that the *P*-value suggests non-normality distributed ($W = 0.47024$, $P = 2.2e–16$), which was confirmed by visual examination of the histogram and the normal Q-Q plot (Figs. 8 and 9), which revealed that

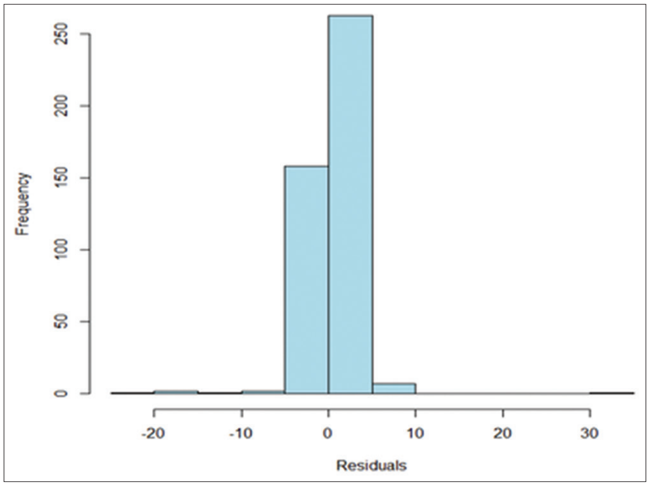



**Fig. 8.** Histogram of the autoregressive integrated moving average model residuals.

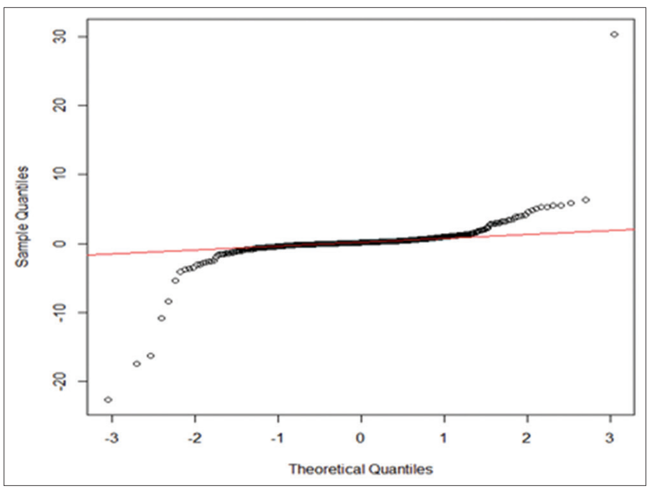



**Fig. 9.** Autoregressive integrated moving average model the normal Q-Q plot of the residuals.

the residues were symmetrically distributed and closely matched with the theoretical normal curve.

Even though the Shapiro-Wilk test gave a *P*-value that indicated non-normality, the histogram and Q-Q plot give further evidence of the residual distribution. The Q-Q plot demonstrates that the theoretical quantiles are not exactly observed, meaning that the residual is not a normal distribution. This is typical of financial time series, where there are usually outliers and heavy tails.

### 4.7. Model Evaluation

The ARIMA model and the LSTM are two significantly different methods of time series prediction. To evaluate and compare the performance of these two models in terms of conventional accuracy measures, such as MSE, Root MSE,and MAPE. Table 4 compares the forecasting performance of the ARIMA model and the LSTM on the basis of standard error measures. The outcome indicates that the ARIMA model has lower error values, which implies better accuracy and a closer fit to the observed data compared to LSTM.

**TABLE 4: Comparative model ARIMA (2,1,1) and LSTM**

| Model | MSE | RMSE | MAPE |
|---|---|---|---|
| ARIMA (2,1,1) | 0.1973 | 2.6028 | 1.7924 |
| Long short-term model LSTM | 0.2014 | 2.9412 | 2.0421 |

ARIMA: Autoregressive integrated moving average, LSTM: Long short-term memory, MSE: Mean squared error, RMSE: Root mean squared error, MAPE: Mean absolute percentage error

### 4.8. Forecast Evaluation

The fitted ARIMA model was used to get the forecasts over the next 3 months. The forecasted silver price series, with 80% and 95% confidence intervals, are shown in Fig. 10 and Table 5, respectively.

The table and plot illustrate the following important points:

1. Point forecasts: The blue line shows the point forecasts of the next 30 days, that is, the values that the series are expected to have at every future time point.
2. Confidence intervals: The dark and light regions around the point forecasting are the 80% and 95% confidence intervals, respectively. These are the intervals that show the maximum and minimum of the future values of the series with the likelihood of 80% and 95%, respectively. These intervals are gradually increasing with time, and this is because of the uncertainty that comes with the longer forecast horizons.

## 5. DISCUSSION

The results show that the ARIMA (2,1,1) specification has a parsimonious but strong representation of the dynamics of the silver price. Although the initial selection of models based on AIC and BIC informed this choice, the suitability of the model is further supported by diagnostic evaluation, where up to minor deviations in the Q-Q plot indicate that the model is selected properly. This is an indication that the model is able to represent the underlying linear form of the series and make statistically significant predictions.

**TABLE 5: Forecasted silver price by autoregressive integrated moving average (2,1,1) from March 11, 2026 to April 9, 2026**

| Date | Forecast | Lower_80 | Upper_80 | Lower_95 | Upper_95 |
|---|---|---|---|---|---|
| March 11, 2026 | 86.0508 | 82.7112 | 89.3903 | 80.9434 | 91.1581 |
| March 12, 2026 | 85.9658 | 81.7742 | 90.1573 | 79.5554 | 92.3762 |
| March 13, 2026 | 85.9244 | 81.0307 | 90.8180 | 78.4402 | 93.4086 |
| March 14, 2026 | 85.8917 | 80.4323 | 91.3510 | 77.5423 | 94.2410 |
| March 15, 2026 | 85.8691 | 79.9202 | 91.8179 | 76.7711 | 94.9670 |
| March 16, 2026 | 85.8529 | 79.4680 | 92.2379 | 76.0879 | 95.6179 |
| March 17, 2026 | 85.8415 | 79.0586 | 92.6244 | 75.4680 | 96.2151 |
| March 18, 2026 | 85.8334 | 78.6816 | 92.9853 | 74.8956 | 96.7713 |
| March 9, 2026 | 85.8277 | 78.3296 | 93.3258 | 74.3604 | 97.2950 |
| March 20, 2026 | 85.8236 | 77.9977 | 93.6495 | 73.8549 | 97.7923 |
| March 21, 2026 | 85.8207 | 77.6823 | 93.9592 | 73.3741 | 98.2674 |
| March 22, 2026 | 85.8187 | 77.3808 | 94.2566 | 72.9140 | 98.7234 |
| March 23, 2026 | 85.8173 | 77.0911 | 94.5434 | 72.4718 | 99.1627 |
| March 24, 2026 | 85.8162 | 76.8117 | 94.8207 | 72.0451 | 99.5874 |
| March 25, 2026 | 85.8155 | 76.5415 | 95.0895 | 71.6321 | 99.9989 |
| March 26, 2026 | 85.8150 | 76.2794 | 95.3506 | 71.2315 | 100.3984 |
| March 27, 2026 | 85.8146 | 76.0246 | 95.6046 | 70.8421 | 100.7871 |
| March 28, 2026 | 85.8144 | 75.7766 | 95.8521 | 70.4629 | 101.1658 |
| March 29, 2026 | 85.8142 | 75.5347 | 96.0936 | 70.0931 | 101.5353 |
| March 30, 2026 | 85.8140 | 75.2985 | 96.3296 | 69.7319 | 101.8962 |
| March 31, 2026 | 85.8139 | 75.0676 | 96.5603 | 69.3788 | 102.2491 |
| April 01, 2026 | 85.8139 | 74.8415 | 96.7862 | 69.0331 | 102.5946 |
| April 02, 2026 | 85.8138 | 74.6201 | 97.0076 | 68.6945 | 102.9331 |
| April 03, 2026 | 85.8138 | 74.4030 | 97.2246 | 68.3625 | 103.2651 |
| April 04, 2026 | 85.8138 | 74.1900 | 97.4375 | 68.0368 | 103.5908 |
| April 05, 2026 | 85.8138 | 73.9808 | 97.6467 | 67.7169 | 103.9106 |
| April 06, 2026 | 85.8138 | 73.7753 | 97.8522 | 67.4026 | 104.2249 |
| April 07, 2026 | 85.8137 | 73.5733 | 98.0542 | 67.0935 | 104.5340 |
| April 08, 2026 | 85.8137 | 73.3745 | 98.2530 | 66.7895 | 104.8379 |
| April 09, 2026 | 85.8137 | 73.1788 | 98.4486 | 66.4903 | 105.1372 |

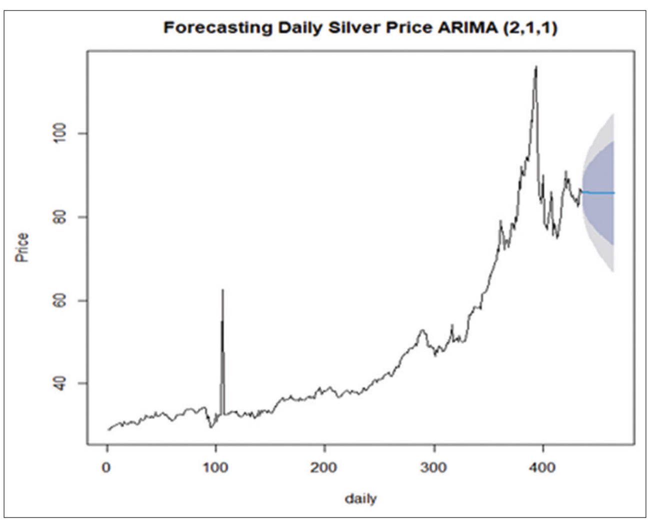



**Fig. 10.** Forecasted silver price by autoregressive integrated moving average (2,1,1).

In contrast, the LSTM model demonstrates relatively poor results in this regard. This is explained by the fact that the series of silver prices itself seems to be largely influenced by the short-term linear interdependence of the silver price series but less by the non-linear patterns. The greater malleability of LSTM makes it more vulnerable to noise and the threat of overfitting, hence its reduced generalization ability, in light of the relatively small dataset. These findings are in line with the bias-variance trade-off, where simpler models, such as ARIMA are likely to be more effective than more complex machine learning models when the process that generates the data is mostly linear.

In practical terms, the fact that the ARIMA model is superior to the other means that there is no need to use computationally intensive approaches to get reliable short-term predictions of silver prices. This has significant implications on investors, policymakers, and financial analysts because the model not only gives point estimates but also gives confidence intervals that measure uncertainty, thus enabling more informed decision-making.

## 6. CONCLUSION

The research was to determine the best model to use in predicting the rates of silver price by analyzing a number of time series models. The ARIMA (2,1,1) model was found to be the best of the models in terms of various performance measures. The tests of residual diagnostics checked the sufficiency of the model, as there was no severe autocorrelation and the normality of the residuals was more or less close. The forecast outcomes also showed the strength of the ARIMA (2,1,1) model in giving strong future price forecasts, and the presence of clear confidence intervals indicated the amount of inherent uncertainty in the future price forecasts. The findings of these studies have been of great benefit to policymakers, investors, and businesses as they can now predict the future patterns of the market, mitigate financial risks, and make strategic decisions. All in all, the results show the usefulness of the ARIMA model as a useful and efficient tool in silver price forecasting, including the significance of strict model testing and the diagnosis of residual values in providing reliable and accurate predictions of time series.

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