# Future Conditions of the Mining Sector Seen from The Viewpoint of Stock Price

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**Abstract.** The daily share price of the mining sector is part of the financial data that is included in the determining criteria that describe the condition of the company. More broadly, the daily share price of the mining sector, especially in Indonesia, impacts the national economy. In these conditions, low-risk decision-making is needed. Methods in economics explaining forecasting of future economic conditions can reduce risk by preparing a treatment plan. Time series financial data, including daily stock prices, can be predicted using the ARIMA model. This study aims to design a time series financial data forecasting model with a low error rate so that the quality of the prepared decisions is of high quality.

**Keywords:** ARIMA, Timeseries, Financial Data, Mining Sector

## 1. Introduction

The mining sector is crucial in every country, including Indonesia, which has abundant mining resources. The mining sector, as well as its derivative industries, significantly affect the level of life. Furthermore, the mining sector is also one of the industries that support economic growth. Forecasting the financial condition of the mining sector is an important thing to do in order to determine the direction of goals, strategies, and policies in the future. Forecasting financial data is one way to predict the future by considering information and data from the previous period [1] ;[2]. Projections or forecasts of financial data can be in the form of daily prices, earnings in each period, and stock prices carried out as an effort to check conditions based on the information obtained [3]; Information obtained earlier by decision-makers can facilitate efforts to minimize risks that may occur in the future.

Forecasting related to daily prices has a high level of data volatility. Daily price volatility indirectly describes the level of risk that occurs in the market. Low daily price volatility will cause downward movement in the market, and it signals a low level of profit from buying and selling transactions (capital gain). In economics science and practice, forecasting with a low error rate is used to plan economic conditions in a wide (macro) and small (micro) environment. The model with the type of data with a high level of volatility often used as a reference for forecasting is through the ARIMA model [4], [5]. Forecasting can show daily stock price figures for the mining sector for three months or 90 days.

## 2. Literature Review

### 2.1 Forecasting

ICEBE 2021, October 07, Lampung, Indonesia

DOI 10.4108/eai.7-10-2021.2316232

The essence of forecasting is quantifying the mapping from the past and present to the future [6]. [7] in his research said that forecasting results can offer a broad horizon and economic events. In the studies that have been carried out, forecasting can be divided into three classifications based on the period, namely short-term forecasting, medium-term forecasting, and long-term forecasting [8]. Concrete short-term forecasts assist management in making decisions that include human resource planning, inventory control, and cash flow management (Fildes dan Goodwin, 2007). ). Successful organizational planning has used good forecasting techniques because of the concrete forecasting results [10].

### 2.2 Forecasting Model for Timeseries Data

Daily stock price movements in the capital market can be interpreted as the gap between increasing or decreasing stock prices. The movement or volatility itself in the capital market can easily change. There are times when volatility will go up and down. High volatility means that stock prices go up and down significantly in a second. Volatility (changes in price) in the capital market significantly affects the return on investment. Volatility is known as the basis for determining asset prices and valuable information for investment. There are two types to measure volatility, namely constant volatility, and non-constant volatility. Constant volatility seems to come with standard deviation or historical simulation methods. Non-constant volatility consists of Autoregressive Moving Average (ARMA), Autoregressive Integral Moving Average (ARIMA), Autoregressive Conditional Heteroskedasticity (ARCH), and Generalized Autoregressive Conditional Heteroskedasticity (GARCH).

### 2.3 Autoregressive Integrated Moving Average (ARIMA)

time-series based forecasting method relies on the classical Box-Jenkins methodology, which uses general model classes such as the Auto-Regressive Moving Average (ARMA(p,q)) model. , or Auto-Regressive Integrated Moving Average (ARIMA (p, d, q)) to get a forecast. [11] time series based forecasting method relies on the classical Box-Jenkins methodology, which uses general model classes such as the Auto-Regressive Moving Average (ARMA(p,q)) model, or Auto-Regressive Integrated Moving Average (ARIMA (p, d, q)) to get a forecast [10], [12].

## 3. Methodology and Data Analysis

### 3.1. Variables and Specifications of the Sample Period

Variables in this study are financial data. In more detail, the financial data is the daily share price of the mining sector. The timing of data collection is from January 1, 2015, to December 31, 2020. The data collected is a record of daily stock price data for the mining sector provided by the Indonesia Stock Exchange (IDX). After the data criteria are determined, then the data processing is carried out. The data processing results will be the basis for determining how the analysis of the results will be carried out.

### 3.2. Research Process

Process in this research is several important steps that will be taken to achieve the research objective, namely to obtain the best model for forecasting daily stock price data for the mining sector. Here is what describes the overall research process:

**Table 1.** Outcomes and Indicators of Research Process

| No. | Activity | Outcomes | Success Indicators |
|---|---|---|---|
| 1 | Collection Data | • Mining Sector Daily Stock Price Data.<br>• Mining sector daily stock price trend chart. | • Complete data in the research period.<br>• 2. The data is visually seen in terms of reasonable volatility. |
| 2 | Stationary Test | • Stationary Graph | SAS Process Output:<br>• Stationary data<br>• The data can be continued with the differencing process. |
| 3 | Data Differencing | • Data After Differencing. | SAS Process Output:<br>• Data and Table after Differencing |
| 4 | Checking *White noise* | • Check *white table noise* | SAS Output Process:<br>• Clean data from *noise.* |
| 5 | ARMA Test | • Table of AR and MA | Output SAS Process:<br>• ARMA |
| 6 | Forecasting ARIMA | • ARIMA forecasting results | • ARIMA forecast table for the next 90 days. |

## 4. Research Result and Discussion

The picture on the SEKTAM chart is an original description of how the volatility of the energy sector stock data with daily timeframe specifications is in Indonesia. The data is included in the extensive data criteria, 1437 days with a recurring volatility trend. A repeating trend is supported on the U curve at momentum A and B (represented by the blue box).

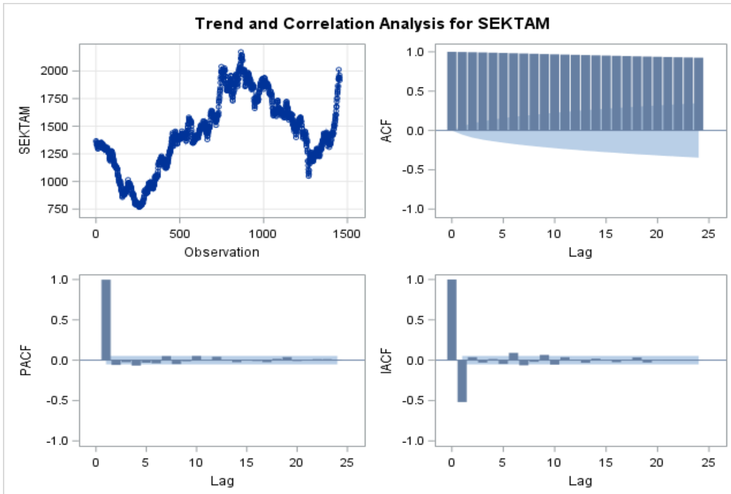


**Fig. 1.** Trend and Correlation Analysis for SEKTAM

From Figure 1. above, this study further investigates the stationary level of volatility in the energy sector stock data. Expect the original data to have stable volatility. The subsequent research will look at the visuals of the Autocorrelation Function or ACF and the Partial Autocorrelation Function or PACF. In the image above, ACF and PACF provide a gradual decrease in visuals. Also, the Inverse Autocorrelation Function (IACF) provides a drastic decrease in visuals. This is a sign that the energy sector stock data is included in the non-stationary data category. Several recommendation steps can be taken to achieve stationary data. One of the most widely used is differentiation. The following is data on shares of the energy sector that have undergone the treatment of the differentiating strategy. Figure 2. gives you a visual of the energy sector stock price data differentiation.

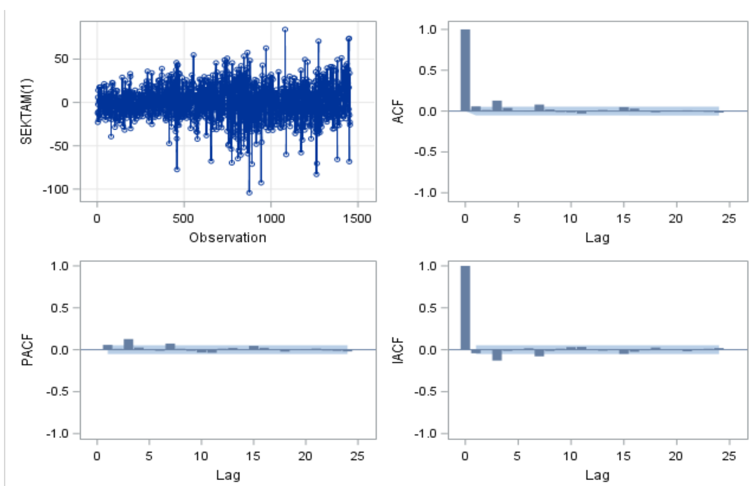

**Fig. 2.** Trend and Correlation Analysis for SEKTAM (After Differing)

With the differentiation strategy, energy sector stock price data processing results show a visual with relatively tight volatility (SEKTAM 1). Furthermore, the description of ACF, PACF, and IACF supports the criteria from data that has been stationary. Confidence in the data that has been stationary in this study also considers the results of the ADF test. The following table 2. shows the ADF test in more detail:

**Table 2.** Augmented Dickey-Fuller Unit Root Test

| Type | Lags | Rho | Pr < Rho | Tau | Pr < Tau | F | Pr > F |
|---|---|---|---|---|---|---|---|
| **Zero Mean** | **0** | -1367.56 | 0.0001 | -35.92 | <.0001 | | |
| | **1** | -1338.58 | 0.0001 | -25.84 | <.0001 | | |
| | **2** | -935.962 | 0.0001 | -18.78 | <.0001 | | |
| | **3** | -861.001 | 0.0001 | -16.40 | <.0001 | | |
| | **4** | -872.859 | 0.0001 | -15.09 | <.0001 | | |
| **Single Mean** | **0** | -1368.12 | 0.0001 | -35.92 | <.0001 | 645.17 | 0.0010 |
| | **-1340.23-25.84** | | 0.0001 | 1 | <.0001 | 333.97 | 0.0010 |
| | **-937,824-18.79** | | 0.0001 | 2 | <.0001 | 176.49 | 0.0010 |
| | **-863,477-16.41** | | 0.0001 | 3 | <.0001 | 134.65 | 0.0010 |
| | **-876,364-15.09** | | 0.0001 | 4 | <.0001 | 113.92 | 0.0010 |
| **Trend** | **-1369.04-35.93** | | 0.0001 | 0 | <.0001 | 645.47 | 0.0010 |
| | **-1342.65-25.85** | | 0.0001 | 1 | <.0001 | 334.24 | 0.0010 |
| | **-940,493-18.80** | | 0.0001 | 2 | <.0001 | 176.69 | 0.0010 |
| | **-866,957-16.42** | | 0.0001 | 3 | <.0001 | 134.84 | 0.0010 |
| | **4** | -881 846 | 0.0001 | -15.11 | <.0001 | 114.16 | 0.0010 |

The results are amazing and in line with expectations. The value of the ADF test with a lag scheme of 1 to 4 shows a positive thing with a p-value <0.0001, which is a valid signal from stationary. So the following process of researching stock prices in the energy sector is to consider the forecasting results from the ARIMA model.

**Table 3.** Conditional Least Squares Estimation

| Parameter | Estimate | Standard Error | t Value | Approx Pr > \|t\| | lag |
|---|---|---|---|---|---|
| **MU** | 0.36312 | 0.67348 | 0.54 | 0.5899 | 0 |
| **MA1.1** | 0.78257 | 0.10237 | 7.64 | <.0001 | 1 |
| **AR1.1** | 0.83860 | 0.08970 | 9.35 | <.0001 | 1 |

**Table 4.** ARIMA Statistical Method

| | |
|---|---|
| **Constant Estimate** | **0.058609** |
| **Variance Estimate** | 363.8594 |

| | |
|---|---|
| **Std Error Estimate** | 19.0751 |
| **AIC** | 12694.44 |
| **SBC** | 12710.28 |
| **Number of Residuals** | 1453 |

Based on tables 3 and 4 above, the ARIMA forecasting model can be formed. The model has shown significant AR(p), MA(q) with a p-value <0.0001 followed by AIC value of 12694.44 and SBC value of 12710.28. Thus, the equation for the ARIMA model of share prices in the energy sector can be arranged as follows:

$$SEKTAM_t = 0.058609 + 0.78257_{t-1} + 0.83860_{t-1} +_t \quad (1)$$

The ARMA model equation provided an opportunity in terms of predictive figures for the mining sector's stock price, of course, with Confidence Limits and predicted errors. More complete numbers of energy sector stock price predictions can be displayed. As soon as the process has been completed, because the basic model of ARIMA has been formed.

## 5. Implication and Suggestion for Future Research

The quantitative approach is used as part of the advantages of this research, namely, based on substantial numbers and based on calculation results with clear assumptions. The initial form of this approach is to determine the size criteria. The criteria are determined to determine which forecasting model is close to actual or can be said to be accurate. In simple terms, we can use an error indicator that is reflected in the values of MSE, MAE, and MAPE. The closer the error is to zero, the better the forecasting model is. The following table 8. is a comparison of the two sizes:

**Table 5.** Comparison Estimates

| Number | ARIMA |
|---|---|
| **MSE** | 110149 |
| **MAE** | 268.893287 |
| **MAPE** | 20.9596766 |

From table 5. it can be seen that quantitatively the ARIMA model gets an average error score component that is relatively small on average. Furthermore, with these results in the decision-making technique, there is a step to test the results of the decision. Figure 3. will display the full ARIMA forecasting results, which can be compared with the actual stock value to get a comparison.

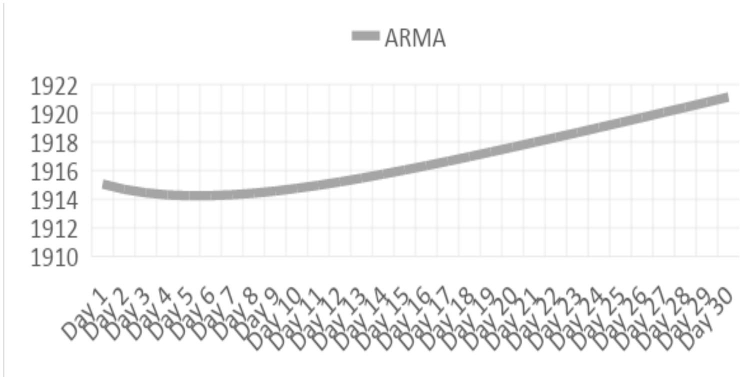


**Fig. 3.** ARIMA Forecasting Output

## 6. Conclusion

The share price of the mining sector is an overview and carries the value of the business entities that are incorporated in it. This research produces a forecasting model, which is important because the mining sector provides benefits, especially in supporting the supply of energy raw materials. Furthermore, entities in the mining sector are companies that are quite crucial because they are used in all business lines that support life. In the end, this research determines that the ARIMA model can accurately predict the financial data of the mining sector. Forecasting the future accurately is ultimately a consideration that management can use in making strategic decisions that are good for the business. The approach in choosing the best model is also important so that the decisions made are supported by definite figures.

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