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# Forecasting Demand for Carry and Return Roller Using Time Series: A Case Study of Mining Andesite in the Cilegon Region †

**Zul Fahmi [1,*] and Jerry Dwi Trijoyo Purnomo [2]**

[1] Technology Management, School of Interdisciplinary Management and Technology, Sepuluh Nopember Institute of Technology, Surabaya 60111, Indonesia
[2] Department of Statistic, Faculty of Science and Data Analytic, Sepuluh Nopember Institute of Technology, Surabaya 60111, Indonesia; jerrypurnomo@gmail.com
* Correspondence: hsbfahmi@gmail.com
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**Abstract**

The availability of spare parts for carry and return rollers is one of the important factors in operating andesite mining operations. Fluctuating and unstable demand often results in an imbalance in stock conditions, such as shortages or excess stock, which can have a direct impact on costs and productivity. This study aims to estimate the demand for these two components using the ARIMA time series forecasting. Historical data on the use of carry and return rollers at PT. ABC for the period 2019–2024 was analyzed, and models were selected based on residual test results and the lowest BIC values. The results show that ARIMA (2,0,0) is suitable for CR210, ARIMA (0,1,1) for CR315, CR370 and CR420, ARIMA (1,0,0) for RR800 and RR1300, and ARIMA (0,1,1) for RR1000 and RR1150. The 2025 projection shows that CR210 will experience a decline in demand, while CR315, CR370 and CR420 will experience demand growth. The returns for RR800 and RR1150 appear to be stable, while RR1000 and RR1300 are likely to increase slowly. These findings have managerial implications for PT. ABC in designing procurement strategies and optimizing warehousing in the supply chain.

**Keywords:** ARIMA; forecasting; andesite mining; time series

## 1. Introduction

Mining andesite plays a strategic role in providing materials for development and construction such as roads, bridges, and buildings. In the production process of rock andesite, conveyor systems are used intensively for material transportation. Two components used in conveyor systems are carry and return rollers. Inventory management is crucial because it can impact operational activities and costs if spare parts are in short supply (understock) or in excess (overstock). One factor that can contribute to reducing operational costs and improving company performance is inventory management [1]. Effective inventory management plays a pivotal role in reducing operational expenditures, improving supply chain agility, and boosting overall company performance [1,2]. Furthermore, recent studies highlight that integrating demand forecasting into inventory strategies substantially minimizes stock imbalances in industrial sectors such as steel manufacturing [3]. According to da Silva et al., [1] inventory storage costs amount to 20–40% of the annual value. With spare part demand forecasting using the time series method, it is hoped that this will assist companies in procurement management and warehouse optimization. According

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to Gaspersz (2011) [2,4], effective inventory policies must balance the trade-off between holding costs and stockout risks to optimize organizational performance. Strategic control over procurement, stock levels, and reorder points not only minimizes total inventory costs but also enhances supply chain responsiveness and operational stability.

Previous research using time series approaches has been widely applied across diverse sectors, such as agriculture [5], public health [6], industrial spare parts [1], and fisheries [7]. The ARIMA model has consistently demonstrated robustness in predicting complex dynamic trends, including inflation dynamics [8], climate and environmental parameters [9,10], electricity demand fluctuations [11], and enterprise sustainability behaviors [12]. These studies reaffirm that time series models are powerful tools for understanding and forecasting industrial demand fluctuations, thus making them suitable for predicting spare part requirements in manufacturing and mining sectors. According to [13], the ARIMA and Holt–Winters models provide reliable forecasting accuracy for variables influenced by seasonal and irregular fluctuations, as demonstrated in the prediction of cephalopod quantities and prices in Malaysia's fisheries industry. Similarly, [8] emphasized that time series methods such as Box–Jenkins ARIMA and Exponential Smoothing effectively capture long-term inflation dynamics within Malaysia's consumer price index data, showing that these techniques are robust for identifying and predicting linear or seasonal patterns in complex economic datasets. These studies reaffirm that time series models are powerful tools for understanding and forecasting industrial demand fluctuations, thus making them suitable for predicting spare part requirements in manufacturing and mining sectors. The objectives of this study are to forecast and develop a forecasting model for the demand for carry and return rollers at PT. ABC, Cilegon, Indonesia, evaluate the accuracy of forecasting and provide managerial recommendations regarding procurement management strategies at PT. ABC, Cilegon, Indonesia.

## 2. Material and Methods

### *2.1. Data Collection*

The data used in this study was obtained from a mining company in the Cilegon area labelled PT. ABC (Cilegon, Indonesia). The data used for forecasting is the usage of both the carry and return roller components from 2019–2024. This time series data will be used to predict demand in the future. These two components consist of four sizes, as follows:

1. Carry roller: this component consists of sizes 210 mm (CR210), 315 mm (CR315), 370 mm (CR370) and 420 mm (CR420).
2. Return roller: this component consists of sizes 210 mm (CR210), 315 mm (CR315), 370 mm (CR370) and 420 mm (CR420).

### *2.2. Autoregressive Integrated Moving Average (ARIMA)*

ARIMA is one of the most commonly used non-stationary models introduced by Box and Jenkins in 1970. Comprehensive statistical foundations and methodology of time series modeling using ARIMA processes are discussed extensively by Box et al. [14] and Wei [15]. The ARIMA process converts non-stationary data into stationary data by summing or integrating the ARMA stationary process. In this study, data analysis uses the ARIMA time series approach. The tool used in the analysis process is Minitab 22 (Minitab, LLC, State College, PA, USA). The ARIMA method generally uses the order (p, d, q), where p is the autoregressive (AR) component, d is the differencing process to obtain data stationarity, and q is the moving average (MA) component. The analysis steps carried out in this study are as follows in Figure 1:

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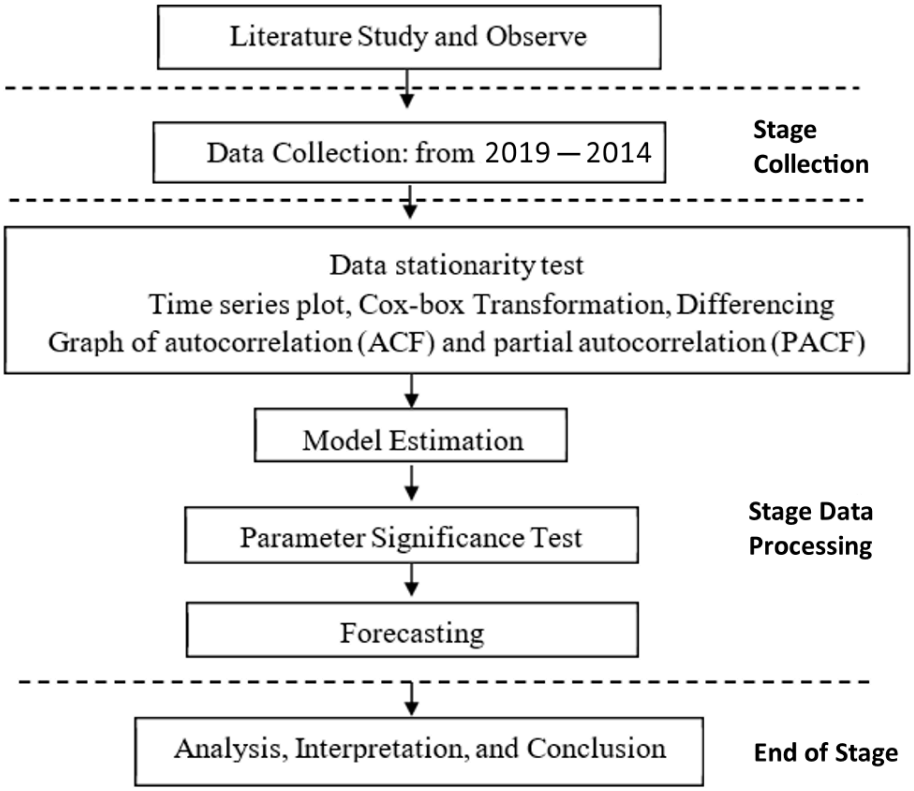


**Figure 1.** Research methodology flowchart.

a. Field and literature studies. At this stage, we studied the field conditions of the procurement of carry and return rollers at PT. ABC (Cilegon, Indonesia) and studied the literature and previous research related to forecasting using the ARIMA time series model approach.
b. Collection of internal data on the use of carry and return rollers at PT. ABC (Cilegon, Indonesia) from 2019–2024. At this stage, data was collected through the ERP tools used by PT. ABC (Cilegon, Indonesia).
c. Data stationarity check. At this stage, the data was checked for stationarity in terms of both variance and mean by plotting time series data, performing an ADF test, and creating ACF and PACF graphs.
d. Formation of a temporary model. At this stage, the temporary ARIMA model determines the order of p, d and q after considering the results of checking the stationarity of the data, both in terms of variance and mean.
e. Parameter significance test. At this stage, a parameter test is carried out on each ARIMA model that has been estimated for use. Then, the model that meets the significance test requirements, such as the Ljung–Box test and the lowest BIC value, is selected.
f. Forecasting. This is the final stage where forecasting is carried out using the best ARIMA model selected. Forecasting is carried out over a period of 1 year (12 months).

## 3. Results and Discussion

### *3.1. Time Series Plotting*

From the data on the use of carry and return rollers, there is fluctuating usage for each size type, as shown in Figures 2 and 3, which plot the following time series and forecasting with red lines:

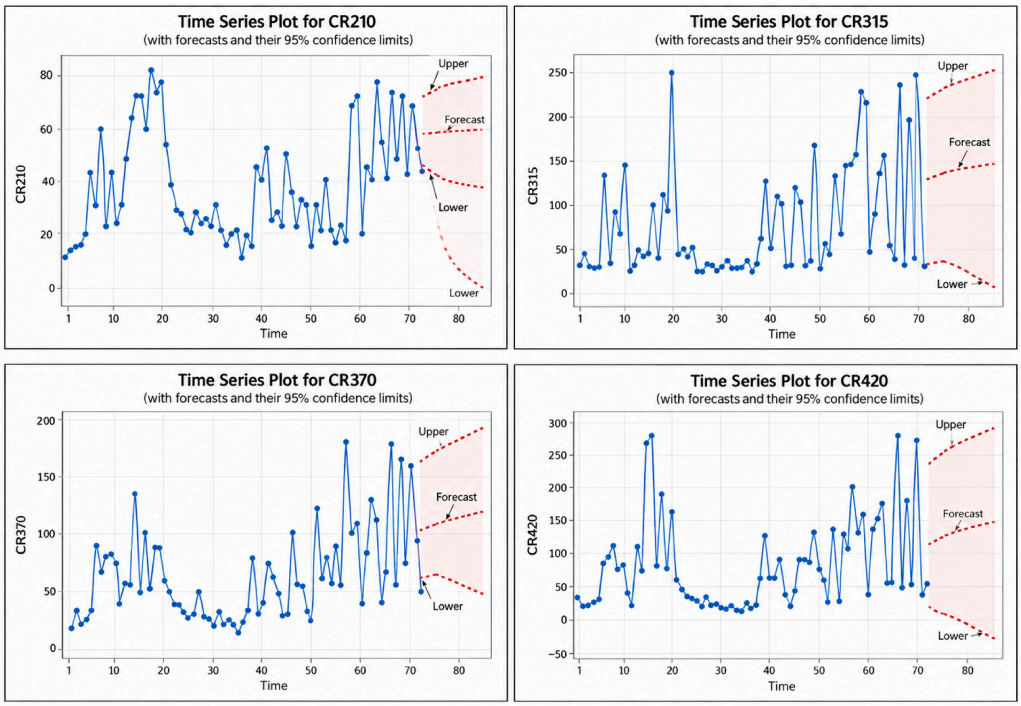


**Figure 2.** Time series components of carry roller.

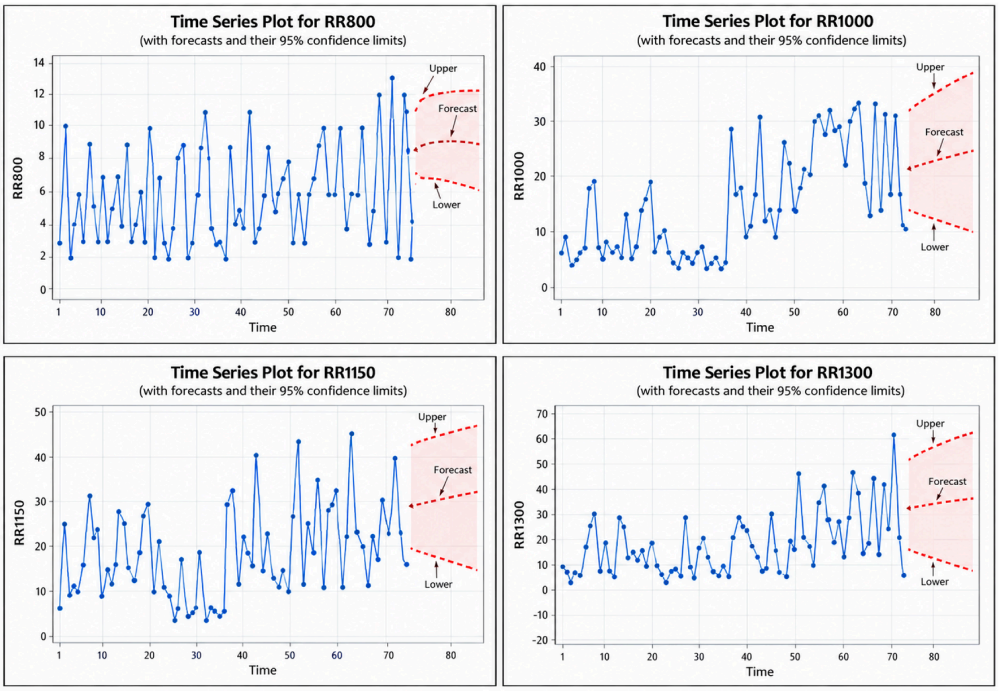


**Figure 3.** Time series components of return roller.

Figure 2 illustrates the time series plots and forecast projections for four types of carry roller, CR210, CR315, CR370, and CR420. Each plot includes the historical demand data, the ARIMA generated forecast, and 95% confidence intervals. The CR210 model shows a declining trend in projected demand, while CR315, CR370, and CR420 exhibit upward trends with varying degrees of fluctuation. These results indicate that certain roller types, particularly CR315 and CR420, are expected to experience increasing demand in 2025, requiring proactive procurement planning to ensure inventory availability.

Figure 3 presents the time series plots and forecast projections for four types of return rollers, RR800, RR1000, RR1150, and RR1300. The charts show historical demand data alongside ARIMA-based forecasts and 95% confidence intervals. The RR800 and RR1150 model indicates a stable demand pattern, while RR1000 and RR1300 demonstrate gradually increasing trends throughout 2025. These upward tendencies suggest that procurement planning for larger roller sizes should consider higher stock availability to accommodate potential growth in demand.

From the time series graph, it can be seen that each type of carry and return roller usage experiences irregular fluctuations in demand. Therefore, stationarity tests were conducted on both the mean and variance through Cox–Box transformation, ADF tests, ACF and PACF graph plotting, and parameter testing of each suspected ARIMA model. The best ARIMA model that met the requirements was then selected and used to conduct forecasting for a 12-month period. The best ARIMA model for each component that meets the requirements is shown in Table 1 below:

**Table 1.** Test results of Ljung–Box and BIC best ARIMA models of every component.

| Component | Model ARIMA | Ljung–Box | | | | BIC Value |
|---|---|---|---|---|---|---|
| | | 12 | 24 | 36 | 48 | |
| CR 210 | 2,0,0 | 0.237 | 0.519 | 0.633 | 0.559 | 621.752 |
| CR 315 | 0,1,1 | 0.168 | 0.314 | 0.274 | 0.156 | 807.751 |
| CR 370 | 0,1,1 | 0.101 | 0.176 | 0.277 | 0.356 | 714.464 |
| CR 420 | 0,1,1 | 0.234 | 0.513 | 0.801 | 0.793 | 801.162 |
| RR 800 | 1,0,0 | 0.456 | 0.677 | 0.753 | 0.665 | 364.718 |
| RR 1000 | 0,1,1 | 0.420 | 0.732 | 0.547 | 0.768 | 493.251 |
| RR 1150 | 0,1,1 | 0.095 | 0.188 | 0.036 | 0.046 | 552.764 |
| RR 1300 | 1,0,0 | 0.139 | 0.212 | 0.149 | 0.080 | 578.503 |

### *3.2. Forecasting Result*

After selecting the best model for each component of the carry and return roller, the next step is to forecast the requirements for these components for the next 12 months. The results of the forecast for the next 12-month period for each component are shown in Table 2 below:

**Table 2.** Forecasting results of every component of carry and return rollers.

| Comp. | Forecasting Year | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Jan. | Feb. | Mar. | April | May | June | July | Aug. | Sep. | Oct. | Nov. | Dec. |
| CR 210 | 44 | 42 | 41 | 40 | 39 | 39 | 39 | 38 | 38 | 38 | 37 | 37 |
| CR 315 | 114 | 115 | 116 | 117 | 118 | 119 | 120 | 121 | 122 | 123 | 124 | 125 |
| CR 370 | 102 | 103 | 104 | 105 | 106 | 106 | 107 | 108 | 109 | 110 | 111 | 112 |
| CR 420 | 114 | 115 | 116 | 117 | 118 | 119 | 120 | 121 | 122 | 123 | 124 | 125 |
| RR 800 | 6 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 5 |
| RR 1000 | 19 | 19 | 19 | 20 | 20 | 20 | 20 | 21 | 21 | 21 | 21 | 21 |
| RR 1150 | 23 | 23 | 23 | 23 | 24 | 24 | 24 | 24 | 24 | 24 | 24 | 24 |
| RR 1300 | 13 | 16 | 17 | 18 | 18 | 18 | 18 | 18 | 18 | 18 | 18 | 18 |

Table 2 shows the forecasting results for a 12-month period for each type of carry roller (code CR) and return roller (code RR) component. The carry roller (CR) component shows a relatively increasing trend in demand over the 12-month period, especially for sizes 315 mm, 370 mm and 420 mm, which will see consistent growth in usage. Only the carry roller (CR) component with size 210 mm with a decline trend. Meanwhile, the return roller component's forecast results tend to be stable for sizes 800 mm and 1150 mm,

while the 1000 mm and 1300 mm return rollers experienced an insignificant (slow) increase. The ARIMA model selected for each component of the carry and return roller is based on the lowest BIC value and meets the Ljung–Box requirement, whereby the results are white noise.

### 3.3. Managerial Implication

The research results provide a managerial basis for spare part planning, particularly for carry and return rollers at PT. ABC. Accurate demand forecasting enables the procurement department to design measurable acquisition strategies that minimize both stockout risks, which can cause production downtime, and overstocking, which leads to excessive storage costs. By using demand projections aligned with lead time and warehouse capacity, inventory planning becomes more effective and capital utilization more efficient.

The 2025 demand forecasts reveal distinct trends between carry and return rollers. Carry rollers show more dynamic variations, with CR210 mm exhibiting a declining trend of 37–44 units per month (473 units/year), while CR315 mm, CR370 mm, and CR420 mm demonstrate consistent growth, with projected monthly demands of CR315 in the range of 114–125 units (1.439 units/year), CR370 in the range of 102–112 units (1.286 units/year), and CR420 in the range of 114–125 units (1.435 units/year). In contrast, return rollers display relatively stable and moderate demand patterns. RR800 mm remains steady at 5–6 units per month (69 units/year), RR1000 mm gradually increases to 19–21 units per month (247 units/year), RR1150 mm maintains a stable level of 23–24 units per month (287 units/year), and RR1300 mm rises slowly from 13 to 18 units per month (212 units/year). These forecasts underscore the importance of tailored procurement strategies, where high-growth carry rollers require closer monitoring and higher inventory turnover, while stable return rollers can be managed more conservatively to optimize storage efficiency. The procurement strategy is as follows:

1. For components experiencing an upward trend in demand, such as CR315, CR370, CR420, RR1000 and RR1300, it is advisable to place orders conservatively by checking the available stock every 1 to 3 months for each component.
2. For components experiencing a downward trend in demand or tending to be stable, such as CR210, RR800, and RR1150, it is advisable to place orders conservatively by checking the available stock every 4 to 6 months for each component and managing the available stock with the aim of avoiding overstocking and ensuring efficiency in warehouse storage.

For future research, it is recommended to extend the analysis by comparing the ARIMA model with alternative forecasting approaches, particularly exponential smoothing methods such as Single Exponential Smoothing (SES) and Double Exponential Smoothing (DES/Holt's method). These methods are widely applied in spare-parts demand forecasting and are known for their simplicity and effectiveness in handling level and trend components. A comparative evaluation using standard accuracy metrics (MAPE, RMSE, and MAE) would provide a more comprehensive assessment of model performance and help determine the most suitable approach for different demand patterns. Such benchmarking would not only strengthen the methodological contribution of the study but also offer more robust guidance for managerial decision-making in spare-part inventory planning.

## 4. Conclusions

This study successfully used the ARIMA time series to forecast demand for the use of carry and return rollers at PT. ABC in the Cilegon area using historical data on the use of these two components for the period 2019–2024. The results of the analysis show that the demand patterns for the two components do not produce clear seasonal patterns, and

the historical data patterns are fluctuating, so transformation and differencing are needed to make the data stationary in terms of both variance and mean. The best forecasting model for the 210 mm carry roller is ARIMA (2,0,0), for the 315 mm carry roller it is the ARIMA (0,1,1) model, for the 370 mm carry roller it is the ARIMA (0,1,1) model, for the 420 mm carry roller it is the ARIMA (0,1,1) model, for the 800 mm return roller it is the ARIMA (1,0,0) model, for the 1000 mm return roller it is the ARIMA (0,1,1) model, for the 1150 mm return roller it is the ARIMA (0,1,1) model, and for the 1300 mm return roller it is the ARIMA (1,0,0) model. The accuracy value of the selected ARIMA model is based on the lowest BIC value and meets the white noise residual test assumption (Ljung–Box test). Based on the forecast results, demand for 210 mm carry rollers has decreased, while demand for 315 mm, 370 mm, and 420 mm carry rollers has consistently increased. For return rollers measuring 800 mm and 1150 mm, the forecast results tend to be stable, while return rollers measuring 1000 mm and 1300 mm are experiencing a slow increase with the minimum stock requirements for each type of roller as follows:

1. For 210 mm carry rollers, 473 units are provided per year; for 315 mm carry rollers, 1439 units are provided per year; for 350 mm carry rollers, 1286 units are provided per year; and for 470 mm carry rollers, 1435 units are provided per year.
2. For 800 mm return rollers, provide 69 units per year; for 1000 mm return rollers, provide 247 units per year; for 1150 mm return rollers, provide 287 units per year; and for 1300 mm return rollers, provide 212 units per year.

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