OPEN ACCESS

Journal of Agribusiness and Natural Resources | Vol. 1 No. 1 (2025)

Research Article

Sales Forecasting Using the SARIMA (Seasonal Autoregressive Integrated Moving Average) Method on Staple Rice Seeds of the Inpari 32 HDB Variety at PT ABC Banyuwangi

Rizka Putri Ramadhani
Agribusiness Study Program, Faculty of Agriculture, University of Muhammadiyah Jember, Jl. Karimata No. 49, Jember 68121, East Java, Indonesia
Email: ramadhaniputri.rizka@gmail.com

Received:	Revised:	Accepted:	Online:
December 28, 2024	January 30, 2025	February 10, 2025	February 12, 2025

Abstract
PT ABC Banyuwangi faces challenges in meeting the demand for rice seeds, especially for the Inpari 32 HDB variety, due to mismatches between inventory and market demand. This issue affects the availability of seeds that match market needs. To address this problem, this study applies the Seasonal Autoregressive Integrated Moving Average (SARIMA) method to forecast the sales of Inpari 32 HDB rice seeds for the year 2025. Historical sales data is analyzed using the SARIMA model to identify seasonal patterns and generate more accurate demand projections. This approach is expected to provide a clearer picture of future rice seed demand. The analysis results show that the SARIMA model provides fairly accurate forecasts, with a Mean Absolute Percentage Error (MAPE) of 6.1%, demonstrating the model's effectiveness in predicting the demand for Inpari 32 HDB rice seeds. With these findings, the company can make more informed decisions in inventory planning and supply chain management. More accurate projections will help PT ABC ensure seed availability aligns with market demand, thus improving distribution efficiency and reducing the risk of seed shortages in the market.

Keywords: Forecasting, SARIMA, Rice Seed

1. Introduction

PT ABC Banyuwangi is one of the 24 certified rice seed breeders in Banyuwangi (Wiratmoko, 2023). The company has been operating for 18 years in the production and distribution of high-quality, certified rice seeds. Every month, PT ABC Banyuwangi distributes approximately 3,600 tons of rice seeds to various regions in East Java, including Banyuwangi, Jember, Bondowoso, Situbondo, Probolinggo, Gresik, Mojokerto, Malang, and Kediri, as well as several areas outside Java, such as Bali (Izaati, 2017). The company offers various primary rice seed varieties, including Inpari 32 HDB.

Despite its wide distribution reach, PT ABC Banyuwangi faces challenges in meeting consumer demand. High demand is often unmet due to discrepancies between the requested quantity and available stock. This issue is particularly evident during the rice planting season when seed demand rises sharply. Each region and planting season has different varietal preferences, requiring the company to accurately forecast demand for each seed variety. The inability to predict demand accurately results in stock shortages, leading to customer dissatisfaction and lost sales opportunities.

To overcome these challenges, the company requires an accurate forecasting method to predict rice seed demand, and the Seasonal Autoregressive Integrated Moving Average (SARIMA) model is effective for analyzing time series data with seasonal patterns. The seasonal pattern in sales data is influenced by the recurring annual rice planting cycle, making SARIMA a relevant choice. This method was selected based on previous studies by Assidiq et al. (2017) and Suseno & Wibowo (2023), which demonstrated that SARIMA outperforms other forecasting methods in handling data with seasonal patterns. SARIMA helps the company forecast rice seed demand by considering annual seasonal trends. Implementing this method enables PT ABC Banyuwangi to make more accurate demand projections, efficiently plan production and distribution, and reduce the risk of stock shortages, ultimately improving customer satisfaction and the company's competitiveness in the market.

2. Literature Review

Based on the study by Katabba (2021) titled "The Seasonal Autoregressive Integrated Moving Average (SARIMA) Method for Predicting the Number of Train Passengers on Sumatra Island," SARIMA has been shown to accurately predict passenger numbers in data with seasonal patterns. A similar study by Anwar et al. (2021), titled "Application of the SARIMA Method for Forecasting the Number of Visitors to Bantimurung Bulusaraung National Park in Maros," also identified seasonal patterns in visitor numbers. Additionally, the research by Nasirudin et al. (2022), titled "Forecasting Coffee Production in East Java for 2020-2021 Using the Seasonal Autoregressive Integrated Moving Average (SARIMA) Method," selected SARIMA because coffee production data exhibited a seasonal pattern suitable for this method. These three studies demonstrate that SARIMA is effective in forecasting data with seasonal patterns, making it the chosen method for predicting rice seed sales.

2.1. Forecasting

Forecasting is the process of predicting the future with a high degree of accuracy by considering all available information, including historical data and an understanding of factors that may influence future predictions (Hyndman, 2018). When planning a forecast, several principles must be considered: forecasts are more accurate for groups, short-term forecasts tend to be more accurate, forecasts can be wrong, forecasts should be tested before being used, and forecasts cannot replace actual demand (Toomey, 2000). The appropriate forecasting method can be determined by first identifying the time series pattern of historical data. The five common time series patterns are linear, trend patterns, cyclical patterns, seasonal patterns, and random events (Toomey, 2000).

3. Methods

The research was conducted at PT ABC, a certified rice seed breeder in the Banyuwangi region. This study employs a descriptive quantitative method, aiming to explain research findings through measurable data collection using statistical, mathematical, or computational techniques. The study utilizes primary data obtained directly by researchers through unstructured interviews and observations, as well as secondary data collected from existing documents, such as sales reports and rice seed inventory records, gathered through documentation techniques. Data management in this study is conducted using computers with several software applications, namely Microsoft Excel 2021 and Minitab 19. The analytical method used is the Seasonal Autoregressive Integrated Moving Average (SARIMA) method, an extension of the ARIMA model specifically designed for forecasting data with seasonal patterns (Katabba, 2021). The following are the forecasting steps using the SARIMA method:

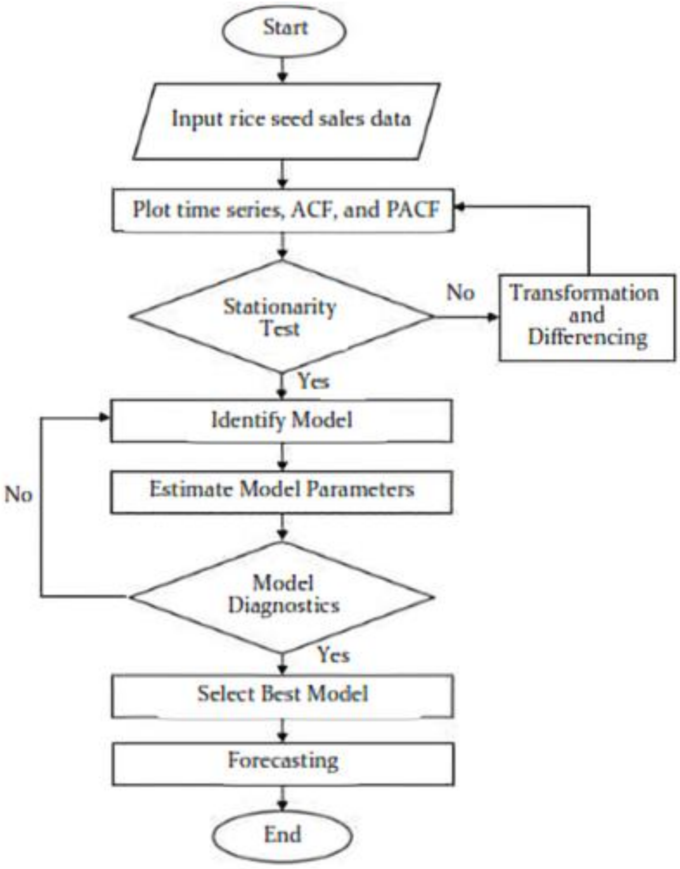


Figure 1. Modified SARIMA Forecasting Stages
Source: Katabba (2021)

4. Results and Discussion

4.1. Data Plotting

The forecasting process uses sales data of 10 kg packaged primary rice seed of the Inpari 21 HDB variety. The sales data analyzed in this study covers the sales of primary rice seeds from 2019 to 2023, with details as follows:

Table 1. Sales Data of Primary Rice Seeds Inpari 32 HDB (2019-2023) (packs)

Year	Month											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2019	410	1025	1960	328	41.5	0	0	745	1080	1835	2745	4090
2020	1900	1310	1895	3592	28	1605	930	834	1440	3448	4400	4643
2021	2111	2535	5205	5565	2705	875	1205	1440	3515	2685	8754	3815
2022	2705	2430	4771	5775	3028	1572	1905	1660	4000	7370	1275	0
2023	4616	4197	7388	5675	6105	1868	2360	1760	2890	6240	12912	5800

Source: Processed Secondary Data from PT ABC Banyuwangi (2024)

Based on Table 1, the sales data of Inpari 32 HDB show several months with zero sales. This condition can affect the accuracy of forecasting. According to Syntetos et al. (2015), the presence of zero values in data can complicate the forecasting process, as such data often have a significant proportion of zeros, with non-zero values appearing randomly. To address this issue, the sales data were converted from monthly data to quarterly data by aggregating sales every three months, effectively eliminating zero values.

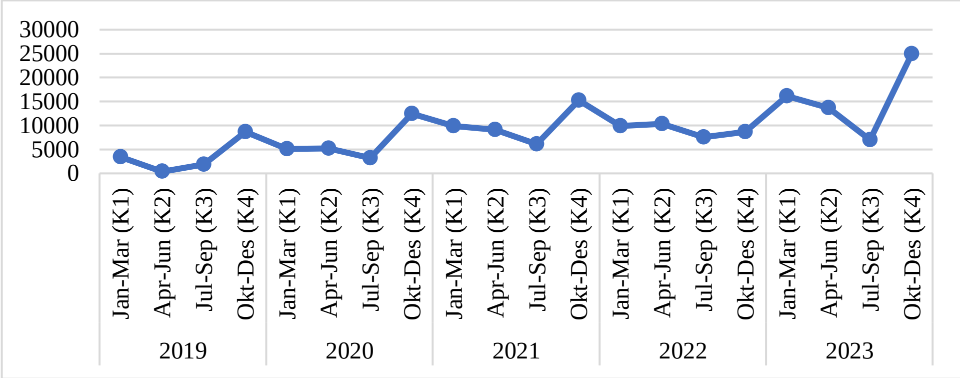


Figure 2. Time Series Plot of Primary Rice Seed Sales Data (Inpari 32 HDB) in Quarters (2019-2023)

In Figure 2, the rice seed sales data, which have been converted into a quarterly format, still show significant increases during certain periods each year. This recurring increase indicates a seasonal pattern in the data, making the SARIMA method suitable for forecasting (Nasirudin et al., 2022).

4.2. Stationarity Test

Stationarity conditions include two aspects: stationarity in mean and stationarity in variance. Stationarity in variance is identified using the Box-Cox transformation until the rounded value reaches 1.00, indicating that the data are stationary in variance (Suseno & Wibowo, 2023). In the initial sales data transformation, the rounded value was 0.50, meaning the data were not yet stationary in variance, as shown in Figure 3. After the first transformation, the rounded value became 1.00, indicating that the data had achieved stationarity, as illustrated in Figure 3.

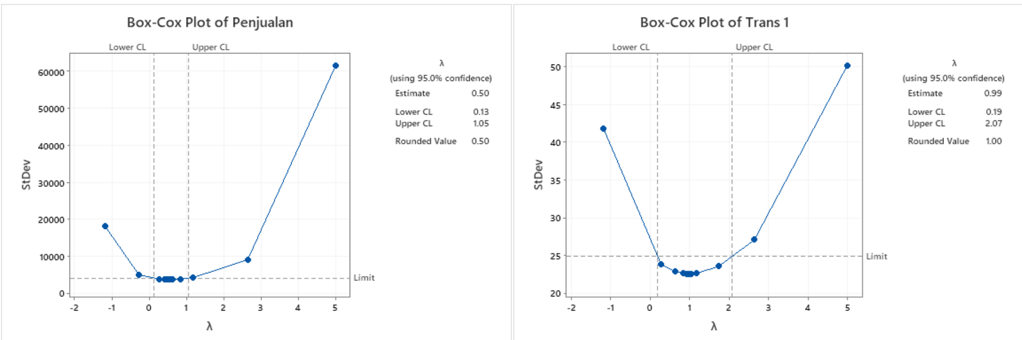


Figure 3. Box-Cox Transformation

The stationarity test in mean can be conducted by analyzing the ACF (Autocorrelation Function) and PACF (Partial Autocorrelation Function) diagrams. If the data are not stationary, differencing must be applied until stationarity is achieved (Anwar et al., 2021). In the first transformation and first differencing, the ACF diagram shows a gradual decline (dies down), indicating that the data are not yet stationary. The data become stationary after the second differencing, as evidenced by the cut-off at the first lag, as shown in Figure 4. In the ACF diagram (Figure 4), a seasonal pattern appears at lags 4, 8, and their multiples, indicating seasonal fluctuations that need to be addressed. To achieve stationarity, seasonal differencing with a lag of 4 is applied (Setiawan & Kusuma, 2024).

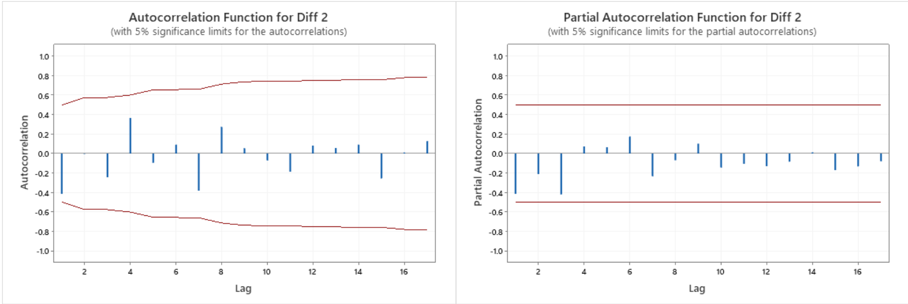
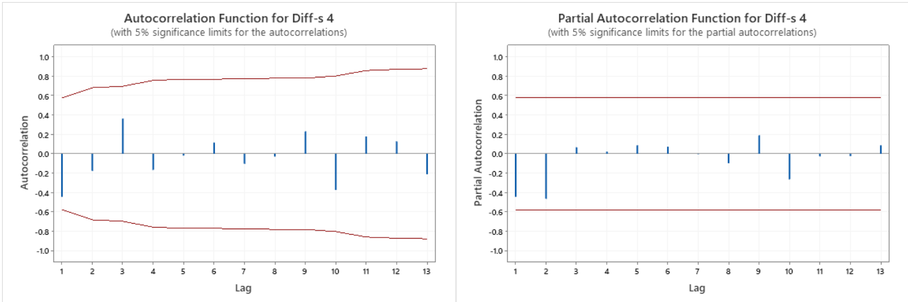


Figure 4. ACF and PACF diagram after Differencing 2

4.3. Preliminary Model Identification

The preliminary model identification is performed by analyzing the ACF (Autocorrelation Function) and PACF (Partial Autocorrelation Function) diagrams of the stationary data, following the theoretical patterns of stationary ACF and PACF, as well as stationary seasonal patterns (Suhartono, 2008).



(a) (b)

Figure 5. ACF and PACF Diagram After Seasonal Differencing

In Figure 5, the ACF diagram gradually dies down, indicating that there is no Moving Average (MA) component in the non-seasonal part. Meanwhile, in the PACF diagram, a cut-off at lag 2 suggests the presence of an AR(2) model for the non-seasonal component. Thus, the non-seasonal SARIMA model is identified as (2,2,0). For the seasonal component, the ACF diagram (Figure 5a) shows a cut-off at lag 1, suggesting an $SMA(1)^4$ model. Additionally, the PACF diagram (Figure 5b) shows a cut-off at lag 2, indicating an $SAR(2)^4$ model. As a result, the potential seasonal SARIMA models are $(2,1,1)^4$, $(2,1,0)^4$, dan $(0,1,1)^4$. Based on this model identification, the preliminary SARIMA models considered as SARIMA $(2,2,0)(2,1,1)^4$, SARIMA $(2,2,0)(2,1,0)^4$, dan SARIMA $(2,2,0)(0,1,1)^4$.

4.4. Parameter Estimation and Model Diagnostics

Parameter estimation uses the maximum likelihood method to get the best value, then model diagnostics are carried out to test its significance.

Table 2. Estimation Value and Significance Test of Temporary SARIMA Model Parameters

SARIMA Model	Parameter	Maximum Likelihood	t-value	p-value	Description
$(2,2,0)(2,1,1)^4$	AR (1)	-0,9994	-12,09	0,000	Significant
	AR (2)	-1,0004	-11,96	0,000	Significant
	SAR (4)	-0,927	-4,85	0,001	Significant
	SAR (8)	-0,997	-4,97	0,001	Significant
	SMA (4)	-0,710	-1,58	0,148	Not Significant
$(2,2,0)(2,1,0)^4$	AR (1)	-0,998	-8,38	0,000	Significant
	AR (2)	-1,000	-9,34	0,000	Significant
	SAR (4)	-0,931	-3,50	0,006	Significant
	SAR (8)	-1,004	-3,90	0,003	Significant

$(2,2,0)(0,1,1)^4$	AR (1)	-1,242	-6,52	0,000	Significant
	AR (2)	-1,002	-5,32	0,000	Significant
	SMA (4)	0,682	1,66	0,124	Not Significant

there is a table 2 SARIMA model of Inpari 32 HDB varieties that passes the significant test is the SARIMA Model $(2,2,0)(2,1,0)^4$, because for the AR(1) and AR(2) parameters the p-value is 0.000, SAR(4) is 0.006, and SAR(8) is 0.003, which indicates that all parameters in this model are significant. A p-value of less than 0.05 indicates that the model is considered significant (Muryanto, 2021).

Table 3. Ljung-Box Calculation Results

SARIMA Model	Lag	Chi-Square	DF	p-value
$(2,2,0)(2,1,0)^4$	12	6,13	9	0,727

Next is model diagnostics using the white noise test on models that are already significant. Based on the results of the Ljung-Box calculation in table 3, the SARIMA model fulfills the white noise test because the p-value is more than 0.05 (Muryanto, 2021).

4.5. Determining the Best Model

The best model for each variety is determined by calculating MAPE to determine the smallest error value, because the smaller the error value, the more appropriate the model (Muzaki & Agustina, 2024). MAPE value obtained from the SARIMA model $(2,2,0)(2,1,0)^4$ is 6,1%, these results show that the model has excellent predictive ability, because MAPE is less than 10% (Muzaki & Agustina, 2024).

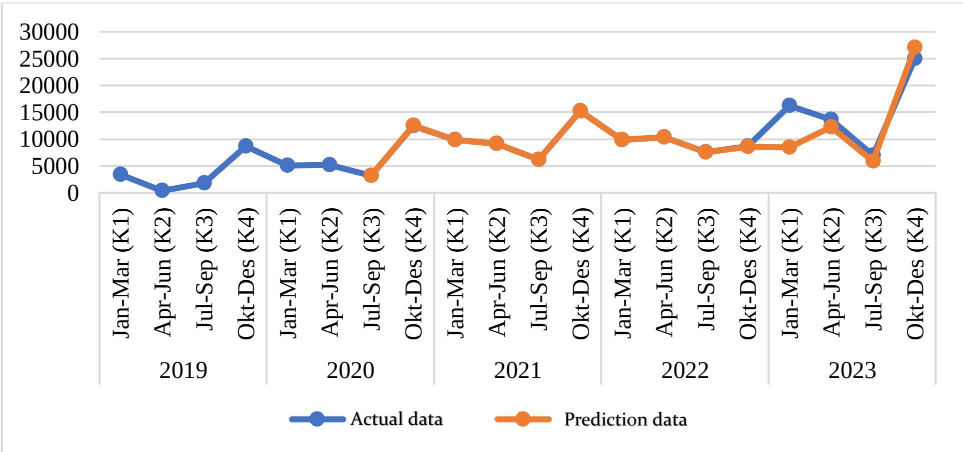


Figure 6. Comparison Plot of Actual Data and Predicted Data of Rice Seeds

4.6. Forecasting

Table 4. Forecasting Results of Main Rice Seed Sales in 2024-2025 in Quarters (pack)

Year	Month	Forecasting Day
2024	Jan-March (K1)	20490
	Apr-Jun (K2)	14910
	Jul-Sep (K3)	20862
	Oct-Dec (K4)	28462
2025	Jan-March (K1)	17545
	Apr-Jun (K2)	27012
	Jul-Sep (K3)	22432
	Oct-Dec (K4)	18015

Based on the figure, it can be seen that the forecasting results have the same pattern as the actual data. In addition, from the forecasting results data in the table in October-December of 2024 has the most number of sales that match the previous data. While in 2025 the most sales are in April-June which has the same pattern as sales in 2022.

5. Conclusion

Based on the results of research on forecasting sales of Inpari 32 HDB staple rice seeds at PT ABC Banyuwangi, the most suitable SARIMA model to use is SARIMA $(2,2,0)(2,1,0)^4$. This model was chosen based on parameter estimation and model diagnostics that showed significant results. In addition, the MAPE value of the selected model is 6.1%, which indicates that the model has excellent predictive ability. The forecasting results show that rice seed sales are predicted to experience a consistent increase and follow a seasonal pattern similar to the previous actual data. This indicates that the selected model is able to capture seasonal patterns well and provide relevant projections to support future production and distribution planning.

6. References

Anwar, M. M., Nurfadilah, K., & Alwi, W. (2021). Penerapan Metode SARIMA untuk Peramalan Jumlah Pengunjung Wisata Taman Nasional Bantimurung Bulusaraung Maros. *Journal of Mathematics: Theory and Applications*, 1–7.

Assidiq, A., Hendikawati, P., & Dwidayati, N. (2017). Perbandingan Metode Weighted Fuzzy Time Series, Seasonal ARIMA, dan Holt-Winter's Exponential Smoothing untuk Meramalkan Data Musiman. *UNNES Journal of Mathematics*, *6*(2), 129–142.

Hyndman, R. J. (2018). *Forecasting: principles and practice*. OTexts.

Izaati, I. (2017). *Analisis Struktur Pasar Benih Padi Di Kabupaten Banyuwangi.* Universitas Brawijaya.

Katabba, Y. I. (2021). *Metode Seasonal Autoregressive Integrated Moving Average (SARIMA) untuk Memprediksi Jumlah Penumpang Kereta Api di Pulau Sumatera*. Matematika.

Muryanto. (2021). Pemodelan Arima Dan Sarima Untuk Peramalan Indeks Harga Konsumen Kota Balikpapan Studi Kasus IHK Kota Balikpapan Bulan Januari 2011-Desember 2020. *Bestari: Buletin Statisitik Dan Aplikasi Terkini*, *1*(2).

Muzaki, F., & Agustina, N. (2024). Peramalan Nilai Tukar Petani Subsektor Tanaman Pangan di Nusa Tenggara Timur Menggunakan Metode SARIMA. *Seminar Nasional Official Statistics*, *2024*(1), 143–152.

Nasirudin, F., Pindianti, M., Said, D. I. S., & Widodo, E. (2022). Peramalan jumlah produksi kopi di jawa timur pada tahun 2020-2021 menggunakan metode seasonal autoregressive integrated moving average (sarima). *AGRIUM: Jurnal Ilmu Pertanian*, *25*(1), 34–43.

Setiawan, R. N. S., & Kusuma, W. (2024). Peramalan Jumlah Produksi Padi Di Nusa Tenggara Barat Menggunakan Metode Seasonal Autoregressive Integrated Moving Average (SARIMA). *Jurnal Agrimansion*, *25*(1), 106–114.

Suseno, S., & Wibowo, S. (2023). Penerapan Metode ARIMA dan SARIMA Pada Peramalan Penjualan Telur Ayam Pada PT Agromix Lestari Group. *Jurnal Teknologi Dan Manajemen Industri Terapan*, *2*(I), 33–40.

Syntetos, A. A., Babai, M. Z., & Gardner Jr, E. S. (2015). Forecasting intermittent inventory demands: simple parametric methods vs. bootstrapping. *Journal of Business Research*, *68*(8), 1746–1752.

Toomey, J. W. (2000). *Inventory management: principles, concepts and techniques* (Vol. 12). Springer Science & Business Media.

Wiratmoko, H. (2023). *Strategi Pengembangan Usaha Benih Padi Menggunakan SWOT dan QSPM di UD. Sri Tanjung, Desa Pondoknongko, Kecamatan Kabat, Kabupaten Banyuwangi*. Politeknik Negeri Jember.