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Research Article [OPEN ACCESS]

Forecasting and Raw Material Planning in Traditional Songkok Production Using ARIMA and Simple Exponential Smoothing

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ABSTRACT

This study investigates the applicability of time series forecasting models—Autoregressive Integrated Moving Average (ARIMA) and Simple Exponential Smoothing (SES)—for optimizing raw material planning in traditional songkok production. Utilizing monthly production data from a small-scale manufacturer in East Java, Indonesia (July 2020–August 2024), the ARIMA(1,1,1) model demonstrated superior forecasting performance, particularly under weak and irregular seasonality. Compared to SES, ARIMA yielded lower MAE, MSE, and MAPE values, enabling more precise production planning. The forecasts were translated into raw material requirements, resulting in improved inventory precision and operational efficiency, with monthly material usage gains ranging from 2.05% to 2.18%. These improvements are especially critical for micro-enterprises constrained by limited resources and seasonally driven demand cycles. While the univariate approach is a limitation, the findings provide a foundation for integrating contextual data in future multivariate models. The study offers practical insights for digital transformation in artisanal sectors and contributes to the broader discourse on data-driven production planning in culturally embedded industries.

Keyword: ARIMA forecasting, raw material planning, traditional manufacturing

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1. INTRODUCTION

The songkok, a traditional Indonesian cap worn predominantly by Muslim men, holds profound historical, cultural, and religious significance in Indonesian society. In addition to its role as a symbol of Islamic identity and tradition (Putra, 2024), the songkok has evolved into an economic commodity that contributes meaningfully to the local creative industry by supporting small-scale manufacturing and sustaining employment. One prominent production hub is a small-scale songkok manufacturer located in Gresik, East Java, which has been in continuous operation since 1993. The enterprise experiences consistent demand fluctuations aligned with religious observances, particularly Ramadan and Eid, underscoring the product's cultural relevance.

Despite its cultural and economic value, songkok production faces significant operational challenges, especially in managing inventory and planning production schedules. As illustrated in Figure 1, historical sales data from July 2020 to August 2024 show irregular and unpredictable seasonal spikes, reflecting inconsistent demand patterns that vary from year to year. These erratic sales surges complicate inventory control and procurement planning. Failure to accurately forecast demand can lead to overstocking, which increases storage costs, or understocking, which causes missed sales opportunities and customer dissatisfaction. Thus, the ability to anticipate demand accurately is critical to maintaining operational efficiency and profitability.

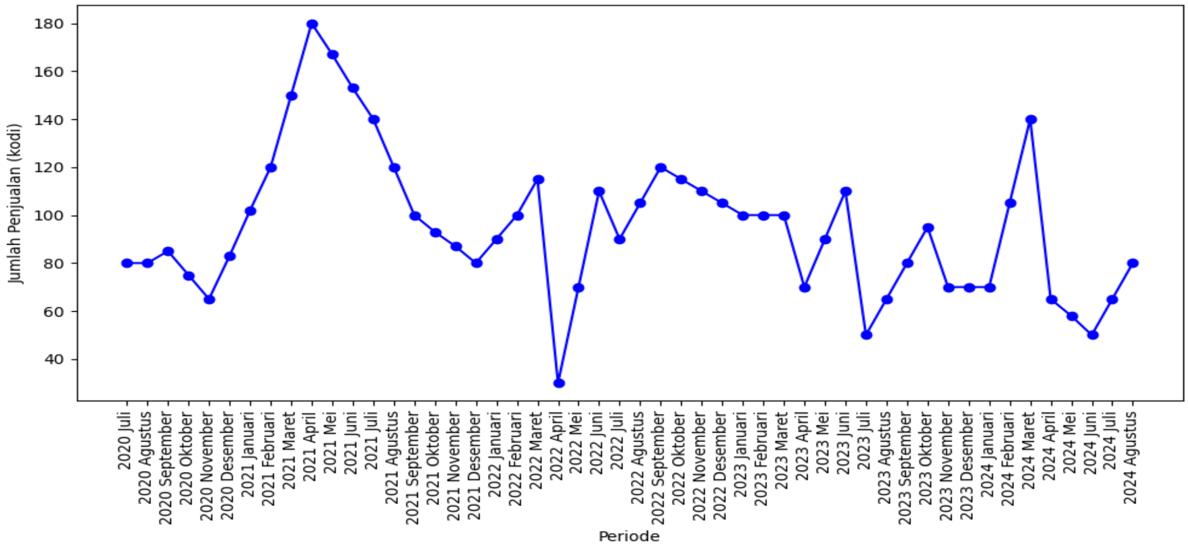

Figure 1. Monthly songkok sales trends from july 2020 to august 2024

Time series forecasting methods such as Autoregressive Integrated Moving Average (ARIMA) and Simple Exponential Smoothing (SES) have demonstrated considerable success in demand prediction across various sectors. Fahmuddin et al. (2023) reported that ARIMA models effectively captured weak seasonal fluctuations in cocoa export forecasting, outperforming SES. Similarly, Toppur & Thomas (2023) found that ARIMA was more robust than SES when applied to datasets with volatile or non-repetitive seasonality. These models have also been validated in other industrial settings by Murpratiwi et al. (2021) and Dao & Chi (2023), confirming their versatility and reliability in forecasting tasks.

However, the majority of existing studies have focused on large-scale industries—such as agriculture, manufacturing, and services—where demand patterns are relatively stable and infrastructure resources are more robust. In contrast, small-scale creative industries like songkok production operate with limited technical capacity and face highly sporadic, seasonal demand. This sector remains underrepresented in forecasting literature, leaving a gap in understanding how predictive models can be effectively applied to artisanal production environments characterized by weak seasonality and operational constraints.

Addressing this research gap, the present study applies ARIMA and SES models to forecast monthly songkok sales at a small-scale manufacturer in Gresik, East Java, using historical data from July 2020 to August 2024. Although the Seasonal ARIMA (SARIMA) model is often favored for strong cyclical patterns, the weak and inconsistent seasonality observed in this dataset renders SARIMA less suitable. Instead, ARIMA offers superior flexibility and avoids overfitting, as it excludes unnecessary seasonal parameters. This modeling decision is supported by Rizvi et al. (2024), who highlighted ARIMA's strength in non-seasonal contexts, and by Chen (2024) and Szostek et al. (2024), who found ARIMA to outperform SARIMA in domains with low or unstable seasonality. The forecasting outputs from this study serve to improve raw material procurement, reduce inventory imbalances, and enable evidence-based decision-making in small-scale creative enterprises, thereby contributing to the broader literature on applied time series forecasting in informal and artisanal sectors.

2. MATERIALS AND METHODS

2.1 Materials

This study utilizes monthly production data from Tebu Mas Gresik, a small-scale songkok manufacturer located in East Java, Indonesia. The data, obtained from internal company documentation, covers the period from July 2020 to August 2024, totaling 50 observations. Production quantities were originally recorded in kodi, a traditional unit equal to 20 songkok units. For clarity and analytical precision, these values were converted into individual units (pieces). Supplementary information regarding raw material usage per kodi was gathered through direct interviews with production personnel. The data included estimates for various materials, such as velvet fabric, Cardillac fabric, carton support, plastic components, waterproof labels, and other accessories essential for songkok assembly.

In addition to primary data, this study employed a range of computational tools to support the forecasting analysis. The forecasting models were implemented using the Python programming language, particularly the *statsmodels* and *pandas* libraries for time series modeling and data manipulation. Microsoft Excel was also used to manually validate early calculations and conduct raw material estimation based on forecast outputs. Prior to model development, the dataset was preprocessed by detecting and addressing outliers using the Interquartile Range (IQR) method. A stationarity check was also conducted using the Augmented Dickey-Fuller (ADF) test. These materials—both data and tools—formed the foundation for constructing reliable forecasts and aligning them with practical raw material planning in a small-scale manufacturing context.

2.2 Methods

This study adopts a quantitative analytical approach to develop a forecasting framework for songkok production using time series data. The methodological structure is divided into five key stages: (1) data collection and preprocessing, (2) stationarity testing, (3) model development for ARIMA and Simple Exponential Smoothing, (4) model implementation and performance evaluation, and (5) conversion of forecast results into raw material planning. These stages are illustrated in Figure 2, which provides a visual overview of the sequential process applied in this study. This structured approach ensures systematic analysis and enhances the reproducibility of forecasting in small-scale, seasonal manufacturing contexts.

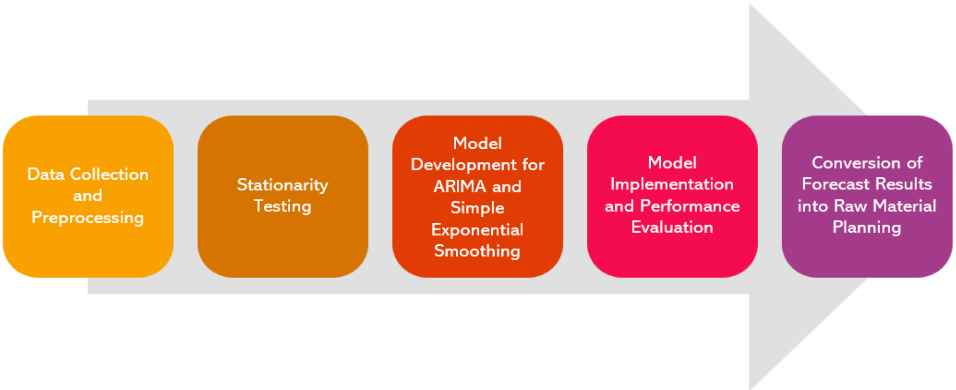

Figure 2. Research methodology

The time series data were first examined for completeness, with missing values and outliers addressed using the Interquartile Range (IQR) method. A stationarity test was then conducted using the Augmented Dickey-Fuller (ADF) method; since the series was found to be non-stationary, first-order differencing was applied. The ARIMA model was developed through identification of appropriate lag parameters using autocorrelation (ACF) and partial autocorrelation (PACF) plots. The chosen specification, ARIMA(1,1,1), integrates autoregressive, differencing, and moving average components. The SES model was also constructed by tuning the smoothing constant (α) to minimize forecasting error.

Both models were implemented using Python, with the statsmodels library for model construction and pandas for data handling. Forecast accuracy was evaluated using three standard metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE). The model with the best accuracy was then used to generate a five-month production forecast. These forecasts were subsequently translated into raw material requirements using material usage coefficients obtained from field interviews. This final step bridges statistical modeling with operational planning, ensuring that forecasted production volumes are directly actionable for inventory management and procurement scheduling.

3. RESULTS AND DISCUSSION

3.1 Time Series Data Description and Preprocessing

The monthly songkok production data, covering the period from July 2020 to August 2024 with 50 observations, is detailed in Table 1. Visual inspection of the time series data revealed moderate fluctuations, with production peaks commonly observed around Islamic religious events such as Ramadan and Eid. This pattern indicates the presence of weak and irregular seasonality.

Table 1. Monthly songkok production data

Year	Month	Sales Quantity (pcs)
2020	July	1600
2020	August	1600
2020	September	1700
2020	October	1500
2020	November	1300
2020	December	1660
2021	January	2040
2021	February	2400
2021	March	3000
2021	April	3600
2021	May	3340
2021	June	3060
2021	July	2800
2021	August	2400
2021	September	2000
2021	October	1860
2021	November	1740
2021	December	1600
2022	January	1800
2022	February	2000
2022	March	2300
2022	April	600
2022	May	1400
2022	June	2200
2022	July	1800
2022	August	2100
2022	September	2400
2022	October	2300
2022	November	2200
2022	December	2100
2023	January	2000
2023	February	2000
2023	March	2000
2023	April	1400
2023	May	1800
2023	June	2200
2023	July	1000
2023	August	1300
2023	September	1600
2023	October	1900
2023	November	1400
2023	December	1400

Table 1. Monthly songkok production data (continued)

Year	Month	Sales Quantity (pcs)
2024	January	1400
2024	February	2100
2024	March	2800
2024	April	1300
2024	May	1160
2024	June	1000
2024	July	1300
2024	August	1600

To ensure data quality, an outlier detection analysis was performed using the Interquartile Range (IQR) method. As summarized in Table 2, the calculated IQR was 38.75, with the first quartile (Q1) at 71.25 and the third quartile (Q3) at 110.00. These values yielded a lower bound of 13.125 and an upper bound of 168.125. Based on these thresholds, April 2021, with a production volume of 180 kodi (3600 pcs), was identified as an outlier. Despite this classification, the value was retained in the dataset to preserve essential seasonal variation characteristics.

Table 2. IQR-based outlier detection summary

Statistic	Value
Q1	71.25
Q3	110.00
IQR	38.75
Lower Bound	13.125
Upper Bound	168.125
Outlier Detected	April 2021 (180 kodi)

3.2 Stationarity Testing and ARIMA Model Development

To meet the stationarity requirement for ARIMA modeling, the Augmented Dickey-Fuller (ADF) test was conducted. The test produced an ADF statistic of -3.21 and a p-value of 0.02. As the p-value was lower than the 5% significance level, the differenced series was confirmed to be stationary. The ADF test results are visually presented in Figure 3, which confirms the stationary property after differencing.

```
ADF Statistic: -3.21
p-value: 0.02
Critical Values:
        1%: -3.57
        5%: -2.92
        10%: -2.60
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Figure 3. Results of augmented dickey-fuller test on differenced data

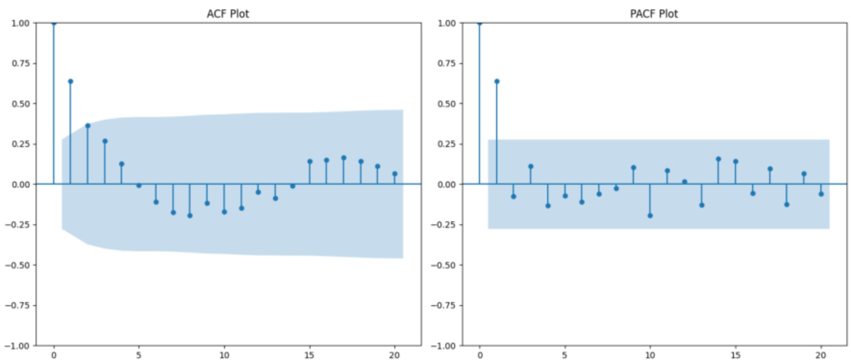

Figure 4. ACF and PACF plot analysis for arima model

Subsequently, autocorrelation function (ACF) and partial autocorrelation function (PACF) plots were analyzed to identify appropriate model lags. These plots, shown in Figure 4, guided the selection of the ARIMA(1,1,1) model specification, as they revealed significant first-lag autocorrelations in both ACF and PACF.

3.3 SES Model Implementation and Comparative Residual Analysis

The SES model was applied in parallel to serve as a benchmark forecasting approach. A smoothing factor (α) of 0.75 was selected based on empirical testing and supported by values commonly used in related studies. While ARIMA models incorporate both autoregressive and moving average terms to capture trends, SES relies on exponentially weighted moving averages, making it more responsive to recent observations in stable data. To validate the ARIMA model's adequacy, residual analysis was conducted, and the results are shown in Figure 5. The residuals exhibited random distribution with no significant autocorrelation, confirming that the model satisfies the white noise assumption.

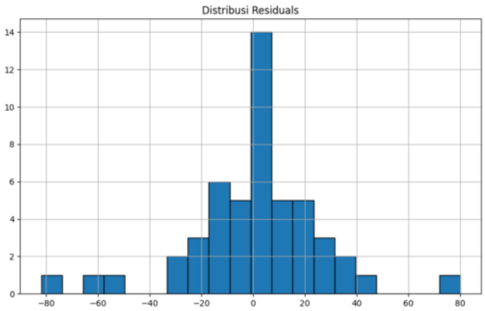

Figure 5. Residual distribution graph

3.4 Forecast Accuracy and Model Comparison

Both models were evaluated using Mean Absolute Error (MAE), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE). The results, summarized in Table 3, indicate that ARIMA provided better predictive accuracy across two of the three metrics.

Table 3. Forecast accuracy metrics of ARIMA and SES

Model	MAE	MSE	MAPE
ARIMA (1,1,1)	17.43	656.38	24.11%
SES	18.02	594.07	24.18%

To interpret MAPE results, the reference classification by Alzeyani & Szabó (2024) and Darmawan & Handoko (2023) was adopted (Table 4).

Table 4. MAPE interpretation categories

MAPE Range	MAPE Range
< 10%	Highly accurate forecast 10%–20%
10%–20%	Good forecast
20%–50%	Reasonable forecast
> 50%	Inaccurate forecast

3.5 Forecast Visualization and Interpretation

The five-month forecasts generated by ARIMA and SES are visualized in Figure 6 to Figure 9. Figure 6 displays the forecasted production trend produced by the ARIMA model, which shows a steady upward movement in line with anticipated peak periods. Figure 7 compares ARIMA predictions with historical data, demonstrating close alignment and validating the model's effectiveness in capturing seasonal fluctuations.

In contrast, Figure 8 illustrates the SES forecast, which presents a smoother yet flatter trend line. Figure 9 compares SES results to actual data, revealing that SES tends to underestimate demand during religious months. This contrast emphasizes the superior responsiveness of ARIMA in modeling irregular seasonal peaks.

Forecast Results:

	Period	Forecast Results
0	Sep 2024	84.613314
1	Oct 2024	87.676087
2	Nov 2024	89.709457
3	Dec 2024	91.059409
4	Jan 2025	91.955640

Figure 6. ARIMA forecasting results

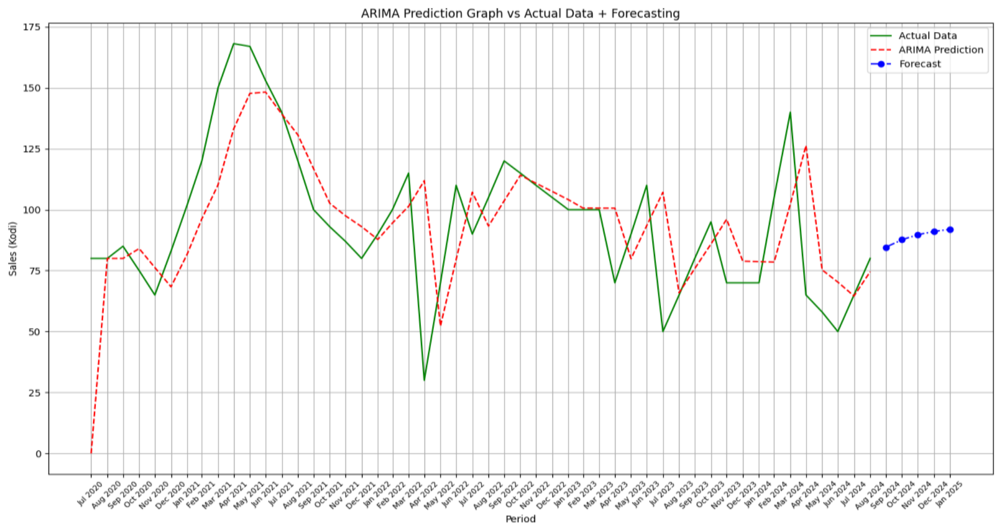

Figure 7. Comparison of ARIMA forecast and historical data

Forecast Result:

	Period	Forecast Result
2024-09-30	Sep 2024	76
2024-10-31	Oct 2024	76
2024-11-30	Nov 2024	76
2024-12-31	Dec 2024	76
2025-01-31	Jan 2025	76

Figure 8. SES forecasting results

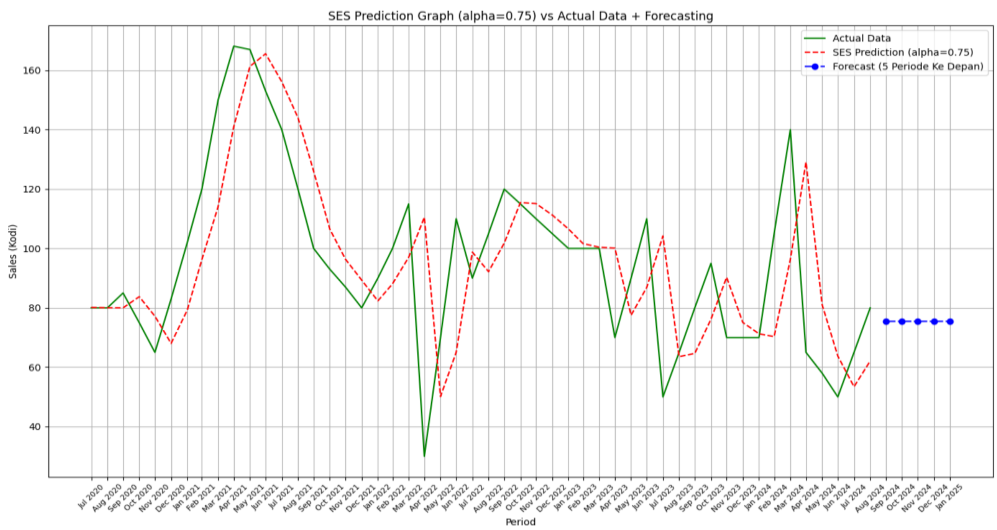

Figure 9. Comparison of SES forecast and historical data

3.6 Forecast-Based Production Planning

To develop an effective production planning strategy, it is essential to select a forecasting model that accurately reflects the underlying demand patterns. As established in the previous sections, the ARIMA(1,1,1) model demonstrated superior performance compared to the SES model. This superiority was evidenced by lower error values across multiple accuracy metrics, particularly Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE), as well as its ability to anticipate demand surges during religious peak seasons. Given its demonstrated accuracy and responsiveness to irregular seasonal trends, the ARIMA model was selected as the basis for production and inventory planning. Table 5 presents the five-month forecast of songkok production output from September 2024 to January 2025, expressed in kodi units (1 kodi = 20 units).

Table 5. ARIMA-based forecasted production output

Period	Forecast (kodi)
September 2024	84.61
October 2024	87.67
November 2024	89.70
December 2024	91.05
January 2025	91.95

These forecasted production volumes were subsequently used to determine raw material requirements. The calculations relied on conversion coefficients derived from field interviews with production staff at the company. Each raw material component, including fabric, packaging, and accessories, was mapped to a per-kodi usage rate to facilitate planning. The detailed estimations for each of the five forecasted production periods are presented in Table 6 to
Table 10, which provide the manual calculation of raw material requirements based on ARIMA(1,1,1)-generated production forecasts.

Table 6. Manual calculation of raw material requirements for periods 1

Raw Material	Raw Material Advice
Velvet Fabric (pcs)	0.067 x 84.61 = 5.66
Cardillac Fabric (pcs)	0.025 x 84.61 = 2.11
Carton Support (kg)	0.3 x 84.61 = 25.38
Plastic Support (pcs)	0.033 x 84.61 = 2.79
Tebu Mas Label (pcs)	(84.61 × 20) ÷ 12 = 142
Size Number (roll)	0.033 x 84.61 = 2.79
Waterproof Label (roll)	0.033 x 84.61 = 2.79
Head Cap Support (pcs)	20 x 84.61 = 1692
Body Cap Support (pcs)	20 x 84.61 = 1692

Table 7. Manual calculation of raw material requirements for periods 2

Raw Material	Raw Material Advice
Velvet Fabric (pcs)	0.067 x 87.67 = 5.87
Cardillac Fabric (pcs)	0.025 x 87.67 = 2.19
Carton Support (kg)	0.3 x 87.67 = 26.30
Plastic Support (pcs)	0.033 x 87.67 = 2.89
Tebu Mas Label (pcs)	(87.67 × 20) ÷ 12 = 147
Size Number (roll)	0.033 x 87.67 = 2.89
Waterproof Label (roll)	0.033 x 87.67 = 2.89
Head Cap Support (pcs)	20 x 87.67 = 1753
Body Cap Support (pcs)	20 x 87.67 = 1753

Table 8. Manual calculation of raw material requirements for periods 3

Raw Material	Raw Material Advice
Velvet Fabric (pcs)	0.067 x 89.70 = 6.009
Cardillac Fabric (pcs)	0.025 x 89.70 = 2.24
Carton Support (kg)	0.3 x 89.70 = 26.91
Plastic Support (pcs)	0.033 x 89.70 = 2.96
Tebu Mas Label (pcs)	(89.70 × 20) ÷ 12 = 150
Size Number (roll)	0.033 x 89.70 = 2.96
Waterproof Label (roll)	0.033 x 89.70 = 2.96
Head Cap Support (pcs)	20 x 89.70 = 1794
Body Cap Support (pcs)	20 x 89.70 = 1794

Table 9. Manual calculation of raw material requirements for periods 4

Raw Material	Raw Material Advice
Velvet Fabric (pcs)	0.067 x 91.05 = 6.10
Cardillac Fabric (pcs)	0.025 x 91.05 = 2.28
Carton Support (kg)	0.3 x 91.05 = 27.32
Plastic Support (pcs)	0.033 x 91.05 = 3
Tebu Mas Label (pcs)	(91.05 x 20) ÷12 = 152
Size Number (roll)	0.033 x 91.05 = 3
Waterproof Label (roll)	0.033 x 91.05 = 3
Head Cap Support (pcs)	20 x 91.05 = 1821
Body Cap Support (pcs)	20 x 91.05 = 1821

Table 10. Manual calculation of raw material requirements for periods 5

Raw Material	Raw Material Advice
Velvet Fabric (pcs)	0.067 x 91.95 = 6.16
Cardillac Fabric (pcs)	0.025 x 91.95 = 2.3
Carton Support (kg)	0.3 x 91.95 = 27.59
Plastic Support (pcs)	0.033 x 91.95 =3.03
Tebu Mas Label (pcs)	(91.95 x 20) ÷ 12 = 154
Size Number (roll)	0.033 x 91.95 = 3.03
Waterproof Label (roll)	0.033 x 91.95 = 3.03
Head Cap Support (pcs)	20 x 91.95 = 1838
Body Cap Support (pcs)	20 x 91.95 = 1838

3.7 Growth Trend in Raw Material Requirements

To enhance inventory and procurement planning, the percentage increase in raw material requirements across the five forecasted periods was analyzed. Table 11 presents the calculated growth rates for each component, highlighting material trends in response to rising production volumes.

Table 11. Percentage growth in raw material requirements across periods

Raw Material	P1 → P2	P2 → P3	P3 → P4	P4 → P5	Average Increase (%)
Velvet Fabric (pcs)	3.71%	2.39%	1.50%	0.98%	2.15%
Cardillac Fabric (pcs)	3.79%	2.28%	1.79%	0.87%	2.18%
Carton Support (kg)	3.62%	2.32%	1.52%	0.99%	2.11%
Plastic Support (pcs)	3.58%	2.42%	1.35%	1.00%	2.09%
Tebu Mas Label (pcs)	3.52%	2.04%	1.33%	1.32%	2.05%
Size Number (roll)	3.58%	2.42%	1.35%	1.00%	2.09%
Waterproof Label (roll)	3.58%	2.42%	1.35%	1.00%	2.09%
Head Cap Support (pcs)	3.62%	2.31%	1.51%	0.98%	2.11%
Body Cap Support (pcs)	3.62%	2.31%	1.51%	0.98%	2.11%

The results indicate a consistent and manageable growth trajectory, with an average increase in raw material usage ranging from 2.05% to 2.18% per month. This stable growth rate allows for the formulation of proactive stock management policies and supports procurement decisions that minimize the risk of material shortages or excessive inventory buildup during critical production cycles.

3.8 Discussion

This study contributes to the ongoing discourse on forecasting accuracy in uncertain and seasonally fluctuating production environments, particularly within small-scale traditional manufacturing. Consistent with the findings of Fahmuddin et al. (2023), the ARIMA model demonstrated superior performance compared to Simple Exponential Smoothing (SES) in handling irregular seasonality in demand. The results also align with the assertions of Toppur & Thomas (2023) regarding the strategic importance of model selection in volatile environments. While prior studies such as those by Dao & Chi (2023) have shown that ARIMA and Holt-Winters are effective in the food production sector. By contrast, the conclusions of Murpratiwi et al. (2021), who reported satisfactory SES performance in stable service environments, underscore that forecasting models must be aligned with the volatility and characteristics of the underlying dataset.

Beyond predictive accuracy, the findings of this research carry broader implications for enhancing operational efficiency and preserving the socio-cultural relevance of traditional crafts. Accurate forecasting ensures consistent production, which is vital for meeting demand during culturally significant periods such as Ramadan and Eid. As the songkok represents religious and cultural identity in Indonesia (Indonesia.go.id, 2019), maintaining stable output supports both business sustainability and cultural continuity. Efficient forecasting enables small and medium enterprises (SMEs) like Tebu Mas Gresik to improve inventory management, reduce material waste, and allocate limited resources more effectively (Adekunle et al., 2021; Aleksandrov, 2020; Bora & Bhonde, 2023; Fattah et al., 2018; Ghosh, 2020; Junthopas & Wongoutong, 2023; Kumar Tiwary et al., 2020; Liu et al., 2020; Lyu et al., 2023; Munyaka & Yadavalli, 2022; Pooniwala & Sutar, 2021).

Nonetheless, this study is subject to limitations. The reliance on univariate forecasting models—ARIMA and SES—excluded potentially relevant external variables such as holidays, promotions, or macroeconomic factors. Future research could address this limitation by implementing multivariate time series models that integrate contextual data for greater forecasting accuracy. Despite this constraint, the study demonstrates the practical viability of ARIMA in guiding short-term production planning for SMEs in traditional sectors.

Overall, the research reinforces the practical viability of ARIMA for guiding short-term production planning in small-scale traditional industries. Although the observed 2.05%–2.18% improvement in raw material efficiency may appear marginal, it holds significant operational value for micro-enterprises with constrained resources. These results also indicate the potential for broader application, especially when integrated with digital tools for forecasting and planning. Beyond the scope of individual enterprises, such data-driven approaches could be leveraged by policymakers to support the digital transformation and long-term sustainability of culturally significant craft sectors.

4. CONCLUSION

This study empirically confirms the applicability of the ARIMA model for short-term production forecasting in small-scale traditional industries characterized by irregular seasonality. Compared to Simple Exponential Smoothing (SES), ARIMA(1,1,1) demonstrated superior performance in modeling demand volatility, supported by lower MAE, MSE, and MAPE values, as well as residual randomness. The model's forecasts were effectively translated into raw material planning, resulting in increased inventory precision and material efficiency gains ranging from 2.05% to 2.18%. These gains are operationally significant for micro-enterprises operating with limited resources, particularly during culturally sensitive periods such as Ramadan and Eid.

Despite its usefulness, the study is constrained by its reliance on univariate models that do not account for external factors such as holidays, economic conditions, or promotional events. Future studies should explore multivariate or hybrid approaches (e.g., ARIMA-LSTM) that incorporate contextual variables to improve accuracy. Moreover, embedding such forecasting models into digital inventory systems could enable more agile and responsive planning. At a broader level, these findings offer a scalable foundation for promoting data-driven decision-making and sustaining the socio-economic relevance of traditional crafts within Indonesia's creative economy.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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