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Forecasting Production Growth of Micro and Small Textile Industries Using SARIMA

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ABSTRACT

Micro and small industry (MSME) is an industrial sector that includes small-scale businesses, both those with limited assets and turnover. MSME is an industrial business that is mostly labor-intensive and plays a role in creating jobs and driving the local economy. One of the largest industries in MSME is the textile industry. Production in the textile industry tends to fluctuate due to market demand, availability of raw materials, and economic conditions. Understanding the dynamics of market demand is very important for the government and business actors in making decisions. This study aimed to predict the growth of MSME production in the textile industry using the seasonal autoregressive integrated moving average (SARIMA) method. Several SARIMA models were used to predict the growth of MSME production in the textile industry. However, only the model with the smallest AIC value was selected to predict the growth of MSME production in the textile industry. The prediction results showed that fluctuations occurred in the growth of the textile industry in each period.

1. Introduction

Micro and small industries (MSMEs) play a vital role in supporting the Indonesian economy. Data from the Ministry of Cooperatives and SMEs indicate that MSMEs currently number around 64.2 million business units and contribute 61.07% to the national gross domestic product (GDP), equivalent to IDR 8,573.89 trillion. In addition, this sector absorbs approximately 117 million workers, representing 97% of the total workforce, and accounts for 60.4% of total investment [1],[2], [3].

The Special Region of Yogyakarta is home to a variety of creative and labor-intensive industries, making MSME a crucial sector in the regional economy. One subsector with a significant contribution is the textile industry [4]. According to the Statistics Indonesia (Badan Pusat Statistik, BPS), in 2023, the textile industry ranked fourth and was among the top five MSME businesses, with 263,304 businesses [5], [6]. However, production growth in the micro and small-scale textile industry tends to fluctuate. This is due to market demand, raw material availability, and economic conditions [7]. Understanding this dynamic market demand is crucial for the government and businesses in decision-making [8].

Based on this, an analytical approach was used to model and forecast the temporal dynamics of textile industry growth to facilitate targeted planning and policymaking. One method that can be used to forecast MSME production growth in the textile industry is the seasonal autoregressive integrated moving average (SARIMA) [9]. The SARIMA method is a development of the autoregressive integrated moving average (ARIMA) method, which examines seasonal patterns [10]. The SARIMA method performs forecasting in the following stages: (1) data stationarity test, (2) identifying the order of the SARIMA model, (3) parameter estimation, (4) diagnostic testing, and (5) forecasting [11].

Several previous studies, such as [12], showed that the SARIMA method with the SARIMA$(1,0,1)(1,0,0)_{12}$ had good forecasting capabilities in the context of the agricultural sector industry, especially palm oil in Indonesia with a mean absolute percentage error (MAPE) of 5.54%. Then, another research showed that SARIMA method with the SARIMA$(0,1,1)(0,1,1)_{7}$ could predict the number of positive COVID-19 patients in Padang City with a MSE value of 330.9333 [13]. Then, [14] showed that the SARIMA method with the SARIMA$(1,1,2)(1,1,1)_{12}$ was the most appropriate model for forecasting rice production in Bone Regency with an Akaike information criterion (AIC) value of 2996.04. By applying the SARIMA model, it is hoped that an accurate picture can be obtained regarding the patterns and trends of the textile industries in Special Region of Yogyakarta and can predict future periods.

2. Method

2.1. Data

The data used in Table 1 are quarterly time series data on MSME production in the textile industry in the Special Region of Yogyakarta. The observation period covered 2012 to 2024. Since each year consisted of four quarters, namely Q1, Q2, Q3, and Q4, the dataset contained 52 quarterly observations. The data were presented in percentage units because the main variable analyzed was the production growth rate, not the absolute production quantity.

In the dataset, the variable Year indicates the calendar year of observation. The variables Q1, Q2, Q3, and Q4 represent the first, second, third, and fourth quarters of each year, respectively. Each value in these quarterly columns shows the percentage change in textile MSME production compared with the previous corresponding period. A positive value indicates an increase in production, while a negative value indicates a decline in production. To obtain the MSME production growth value, (1) is used:

$$Production\ growth = \frac{I_{i,t} - I_{i,t-1}}{I_{i,t-1}} \times 100\% \quad (1)$$

where $I_{i,t}$ denotes the production quantity in the i quarter at time *t*; $I_{i,t-1}$ denotes the production quantity in the i quarter at time *t-1*; i denotes 1,2,3,4; t denotes 1,2,…,*n*; and n denotes the quantity of data.

Table 1. Growth of Micro and Small Textile Industry Production

Year	Q1	Q2	Q3	Q4
2012	−2.7	−5.52861	−5.73428	0.650671
2013	−1.89974	13.52156	11.88547	10.47474
2014	8.55	4.69	−19.23	−10.13
⋮	⋮	⋮	⋮	⋮
2023	62.80292	20.21481	47.65274	38.12626
2024	34.72581	22.72374	15.7505	44.63928

2.2. Stationarity

To forecast with SARIMA, the data must meet the stationary assumption. Data are said to be stationary if the means and variance are constant for each observation [15]. If the data are nonstationary, differencing can be applied to achieve stationarity. In this study, the augmented Dickey–Fuller (ADF) test was used to assess stationarity in the mean, while the Levene test was employed to examine stationarity in the variance.

To determine the stationarity of the series mean, the Augmented Dickey-Fuller (ADF) test was used using the following hypotheses and a test statistic [16]. The hypothesis used is the following.

H_0: data contains a unit root
H_1: data does not contain a unit root

Meanwhile, (2) is a test statistic used.

$$\Delta Y_t = \beta_1 + \beta_2 + \delta Y_{t-1} + \phi_i \sum_{i=1}^{k} \Delta Y_{t-1} + \varepsilon_t \tag{2}$$

Critical region:

Reject H_0 if $t_{value} < t_{table}(\alpha; n-1)$ or $p-value < \alpha(0.05)$

where ΔY_t is the first difference Y, β_1 is the constant or intercept value, β_2 is the coefficient for trend, δ is the coefficient for lag Y, ϕ is the coefficient for difference lag Y, ε is the error, k is the lag, and t is the time.

Meanwhile, to determine the stationarity of variance, Levene test was used using the following hypothesis and test statistic [17]:

$H_0: \sigma_1^2 = \sigma_2^2 = \cdots = \sigma_k^2$ (variances between groups are equal)

$H_1: \sigma_i^2 \neq \sigma_j^2$ for at least one pair (i, j)

The test statistic is showed in (3).

$$W = \frac{(N-k)}{k-1} \times \frac{\sum_{i=1}^{k} n_i (Z_{i.} - \bar{Z}_{..})^2}{\sum_{i=k}^{k} \sum_{j=1}^{n_i} \left(Z_{ij} - \bar{Z}_{i.}\right)^2} \tag{3}$$

Critical area:

Reject H_0 if $W > F_{table(\alpha; k-1, n-k)}$ or $p-value < \alpha(0.05)$

with $Z_{ij} = \left|y_{ij} - \bar{y}_i\right|$, $\bar{Z}_{..} = \frac{\sum_{i=1}^{k} \sum_{j=1}^{n_i} Z_{ij}}{N}$, and $\bar{Z}_{i.} = \frac{\sum_{j=1}^{n_i} Z_{ij}}{N_i}$. Meanwhile, N denotes the total number of observations from all groups, $k$denotes the number of groups, and n_i denotesnumber of observations in group i

2.3. Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF)

In time series analysis, autocorrelation function (ACF) is a measure of the relationship between observations at time t and the previous time [18], [19]. The equation for the ACF at lag k (ρ_k) is shown in (4) [20]:

$$\rho_k = \frac{\sum_{t=1}^{n-k} (y_t - \bar{y})(y_{t+k} - \bar{y})}{\sum_{t=1}^{n} (y_t - \bar{y})^2} \tag{4}$$

where ρ_k denotes the autocorrelation coefficient at lag k, y_t denotes the data value at time t; $\bar{y}$ denotes data mean; t denotes 1,2,3,…,n; n denotes the number of data points; and k denotes lag (time interval between two observations being compared).

If value of ρ_k is in the interval -1 to 1 and if $\rho_k = 0$, then it indicates that there is no autocorrelation in the data. Meanwhile, the partial autocorrelation function (PACF) is a measure of the relationship between two different time series data when the influence of other variables has been removed [17]. Equation (5) was used to calculate the PACF (ϕ_{kk}) [21]:

$$\phi_{kk} = \begin{cases} \rho_1, & k = 1 \\ \frac{\rho_k - \sum_{i=1}^{k-1} (\phi_{k-1,i})(\rho_{k-i})}{1 - \sum_{i=1}^{k-1} (\phi_{k-1,i})(\rho_i)}, & k > 1 \end{cases} \tag{5}$$

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where ϕ_{kk} is the partial autocorrelation coefficient at the k lag, $\phi_{k-1,i}$is the partial autocorrelation coefficient at the i lag of the *k-1* order model, ϕ_{k-i} is the autocorrelation coefficient at the *k-i* lag, and ρ_i is the autocorrelation coefficient at the i lag.

2.4. Seasonal Autoregressive Integrated Moving Average (SARIMA)

The SARIMA method is a development of the ARIMA method that can analyze seasonal data patterns [22]. Data are said to have a seasonal pattern if there is a recurring pattern in certain periods, such as weekly, monthly, quarterly, semi-annually, and annually. The SARIMA method combines nonseasonal and seasonal components in one analytical framework with the notation $(p,d,q)(P,D,Q)_S$ [23]. The general equation for the SARIMA method is shown (6) [24]:

$$\Phi_p(B^S)\Phi_P(B)(1-B)^d(1-B^S)^D y_t = \theta_q(B)\Theta_Q(B^S)\varepsilon_t \quad (6)$$

where $\Phi_p(B^S)$ represents the seasonal autoregressive (AR) rate, $\Phi_P(B)$ represents the nonseasonal AR rate, $(1-B)^d$ represents the nonseasonal differencing rate, $(1-B^S)^D$ represents the seasonal differencing rate, $\theta_q(B)$ represents the nonseasonal moving average (MA), $\Theta_Q(B^S)\varepsilon_t$ represents the seasonal MA, y_t represents the actual value of period t, ε_t represents the error of period t, p represents order of the nonseasonal AR model, P represents the order of seasonal AR model, q represents the order of nonseasonal MA model, Q represents the order of the seasonal MA model, d represents the nonseasonal differencing, and D represents the seasonal differencing.

2.5. Diagnostic Test

Diagnostic tests were employed to determine model adequacy by examining the independence and normality of residuals. To check the independence of residuals, the Ljung-Box test was used with the following hypotheses and test statistics [21], [25]. The hypothesis is shown below.

$H_0: \rho_i = 0$ (no residual autocorrelation)
$H_1: \exists \rho_i \neq 0$ (residual autocorrelation exists)

The test statistic is showed in (7).

$$Q_{LB} = n(n+2)\sum_{i=1}^{k}\left(\frac{1}{n-k}\right)\rho_k^2 \quad (7)$$

Critical area:

Reject H_0 if $Q_{LB} > \chi^2{}_{(\alpha;k-p)}$ or $p-value < \alpha(0.05)$

with k denotes the maximum number of lags and ρ_k denotes the autocorrelation coefficient at the k lag.

To check the normality of the residuals, the Jarque-Berra test was used with the following hypothesis and test statistics [26], [27]. The hypothesis is shown below.

H_0: residuals are normally distributed
H_1: residuals are not normally distributed

The test statistic is showed in (7).

$$JB = \frac{n}{6}\left(S^2 + \frac{(K-3)^2}{4}\right)(8)$$

Critical area:

Reject H_0 if $JB > \chi^2{}_{(2;\alpha)}$ or $p-value < \alpha(0.05)$

with:

$$\boldsymbol{S^2} = \frac{\sum_{t=1}^{n}(\varepsilon_t-\bar{\varepsilon})^3}{n\left(\frac{1}{n}\sum_{t=1}^{n}(\varepsilon_t-\bar{\varepsilon})^2\right)^{3/2}} \text{ (skewness value)}$$

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$$K = \left(\frac{\sum_{t=1}^{n} (\varepsilon_t - \bar{\varepsilon})^4}{n \left(\frac{1}{n} \sum_{t=1}^{n} (\varepsilon_t - \bar{\varepsilon})^2 \right)^4} \right) \text{(kurtosis value)}$$

2.6. Model Evaluation

In determining the best model to be used for forecasting, AIC was used [25]. The AIC value can explain how well a model fits existing data and future values [28]. Asymptotically, the AIC selects the model that minimizes the squared error of the prediction or estimate. The best SARIMA model is determined by selecting the smallest AIC value. To find the AIC value, (9) was used [21]:

$$AIC = n \ln \left(\frac{SSE}{n} \right) + 2(p + q + 1) \quad (9)$$

where n is the number of data, SSE the sum of squared errors, p is the order of AR, and q is the order of MA.

In addition to the AIC value, another model evaluation used was the MAPE. MAPE was used to see the error value in predictions against actual data [29], [30]. The smaller the MAPE value, the more accurate the forecasting results. Equation (1) is MAPE values are, while its categorization is presented in Table 2.

$$MAPE = \frac{100\%}{n} \sum_{t=1}^{n} \left| \frac{A_t - F_k}{A_t} \right| \quad (10)$$

with A_t represents the actual value at time *t; F_t* represents the predicted value at time *t*; t represents 1,2,3,…,*n; n* represents the amount of data.

Table 2. MAPE Value Categorization

MAPE Value (%)	Category
< 10	High prediction accuracy
$10 - 20$	Prediction accuracy is good
$20 - 50$	Prediction accuracy is sufficient
> 50	Inaccurate/poor prediction accuracy

The steps in this work are presented in Fig. 1.

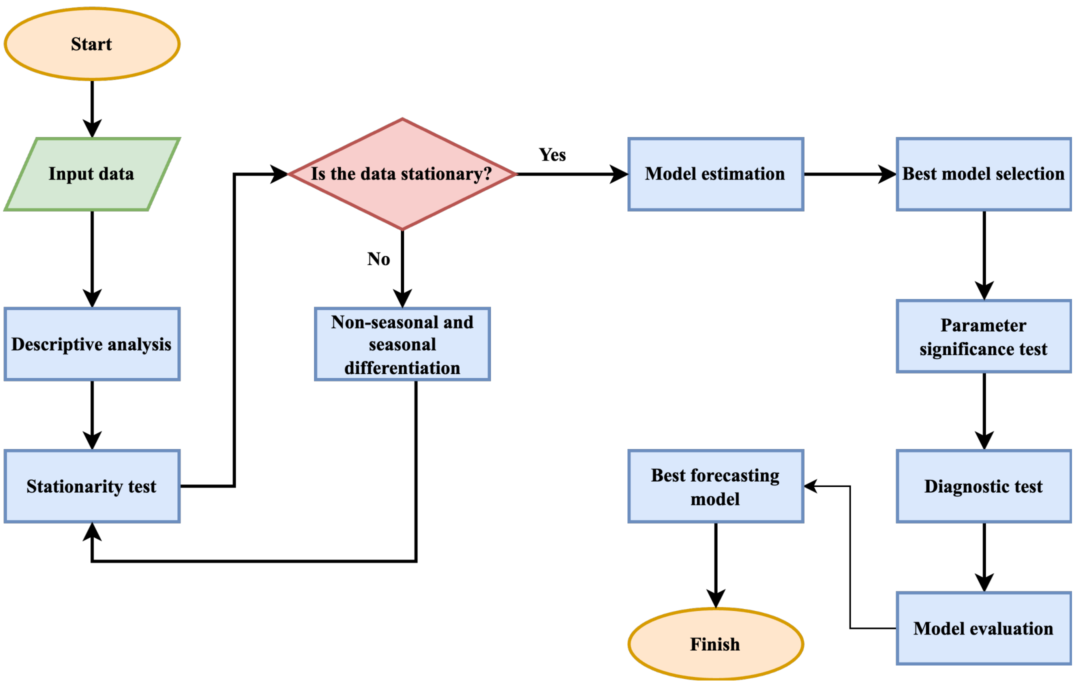

Fig 1. Research flow.

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3. Results and Discussion

To perform time series analysis using the SARIMA method, the assumption of stationary data must first be met. To determine whether the data were stationary on average, the ADF test was used (Table 3).

Table 3. ADF Test Result

	Dickey-Fuller	*p*-Value
ADF Test	−3.9289	0.0194

Based on the results of the ADF test in Table 3, $t_{value} = -3.9289 < t_{table} = -2.89$ and $p-$value $= 0.0194 < \alpha = 0.05$ so that the H_0 was rejected or the data did not contain a unit root. Therefore, the growth data of the micro and small textile industry sector were already stationary in the mean. Next, a Levene test was carried out to determine whether the data were stationary in terms of variance, the results are presented in the Table 4.

Table 4. Levene's Test Result

	W	*p*-Value
Levene's Test	0.1207	0.9475

Based on the Levene test results in Table 4, $W = 0.1207 < F_{(0.05;3,48)} = 2.8$ and $p -$ value $= 0.9475 > \alpha = 0.05$, thus failing to reject H_0. Therefore, the data on the growth of micro and small textile industries had the same variance, indicating that the data were stationary in variance.

In addition to the ADF and Levene's tests, the ACF and PACF plots were also examined to identify the model, as shown in Fig. 2.

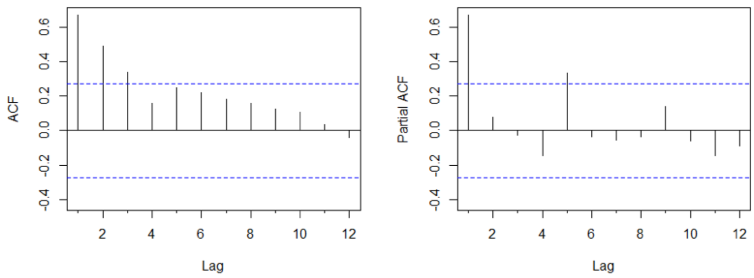

Fig. 2 ACF and PACF plot.

Based on the ACF and PACF plots in Fig. 2, ACF plot showed a gradual decline (tailing off) and a cut-off occurred in the PACF plot at the first lag, indicating AR(1). Although the data were stationary, the ACF and PACF plots showed a seasonal pattern. Therefore, the nonseasonal and seasonal differencing was performed using the ADF test results as shown in Table 5 and the ACF and PACF plots in Fig. 3 and Fig. 4.

Table 5. ADF Test Results After One-Time Differencing

Differencing	ADF	*p*-Value
Nonseasonal ($d = 1$)	−5.922	0.01
Seasonal ($D = 1$)	−6.8722	0.01

Based on the results of the ADF test in Table 5, $\tau_{non-seasonal} = -5.922 < t_{table} = -2.89$ and $\tau_{seasonal} = -6.8722 < t_{table} = -2.89$ and $p -$ value $= 0.01 < \alpha = 0.05$ for both nonseasonal and seasonal so that H_0 was rejected or the data did not contain a unit root. Therefore, the growth data of the micro and small textile industries was stationary nonseasonally and seasonally after the first differencing. Fig. 3 and Fig. 4 shows plot of ACD and PACF after one-time nonseasonal and seasonal differencing.

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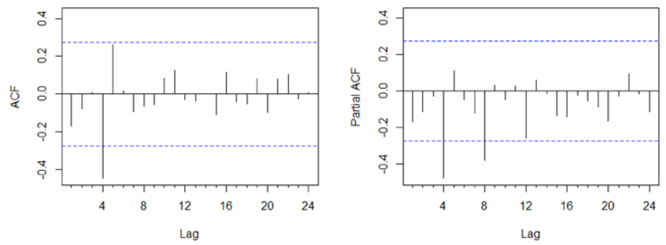

Fig. 3 Plot of ACF and PACF after one-time nonseasonal differencing.

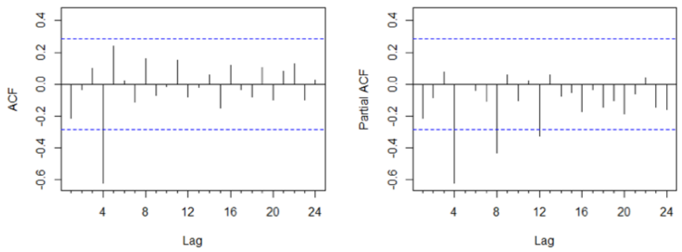

Fig. 4 Plot of ACF and PACF after one-time seasonal differencing.

Based on Fig. 3 and Fig. 4, the SARIMA model was obtained SARIMA(1,1,1)(3,1,1)$_4$. From this SARIMA model, overfitting was performed by selecting a lower order or a combination of the main orders. The several SARIMA models are formed and presented in the Table 6.

Table 6. Significant Parameter Test

Model	Coefficient Estimation		p-value	Parameter Significance
SARIMA$(1,1,1)(3,1,1)_4$	AR1	-0.6846	NaN	Not Significant
	MA1	0.5478	NaN	Not Significant
	SAR1	-0.7482	0.0002	Significant
	SAR2	-0.5677	0.0159	Significant
	SAR3	-0.4297	0.0359	Significant
	SMA1	-0.7578	0.0062	Significant
SARIMA$(1,1,1)(1,1,1)_4$	AR1	0.62	1.06×10^{-3}	Significant
	MA1	-0.955	6.5419×10^{-4}	Significant
	SAR1	-0.3473	1.2061×10^{-2}	Significant
	SMA1	-0.9999962	2.1543×10^{-6}	Significant
SARIMA$(1,1,1)(0,1,1)_4$	AR1	0.5451	3.0255×10^{-5}	Significant
	MA1	-0.9999989	1.0877×10^{-9}	Significant
	SMA1	-0.9999994	1.3189×10^{-13}	Significant
SARIMA$(1,1,1)(3,1,0)_4$	AR1	0.7349	4.3477×10^{-9}	Significant
	MA1	-0.9999	1.3074×10^{-4}	Significant
	SAR1	-1.1671	0	Significant
	SAR2	-0.9726	1.9062×10^{-8}	Significant
	SAR3	-0.6013	3.1921×10^{-5}	Significant
SARIMA$(0,1,1)(3,1,1)_4$	MA1	-0.2715	0.1257	Not Significant
	SAR1	-0.7054	0.0007	Significant
	SAR2	-0.5329	0.0225	Significant
	SAR3	-0.39	0.0761	Not Significant
	SMA1	-0.785	0.0036	Significant

A parameter is said to be significant if the $p - \text{value} < \alpha = 0.05$. Based on Table 6, the SARIMA$(1,1,1)(1,1,1)_4$, SARIMA$(1,1,1)(0,1,1)_4$, and SARIMA$(1,1,1)(3,1,0)_4$ models were models with all significant parameters. Hence, the three models were continued for diagnostic testing. The diagnostic tests consisted of autocorrelation and residual normality tests. The residual autocorrelation hypothesis was tested using the Ljung-Box method, and the results are presented in Table 7.

Table 7. Results of Residual Autocorrelation Test

Model	Q_{LB}	*p*-Value	Decision
$\text{SARIMA}(1,1,1)(1,1,1)_4$	0.044755	0.08325	Failed to reject H_0
$\text{SARIMA}(1,1,1)(0,1,1)_4$	0.001662	0.9675	Failed to reject H_0
$\text{SARIMA}(1,1,1)(3,1,0)_4$	0.020159	0.8871	Failed to reject H_0

Based on the results of the Ljung-Box test in Table 7.

Table 7, the data supported the rejection of H_0. Therefore, the $\text{SARIMA}(1,1,1)(1,1,1)_4$, $\text{SARIMA}(1,1,1)(0,1,1)_4$, and $\text{SARIMA}(1,1,1)(3,1,0)_4$ models did not have residual autocorrelation. Next, the normality test was conducted for residuals using Jarque-Bera, and the results are presented in Table 8.

Table 8. Results of the Residual Normality Test

Model	JB	*p*-Value	Decision
$\text{SARIMA}(1,1,1)(1,1,1)_4$	80.506	2.2×10^{-16}	Reject H_0
$\text{SARIMA}(1,1,1)(0,1,1)_4$	115.02	2.2×10^{-16}	Reject H_0
$\text{SARIMA}(1,1,1)(3,1,0)_4$	152.24	2.2×10^{-16}	Reject H_0

Based on the results of the Jaque Bera test in Table 8, the data supported the rejection of H_0. Therefore, the residuals in the $\text{SARIMA}(1,1,1)(1,1,1)_4$, $\text{SARIMA}(1,1,1)(0,1,1)_4$, and $\text{SARIMA}(1,1,1)(3,1,0)_4$ models were not normally distributed.

Subsequently, a model evaluation was conducted to select the best SARIMA model from the three obtained models. The best model was used to forecast the growth of the textile industry's MSME in the Special Region of Yogyakarta. The AIC values for each SARIMA model are presented in Table 9.

Table 9. Model Evaluation

Model	AIC
$\text{SARIMA}(1,1,1)(1,1,1)_4$	175.9681
$\text{SARIMA}(1,1,1)(0,1,1)_4$	179.355
$\text{SARIMA}(1,1,1)(3,1,0)_4$	176.1909

Based on the results in Table 9, the best model for predicting the growth of the textile industry's MSME in Special Region of Yogyakarta was the $\text{SARIMA}(1,1,1)(1,1,1)_4$ with the smallest AIC value, namely 175.9681. The forecasting results of the model are shown in Fig. 5 and Table 10.

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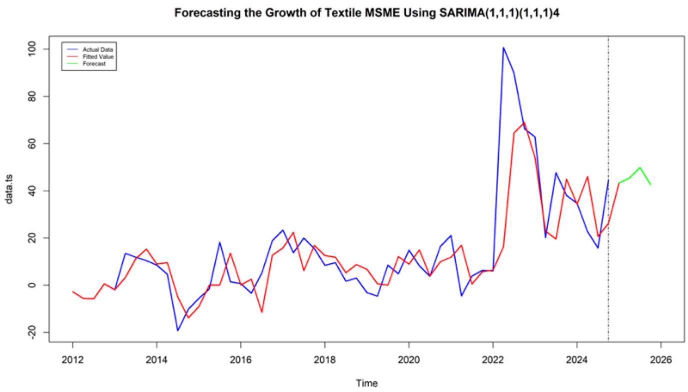

Fig. 5 Comparison plot of actual and forecasted data.

Table 10. Forecast results for 2025

Period (Quarter)	Forecast
Quarter 1	43.38008
Quarter 2	45.5073
Quarter 3	49.90919
Quarter 4	42.66065

Based on Tabel 10, the predicted increase from the first to the third quarter indicates potential growth improvement during the middle of the year, while the decline in the fourth quarter suggests a possible weakening toward the end of the year. The MAPE value of 34.81% indicates moderate forecasting accuracy, meaning that the SARIMA model can be used as an initial forecasting tool, although further improvement may be needed by incorporating external factors such as market demand, raw material availability, and economic conditions.

4. Conclusion

Based on the analysis and discussion, the $\text{SARIMA}(1,1,1)(1,1,1)_4$ model was identified as the best model for forecasting the production growth of micro and small textile industries in the Special Region of Yogyakarta. The forecasting results indicate that production growth is expected to fluctuate throughout 2025, with an increase from the first to the third quarter followed by a decline in the fourth quarter. This pattern suggests that textile MSMEs may still face unstable production dynamics, which should be considered in production planning, raw material management, and policy support. The MAPE value of 34.81% indicates moderate forecasting accuracy; therefore, the model can be used as an initial forecasting tool, although future studies may improve the prediction by incorporating external factors such as market demand, raw material availability, and economic conditions.

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