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Implementation of The Seasonal Autoregressive Integrated Moving Average Predictive Model on Raw Material Usage Data at PT. Plastik Karawang Flexindo

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Abstract

Fluctuations in raw material utilization in the manufacturing industry significantly impact production process efficiency, operational costs, and supply chain stability. Inaccurate planning and management of raw material inventories can lead to two extreme conditions: excess stock, which increases storage costs and the risk of expiration, or stock shortages, which could halt the production process and reduce productivity. To improve the accuracy of raw material consumption planning, this study applies the Seasonal Autoregressive Integrated Moving Average (SARIMA) model to predict raw material needs periodically based on historical data. The dataset used includes the consumption of Polyethylene (PE), High Density Polyethylene (HDPE), and Polypropylene (PP) from 2019 to 2025. The data is analyzed using a time series forecasting approach to identify trends and seasonal patterns. The SARIMA model is developed and optimized using three methods to search for the best parameters: Grid Search, Random Search, and Bayesian Optimization, to enhance prediction performance. The model's evaluation calculates the Mean Absolute Percentage Error (MAPE) as an accuracy indicator. The evaluation results show that although SARIMA can recognize seasonal patterns in raw material consumption, the prediction accuracy varies, with the best MAPE value being 16% and the highest being 34%. This indicates that external factors, such as market dynamics, government policies, global price fluctuations, and internal variables such as production schedules and customer demand, need to be considered to improve the model's precision. Overall, the application of SARIMA in this context provides a strategic contribution to supply chain management in the manufacturing industry, particularly in anticipating raw material needs, reducing uncertainty, and supporting more efficient and adaptive data-driven decision-making.

Keywords: *Forecasting, SARIMA, Overstock, Stockout, Optimization.*

1. Introduction

In the manufacturing industry, efficient raw material management is one of the main factors in maintaining smooth production and increasing profitability [1]. One approach increasingly applied is using *machine learning* technology with predictive models to control raw material usage and stock [2]. With this technology, companies can estimate material needs more accurately, reduce waste, and prevent the risk of excess or insufficient stock that can disrupt operations [3].

In addition to improving planning accuracy, predictive models also reduce storage costs. The risk of expiration or deterioration of raw materials can be reduced by minimizing excess stock. On the other hand, stock shortages that could potentially halt production and disrupt delivery schedules can also be prevented, thus maintaining customer satisfaction [4].

One method that can predict the amount of raw material usage in the future is seasonal autoregressive integrated moving average (SARIMA). This model is designed to handle time series data with seasonal patterns, such as raw material consumption patterns that repeat in a particular cycle. Considering seasonal trends and fluctuations can provide more accurate predictions than conventional methods [5].

The main advantage of SARIMA lies in its ability to recognize seasonal patterns in historical data. By considering autoregressive components, moving averages, and data differentiation, the model can adjust to evolving trends and provide more stable prediction results. In addition, compared to machine learning models that require a large amount of training data, SARIMA is more straightforward to implement because it only relies on historical data that is already available [6].
On the other hand, this model also has advantages in terms of interpretability. Unlike some complex and difficult-to-understand algorithms, SARIMA works with clear statistical principles, so its prediction results can be easily analyzed and optimized according to industry needs. The stability of the model also reduces the risk of overfitting, making it a reliable solution for efficiently planning raw material procurement [7].

2. Research Methods

2.1. Research Tools

This research uses various libraries in the Python programming language, including Pandas, NumPy, Matplotlib, Statsmodels, and Scikit-Learn, which are used for data manipulation, statistical analysis, and predictive modeling [8], [9]. The modeling and analysis were run using Google Colab, which was chosen for its ease of access and flexibility, so it does not require high hardware specifications for the training, evaluation, and validation of the models [10]. For the data collection and filtration process, SQL Server was used, which enabled the extraction of historical raw material usage data from the manufacturing system. The obtained data was then processed and converted into time series format for further analysis [11], [12], [13].

2.2 Research Design

This research uses a quantitative method with a time series forecasting approach to predict raw material usage in manufacturing [14], [15]. The model used is Seasonal Autoregressive Integrated Moving Average (SARIMA) because the data shows repeated seasonal patterns. The research steps are shown in Figure 1 below.

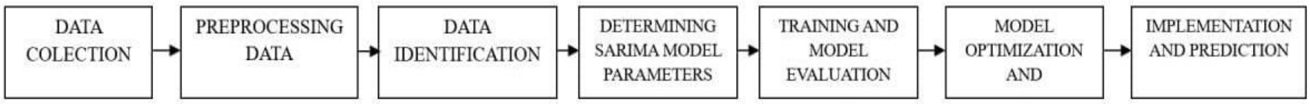

Fig 1. Research Steps

2.3 Data Collection

The data used in this study comes from a manufacturing system that records the use of raw materials over seven years (January 2019 - February 2025). This data is obtained through querying the SQL Server database, with the primary hyperparameters in the form of transaction periods and the amount of raw materials used which are separated based on three types of raw materials in the form of plastic seeds, namely PE (Low Density Polyethylene), HD (High Density Polyethylene) and PP (Polypropylene).

2.4 Data Preprocessing

Before modeling, the data goes through a preprocessing stage, namely performing data cleaning, which aims to remove duplicate data and handle outliers using the Interquartile Range (IQR) method. The next step is to perform data transformation (data transformation). The data is converted to time series format with monthly and annual (yyy-MM) aggregation to analyze seasonal patterns.

2.5 Data Identification

The data is analyzed using graph visualization to identify trend, seasonal, and residual patterns. Classical Seasonal Decomposition of Time Series is applied to distinguish trend, seasonal, and residual components to ascertain whether there is a significant seasonal pattern in the data.

2.6 Determining The Hyperparameters of The SARIMA Model

The SARIMA model has 4 hyperparameter functions, namely Autoregressive Hyperparameter (p), Differencing (d), Moving Average (q), Seasonal (s). Hyperparameters p and q are determined based on patterns identified from the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF). The hyperparameter d is first determined using an intuitive approach according to the ACF and PACF data patterns. The hyperparameter s is determined based on the seasonal period in the data. For example, if the hyperparameter s is six then the period is 6 monthly, if the value is 12 then the period is 12 months or yearly.

2.7 Training and Model Evaluation

The SARIMA model was trained using a train-test split with 80% of the data for training and 20% for testing. Model evaluation is performed with two main metrics, namely Mean Absolute Error (MAE) to measure the average absolute error between actual and predicted values, and Root Mean Squared Error (RMSE) to measure the average squared error of predictions.

2.8 Model Optimization and Validation

The model was tested with various combinations of SARIMA hyperparameters to obtain results with the lowest MAE and RMSE values. Validation is done by comparing the prediction results of the SARIMA model to the actual data in the latest period.

2.9 Implementation and Prediction

After the best model is obtained, predictions of raw material usage for the coming period are made. The results of this prediction can be used as a basis for decision making in controlling raw material stocks, so as to reduce the risk of overstock and stockout in the manufacturing industry.

3. Results and Discussion

3.1. Dataset Collection

The PE, HD, and PP raw material usage data collected consists of 222 rows of data. Each type of plastic seed has 74 rows of data with two columns, namely Period and Qty. The Period column shows the sequence of months sequentially from 2019 to 2025, while the Qty column contains numerical values that represent the amount of raw material usage in each period. An illustration of the data division is shown in Figure 2 below.

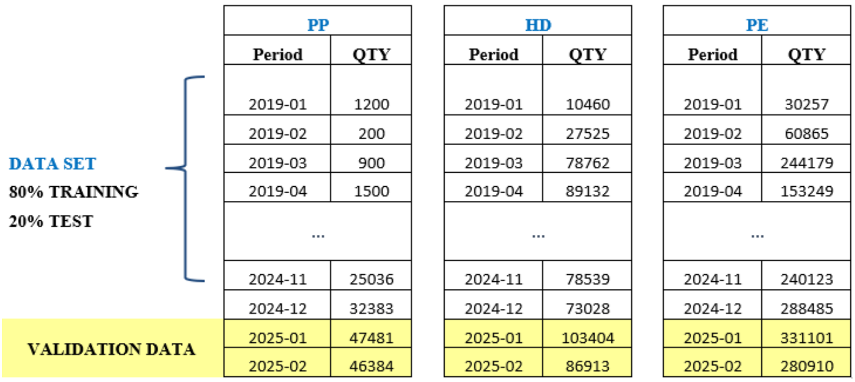

Fig 2. Dataset Sharing

To ensure the accuracy of the model used, raw material usage data in the January and February 2025 periods were separated and used as validation data for prediction trials. Thus, the dataset used in the model training process consists of 72 data each, covering raw material usage from 2019 to December 2024.

3.2. Data Preprocessing

Data preprocessing is done by starting the outlier search process using the Interquartile Range (IQR) method and then changing the value to the middle value or Median (Q2). This is done so that the data pattern is not too scattered.

Data preprocessing is done by starting the outlier search process using the Interquartile Range (IQR) method and then changing the value to the middle value or Median (Q2). This is done so that the data pattern is not too scattered. To find out the outlier data, the lower bound and upper bound in the Qty column need to be known first with the following formula:

$$LB = Q1 - (1.5 * (Q3 - Q1)) \;\; dan \;\; UB = Q3 + (1.5 * (Q3 - Q1)) \tag{1}$$

Based on calculations using formula 3.1 above on the three datasets, the results of the calculation of upperbound (UB), lower bound (LB) and interquartile range are obtained as shown in table 1.

Table 1. Calculation of Bounds and Interquartile Range (IQR)

TYPE	IN KILOGRAMS (KG)					
	Q1	**Q2**	**Q3**	**IQR**	**LB**	**UB**
PE	173211.38	199505.14	233209.70	59998.32	83213.90	323207.19
HD	83109.35	98192.28	114744.87	31635.53	35656.05	162198.16
PP	788.75	2017.74	43120.08	42331.33	-62708.24	106617.07

After the calculation of IQR, lower bound and upper bound is complete, the next step is to replace the Qty value in each dataset whose value is below the lower bound (LB) and above the upper bound (UB) with the median value or Q2. Given that this detection model is a time series type, it is important to transform the data, especially in the Period column, into a date type with yyy-MM format.

3.3. Data Identification

The following is a graph visualization using Classical Seasonal Decomposition of Time Series and an explanation of the identification results of each data based on the type of plastic seeds.

3.3.1. PE (*Low Density Polyethylene*)

LDPE is a type of thermoplastic plastic made from ethylene monomers with a branched molecular structure, making it flexible, transparent, and resistant to impact. It is commonly used for plastic bags, packaging films, flexible bottles, and protective coatings [16].

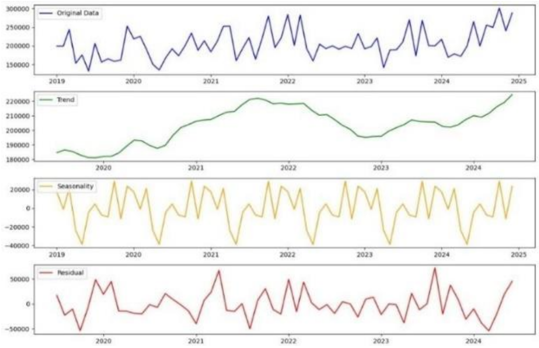

Fig3. PE Data Decomposition Chart

Figure 3 shows that the PE raw material usage data fluctuates every period, with an increasing trend until 2022, slightly decreasing in 2023, then increasing again towards 2025. The seasonal pattern is consistent every year, indicating a recurring cycle in raw material usage. Meanwhile, the residual component reflects random variations that cannot be explained by the trend or seasonality, possibly caused by external factors such as changes in market demand, supply chain disruptions, production policies, economic or regulatory conditions, and others.

3.3.2. HD (*High Density Polyethylene*)

HDPE has a denser molecular structure and fewer branches, making it stronger, stiffer, and resistant to high temperatures and chemicals. HDPE is used in making sturdier pipes, water gallons, detergent bottles, and food containers [17].

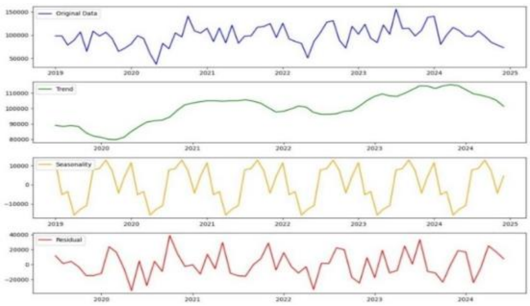

Fig 4. HD Data Decomposition Chart

The decomposition analysis of HD raw material usage data in Figure 4. shows an increasing trend in usage until 2023 before decreasing. The seasonal pattern is consistent, indicating a recurring cycle in raw material usage. Meanwhile, the residual component shows random variations that may be caused by external factors such as supply chain disruptions or changes in market demand.

3.3.3. PP (Polypropylene)

PP is a thermoplastic plastic with lightweight, heat-resistant, chemical-resistant properties, and has good mechanical resistance. PP is often used in food packaging, medical devices, automotive components, and textiles such as carpets and plastic cords [18].

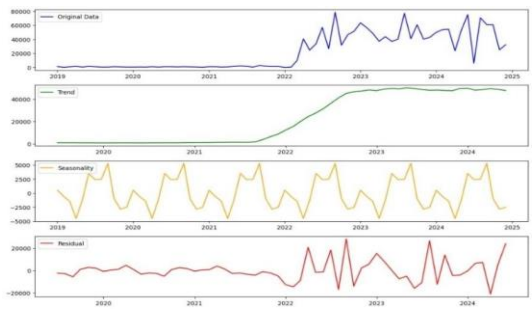

Fig 5. PP Data Decomposition Chart

The decomposition analysis of PP raw material usage data in Figure 5 shows that the trend of raw material usage has increased sharply since the beginning of 2022 and stabilized thereafter. The increase in PP raw material usage can be assumed to be related to surging market demand or influenced by production policies. The seasonal pattern remains consistent, indicating a recurring cycle in raw material usage. Meanwhile, the residual component shows significant fluctuations, possibly due to external factors.

3.4. Determine The Hyperparameter Model

The previous discussion shows that all three datasets show seasonal patterns or trends. It can be said that using the SARIMA model as a predictive model is the right step considering that SARIMA is a predictive model that is able to capture seasonal patterns in time series data. However, there are things that need to be considered before using the SARIMA model. This model has several hyperparameter functions so that it can run optimally.

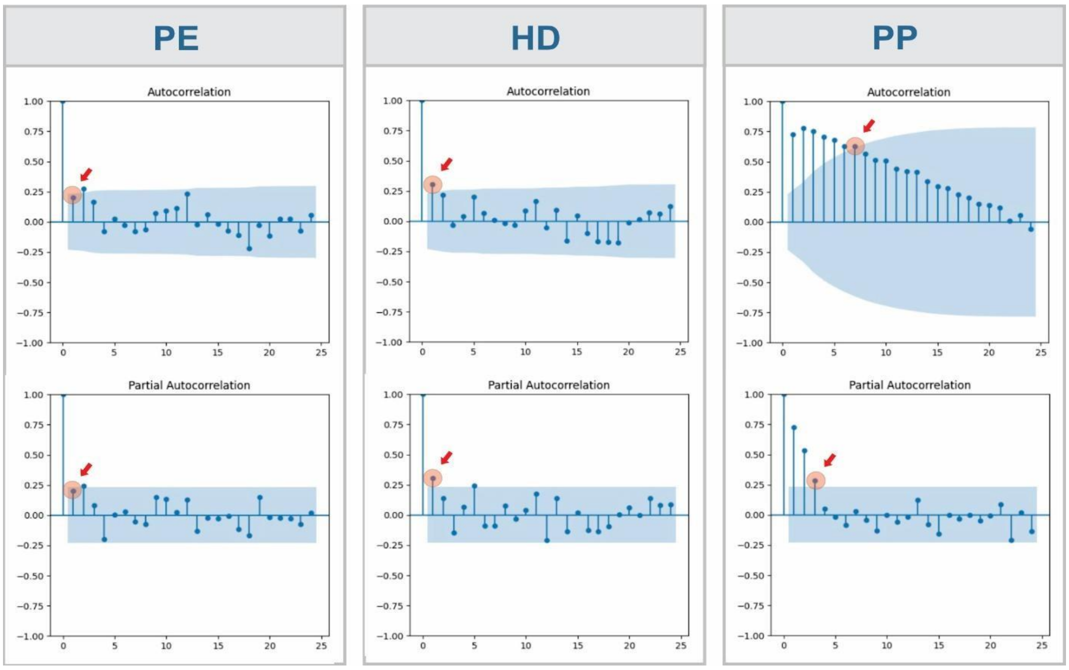

Fig 6. ACF and PACF Analysis Graphs

Based on the ACF and PACF analysis, the PE and HD datasets have similar patterns where the ACF and PACF patterns both have a sharp cutoff at the first lag. This indicates that the value of p and q in the PE and HD datasets is 1. Meanwhile, the PP dataset has an ACF that shows a slow decay indicating the hyperparameter q is 0 and the PACF cutoff occurs at lag 3, so the hyperparameter p in the PP dataset is 3.

3.4.2. Differencing Hyperparameter (d)

The differencing value can be determined from the ACF pattern and PACF cutoff. Figure 3.5 shows that the PE and HD datasets both have a rapidly decaying ACF pattern and have a PACF cutoff at lag 1. That indicates that the trend has been captured enough and is not too strong so that the value of 1 in the differencing hyperparameter is considered sufficient for the data to become stationary. In contrast to the PP dataset where the ACF pattern shows a slow decay which means that the trend captured is strong enough that the differencing value needs to be raised even higher. In this study, the differencing value in the model training process will be initiated using a value of 2.

3.4.3. Seasonal Hyperparameter (s)

The seasonal hyperparameter (s) is given a value of 12 for the entire dataset because all data uses time series data with a 12-month or annual period.

3.4.4. Model Hyperparameters

Table 2. SARIMA Hyperparameters

DATASET	HYPERPARAMETER			
	p	d	q	s
PE	1	1	1	12
HD	1	1	1	12
PP	3	2	0	12

Analysis results to determine model hyperparameters such as Autoregressive (p), Differencing (d), Moving Average (q) and Seasonal (s) which will be used for the SARIMA model training process are shown in table 2.

3.5. Determine The Hyperparameter Model

Evaluation calculations need to be performed to assess the reasonable limits of error metrics. One common way is to compare the Mean Absolute Error (MAE) value with the Mean Actual Value (MAV) value or determine the Mean Absolute Percentage Error (MAPE) value.

If the MAE value is smaller than the MAV value and the MAPE value is below 10%, the MAE value is still considered reasonable and the error is considered small. The Mean Actual Value (MAV) value can be calculated with the following equation:

$$MAV = \frac{1}{n}\sum_{i=1}^{n} y_i \quad (2)$$

Where:
MAV = Mean Actual Value
y_i = Actual value at the i-th point
n = Total amount of data
$\sum$ = Sum symbol (sigma)

After finding the MAV value of each *dataset*, then the *Mean Absolute Percentage Error* (MAPE) value is calculated using the following equation.

$$MAPE = \frac{1}{n}\sum \left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100\% \quad \text{or} \quad MAPE = \left(\frac{MAE}{MEAN\ ACTUAL\ VALUE}\right) \times 100\% \quad (3)$$

Where:
$MAPE$ = Mean Absolute Percentage Error
y_i = Actual value at the i-th point
$\hat{y}_i$ = Predicted value at the i-th point
n = Total amount of data
$\sum$ = Sum symbol (sigma)
$\left|\frac{y_i - \hat{y_i}}{yi}\right|$ = Relative error in absolute form

Based on the model training process and calculations using formula 3.2 and formula 3.3 for each dataset, the resulting data value of the training model is shown in table 3.3 below.

Table 3. Model Training Results

DATA SET	DATA (%)		MODEL	HYPER PARAMETERS	ERROR METRIC		MAV	MAPE (%)
	TRAIN	TEST			MAE (KG)	RMSE (KG)		
PE	80	20	SARIMA	(1, 1, 1, 12)	33853.65	40473.38	205718	16.46
HD	80	20	SARIMA	(1, 1, 1, 12)	27445.59	32012.93	99913	27.47
PP	80	20	SARIMA	(3, 2, 0, 12)	59289.08	81156.31	22088	268.42

Based on the calculation results shown in table 3 it can be concluded that the training results on the PE and HD datasets are still within reasonable limits even though the MAPE value exceeds 10%. The MAPE value on the PE dataset is quite low when compared to the HD dataset. The MAPE value of the HD dataset reaches 27%, indicating that the prediction model is less accurate than PE. Some efforts need to be made to reduce the MAPE value on the HD dataset such as trying other hyperparameter variations and checking data stationarity.
In contrast to the training results of the PE and HD datasets, the model training results on the PP dataset show unnatural results because it has an MAE value that far exceeds the MAV value and has a MAPE value of 286%. This shows that the model fails to understand the data pattern. The next step that needs to be done is tunning each hyperparameter combination to see if there is a decrease in MAE and MAPE values. If it does not work, perhaps the SARIMA model is not the right model for this data pattern.

3.6. Model Optimization and Validation

Model optimization is done by performing auto hyperparameter tuning to find out which hyperparameter combination from each dataset has the lowest MAE, RMSE and MAPE values to ensure the model has a minimum error metric. Auto Hyperparameter Tuning uses 3 types of methods namely grid search, random search and Bayessian optimization Model validation is performed using the Cross-Validation method because it is known to provide an average picture of model performance on various subsets of data and can avoid bias due to using only one train-test split.

Furthermore, the hyperparameters with minimal MAE, RMSE and MAPE and having the smallest validation RMSE will be used for prediction implementation. Meanwhile, the optimization process frees all hyperparameters to be able to produce the minimum error metric including the seasonal hyperparameter (s) in order to show the true seasonal pattern.

Table 4. Model Optimization Results Using Auto Tuning Hyperparameter

DATA SET	METHODS	BEST HYPERPARAMETER				MAE	RMSE	MAV	MAPE
		p	d	q	s				
PE	***Grid Search***	**0**	**1**	**1**	**2**	**28444.48**	**34854.10**	**205718**	**13.83%**
	Random Search	1	1	0	2	31476.72	36619.87	205718	15.30%
	Bayesian Optimization	1	0	0	11	33533.67	39277.96	205718	16.30%
HD	***Grid Search***	**1**	**0**	**0**	**5**	**11446.46**	**14177.44**	**99913**	**11.46%**
	Random Search	0	0	0	8	14144.78	17219.81	99913	14.16%
	Bayesian Optimization	1	0	0	7	15859.44	19626.63	99913	15.87%
PP	***Grid Search***	**1**	**1**	**0**	**10**	**11317.03**	**14585.06**	**22088**	**51.24%**
	Random Search	1	1	1	7	14981.84	18852.58	22088	67.83%
	Bayesian Optimization	1	1	0	10	11317.03	14585.06	22088	51.24%

The results of the error metric measurement in table 4 show a significant decrease for the PP dataset by using the grid search method, the best hyperparameter combination is obtained, namely (1,1,0,10) and is able to reduce the MAPE value by 217% from what was previously in the unreasonable category to 51.24%. Meanwhile, the MAPE value on the PE dataset decreased by about 5% and the MAPE value on the HD dataset also experienced a significant decrease of approximately 16%. The best hyperparameter combination for PE and HD datasets is also generated from the grid search method, namely (0,1,1,2) for PE dataset and (1,0,0,5) for HD dataset

However, the results of the validation of each dataset that has been auto-tuned for hyperparameters using Cross-Validation show different things and require us to consider once again which hyperparameters should be used. The validation results are shown in table 5 below.

Table 5. Model Validation Results

DATA SET	METHODS	BEST HYPERPARAMETER				VALIDATION METHOD	RMSE
		p	d	q	s		
PE	*Grid Search*	0	1	1	2	Cross-Validation	2278824.00
	Random Search	1	1	0	2	Cross-Validation	129394.55
	Bayesian Optimization	**1**	**0**	**0**	**11**	**Cross-Validation**	**48845.42**
HD	*Grid Search*	1	0	0	5	Cross-Validation	25339.94
	Random Search	**0**	**0**	**0**	**8**	**Cross-Validation**	**23205.76**
	Bayesian Optimization	1	0	0	7	Cross-Validation	26351.18
PP	*Grid Search*	1	1	0	10	Cross-Validation	59776.95
	Random Search	**1**	**1**	**1**	**7**	**Cross-Validation**	**12077.04**
	Bayesian Optimization	1	1	0	10	Cross-Validation	59776.95

The validation results show that although the grid search method produces the smallest MAPE value on the PE dataset, when validated, the validation RMSE shows a very large number. This means that the model with hyperparameter (0,1,1,2) on the PE dataset is great in the training process but fails in the validation process. This symptom usually indicates that the model is overfiting when using hyperparameter (0,1,1,2) so it is better to use hyperparameter from Bayesian optimization method because it has a smaller and reasonable validation RMSE. In addition, the validation RMSE is more reliable because it measures the model's performance on data that is not seen during training [19]. It better reflects the model's ability to predict new data. The validation results on the HD dataset did not change significantly, based on that, the hyperparameters used still follow the best hyperparameters from the training results with the lowest MAPE generated by the grid search method, namely (1,0,0,5).

The lowest validation RMSE value on the PP dataset is actually generated from the random search method where the method produces the highest MAPE value on the PP dataset. This indicates that there is a possibility that the hyperparameter (1,1,1,7) is underfitting. However, there is also the possibility that the coincident validation data is easier to predict. The hyperparameters used for the PP dataset will still refer to the validation results, namely (1,1,1,7).

3.7. Implementation and Prediction Results

Table 6 shows the prediction results of raw material consumption for January and February 2025. The SARIMA model shows variable performance, with the lowest MAPE of 16% for HD, while PE has the highest MAPE of 34%. This indicates that although the model showed high accuracy in the training and validation stages, the actual trend of PE raw material consumption has not been fully captured.

Table 6. Prediction Results

IN KILOGRAM (KG) HYPERPARAMETER DATA	p	q	d	s	PERIOD	ACT (y)	MAV	PRED (ŷ)	| ACT - PRED	MAE	MAPE
PE	1	0	0	11	2025-01	331101	306006	195632.07	135468.56	104782.03	**34.24%**
	1	0	0	11	2025-02	280910		206814.97	74095.51		
HD	0	0	0	8	2025-01	103404	95159	111914.29	8510.26	15604.03	**16.40%**
	0	0	0	8	2025-02	86913		109610.95	22697.79		
PP	1	1	1	7	2025-01	47480.99	46932.54	56719.42	9238.43	10062.39	**21.44%**
	1	1	1	7	2025-02	46384.08		57270.42	10886.34		

This difference in accuracy can be caused by a lack of relevant supporting variables or limited historical data, which affects the model's ability to recognize trend patterns. The more data and features that are taken into account, the better the model will be at understanding raw material usage patterns [20].

Beyond technical aspects, fluctuations in raw material consumption are also influenced by external factors such as production policies, purchasing power, budget efficiency, and market sentiment towards products [21]. The instability of the number of orders directly contributes to the volatility of raw material consumption [22]. Although there is still room for improvement, the implementation of SARIMA has been successfully carried out, providing initial insights that can be used for the optimization of production planning and raw material management.

4. Conclusions

Based on the results of the implementation of the SARIMA model for predicting raw material usage, it can be concluded that this model is able to predict usage trends with varying degrees of accuracy depending on the type of data. In prediction trials for the January and February 2025 periods, the model showed quite good performance on some data with a MAPE value of around 16%, but was less optimal on other data with MAPE reaching 34%. This shows that although the model has been optimized in the training and validation process, there are still patterns in the actual data that have not been fully captured by the model.

External factors such as production policy, purchasing power, budget efficiency, and fluctuations in the number of orders affect the accuracy of the model's predictions. In addition, the limited amount of historical data also affects the accuracy of the model, because the more data available, the better the model can recognize patterns. Overall, the SARIMA model has been successfully applied in the prediction process of raw material usage. However, to improve prediction accuracy and stability, further improvements need to be made to the data and model aspects.

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