Demand Forecasting of NPK Phonska Fertilizer in Central Java Using SARIMA Method

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Abstract. Fertilizer is essential to Indonesia's agricultural productivity, yet subsidized fertilizer distribution often suffers from supply and demand mismatch. This study discusses the forecasting of subsidized fertilizer demand, particularly NPK Phonska fertilizer in Central Java. The forecasted demand data is intended to support distribution planning and assist in estimating warehouse capacity. The SARIMA (Seasonal Autoregressive Integrated Moving Average) method was applied to 29 regional / sales area time series using KNIME, an open-source analytic platform that simplifies complex modeling tasks. Model performance was evaluated using Mean Absolute Percentage Error (MAPE) and model provided satisfactory result in most of sales areas. While accuracy varied across regions due to external factors such as climate variability and policy constraints, the results demonstrate that SARIMA, combined with KNIME, is an effective and scalable tool for regional-level fertilizer demand forecasting.

Keywords: Fertilizer Distribution Planning, Time Series Forecasting, KNIME Analytics Platform.

1 Introduction

Agriculture is an important for Indonesia and contribute as the largest working population [10]. Government provides fertilizer subsidy to support farmer, and one type of these subsidized fertilizers is the NPK fertilizer under the brand name Phonska. The distribution of subsidized fertilizers is prone to scarcity issues. According to [4] the demands for subsidized fertilizers in 2024 is 10.7 million tons. The allocation of national subsidized fertilizers in 2024 is 9.55 million tons while the demands for subsidized fertilizers reached 14.5 million tons. This discrepancy may compel farmers to purchase non-subsidized fertilizers, which in turn diminishes their income [17]. This gap also indicates that there is still a mismatch between the supply and demand in subsidized fertilizers.

This demands and supply mismatch can be caused by the pattern of fertilizer demands that vary every month, while the production carried out in constant rate. This seasonal sales or distribution pattern is also mentioned in [13] where the provisions for the provision of subsidized fertilizers in warehouses at the Regency/City Level are divided into the usual planting season April-September and the peak planting season

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which takes place in October-March. The regulation also stipulates minimum stock for each area in accordance with its demand. This study discusses the demand forecasting of subsidized fertilizer demands, especially NPK fertilizer (Phonska) in Central Java.

With the estimated data on fertilizer demand, it will later be used to predict demand or by creating distribution requirement planning to fulfil seasonal demands in each area. Thus, it can minimize supply and demand mismatch. Demand forecasting can also be used to estimate warehouse capacity that shall be prepared to accommodate minimum stock/supplies in accordance with regulations. This forecasted demand data is intended to support supply planning and assist in estimating warehouse capacity. With accurate demand forecasting data, companies can optimize production planning, develop more efficient distribution requirement planning (DRP), and proactively manage inventory in each sales area. This is crucial to ensure fertilizer availability in accordance with seasonal demand patterns, thereby minimizing the risk of scarcity and excess stock.

2 Literature Review

Research related to fertilizer demand forecasting has been carried out with various approaches and scales. One study used the Fuzzy Inference System method with the Mamdani approach to predict fertilizer demand at the stall level, resulting in a prediction accuracy with MAPE of 15 %, but limited to a very small area scale [6]. In contrast, another study conducted long-term forecasting of the global demand for N, P, and K fertilizers using multivariate linear regression, but the data are annual and global, so they do not reflect local demand or seasonal fluctuations that are relevant for distribution planning at the company level [15].

Other research examined the influence of weather on fertilizer consumption globally with Spatio-temporal data but found that the climate impact in Southeast Asia was not significant, likely due to farmers' limited purchasing power. This study highlights socio-economic factors that cannot always be captured by historic-based forecasting models [2].

The time series approach was also applied using the ARIMA method to predict fertilizer consumption in India, but the use of annual data and national scope makes it less adaptive to the needs of companies in adapting quick seasonal changes for distribution planning [3]. Another comparison between statistical and machine learning methods to predict monthly fertilizer sales and found that the ANN model produced the smallest errors, albeit with limited time and region coverage [7].

A causal approach based on environmental and agronomic data with high accuracy results, but this model is considered less practical to apply because it requires very complex data [5]. Another study used the SARIMA model to forecast organic fertilizer demand in Malang Regency. In the study, Arviani demonstrated that the SARIMA model yielded a smaller Mean Squared Error (MSE) compared to the Exponential Smoothing model [1]. However this study has different product in smaller scale than Central Java.

In general, previous studies have focused more on a national or local scale (kios/subdistrict) and often do not consider integration with a company's distribution system.

One recent study emphasizes the importance of using monthly data per region to improve accuracy and relevance in the context of corporate supply chain management [16].

Thus, there is still a need for an accurate fertilizer demand forecasting model, adaptive to seasonal changes, and can be applied practically in a company's distribution system on a regional scale.

Table 1. Research Mapping.

Study	Methodology								Area Level				
	A	B	C	D	E	F	G	H	I	J	K	L	M
Arviani [1]			x						x				
Fitriani [6]		x										x	
Tenkorang [14]									x				
Bille [2]	x											x	
Borkar [3]			x								x		
Hasan [7]				x	x	x	x				x		
Devi [5]								x			x		
This Research			x							x			

A: Multivariate Linear Regression
B: Fuzzy Inference
C: ARIMA/SARIMA
D: Moving Average
E: Exponential Smoothing
F: Linear Regression
G: Artificial Neural Network
H: Causal Method
I: Subdistrict
J: Province
K: Country
L: Macro Region
M: Global

3 Methodology

Central Java Province was chosen as the research location because it holds the second largest recipient of the subsidized fertilizer allocation in Indonesia. The object of this research is NPK Phonska fertilizer. This product was chosen because it is a compound fertilizer that contains three main nutrients, namely Nitrogen (N), Phosphate (P), and Potassium (K), so that it is able to provide more complete nutrients than single nutrient fertilizer.

Demand forecasting is carried out to predict demand data for a period of up to 12 months. The resulting forecasting model is expected to have a longer period than the currently used method, namely sales force composite. Sales force composite method currently has short term forecasting horizon and subject to routine evaluation since it has subjective tendency from its qualitative nature. A longer forecasting period is expected to facilitate the planning of other processes such as production planning, distribution and warehouse capacity evaluation within the Company.

The selection of the SARIMA (Seasonal Autoregressive Integrated Moving Average) method in this study was based on the need for medium to long term forecasting on fertilizer sales data from five years (60-point data) training data. Methods such as Neural Network were not chosen because they required much larger datasets and longer time series, whereas linear regression was not suitable because it was not able to handle seasonal patterns that emerged as outliers. Causal method required extensive data and considered less practical in operation management. Therefore, SARIMA was chosen because it can accommodate seasonal elements and produce more flexible and accurate predictions for univariate time series.

This approach was specifically chosen for its ability to capture the inherent seasonal patterns in monthly fertilizer sales data, a characteristic that often becomes an anomaly for simple linear regression models. This requirement forecast should also be designed with monthly granularity level to facilitate the operational planning and evaluation process conducted in regular monthly S&OP meetings. Forecasting data at the monthly data level will also reflect seasonal sales trend data. The stages of research that will be carried out include:

1. Data Collection

   Demand forecasting using the SARIMA method using historical sales data in the 2019–2023 period. This period of 5 years is considered sufficient to represent demand forecasting models If a longer time period is used, there is a concern that the model may be affected by structural changes resulting from shifts in subsidized fertilizer sales policies.

2. SARIMA Modelling

   For this study, each sales area will be modelled with the tools in the KNIME software. KNIME is analytical data platform with visual programming concept (low code or no code platform). KNIME available in free use license and an open-source software.

   The expected output is the SARIMA equation order data, namely the P, Q, D, s parameters which represent the seasonal elements and p, q, d which represent the basic model of ARIMA. Each sales area is likely to have different parameters according to the characteristics of their respective sales data.

   KNIME provide four optimization method which is Brute Force/Grid Search, Random Search, Hill-climbing and Bayesian Optimization. Bayesian Optimization was chosen over Grid Search, Random Search, and Hill-climbing for tuning SARIMA parameters in KNIME due to its balance of computational efficiency and forecasting accuracy. Grid Search guarantees optimality by exhaustively testing all parameter combinations but is highly time-consuming. Random Search is faster but less reliable with limited trials, while Hill-climbing converges quickly yet risks getting stuck in local optima. In contrast, Bayesian Optimization in KNIME uses prior evaluation results to guide the search toward promising regions of the parameter space, enabling more efficient convergence [14]. A limit of 100 iterations was applied, making this approach well-suited for the setting.

3. Evaluation of Results

   After modelling is carried out using sales data for each region between respected period, SARIMA model creates monthly forecast data for 2024. Furthermore, a comparison will be made with 2024 sales data as a baseline to calculate the accuracy level of each model. Measurement of the quality of demands forecasting data can use MAPE parameters to evaluate the quality of forecasting model. Formula of MAPE:

$$MAPE = \frac{1}{n} \times \sum_{i=1}^{n} \left| \frac{yi - \hat{y}i}{yi} \right| \times 100\ \% \tag{1}$$

where:

n: amount of samples/observation in data
yi: actual value
$\hat{y}i$: predicted value

4 Methodology

A time series forecasting model was built to predict demand for subsidized fertilizers, especially NPK Phonska fertilizers in the Central Java region. The SARIMA model is optimized by finding the best tuning hyperparameters with the smallest error rate. Furthermore, model performance metrics are measured to evaluate the quality of the resulting model. This research uses KNIME software to build the model. The results of the workflow design in this study using KNIME software can be seen in Fig. 1.

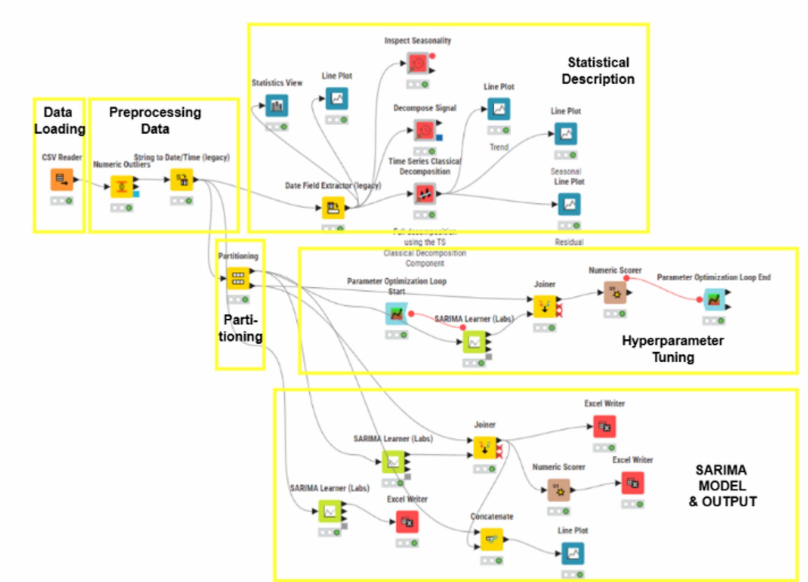

Fig. 1. Workflow Model Building

The time series workflow shown in Fig. 1 consists of six main blocks that form a complete process from data loading to model evaluation. The first block, Data Loading, is responsible for importing raw data into the workflow using the CSV Reader node. Once the data is loaded, the process continues to the Preprocessing block, where outliers are handled and the date column is converted from string format to a proper date type to enable time series processing.

Next, the Statistical Description block is used to explore the statistical characteristics of the data. Additionally, time series decomposition is performed to separate the data into trend, seasonal, and residual components, helping to better understand its underlying patterns. This block serves an exploratory purpose only and does not directly contribute input to the modelling process. After exploration, the data is split in the Partitioning block into 60 training points and 12 testing points, allowing the model to be validated on previously unseen data. The next stage is Hyperparameter Tuning, which aims to identify the best parameter configuration for the SARIMA model.

The optimal parameters obtained from this process are then used in the final block, SARIMA Model & Output, where the SARIMA model is built and used for forecasting. The forecast results are compared with the actual testing data, and the model's performance is evaluated using the Numeric Scorer node by calculating accuracy metrics such as MAPE. Evaluation of SARIMA model using MAPE can be viewed in Table 2.

According to [9] MAPE value can be interpreted as follows, highly accurate forecasting < 10 %, good forecasting 10-20 %, reasonable forecasting 20-50 % and inaccurate forecasting >50 %. To this day, this threshold remains a standard reference for assessing the quality of demand forecasting.

Table 2. Forecasting Accuracy Metrics of SARIMA Models for NPK Phonska Fertilizer Demand Across Central Java Regions.

Sales Area	SARIMA parameter							Evaluation
	p	d	q	P	D	Q	s	MAPE
A1	1	1	0	3	1	2	11	22.50 %
A2	4	0	1	0	0	2	10	37.98 %
A3	5	3	1	0	0	1	10	25.29 %
A4	1	1	1	2	1	2	11	26.01 %
A5	1	4	4	3	0	1	12	17.94 %
A6	2	2	0	4	2	3	10	24.17 %
A7	4	2	2	0	0	3	7	38.60 %
A8	3	2	5	5	0	0	6	53.95 %
A9	0	0	2	2	2	1	9	32.23 %
A10	1	1	1	2	1	1	11	47.79 %
A11	1	4	4	3	0	1	12	14.96 %
A12	5	0	0	2	0	0	8	47.39 %
A13	1	4	5	1	0	3	9	8.66 %
A14	5	0	1	3	1	0	6	36.71 %
A15	5	4	5	1	0	0	6	21.24 %
A16	2	3	5	1	1	2	10	37.08 %
A17	0	4	5	1	0	3	10	19.36 %
A18	0	3	5	1	2	1	9	74.87 %
A19	5	2	0	1	1	2	8	25.66 %
A20	1	4	3	0	1	2	12	33.97 %
A21	4	2	1	2	0	0	7	32.48 %
A22	1	1	0	1	1	2	11	20.69 %
A23	4	1	0	2	1	2	11	29.70 %
A24	5	2	0	2	1	2	11	39.04 %
A25	1	1	0	1	1	1	10	34.93 %
A26	2	1	0	1	1	2	11	38.88 %
A27	1	2	0	2	1	1	11	17.80 %
A28	4	1	5	3	0	0	8	21.16 %
A29	2	2	0	2	1	2	8	29.46 %

The sales area with the lowest MAPE is A13 with a value of 8.66 % while the highest is A18 which reaches 74.87 %. The average MAPE value of all sales area reached 31.4 %. The median of this MAPE reaches 29.7 % which illustrates that this shows that the distribution of data tends to be tilted to the right. This illustrates the existence of high-value outlier data.

From Table 2 the parameter s has very diverse values. This indicates the length of the seasonal cycle that varies for each time series. This is interesting to compare with the general reference in the regulations that divide the planting season into 2 periods (October-March and April-September). By looking at the value of various parameters, it can be confirmed that companies need to develop their own demand forecasting system because of the differences between seasonal patterns and general regulations according to regulations. This can be understood because the provisions in the regulations are a simplification of the general pattern of demands.

Time series that have MAPE values above the threshold are A8 (53.95 %) and A18 (74.87 %). To understand these results, an analysis of descriptive statistical data from each time series displayed in Table 3 was carried out. Table 3 displays data on the minimum value in the training period (2019–2023), the average value of the training period, the minimum value in the baseline period (2024) and the MAPE value of each sales area.

In Table 3, there are anomalies that can be found on A8 and A18. In A8, the minimum value of the time series is 0 (zero). This will inherently cause the time series to not be properly modelled through SARIMA. This sales data with a value of zero also indicates the existence of an intermittent trait in this time series. Upon verification, this data reflects real-world sales impacted by changes in local government policies in A8. This observation highlights a limitation of purely time-series models like SARIMA in capturing the effects of unexpected and non-stationary external variables, such as sudden policy shifts.

Evaluation of demand data that has an intermittent trait such as the A8 time series itself also brings challenges for measurement using MAPE. Hyndman (2006) states that MAPE cannot be used to evaluate forecasts with actual data of zero or close to zero. This happens because MAPE uses the actual data value as a divisor so that when the actual data is zero or close to zero, the MAPE value becomes undefinable or jumps unnaturally.

Based on Table 3, it can also be seen that A18 is the sales area with the highest MAPE and exceeds the threshold from [9]. In the descriptive statistical value of A18, a pattern was found where A18 is the sales area with the lowest average in Central Java. This consistently appears compared to average demands from other sales areas. While the absolute difference between actual and predicted values for A18 may be small, the nature of MAPE, which calculates error relative to the actual value, makes it highly sensitive to small actual values. Consequently, for time series with a high frequency of small actual values, such as A18, MAPE tends to yield high values and may not always be representative of the overall model performance.

Generally, MAPE tends to give high values on time series with many small actual values. This happens because MAPE calculates errors relative to the actual value. When the actual value is small, it will produce large deviation data, even though the absolute difference is small. If this happens repeatedly, the overall MAPE becomes high. Therefore, MAPE is not suitable for sequences with high small-value frequency values because the evaluation results become inconsistent [8].

Although there are some shortcomings in the MAPE evaluation matrix, it is still one of the most popular evaluation matrices. This is due to the ease of MAPE calculation and its simplicity. The MAPE matrix is indeed more popular than another matrix as mentioned by [8] and [16].

Table 3. Descriptive Statistical Values of Time Series

Sales Area	Training Period		Baseline	MAPE
	Min	Average	Average	
A1	550	1014	1104	22.50 %
A2	108	711	973	37.98 %
A3	249	748	881	25.29 %
A4	1082	2695	3752	26.01 %
A5	452	1222	1831	17.94 %
A6	283	1224	1527	24.17 %
A7	115	1106	1805	38.60 %
A8	0	1488	1643	53.95 %
A9	1185	3106	4699	32.23 %
A10	174	921	830	47.79 %
A11	37	1055	1355	14.96 %
A12	159	1062	1520	47.39 %
A13	667	1280	1867	8.66 %
A14	576	967	1223	36.71 %
A15	100	564	864	21.24 %
A16	350	801	905	37.08 %
A17	761	2129	3298	19.36 %
A18	173	465	573	74.87 %
A19	402	861	1128	25.66 %
A20	133	539	623	33.97 %
A21	276	827	1006	32.48 %
A22	657	1587	2341	20.69 %
A23	292	671	997	29.70 %
A24	80	2103	2959	39.04 %
A25	291	724	1068	34.93 %
A26	268	760	1048	38.88 %
A27	128	754	1315	17.80 %
A28	721	1761	2202	21.16 %
A29	219	636	850	29.46 %

Furthermore, MAPE data results are also classified for each quality range to see the quality of demand forecasting carried out. according to [9] and the results of the grouping can be seen in Table 4. It is used to see the distribution of MAPE values within the quality range proposed by [9].

Table 4. Classification of Forecasting Quality

MAPE Range	Forecast Quality	Sales Area
<10 %	Highly Accurate	1
10-20 %	Good	4
20-50 %	Reasonable	22
>50 %	Inaccurate	2

In Table 4, most models have reasonable and good MAPE values. Although there are 2 time series that have MAPE values that exceed the threshold set by Lewis, it can be concluded that the SARIMA model provides a satisfactory level of accuracy and can be considered a reliable approach for time series forecasting in most sales areas.

This result is likely to occur due to anomalies/outliers and exogenous variables that affect the demand for NPK Phonska fertilizer. These anomalies and exogenous variables include weather conditions and subsidized fertilizer policy variables. According to [11], extreme climates are steadily increasing and correlated with the El Niño Southern Oscillation (ENSO) event. ENSO consists of two opposing phenomena: the warm-phase El Niño and the cold-phase La Niña. El Niño is most likely to cause droughts, while La Niña causes floods. This study found that ENSO significantly reduces Southeast Asia's rice production. Since rice is the main staple food in Indonesia, this case is also likely to affect fertilizer demand or sales. This study also highlighted that, since the 1980s, ENSO-related inter-annual climate variability has been occurring at shorter intervals—every four to five years—and with increased intensity. This inter-annual climate variability disrupts normal seasonal trends and reduces forecast accuracy.

5 Conclusion

Fertilizer is a product with a seasonal sales trend and is vital for the people of Indonesia. This fertilizer demand modelling uses NPK Phonska fertilizer sales data in twenty-nine sales areas representing districts and cities in Central Java. Modelling carried using the KNIME Analytic Platform Software, which utilizes visual programming to create forecasting simulations efficiently. It can be concluded from MAPE evaluation that the SARIMA model is able to provide reasonable and acceptable results in most sales areas. However, the SARIMA model has not been able to deliver results with remarkably high accuracy.

As a time series model, SARIMA relies on historical patterns and may be unable to capture sudden policy changes or the intermittent trait of extreme data. This can be seen from the anomaly in the A8 sales area. Furthermore, the establishment of these subsidy allocations is significantly dependent on the availability of budgetary resources. Effect of regulation on subsidized fertilizer allocations has been mentioned in [4] and [17].

The forecasting results obtained in this study can be directly utilized by companies to support various operational functions. First, the 12-month demand projection enables the formulation of minimum stock levels for each sales area, aligned with both regulatory requirements and the actual seasonal patterns identified in the time series data. Second, the forecasted demand figures can be used as distribution requirement planning reference. In addition, the forecasting output can be used to estimate warehouse capacity requirements more accurately, thereby minimizing both the risk of undercapacity and the cost of excess storage. As a result, the implementation of this forecasting model not only supports strategic planning but also contributes directly to improved operational efficiency across the fertilizer distribution system.

This study has demonstrated that, despite the inherent limitations of the SARIMA model, it can produce acceptable forecasting results across most sales areas. The practical implementation of KNIME has proven highly effective in streamlining the SARIMA modelling process, particularly in automating workflows and managing the model's seven hyperparameters. These results demonstrate that SARIMA, when deployed via a capable modelling platform like KNIME, offers a scalable and efficient solution for multi-series time series forecasting A total of twenty-nine time series were modelled in this research, which would have required substantial computational resources and time if conducted manually.

For future work, it is recommended to broaden the scope of model comparison by incorporating alternative forecasting techniques commonly used in industry, such as the Winters-Holt method or SARIMA variants that include exogenous variables (SARIMAX) or using demand models for intermittent data. In addition, exploring machine learning algorithms such as neural networks may enhance predictive performance, particularly when supported by a richer set of independent variables to address the limitations posed by short time series data. Meanwhile, the use of a forecasting model incorporating exogenous variables may be more effective when applied to regions dependent on rainfall, such as rainfed agricultural areas.

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