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Optimizing Fresh Orange Juice Production at XYZ MSME Bogor Using Forecasting and Sugeno Fuzzy Logic

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ABSTRACT

Determining the optimal daily production quantity is a major challenge for XYZ MSME, a small-scale fresh orange juice producer in Bogor, due to fluctuating demand and the perishable nature of its products. The purpose of this research is to forecast daily production using the Sugeno fuzzy logic method to minimize overproduction and underproduction. The study employs a Sugeno fuzzy inference system (FIS) with input variables including previous day sales and available raw materials. A set of fuzzy rules maps these inputs to recommended production quantities. The results show that the Sugeno FIS produces accurate and adaptive forecasts that closely match actual demand patterns, enabling XYZ MSME to adjust production efficiently. This method helps reduce raw material waste, optimize resource use, and improve overall production efficiency. The study concludes that applying the Sugeno fuzzy logic approach is effective for short-term production planning in MSMEs, particularly for perishable food products.

Keywords: Sugeno fuzzy logic, production forecasting, MSME, fresh orange juice.

INTRODUCTION

Micro, Small, and Medium Enterprises (MSMEs) play a crucial role in supporting Indonesia's economic growth, especially in the food and beverage sector. One of these businesses, XYZ MSME, located in Bogor City, is engaged in the production of freshly squeezed orange juice. This product has become increasingly popular among consumers due to its refreshing taste, high vitamin C content, and the absence of artificial sweeteners or preservatives, making it healthier compared to other processed beverages (Jannah & Rahmawati, 2020).

The demand for fresh orange juice continues to grow, particularly during the dry season and weekends, when consumers seek more refreshing drinks. However, XYZ MSME faces a major challenge in determining the optimal daily production quantity. Inaccurate production decisions can lead to two main problems: overproduction, which causes raw material waste due to the short shelf life of the product, and underproduction, which results in lost sales opportunities (Warmansyah & Hilpiah, 2019). To maintain product freshness and quality, XYZ MSME adopts a daily production system without long-term storage. While this system ensures product quality, it also demands accurate and efficient production planning. A well-managed production process not only guarantees product quality but also enhances profitability through optimal sales (Indroyono, Churniawan, & Nurcahyawati, 2024).

Several previous studies have demonstrated that forecasting methods and fuzzy logic approaches can improve production efficiency and minimize the risk of excess inventory in the food and manufacturing industries (Muflihunna & Mashuri, 2022; Sekawan, 2021). However, most of these studies focused on large-scale enterprises with automated production systems. The application of fuzzy logic, particularly the Sugeno inference model, remains limited at the MSME level, especially for products with a short shelf life such as fresh juice.

Therefore, this study aims to apply the Sugeno fuzzy logic method to forecast and determine the optimal production quantity of fresh orange juice at XYZ MSME. The proposed model adapts fuzzy logic principles to the operational characteristics of small-scale enterprises, providing a flexible, adaptive, and data-driven decision-support system. By implementing this approach, XYZ MSME is expected to improve production efficiency, reduce waste, and better align daily production with fluctuating market demand.

METHODS

Research approach

This study uses a quantitative approach to forecasting using two methods, namely the moving average method and fuzzy logic to estimate the amount of orange juice production in XYZ MSME. The quantitative approach was chosen because it is able to provide a measurable picture of the moving average and fuzzy logic methods to help plan a more efficient production process. The use of Sugeno fuzzy logic was chosen because this fuzzy logic model is able to describe complex and uncertain systems with a flexible approach, making it suitable for forecasting with fluctuating demand (Darmawan et al. 2024). Meanwhile, the use of the moving average method was chosen because this method has proven effective in handling data with unclear seasonal patterns. By using an approach using two different methods, the study aims to analyze and compare two models for forecasting planning to increase efficiency and minimize the potential waste of raw materials in the orange juice manufacturing process (Kadarusman et al. 2024).

Data Collection

The research was conducted at XYZ MSME located in Central Bogor, Bogor City, for 3 months, from August 1, 2025 to October 1, 2025. This MSME was chosen as the research location because it has a regular orange juice production activity, enabling researchers to obtain relevant and consistent data.

Data collection for this study was conducted using secondary data. Secondary data was collected from records of total daily sales of orange juice over a period of 10 weeks. The data included production quantity, raw material quantity (orange), and total daily production over 10 weeks. The data source is derived from operational records and production process reports from XYZ MSME. The data is then prepared in the form of a time series to facilitate the forecasting process using the moving average and fuzzy logic methods. The use of time series in data collection will produce more optimal data for the subsequent data processing stages (Kusumawati et al. 2021)

Data Analysis

Moving average is a forecasting method performed by calculating the average value of several recent data within a certain period of time, so that short term fluctuations in sales data can be minimized. The steps in determining forecasts using this method are data preprocessing. This step is to ensure data quality, address missing values and outliers that can affect data accuracy, and simplify daily data into monthly data so that sales patterns are more apparent for forecasting purposes (Khadarusman et al. 2024). The next steps are to apply the moving average method using the average sales from the previous months as a basis for estimating sales for the following month. The final steps are to evaluate performance by calculating the Mean Squared Error (MSE) to measure the average square of the difference between the predicted and actual values, providing an indication of the extent of the difference between the prediction and reality. In addition, the Mean Absolute Percentage Error (MAPE) is also calculated by measuring the percentage error between the predicted value and the actual value, which can determine how accurate the prediction results are (Khadarusman et al. 2024).

In addition to the moving average method, this research also applies the fuzzy logic method as an approach in the forecasting process. The fuzzy logic method is used to measure uncertainty in the decision making process. This is because this method allows membership values to be in the range between 0 and 1, so that it can show the level of certainty or uncertainty of a statement (Afivah et al. 2025). The method used in this study is Sugeno fuzzy logic. This method produces output (consequences) in the form of constants or linear equations (Tundo, 2021). The stages consist of three main components, namely fuzzification, fuzzy inference, and defuzzification. In the fuzzification step, the input data is converted into membership values in a fuzzy set. Next is the fuzzy inference step, which is carried out by processing membership values using predetermined fuzzy rules to produce the appropriate output. Finally, in the defuzzification stage, the fuzzy output is converted into definite values that can be used for decision making (Tundo, 2021). The fuzzy logic method has the potential to handle simple and complex management variables, especially cases where the data and results are uncertain or biner.

RESULTS AND DISCUSSION

Data Collection

In the research conducted, primary data obtained through observations and direct interviews with XYZ MSMEs were used. The data used were sales data, raw material inventory data, and sales data for a period starting from 18th of August 2025, to 25th of October 2025. The collected data were data from 3 product variants, namely lemon, sunkist, and orange, which will be used as a basis for conducting forecasting analysis and applying fuzzy logic with the Sugeno method. This analysis aims to see the relationship pattern between sales, raw material inventory, and production quantity, in order to determine the most optimal production quantity. This step was taken to reduce the risk of losses due to unsold products. The discussion presents data regarding sales, production, and raw material inventory.

Table 1. Data of Sales, Raw Material Supplies, and Production

Week	Sales	Raw Material	Production
1	327	412	330
2	418	463	458
3	252	507	376
4	389	529	427
5	350	548	312
6	233	567	491
7	356	451	358
8	278	484	445
9	425	522	284
10	301	576	408

The data in Table 1 shows fluctuations in sales and production during the 10 weeks of observation. Production tends to follow the sales pattern, but there are still discrepancies in some weeks. For example, in week 6, production reached 491 units, while sales were only 233 units, potentially causing overproduction. Another discrepancy also occurred in week 9, where production was lower than sales, risking lost sales. This shows the need for a production decision-making system that is more adaptive to fluctuations in demand.

Product Sales Forecasting and Raw Material Inventory Forecasting

Forecasting was conducted using Moving Average on weekly sales and raw material availability data. The evaluation results showed the error rate (MAPE):

Table 2. Forecasting Results for Sales and Raw Materials Using the Moving Average Method

Forecasting Method	Sales	Raw Material
MAD	58,9	57,48
MSE	5163,3	3999,25
MAPE	18,29	11,39
Forecasting Result	332	460,67

Forecasting using the Moving Average method is used as a quantitative basis for determining the production volume for the next period. The forecasting performance evaluation shows a MAPE value of 18.29% for sales and 11.39% for raw material requirements. This value is still acceptable for short-term planning, but significant fluctuations in sales require fuzzy system support to minimize deviations in production decisions.

Needs Analysis

1. **Input & Output Analysis**

Table 3. Variables for Input and Output

	Variable	Low	Medium	Production
Input	Sales	<250	150-450	>450
	Raw Material Supplies	<400	300-500	>500
Output	Production	<300	250-450	>450

The Sugeno fuzzy system processes input variables in the form of sales and raw material availability to produce output in the form of production quantity recommendations. The recommendation values are divided into three categories, namely Less (200), Optimum (335), and Over (500). The defuzzification results show that changes in input values have a proportional effect on the output, so that the model can follow the fluctuations in MSME operational conditions logically and consistently.

2. **Parameter Input**

Table 4. Input Variable Parameters

Sales			
Few	a = 0	b = 100	c = 250

Moderate	a = 150	b = 300	c = 450	
Many	a = 300	b = 450	c = 600	
Raw Material Supplies				
Few	a = 0	b = 115	c = 200	d = 300
Moderate	a = 250	b = 350	c = 400	d = 500
Many	a = 400	b = 500	c = 600	d = 810

The input variables in this study consist of sales and raw material availability, each of which is divided into three fuzzy sets, namely Few (low), Moderate (medium), and Many (high). The parameter values a, b and c in each set are determined based on the actual data range during observation in order to accommodate the uncertainty that occurs in operational conditions. These parameters form the basis for the formation of fuzzy membership functions before being used in the inference process.

The figure of the membership function for both sales and raw material supplies input can be seen below:

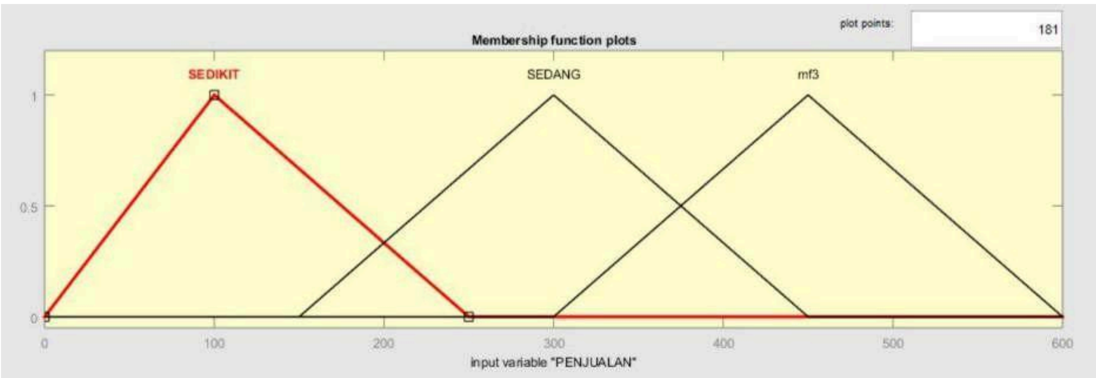

Figure 1. Membership Function for Sales Input

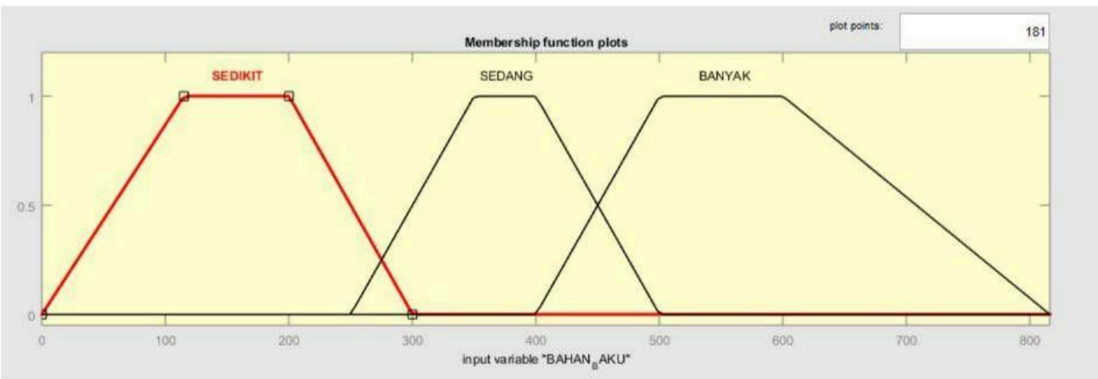

Figure 2. Membership Function for Raw Material Supplies Input

3. **Rule**

Table 5. Expert Value

Expert Value	
Less	200
Optimum	335
Over	500

The crisp values used in the Sugeno model were obtained through analysis of actual production capacity and discussions with MSMEs. Outputs of 200, 335, and 500 units reflect the minimum, optimal, and maximum production levels that can be applied without causing the risk of excess production.

Table 6. Fuzzy Rules

Sales	Raw Material Supplies	Production	Expert Value
Few	Few	Less	200
Few	Moderate	Less	200
Few	Many	Less	200
Moderate	Few	Less	200
Moderate	Moderate	Optimum	335
Moderate	Many	Optimum	335
Many	Few	Less	200
Many	Moderate	Optimum	335
Many	Many	Over	500

Fuzzy logic rules are a set of guidelines that link input variables to output variables in order to handle uncertainty in data and support decision-making regarding final stock values based on combinations of input variable values. This system uses "if-then" rules that describe the relationship between inputs and outputs. There are 9 potential combinations that can be formed to create various fuzzy rules that support these decisions.

Fuzzy Sugeno Design

Tabel 7 Validation of Membership Functions

Minggu	Sales	Raw Material	μ_Sales:Few	μ_Sales:Moderate	μ_Sales: Many	μ_Raw:Few	μ_Raw:Moderate	μ_Raw: Many	Output Sugeno (y)	Produksi Aktual	Error (%)
1	327	412	0.000	0.820	0.180	0.000	0.880	0.120	350.968	330	6.36
2	418	463	0.000	0.213	0.787	0.000	0.370	0.630	460.031	458	0.44
3	252	507	0.008	0.840	0.152	0.000	0.000	1.000	472.500	376	25.66

4	389	529	0.000	0.240	0.760	0.000	0.000	1.000	472.500	427	10.66
5	350	548	0.000	0.667	0.333	0.000	0.000	1.000	472.500	312	51.43
6	233	567	0.544	0.456	0.000	0.000	0.000	1.000	322.500	491	34.34
7	356	451	0.000	0.733	0.267	0.000	0.592	0.408	364.762	358	1.91
8	278	484	0.112	0.888	0.000	0.000	0.222	0.778	446.250	445	0.28
9	425	522	0.000	0.133	0.867	0.000	0.000	1.000	472.500	284	66.37
10	301	576	0.004	0.993	0.007	0.000	0.000	1.000	336.100	408	17.63

To ensure that the membership functions (MFs) presented in Table 4 accurately represent the operational conditions of the XYZ MSME, numerical validation was conducted by comparing the fuzzy outputs with the actual production data over a 10-week observation period. For each week, the membership degree (μ) of each fuzzy set (Few, Moderate, Many) for both input variables (Sales and Raw Material Supplies) was calculated using the defined triangular and trapezoidal functions. A sample of the computed membership degree results for the entire period is provided in Table 7.

The Sugeno (zero-order) output was obtained using the fuzzy rules in Table 6, where constant output values were assigned to each rule (Less = 200, Optimum = 335, Over = 500). The final output was calculated using the weighted average method, in which the weight of each rule was determined by w_i=min(μsales, set, μraw, set).

Across the 10-week observation period, a comparison between the Sugeno outputs and actual production values is presented in Table 7. The MAPE value for the full period was 20.32%. These results indicate two key findings: (1) the defined membership functions provide a distribution of μ values that is consistent with the position of the input data (e.g., sales values within the range of 300–400 produce a high μ in the Moderate fuzzy set), meaning that the MF structure is relevant to actual operating conditions; however, (2) the use of constant outputs in the zero-order Sugeno model results in relatively high prediction errors in several weeks, indicating that the forecasting accuracy still needs improvement.

Therefore, future improvement steps are recommended, including tuning the MF parameters through MAPE-based optimization or adopting a first-order Sugeno model (linear output functions) to better capture subtle variations in actual production. The inclusion of contextual variables (e.g., working days/holidays, promotions) may also enhance forecasting accuracy.

1. Membership Function for Sales Input

   The Sales variable represents the number of orange juice units sold in each observation period. This variable directly affects the production planning process and is, therefore, categorized into three fuzzy sets to accommodate demand fluctuations: Few, Moderate, and Many. The fuzzy sets are defined using triangular membership functions based on the range of sales data obtained from the 10-week observation.

   The domain and parameters used for the triangular membership functions are:

   a. Few : a=0, b=150, c=250a=0,b=150,c=250

b. Moderate : a=150, b=300, c=450a=150,b=300,c=450

c. Many : a=300, b=450, c=600a=300,b=450,c=600

The membership functions are expressed as:

$$\mu_{\text{Few}}(x) = \begin{cases} 1 & x \le a \\ \frac{b-x}{b-a} & a < x \le b \\ \frac{x-c}{c-b} & b < x \le c \\ 0 & x \ge c \end{cases}$$

$$\mu_{\text{Moderate}}(x) = \begin{cases} 0 & x \le a \\ \frac{x-a}{b-a} & a < x \le b \\ \frac{c-x}{c-b} & b < x \le c \\ 0 & x \ge c \end{cases}$$

$$\mu_{\text{Many}}(x) = \begin{cases} 0 & x \le a \\ \frac{x-a}{b-a} & a < x \le b \\ 1 & x > b \end{cases}$$

$$\mu_{\text{Few}} = \frac{250-200}{250-100} = \frac{50}{150} = 0.33$$

$$\mu_{\text{Moderate}} = \frac{200-150}{300-150} = \frac{50}{150} = 0.33$$

$$\mu_{\text{Many}} = 0$$

In the first stage, the sales value of 200 units was evaluated using three predefined fuzzy sets: Few, Moderate, and Many. The computational results indicate that this value exhibits a moderate degree of membership in both the Few and Moderate sets, suggesting that 200 units fall within a transitional region between low and moderate sales conditions. It does not represent an extreme situation (neither very low nor high sales), but rather a level with potential for upward movement. Meanwhile, the degree of membership in the Many set is zero, confirming that a value of 200 units does not correspond to the characteristics of high sales.

These fuzzy sets allow the system to map crisp sales data into linguistic variables, enabling more flexible decision-making.

2. Membership Function for Raw Material Supplies Input

The second input variable is Raw Material Supplies, referring to the available stock of fresh oranges used in juice production. Since raw material availability fluctuates significantly and directly affects production capability, the variable is categorized into three fuzzy sets:

a. Few
b. Moderate
c. Many

The fuzzy sets use trapezoidal or triangular functions based on the observed supply range:

a. Few : a=0, b=115, c=200, d=300a=0,b=115,c=200,d=300

b. Moderate : a=250, b=350, c=400, d=500a=250,b=350,c=400,d=500

c. Many : a=400, b=500, c=600, d=810a=400,b=500,c=600,d=810

The membership functions are defined as:

$$\mu_{\text{Few}}(x) = \begin{cases} 1 & x \le b \\ \frac{c-x}{c-b} & b < x \le c \\ 0 & x > c \end{cases}$$

$$\mu_{\text{Moderate}}(x) = \begin{cases} 0 & x \le a \\ \frac{x-a}{b-a} & a < x \le b \\ 1 & b < x \le c \\ \frac{d-x}{d-c} & c < x \le d \\ 0 & x > d \end{cases}$$

$$\mu_{\text{Many}}(x) = \begin{cases} 0 & x \le a \\ \frac{x-a}{b-a} & a < x \le b \\ 1 & x > b \end{cases}$$

$$\mu = 0$$

$$\mu_{\text{Moderate}} = \frac{335-250}{350-250} = \frac{85}{100} = 0.85$$

$$\mu = 0$$

The raw material availability of 335 units was then evaluated using the three fuzzy categories: Few, Moderate, and Many. The results show that 335 units have a significant membership degree only in the Moderate category, while the membership values in the Few and Many categories are zero. This indicates that the inventory level is stable and sufficient to support the production process, although it has not reached a condition classified as highly abundant. In other words, the raw material availability is at an optimal level for production without resulting in excess stock.

These fuzzy sets allow the model to capture changes in supply conditions and adjust production estimates accordingly.

3. Rule Evaluation

$$\alpha_i = \min(\mu_A, \mu_B)$$

a. IF Sales = Few and Raw = Moderate → Output = 200

$$\alpha_1 = \min(0.33,\ 0.85) = 0.33$$

b. IF Sales = Moderate and Raw = Moderate → Output = 335

$$\alpha_2 = \min(0.33,\ 0.85) = 0.33$$

Based on the obtained membership degrees, only three conditions have non-zero μ values: Sales–Few (0.33), Sales–Moderate (0.33), and Raw–Moderate (0.85). Therefore, two

fuzzy rules are activated:
(1) when Sales is categorized as Few and Raw Materials as Moderate, producing a consequent output of 200 with a firing strength α_1 = min(0.33,0.85) = 0.33 α_1 = min(0.33, 0.85) = 0.33 α_1
= min(0.33,0.85) = 0.33; and
(2) when Sales is categorized as Moderate and Raw Materials as Moderate, producing a consequent output of 335 with a firing strength α2=min(0.33,0.85) = 0.33 α_2 = min(0.33, 0.85)
= 0.33 α_2= min(0.33,0.85) = 0.33.
All other rules remain inactive due to zero membership values in the corresponding fuzzy sets. These results indicate that both active rules have equal firing strengths, implying an equivalent level of influence on determining the final crisp output. Since the sales value does not fall into the Many category and the raw material availability does not belong to either Few or Many, the decision-making process is primarily influenced by the combination of low-to-moderate sales and sufficient raw material supply.

4. Defuzzification Output Sugeno

The following section presents the defuzzification sugeno (Weighted Average) process used to obtain the final script output:

$$Z = \frac{\sum(\alpha_i \cdot z_i)}{\sum \alpha_i}$$

$$Z = \frac{(0.33 \cdot 200) + (0.33 \cdot 335)}{0.33 + 0.33}$$

$$0.33(200 + 335) = 0.33(535) = 176.55$$

$$0.66$$

$$Z = \frac{176.55}{0.66} = 267.5$$

In the final stage, the Sugeno method computes the crisp output based on the contribution of the activated rules. Each rule provides a constant consequent value, which is weighted by its respective firing strength. The results indicate that the final output value lies in the mid-range of the consequences of the active rules, reflecting a condition of moderate sales and sufficient raw material availability. Conceptually, this output represents a recommendation for a moderate production level—neither too low nor at peak capacity—indicating a relatively stable operational condition for the observed week.

Production Optimization

Production quantity optimization is a crucial stage in the operational planning chain, serving as a bridge between market demand and the company's internal resource capacity. This stage primarily aims to establish ideal optimal production values to ensure production capacity is adjusted to market dynamics and resource constraints. In this study, optimization decisions are based on two critical input variables, sales and level, which reflects market demand, and raw material availability, which represents logistical and inventory constraints.

To formulate a decision-making model amidst market and resource data ambiguity, this study adopted a Fuzzy Inference System (FIS) with the Sugeno Method. The selection of the Sugeno FIS is based on its structural advantages, particularly in providing more measurable outputs and high numerical precision, which differs from the Mamdani method (Purba & Gultom, 2024). Sugeno's output, a linear function or constant, can be directly interpreted as a definite production quantity, making it an efficient and easy-to-implement method in the context of a data-based decision support system (Kusumadewi, 2010; Warmansyah & Hilpiah, 2019). Thus, the Sugeno model can provide optimal production recommendations that are ready to be executed by company management.

4. Defuzzification

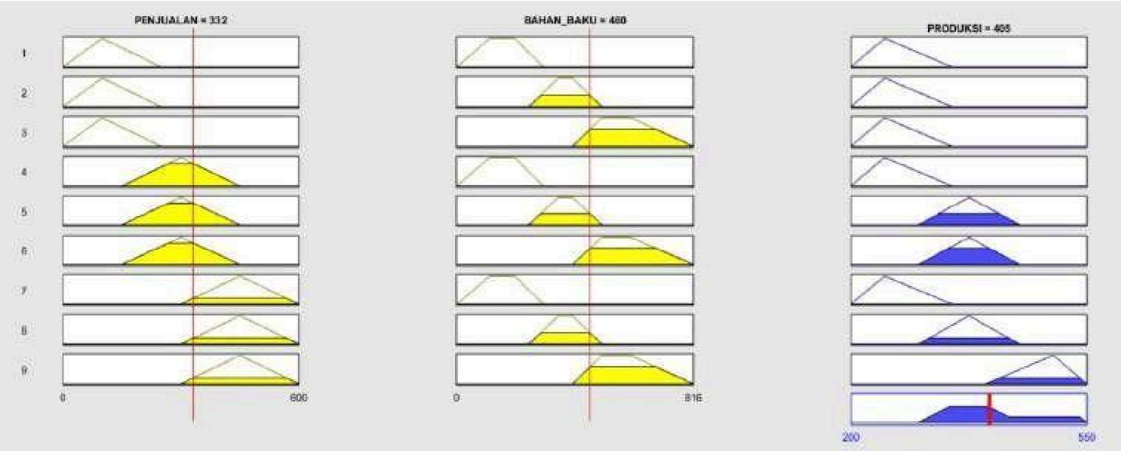

Figure 3. Defuzzification of The Rules Results

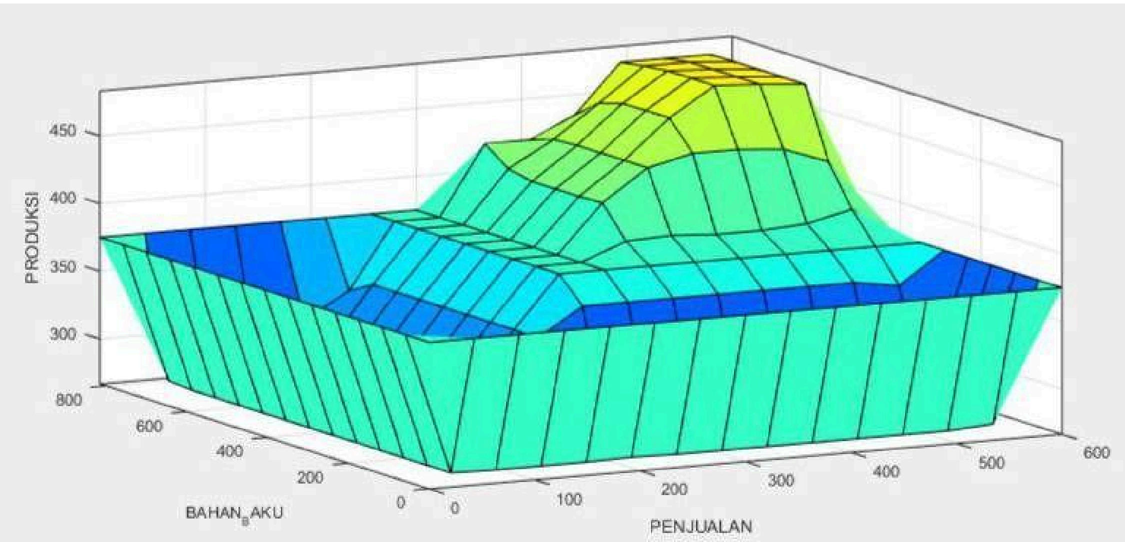

Figure 4. Surface of Defuzzification Results

The figure illustrates the defuzzification surface, which describes the interaction between raw material availability, sales level, and production output. In fuzzy logic systems, defuzzification. Defuzzification is conversion of fuzzy numbers resulting from the fuzzy inference process into definite numbers (Adrial, 2018). The surface shows that production tends to increase as both raw material supply and sales rise. At low levels of raw materials and sales, the production value remains low, which is represented by the blue area on the graph. As both variables gradually increase, the production value also rises, forming a smoother transition toward the green and yellow regions. The highest part of the surface, indicated in yellow, represents the condition of optimum or overproduction, where both sales and raw material supplies are at their highest levels.

This pattern shows that the fuzzy logic model functions as expected, with production responding proportionally to changes in sales and raw material inputs. The surface provides a clear visualization of how the system adapts production levels based on varying input conditions, ensuring that decision-making remains consistent and responsive to actual production needs.

CONCLUSION

This research demonstrates that the integration of forecasting analysis and fuzzy logic using the Sugeno method is effective for supporting production planning and raw material inventory management at XYZ MSME. The 10-week observational data show consistent patterns between sales, raw material availability, and production output, indicating that the company already aligns its production with actual demand. The forecasting results using the Simple Moving Average method produce relatively low error values, particularly for raw material prediction, with a MAPE of 11.39 percent, confirming the method's reliability. The estimated demand of 332 units for sales and 460.67 units for raw materials provides a solid basis for short-term production decisions.

The Sugeno Fuzzy Inference System further strengthens decision-making by translating uncertain and fluctuating operational data into clear production recommendations. The fuzzification of sales and raw material inputs into Low, Medium, and High categories, along with expert-based output values of 200, 335, and 500 units, enables the system to model real conditions accurately. The resulting rule base shows that production levels increase consistently with higher sales and material availability, while the defuzzification surface confirms a proportional relationship between input variables and production output.

Overall, the combination of forecasting and fuzzy logic provides a robust, data-driven framework that supports optimal production quantity decisions, minimizes the risk of overproduction or material shortages, and enhances operational efficiency at XYZ MSME. This approach can be adopted as a reliable decision-support tool for similar small-scale manufacturing operations facing uncertain demand patterns.

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