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Analysis of Mill Motor Speed on the Sugar Value in Bagasse Using the Fuzzy Logic Method at the Sugar Factory of PT. Pratama Nusantara Sakti

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ABSTRACT

The Indonesian sugar industry faces a serious challenge in the form of low efficiency in sugarcane milling, which is indicated by the high pol value in bagasse. This condition indicates that a considerable amount of sugar remains trapped in the bagasse, resulting in sugar losses and reduced productivity. One of the operational factors contributing to this phenomenon is the rotational speed of the mill motor, as non-optimal speed can affect the level of juice extraction and the amount of sugar remaining in the bagasse. Therefore, this study aims to analyze the effect of mill motor rotational speed on the pol value of bagasse and to optimize this parameter using the fuzzy logic method. The fuzzy system was designed to process machine variables (motor speed and motor load) as well as supporting factors (moisture content, temperature, service life, and harvesting age) through inference rules based on membership functions. Results show that most fuzzy predictions are consistent with the actual data from the quality control division, with a high level of accuracy indicated by an RRMSE of 7.84%, MAE of 0.0603, and MAPE of 3.34%. These findings demonstrate that fuzzy logic is capable of handling uncertainty and the complexity of variables in the milling process, while also providing a practical solution to reduce sugar losses, improve quality, and enhance the productivity of the national sugar industry.

1. INTRODUCTION

The sugar industry is a strategic sector in the Indonesian economy due to its crucial role in providing food, industrial raw materials, and absorbing labor. According to data from the Ministry of Agriculture, national sugar demand continues to increase in line with population growth and the development of food-based industries, while domestic sugar productivity still faces various technical and managerial challenges (Kementerian Pertanian, 2023).

Indonesia's heyday as a sugar producer and exporter occurred in the early 20th century. However, since 1975, national sugar productivity has begun to decline significantly. This decline is influenced by various factors, including government policies that are less supportive of sugarcane farmers, frequent crop failures, and the relatively old condition of sugar mills and suboptimal production processes (Yuliandri *et al*., 2010). The technical conditions of the mills, particularly the limited performance of the milling machines, contribute to low juice extraction efficiency and increased sugar loss during the milling process. Therefore, efforts are needed to improve milling machine performance by adjusting operational parameters appropriately, such as milling motor speed, using a fuzzy logic-based optimization approach to address uncertainties in the production process.

One of the crucial processes in a sugar factory is sugarcane milling, which aims to extract the sap, the primary raw material for sugar production. Sugarcane stalks contain approximately 75% water (sap) and 25% dry matter (bagasse). The sap consists of various organic and inorganic substances, both soluble and insoluble. Sucrose is the main soluble organic component, while the bagasse contains insoluble organic and inorganic materials (Husna *et al*., 2023).

According to Notojoewono (1984), sugarcane contains simple sugars from the disaccharide group (sucrose) and monosaccharides such as glucose, fructose, and invert sugar. These sugars are extracted through a milling process to produce the sap, the raw material for sugar production. The efficiency of the milling process is not determined by the type of sugar compound contained in the sugarcane, but rather by the performance of the milling machine and its operational parameter settings. One important parameter that influences the rate of sap extraction and the sugar residue in the bagasse is the speed of the milling motor.

Motor speed plays a crucial role in determining the effectiveness of the milling process. Too low a speed will result in the sugarcane not being fully milled, resulting in less than optimal sap yield. Conversely, excessively high speeds can cause over-milling, which actually increases the sugar content in the bagasse (Srichaipanya & Chuan-Udom, 2020). This condition is reflected in the bagasse pol value, which is the sugar content remaining in the bagasse and is measured using a polarimeter (Ridho *et al*., 2016).

Sugarcane bagasse is a milling byproduct that can be used as a raw material for various value-added products, such as activated carbon, composite panels, furniture, and bioenergy (Kusuma *et al*., 2023; Imani *et al*., 2021). However, in the context of milling performance evaluation, high pol content in bagasse is still used as an indicator of inefficiency in the sugar extraction process. Therefore, the bagasse pol value needs to be reduced through precise operational parameter control. One important parameter that can be optimized is the speed of the milling motor.

Motor speed control can be achieved using various control methods, one of which is based on fuzzy logic. Fuzzy logic was developed by Zadeh (1965) and is designed to handle uncertainty through the concept of degree of membership, making it more flexible than conventional control systems. This method enables control systems to make rule-based decisions that mimic human reasoning. In various studies, fuzzy logic has been effectively applied to the speed control of electric motors, such as induction motors, DC motors, and brushless DC (BLDC) motors, resulting in improved response stability, speed accuracy, and system performance efficiency (Sukamto, 2022; Punat *et al*., 2020; Maulana & Endryansyah, 2018). Furthermore, the application of fuzzy logic has also been shown to improve the overall operational performance of industrial machinery (Zulfahmi *et al*., 2021).

PT. Pratama Nusantara Sakti, a swampy sugar mill with a milling capacity of approximately 6,000 tons of sugarcane per day, still faces the problem of high pol content in the bagasse, which is around 15%, according to factory operational data. This value indicates low juice extraction efficiency due to suboptimal milling machine operational parameters, particularly motor speed. Therefore, this study was conducted to analyze the effect of motor speed on bagasse yield and optimize these parameters using a fuzzy logic approach. Thus, it is hoped that the research results can provide solutions to improve milling efficiency, reduce sugar loss, and enhance the productivity of the national sugar industry.

2. MATERIALS AND METHODS

2.1. Research Time and Location

This research was conducted from May to September 2024. The research location was at the PT. Pratama Nusantara Sakti site in Sungai Menang District, Ogan Komering Ilir Regency, South Sumatra, specifically in the milling area of the production division.

2.2. Equipment and Materials

This research used complete sugarcane milling equipment, from the cane preparation stage to the milling process, as well as a Distributed Control System (DCS) to monitor and regulate the milling motor speed. The pol value of the bagasse was measured using a polarimeter, while the physical quality of the bagasse was analyzed based on color, moisture, and texture.

The main material for this study was bagasse milled by PT. Pratama Nusantara Sakti. Sample was taken during the milling process at various motor speed settings, from low to high. Data obtained from the bagasse measurements and physical analysis were used as the basis for optimizing motor speed using the Mamdani fuzzy logic method, with the goal of achieving optimal sugarcane extraction and minimizing sugar loss in the bagasse.

2.3. Research Stages

The research phase began with preparing the sugarcane milling equipment, followed by calculations of milling speed estimates to determine a stable motor speed to produce optimal bagasse yields. After the milling process, bagasse yield data was collected through the control department, based on laboratory testing results. Next, the equipment's performance was tested under various motor speed conditions using the fuzzy logic method.

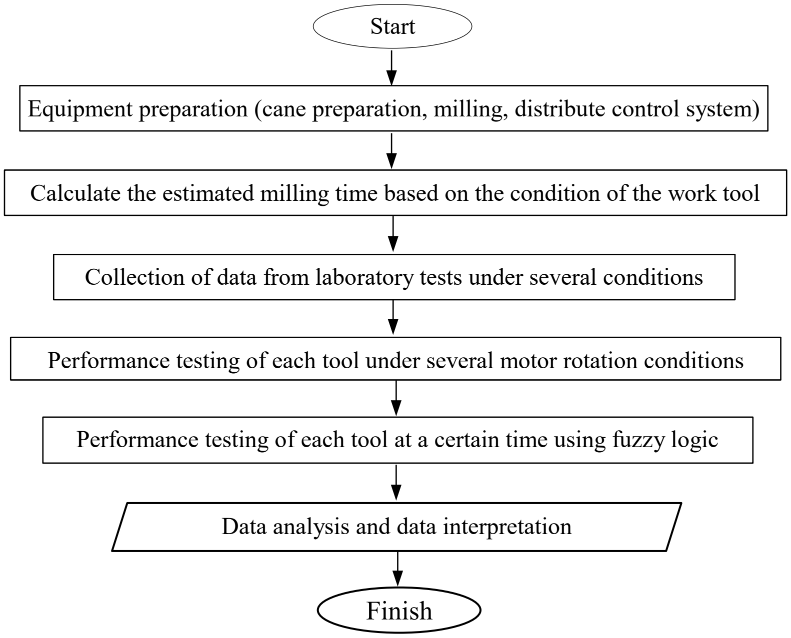
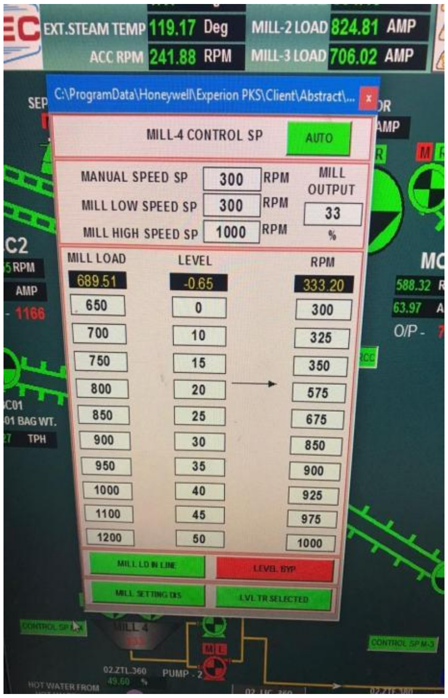


Figure 2. Research steps flowchart



EXT.STEAM TEMP 119.17 Deg
ACC RPM 241.88 RPM
MILL-2 LOAD 824.81 AMP
MILL-3 LOAD 706.02 AMP

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MILL-4 CONTROL SP

MANUAL SPEED SP 300 RPM
MILL LOW SPEED SP 300 RPM
MILL HIGH SPEED SP 1000 RPM
MILL OUTPUT 33 %

MILL LOAD	LEVEL	RPM
689.51	-0.65	333.20
650	0	300
700	10	325
750	15	350
800	20	575
850	25	675
900	30	850
950	35	900
1000	40	925
1100	45	975
1200	50	1000

Figure 3. Milling speed logic set by DCS mill operator

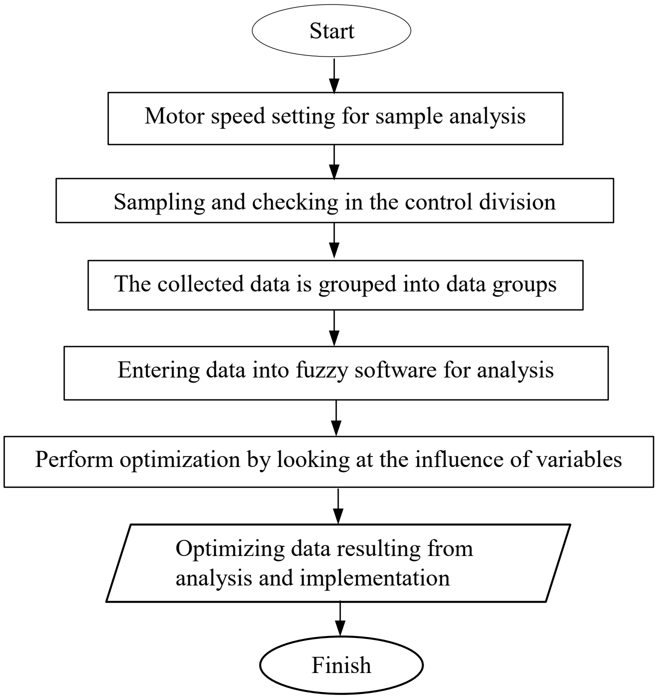


Figure 4. Fuzzy Set Flowchart

2.4. Milling Logic Settings

Milling analysis was performed using the motor rotation logic in the DCS Mill system. This setting involved changing and monitoring the motor rotation so that the bagasse pol value parameter meets the standards set by management. The milling rotation control logic considers several parameters, including:

1. Load – the load generated by the motor rotation during milling.
2. Sugarcane Input Capacity – the amount of sugarcane entering the mill.
3. Equipment parameters – the operating conditions of the milling machine used.

Figure 3 shows a logic diagram of the milling speed set by the operator via the DCS Mill system. The milling rotation value generated from this setting was then used as the basis for the pol value analysis by the production controller, thus ensuring that bagasse quality meets the target.

2.5. Fuzzy Input and Output Variables

The input and output flowchart can be seen in Figure 4. This fuzzy set flowchart processes six input variables, which are then grouped into two groups to produce two new inputs. The first group is summarized as machine factors (Table 1), while the second group is summarized as milling factors (Table 2). These two new inputs are then used to determine the final value, which is used in calculating the sugar content (pol) in bagasse (Table 3). Tables 1 – 3 list a complete list of fuzzy sets for each input and output variable in this study.

Table 1. Fuzzy membership sets for the machine factor

Function	Variable Name	Fuzzy Set	Domain
Input	Rotational Speed (RPM)	Slow	600–700
		Medium	700–800
		Fast	900–1000
	Equipment Service Life (years)	New	1–4
		Old	4–10
		Very Old	>10
	Motor Load (Watt or Ampere)	Low	500
		Medium	800
		High	900
Output	Machine Factor	Very optimal	7–10
		Optimal	6–8
		Moderately optimal	4–6
		Less optimal	3–5
		Not optimal	0–4

Table 2. Fuzzy membership sets for supporting (milling) factor

Function	Variable Name	Fuzzy Set	Domain
Input	Water Content (%)	Low water	<30%
		Normal	31–35%
		Excess water	>35%
	Water Tempera-ture (°C)	Low temperature	<70°C
		Hot	85°C
		Very hot	90°C
	Harvesting Age (days or weeks)	Early	1
		Ideal	2
		Late	4
Output	Milling Factor	Highly supportive	7–10
		Supportive	5–7
		Moderately Supportive	4–6
		Less supportive	3–5
		Not supportive	0–4

Table 3. Fuzzy membership sets for bagasse pol quality

Function	Variable Name	Fuzzy Set	Domain
Input	Machine Factor	Highly Supportive	7–10
		Supportive	6–8
		Moderately Supportive	4–6
		Less Supportive	3–5
		Not Supportive	0–4
Input	Milling Factor	Highly Supportive	7–10
		Supportive	5–7
		Moderately Supportive	4–6
		Less Supportive	3–5
		Not Supportive	0–4
Output	Bagasse Pol Quality	Quality 1 (Very Good)	7–10
		Quality 2	5–8
		Quality 3	4–6
		Quality 4	3–5
		Quality 5 (Very Poor)	0–4

2.6. Fuzzy Rules

2.6.1. Membership Rules for Machine Factors (Primness)

The fuzzy rules for the machine factor are formed from three input variables—rotational speed (RPM), tool life, and motor load—each with three linguistic levels, resulting in 27 combinations. The thresholds for each variable are determined based on technical parameters and observations of the machine's condition. The output is a machine's primacy level, from very prime to not prime, summarized in Table 4.

Table 4. Fuzzy rules for the machine factor variable (machine condition)

No	RPM	Equipment Service Life	Motor Load	Machine Factor (Condition)
R1	Slow	New	High	Optimal
R2	Slow	New	Medium	Very Optimal
R3	Slow	New	Low	Very Optimal
R4	Slow	Old	High	Optimal
R5	Slow	Old	Medium	Optimal
R6	Slow	Old	Low	Very Optimal
R7	Slow	Very Old	High	Moderately Optimal
R8	Slow	Very Old	Medium	Moderately Optimal
R9	Slow	Very Old	Low	Moderately Optimal
R10	Medium	New	High	Moderately Optimal
R11	Medium	New	Medium	Optimal
R12	Medium	New	Low	Optimal
R13	Medium	Old	High	Less Optimal
R14	Medium	Old	Medium	Moderately Optimal
R15	Medium	Old	Low	Moderately Optimal
R16	Medium	Very Old	High	Not Optimal
R17	Medium	Very Old	Medium	Less Optimal
R18	Medium	Very Old	Low	Less Optimal
R19	Fast	New	High	Not Optimal
R20	Fast	New	Medium	Less Optimal
R21	Fast	New	Low	Less Optimal
R22	Fast	Old	High	Not Optimal
R23	Fast	Old	Medium	Less Optimal
R24	Fast	Old	Low	Less Optimal
R25	Fast	Very Old	High	Not Optimal
R26	Fast	Very Old	Medium	Not Optimal
R27	Fast	Very Old	Low	Less Optimal

2.6.2. Membership Rules for Milling (Supporting) Factors

These fuzzy rules are formed from three input variables—water quantity, water temperature, and cutting period—each with three linguistic levels, resulting in 27 rule combinations. The output is the milling support factor, from strongly supporting to not supporting, which is summarized in Table 5.

Table 5. Fuzzy rules for the milling factor variable (supporting factor)

No	Water Content	Water Temperature	Harvest Age	Milling Factor (Support Level)
R1	Normal	Very Hot	Ideal	Highly Supportive
R2	Normal	Very Hot	Early	Highly Supportive
R3	Normal	Very Hot	Late	Supportive
R4	Normal	Hot	Ideal	Highly Supportive
R5	Normal	Hot	Early	Supportive
R6	Normal	Hot	Late	Moderately Supportive
R7	Normal	Low Temperature	Ideal	Supportive
R8	Low	Low Temperature	Early	Moderately Supportive
R9	Low	Low Temperature	Late	Moderately Supportive
R10	Low	Very Hot	Ideal	Supportive
R11	Low	Very Hot	Early	Supportive
R12	Low	Very Hot	Late	Less Supportive
R13	Low	Hot	Ideal	Supportive
R14	Low	Hot	Early	Supportive
R15	Low	Hot	Late	Moderately Supportive
R16	Low	Low Temperature	Ideal	Less Supportive
R17	Low	Low Temperature	Early	Moderately Supportive
R18	Low	Low Temperature	Late	Less Supportive
R19	Excess Water	Very Hot	Ideal	Moderately Supportive
R20	Excess Water	Very Hot	Early	Moderately Supportive
R21	Excess Water	Very Hot	Late	Less Supportive
R22	Excess Water	Hot	Ideal	Moderately Supportive
R23	Excess Water	Hot	Early	Less Supportive
R24	Excess Water	Hot	Late	Not Supportive
R25	Excess Water	Low Temperature	Ideal	Less Supportive
R26	Excess Water	Low Temperature	Early	Not Supportive
R27	Excess Water	Low Temperature	Late	Not Supportive

2.6.3. Membership Rules for Final Bagasse Pol Quality

Table 6 shows the combination of machine factor conditions (FM) and supporting factors (FP) in determining the final quality of bagasse. Each combination represents a fuzzy rule that reflects the logical relationship between input and output. From this table, it can be concluded that the best quality (Quality 1) is achieved when the machine condition is at "Very Excellent" and supported by supporting factors that are "Very Supportive" or "Supportive." Conversely, the lowest quality (Quality 5) occurs when both factors are in "Not Excellent" and "Not Supportive" conditions. Therefore, these fuzzy rules serve as the basis for decision-making in the fuzzy inference system used in this study.

Table 6. Fuzzy rules for the final bagasse pol quality variable

FM	Highly Supportive	Supportive	Moderately Supportive	Less Supportive	Not Supportive
Very Optimal	Quality 1	Quality 1	Quality 2	Quality 3	Quality 4
Optimal	Quality 1	Quality 2	Quality 3	Quality 3	Quality 4
Moderately Optimal	Quality 2	Quality 3	Quality 3	Quality 4	Quality 4
Less Optimal	Quality 3	Quality 4	Quality 4	Quality 4	Quality 5
Not Optimal	Quality 4	Quality 4	Quality 5	Quality 5	Quality 5

2.7. Model Calculation and Validation Stages

The prediction value calculation is performed using a fuzzy inference system consisting of fuzzification, inference, aggregation, and defuzzification stages. Each observation data (27 samples) is processed based on predetermined membership functions for each input variable: rotational speed, motor current (load), service life, water content, water temperature, and cutting period.

Input values are fed into a membership function to obtain the membership degree for each variable. These degrees are then processed using a pre-designed rule base. Active rules generate output values in the form of output membership degrees, which are then combined through an aggregation process. The final stage is defuzzification using the centroid method to obtain the final numerical values. This process yields output values of 4 for System 1 (machine factor) and 8.55 for System 2 (milling factor).

To ensure model consistency and accuracy, all predictions are compared with actual data from the quality control (QC) division. Error calculations are performed manually for each observation date, including the difference between the predicted and actual values, the squared error, and the RMSE, RRMSE, MSE, and MAPE calculations.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \tag{1}$$

$$RMSE = \sqrt{MSE} \tag{2}$$

$$RRMSE = \frac{RMSE}{\bar{y}} \times 100\% \tag{3}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i| \tag{4}$$

$$MAPE = \frac{100\%}{N}\sum_{i=1}^{N}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{5}$$

with y_i = actual QC value, $\hat{y}_i$ = fuzzy predicted value, $\bar{y}$ = average actual value, N = number of test data (27 samples).

3. RESULTS AND DISCUSSION

3.1. Observation Data

Observation data was obtained through a systematic field information collection process to support system analysis. These observations included recording actual conditions, characteristics of the research object, and factors influencing system performance. The observation stage is crucial because the quality of the resulting data will determine the validity of subsequent data processing (Abdussamad, 2021).

The obtained data was then processed using a fuzzification method so that it could be interpreted into fuzzy logic-based rules. This approach is effective in research with complex and dynamic variables, such as in agriculture, mechanical engineering, and signal processing (Erdoğdu *et al*., 2025; Hartadi *et al*., 2024).

In addition, observation also functions to identify the presence of disturbing factors, both from technical and environmental aspects. This aligns with recent research findings that emphasize the importance of consistent observational data collection to ensure accurate results from fuzzy-based analysis and other artificial intelligence methods (Göktepe Körpeoğlu *et al*., 2025). The observation data in this study are shown in Table 7.

Based on the data in Table 7, the machine rotational speed ranged from 650–950 rpm, while the harvesting period ranged from 1–4 days. Rotational speed is a technical parameter that directly influences the efficiency of sugarcane juice extraction and the stability of the machine's operation. At speeds that are too low (<700 rpm), the squeezing process tends to be suboptimal, resulting in suboptimal sucrose extraction and sugar remaining in the pulp. Conversely, speeds that are too high (>900 rpm) can increase mechanical friction, increase the motor's workload, and raise temperatures during the extraction process. Excessive temperature increases and mechanical stress can potentially accelerate sucrose degradation and reduce the quality of the juice (Winata & Susanto, 2014). Sugar industry practice also shows that adjusting mechanical parameters, including rotational speed, aims to maintain a balance between optimal yield and energy efficiency (Srichaipanya & Chuan-Udom, 2020).

A medium speed range, such as 750 rpm in the machine configuration in this study, tends to maintain a more stable motor load than 950 rpm, especially when combined with specific moisture content and temperature. This stability is crucial because high motor load fluctuations can increase energy consumption and accelerate wear on mechanical components. In the context of a fuzzy logic-based system, these variations in rotational speed represent low, medium, and high linguistic conditions, contributing to a comprehensive assessment of sugarcane quality.

Table 7. Observational data results

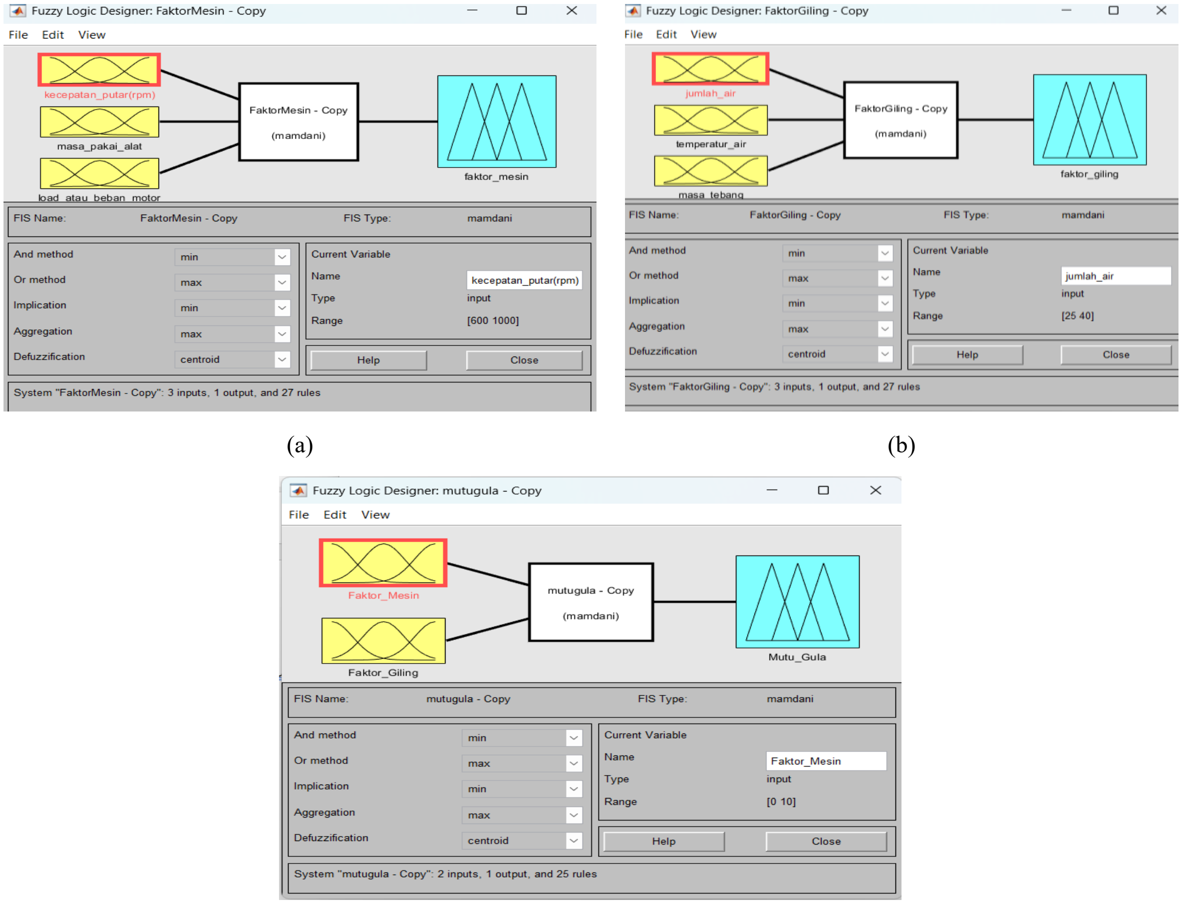
Date	Rotational Speed (RPM)	Motor Load (A)	Equipment Service Life (Weeks)	Water Content (%)	Water Temperature (°C)	Harvest Age (Days)
18-04-25	650	950	2 weeks	31.5	90	2
19-04-25	650	865	2 weeks	31.5	90	1
20-04-25	650	500	2 weeks	31.5	90	4
21-04-25	750	950	2 weeks	30	90	2
22-04-25	750	865	2 weeks	30	90	1
23-04-25	750	500	2 weeks	30	90	4
24-04-25	950	950	2 weeks	35	90	2
25-04-25	950	865	2 weeks	35	90	1
26-04-25	950	500	2 weeks	35	90	4
05-05-25	950	950	4 weeks	35	80	2
06-05-25	950	865	4 weeks	35	80	1
07-05-25	950	500	4 weeks	35	80	4
08-05-25	750	950	4 weeks	30	80	2
09-05-25	750	865	4 weeks	30	80	1
10-05-25	750	500	4 weeks	30	80	4
11-05-25	650	950	4 weeks	31.5	80	2
12-05-25	650	865	4 weeks	31.5	80	1
19-05-25	650	500	4 weeks	31.5	80	4
20-05-25	750	950	6 weeks	30	70	2
21-05-25	750	865	6 weeks	30	70	1
22-05-25	750	500	6 weeks	30	70	4
23-05-25	950	950	6 weeks	35	70	2
24-05-25	950	865	6 weeks	35	70	1
25-05-25	950	500	6 weeks	35	70	4
26-05-25	650	950	6 weeks	31.5	70	2
27-05-25	650	865	6 weeks	31.5	70	1
28-05-25	650	500	6 weeks	31.5	70	4

In addition to technical factors, the cutting period is an environmental variable that significantly determines raw material quality. Harvested sugarcane undergoes respiration and the activity of the invertase enzyme, which converts sucrose into reducing sugars. Delaying milling for more than 48 hours has been reported to significantly reduce sucrose content, especially under high ambient temperatures (Kuspratomo *et al*., 2012). A cutting period of 1–2 days is generally within the safe range for maintaining yield, while on days 3–4 the risk of sucrose loss and an increase in reducing sugar content increases.

The variation in cutting period in this study (1–4 days) demonstrates realistic raw material quality dynamics, as observed in field practice. The integration of cutting period parameters with rotational speed, motor load, water content, and water temperature in a fuzzy system allows for more adaptive modeling to actual conditions. The interaction between technical and environmental factors explains why both play a significant role in determining sugarcane quality and processing efficiency.

3.2. Fuzzification Process

Fuzzification is the initial stage in implementing a fuzzy logic system, transforming input values in the form of numerical data into linguistic values through membership functions. This process allows quantitative data from observations to be represented in the form of linguistic variables such as "low," "medium," or "high" (Santoso, 2023). In this study, the input variables from observations, including the engine, mill, and other related parameters, were fuzzified using triangular and trapezoidal membership functions. The input fuzzification process for each factor is shown in Figure 5.



FIS Name: FaktorMesin - Copy
FIS Type: mamdani
And method: min
Or method: max
Implication: min
Aggregation: max
Defuzzification: centroid
Current Variable
Name: kecepatan_putar(rpm)
Type: input
Range: [600 1000]
System "FaktorMesin - Copy": 3 inputs, 1 output, and 27 rules

(a)

FIS Name: FaktorGiling - Copy
FIS Type: mamdani
And method: min
Or method: max
Implication: min
Aggregation: max
Defuzzification: centroid
Current Variable
Name: jumlah_air
Type: input
Range: [25 40]
System "FaktorGiling - Copy": 3 inputs, 1 output, and 27 rules

(b)

FIS Name: mutugula - Copy
FIS Type: mamdani
And method: min
Or method: max
Implication: min
Aggregation: max
Defuzzification: centroid
Current Variable
Name: Faktor_Mesin
Type: input
Range: [0 10]
System "mutugula - Copy": 2 inputs, 1 output, and 25 rules

(c)

Figure 5. Fuzzy input for (a): Machine factor; (b): Grinding factor; (c): Final quality

3.3. Simulation Data

Simulation data are the output values and predictions that have been input according to the experimental data, so they can be compared with the required output data. The following are the simulation data results from the two-factor experiment: the salt factor and the grinding factor. The fuzzy logic approach has proven effective in determining sugarcane poll values because it can handle complex, varied, and uncertain data. This system utilizes input variables that are not always linear, such as machine speed, motor load, service life, water content, water temperature, and harvesting period. In this study, two assessment systems were used: System 1, which emphasizes machine factors (motor speed and load), and System 2, which is more influenced by supporting milling factors (water content and temperature). Validation in this study is demonstrated through the response of the output values in Table 8, which change according to variations in input parameters.

Observations indicate that System 1 is highly sensitive to changes in motor speed and load. At low speeds (650 rpm) with high loads (900 A), relatively high poll values can be achieved (±9.05), especially when the water content is quite high and the machine's service life reaches six weeks. Conversely, System 2 exhibits greater sensitivity to milling

Table 8. Fuzzy value results for machine factor and milling factor

Date	Machine Factor			Supporting Factor			Test Results	
	Rotational Speed (RPM)	**Motor Load (A)**	**Service Life (weeks)**	**Water Content (%)**	**Water Temperature (°C)**	**Harvest Age (days)**	**System 1 (Machine Factor)**	**System 2 (Milling Factor)**
18-4-25	650	900	2	31.5	90	2	4	8.55
19-4-25	650	865	2	31.5	90	1	4	8.59
20-4-25	650	500	2	31.5	90	4	9.09	6.14
21-4-25	750	900	2	30	90	2	5.5	7
22-4-25	750	865	2	30	90	1	5.5	7
23-4-25	750	500	2	30	90	4	7	4
24-4-25	950	900	2	35	90	2	1.53	7.22
25-4-25	950	865	2	35	90	1	1.53	7.22
26-4-25	950	500	2	35	90	4	4	5.27
05-5-25	950	900	4	35	80	2	1.85	7.22
06-5-25	950	865	4	35	80	1	1.85	5.27
07-5-25	950	500	4	35	80	4	4	2.63
08-5-25	750	900	4	30	80	2	4.89	7
09-5-25	750	865	4	30	80	1	4.89	7
10-5-25	750	500	4	30	80	4	6.39	5.50
11-5-25	650	900	4	31.5	80	2	5.23	8.55
12-5-25	650	865	4	31.5	80	1	5.23	7
19-5-25	650	500	4	31.5	80	4	8.87	5.5
20-5-25	750	900	6	30	70	2	4	4
21-5-25	750	865	6	30	70	1	4	5.5
22-5-25	750	500	6	30	70	4	5.5	4
23-5-25	950	900	6	35	70	2	1.59	5.27
24-5-25	950	865	6	35	70	1	1.59	1.74
25-5-25	950	500	6	35	70	4	4	1.74
26-5-25	650	900	6	31.5	70	2	7	6.14
27-5-25	650	865	6	31.5	70	1	9.05	5.5
28-5-25	650	500	6	31.5	70	4	9.05	4

or supporting factors. Moisture content above 35% and high water temperature reduce milling efficiency, resulting in lower poll values. These findings align with research confirming that a combination of environmental and technical factors significantly influences the quality of sugarcane and its derivatives (Carani *et al*., 2024).

The inference process in a fuzzy system works by combining all established rules based on input conditions. The result is still a value in the form of a degree of membership. The defuzzification stage then converts this value into a precise number that can be used for analysis. Through this stage, the system's output reflects the combination of all involved parameters, rather than a rigid decision like in deterministic methods that use fixed boundaries between categories (Elsevier, 2018).

Previous studies also emphasized that integrating fuzzy methods with optimization algorithms can help improve the efficiency of the overall sugarcane processing system (Rezk & Faraji, 2024; Nurmuslimah, 2020). Thus, fuzzy logic is not only capable of modeling real, non-deterministic conditions but also has great potential as a basis for intelligent decision-making in the future sugarcane processing industry.

3.4. Comparison of Simulation Results and Quality Values

System 3 is a fuzzy logic-based sugar quality evaluation system that integrates all process parameters—machine rotational speed, motor current (load), service life, water content, water temperature, and cutting time—in a single inference model. Unlike Systems 1 and 2, which separate machine and milling factors, System 3 combines all these variables to obtain a comprehensive quality assessment. Test results on System 3 indicate that the combination of machine parameters and supporting factors plays a significant role in determining sugar quality. The majority of experimental data yielded values consistent with those measured by the quality control division (status SAME). For example, at low speed (650 rpm) and relatively stable water content (31.5%), sugar quality was recorded as high and close to the reference value, as seen in data from May 26–27, 2025, with a result of 2.5. Conversely, at high speed (950 rpm) and high moisture content (35%), sugar quality actually decreased, with values ranging from 1.1038 to 1.6513 on May 24–25, 2025, and differing from the actual results of the quality control division (status DIFFERENT). This condition can be attributed to the phenomenon of overgrinding, which occurs when operating parameters such as rotational speed and machine load are operated at excessively high levels, which can reduce extraction efficiency and affect the quality of the juice. Several technical reports on sugarcane processing also state that unbalanced operating conditions have the potential to affect the yield and stability of the milling process (Kwenda, 2015).

Operationally, fuzzy inference rules such as "If the speed is low AND the moisture content is moderate AND the temperature is moderate, THEN the sugar quality is high" can be used to support decision-making. Through inference and defuzzification, the system is able to evaluate non-linear interactions between variables and provide results that approximate the reality of industrial processes (Athiyah *et al*., 2021).

Table 9. Final comparison data between fuzzy simulation and the quality control division

Date	Machine Factor				Supporting Factor			Quality Control Result	Remarks
	Motor Speed (RPM)	Motor Load (A)	Service Life (weeks)	Water Content (%)	Water Temperature (°C)	Harvest Age (days)	Fuzzy Sugar Quality		
18-4-25	650	900	2	31.5	90	2	2.25	2.2	Same
19-4-25	650	865	2	31.5	90	1	2.25	2	Same
20-4-25	650	500	2	31.5	90	4	1.5	1.5	Same
21-4-25	750	900	2	30	90	2	2.51	2.2	Different
22-4-25	750	865	2	30	90	1	2.51	1.9	Different
23-4-25	750	500	2	30	90	4	2	2	Same
24-4-25	950	900	2	35	90	2	1.5	1.5	Same
25-4-25	950	865	2	35	90	1	1.5	1.5	Same
26-4-25	950	500	2	35	90	4	1.5	1.5	Same
05-5-25	950	900	4	35	80	2	1.5	1.5	Same
06-5-25	950	865	4	35	80	1	1.65	1.5	Same
07-5-25	950	500	4	35	80	4	1.11	1.1	Same
08-5-25	750	900	4	30	80	2	2.25	2.25	Same
09-5-25	750	865	4	30	80	1	2.25	2.25	Same
10-5-25	750	500	4	30	80	4	2.25	2.25	Same
11-5-25	650	900	4	31.5	80	2	2.50	2.5	Same
12-5-25	650	865	4	31.5	80	1	2.51	2.5	Same
19-5-25	650	500	4	31.5	80	4	2.5	2.5	Same
20-5-25	750	900	6	30	70	2	1.5	1.5	Same
21-5-25	750	865	6	30	70	1	1.5	1.5	Same
22-5-25	750	500	6	30	70	4	1.5	1.5	Same
23-5-25	950	900	6	35	70	2	1.65	1.5	Same
24-5-25	950	865	6	35	70	1	1.10	1.1	Same
25-5-25	950	500	6	35	70	4	1.10	1.2	Different
26-5-25	650	900	6	31.5	70	2	2.5	2.5	Same
27-5-25	650	865	6	31.5	70	1	2.5	2.5	Same
28-5-25	650	500	6	31 .5	70	4	2.5	2.5	Same

3.5. Model Performance Analysis with RRMSE

The analysis data is obtained from Table 9, which compares the fuzzy prediction results with actual data from the quality control division. Calculations were performed for each observation date and presented in interactive CSV format, making it easy to check the predicted values, actual data, and the difference (error) in each row of data.

The calculation results show a total of 27 test data samples. The Root Mean Square Error (RMSE) value of 0.1465 with an average observation (QC) of 1.8685 results in a Relative Root Mean Square Error (RRMSE) of 7.84%. In predictive model evaluation, RRMSE values below 10% are generally reported as low error, while a range of 10–20% is still considered acceptable depending on the application context. The Mean Absolute Percentage Error (MAPE) of 3.34% is also below the 10% threshold, which in forecast evaluation literature is often associated with a very good criteria (Pohan & Aprilia, 2025). Furthermore, the Mean Absolute Error (MAE) of 0.0603 indicates that the average absolute difference between predictions and actual data is relatively small compared to the observed range of sugar quality values.

4. CONCLUSIONS AND SUGGESTIONS

Based on the analysis of 27 experimental datasets, milling motor speed was found to significantly affect bagasse quality through its interaction with motor load and other operational variables. Under high-load conditions (900 A), increasing the motor speed from 650 rpm to 950 rpm reduced the System 1 evaluation score from approximately 4 to 1.53–1.85. Conversely, at a lower motor load (500 A), the evaluation score exceeded 4 for several parameter combinations. These results suggest that the influence of motor speed on bagasse quality is not independent but depends on the interaction among multiple operating parameters. The optimum operating condition was identified at a motor speed of 950 rpm, a motor load of 500 A, a water content of 35%, and a cane age of one day after harvesting, yielding the lowest quality index value of 1.1 and the minimum extraction loss in bagasse.

The integration of machine parameters (motor speed and load) with supporting factors (moisture content, temperature, service life, and cutting period) in a fuzzy system resulted in predictions that closely approximated the actual data from the quality control division. Model evaluation showed a RRMSE of 7.84%, MAE of 0.0603, and MAPE of 3.34% for 27 test samples. These values are within the low error range based on the literature on predictive model evaluation. The developed fuzzy model is able to represent nonlinear interactions between process parameters and provides a more flexible evaluation approach than fixed-boundary methods, making it suitable for decision-making in setting sugarcane milling parameters.

AUTHOR CONTRIBUTION STATEMENT

Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
RRN	✓	✓		✓	✓	✓		✓	✓	✓	✓			
HF	✓	✓		✓	✓		✓			✓		✓		
SRS	✓			✓			✓			✓		✓	✓	

C: Conceptualization
M: Methodology
So: Software
Va: Validation
Fo: Formal Analysis
I: Investigation
D: Data Curation
R: Resources
O: Writing - Original Draft
E: Writing - Review & Editing
Vi: Visualization
Su: Supervision
Fu: Funding Acquisition
P: Project Administration

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