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Fuzzy Logic Design for Mocaf and Mung Bean Flour Substitution Effect on Noodle Protein Content

Alysha Revalina Nugraha[1]
[1]Food and Quality Assurance Supervisor, College of Vocational Studies IPB University
alysharevalina@apps.ipb.ac.id
Adinda Dwi Wahyuni[2]**, Ananti Nur Mala**[3]**, Arifi Keisya Azahra**[4]**, Aurelia Salsabila**[5]**, Daffa Athallah Umbara**[6]**, Naila Nabiha Fidzri**[7]**, Soelthan Ramzy Kastio**[8]**, Mrr. Lukie Trianawati**[9]**, Wuliddah Tamsil Barokah**[10]**, Annisa Raihanah Maimun**[11]**, Roma Juliana Arios**[12]
[23456789]Food and Quality Assurance Supervisor, College of Vocational Studies IPB University
[101112]Computer Engineering Technology, College of Vocational Studies, IPB University
[2]adindadwahyuni@apps.ipb.ac.id, [3]anantimala@apps.ipb.ac.id, [4]arifikeisya@apps.ipb.ac.id,
[5]salsabilaaurelia@apps.ipb.ac.id, [6]daffaumbara@apps.ipb.ac.id, [7]fidzrinaila@apps.ipb.ac.id,
[8]soelthanramzy@apps.ipb.ac.id, [9]mrr.lukietrianawati@apps.ipb.ac.id, [10]19tamsilwuliddah@apps.ipb.ac.id,
[11]annisaraihanah@apps.ipb.ac.id, [12]romajarios@apps.ipb.ac.id.

ABSTRACT

Wet noodles are a widely consumed food in Indonesia, but their protein content is relatively low because they are made from wheat flour. Nutritional value can be increased by substituting some of the wheat flour with local ingredients such as protein-rich mung bean flour and mocaf, which improves texture despite its low protein content. Previous studies have shown that adding mung bean flour increases the protein content of wet noodles, while mocaf does not have a significant effect. Based on these conditions, this study aims to model the relationship between the composition of mung bean flour and mocaf on the protein content of wet noodles using Mamdani fuzzy logic, which is effective in handling uncertain data and non-linear variable relationships. The study used secondary data from previous research with three substitution treatments: MB2 (50:10), MB4 (30:30), and MB6 (10:50). Two input variables (the percentage of mocaf and mung bean flour) and one output variable (protein content), were divided into three linguistic categories: low, medium, and high. The fuzzy process included fuzzification, IF–THEN rule formulation, inference using the MIN–MAX operator, and centroid defuzzification. The modeling results showed that an increase in mung bean flour was associated with an increase in protein content, while mocaf reduced protein when used in high amounts. The Mamdani method proved to be able to describe the relationship between ingredient composition and protein content in a more adaptive and representative manner.

Keywords: fuzzy logic mamdani, mung bean flour, mocaf, protein content, wet noodles.

INTRODUCTION

Currently, Indonesians of all ages, from children to adults, consume noodles. There are several types of noodles, namely dry noodles, wet noodles, and instant noodles. One type of noodle that is often used is wet noodles. According to SNI 2987:2015, wet noodles are f -ood products made from wheat flour with other permitted ingredients and have undergone a boiling or steaming process. In addition, based on BPOM Regulation Number 13 of 2023 about Food Categories, wet noodles are included in the group of cereal-based processed foods that have high water content and require special handling in storage to maintain product quality and safety.

The nutritional content of wheat flour-based wet noodles consists mostly of carbohydrates. Wet noodles have a carbohydrate content of 48.07% compared to a protein content of only 6.49% (Kardina & Eka, 2017). One method to increase the protein content in wet noodles is by adding additional ingredients. Wafiyah *et al.* (2025) conducted research on the addition of ingredients to wet noodles, namely mung bean flour and mocaf (modified cassava flour). Mung bean flour (*Vigna radiata*) was chosen because it is known to have a high protein content, ranging from 20-25%. This study statistically used a Completely Randomized Design (CRD) analyzed with ANOVA and followed by a Significant Difference Test (SDT) at a significance level of 5%. The results of the analysis showed that the addition of mung bean flour had a significant effect on the protein content of wet noodles, while the addition of mocaf did not show a significant effect. Furthermore, an increase in the amount of mung bean flour was consistent with an increase in the protein content of wet noodles.

Based on these results, this study will design a fuzzy logic model to model the relationship between the addition of mung bean flour and the protein content in wet noodles, as in the study by Wafiyah *et al*. (2025). According to Saputri (2025), fuzzy logic is a fuzzy mathematical method that can be used to analyze data containing elements of uncertainty. Fuzzy logic has the advantage of being able to model highly complex non-linear functions, is very flexible, and has tolerance for fuzzy data (Athiyah *et al*., 2021). The application of fuzzy logic aims to model and analyze the effect of adding mung bean flour and mocaf on the protein content of wet noodles more flexibly and accuracy, especially on data containing uncertainty.

METHODS

This research is based on a literature study that examines various theories and applications of fuzzy logic systems, particularly the Madani Fuzzy Inference System (FIS Madani) method, in various situations that will form the basis for descriptive-qualitative discussion. The research data is secondary data obtained from the study by Wafiyah *et al*. (2025) entitled "The Effect of the Ratio of Wheat Flour, Mocaf, and Mung Bean Flour on the Quality of Wet Noodles," which is data obtained from observations based on chemical parameters, namely the effect of the ratio of mocaf and mung bean flour on the protein content in wet noodles. The data used consisted of three combinations of flour substitution treatments, namely MB2, MB4, and MB6. Due to the limited amount of data, this study focused on demonstrating the application of the fuzzy method to describe the non-linear relationship between ingredient composition and protein content.

This study used two input variables, namely the percentage of mocaf and the percentage of mung bean flour with a value range of 10–50%. Each input variable was divided into three fuzzy sets (low, medium, and high) using trapezoidal and triangular membership functions adjusted to the lower limit, upper limit, and midpoint of the data. The output variable, protein content, was also divided into three fuzzy sets, namely low, medium, and high, based on the range of observed values. The method used in this study is the Mamdani fuzzy inference system, which was chosen because of its intuitive nature and suitability for modeling uncertain and non-linear relationships between variables. In the Mamdani method, the process begins with the formation of fuzzy sets for each variable, then crisp input values are converted into membership degrees through the fuzzification stage. After that, the relationship between the two input and output variables is represented through IF–THEN rules (rule base). The rules are arranged based on the characteristics of the ingredients, where mung bean flour has the effect of increasing protein content, while mocaf
tends to contribute less protein.

The implication process for each rule is performed using the MIN operator, which determines the degree of rule activation based on the smallest membership value of each input condition. Next, all the implication results from the rules are combined using the MAX operator to form a single fuzzy output set. The final stage is defuzzification using the centroid method, which produces a single crisp value as an estimate of the protein content. The centroid method was chosen because it provides a representative value of the fuzzy distribution formed.

The defuzzification results are then compared with the original observation values to see the suitability of the model's tendencies. This comparison is used as a basic form of evaluation of fuzzy model performance, especially in conditions of limited data.

RESULTS AND DISCUSSION

In noodle formulation, wheat flour is the main source of protein and gluten structure. However, to increase nutritional value, several studies have explored substituting some wheat flour with local flours such as mung bean flour and mocaf (modified cassava flour). These two ingredients have different characteristics in terms of protein content and functionality.

Mung bean flour is a semi-finished product that can be used to make processed foods (Ponelo *et al*. 2022). Mung bean flour has a relatively high protein content, ranging from 20–24%, and contains essential amino acids that are important for the formation of noodle dough. Substituting wheat flour with mung bean flour in the range of 20–30% has been shown to significantly increase the protein content of noodles without drastically affecting their texture. Research by Athiyah *et al.* (2021) shows that using 30% mung bean flour can increase the protein content of noodles by 15–18%, compared to standard wheat flour-based formulations.

In contrast, mocaf has a much lower protein content, ranging from 1–2%. Although mocaf plays a role in the texture and softness of noodles, its contribution to protein content is minimal. This is reinforced by research by Afriliyanti *et al*. (2023), which states that mocaf's contribution to protein content is relatively low, so that improvements in noodle quality are more physical and organoleptic in nature, rather than nutritional. Substituting wheat flour with mocaf does not significantly increase the protein content of noodles. A study by Lestari (2020) shows that using up to 30% mocaf only increases the protein content by around 0.5–1% and has a greater effect on the physical characteristics of noodles than their nutritional value.

If the formulation objective is to increase the protein content of noodles, then mung bean flour is a more appropriate choice than mocaf flour. Based on the results of research by Ponelo *et al*. (2022), the addition of modified mung bean flour can significantly increase protein content. Therefore, the greater the proportion of mung bean flour in the noodle formulation, the greater the protein contribution from the raw materials. This is due to the high protein content in mung bean flour, as well as the stability of the protein during the modification and processing stages, which enables it to maintain the nutritional value of the final product. This is also reinforced in the research by Pitaloka *et al*. (2024), which found that the higher the protein content is influenced by mung bean flour; the higher its usage, the higher the total protein content.

The use of fuzzy systems in this formulation allows inputs to be grouped based on linguistic categories such as low, medium, and high, as well as flexible modelling of the relationship between flour proportion and protein content. Fuzzy logic is considered capable of mapping an input to an output without ignoring existing factors, making it suitable for use in the context of complex food formulations (Indra, 2016). Fuzzy rules such as 'If there is a lot of mung bean flour, then the protein content is high' can be used to support decision-making in the development of high nutritional value noodle products.

Data collection

Table 1 Results of observations on the effect of mocaf and mung bean flour substitution on noodle protein content

Treatment	Mocaf (%)	Mung Bean Flour (%)	Protein Content (%)
MB2	50	10	4.16
MB4	30	30	6.13
MB6	10	50	8.45
	Average		6.25

Source: Wafiyah *et al*. (2025)

The data above is sourced from a study titled "The Effect of Wheat Flour, Mocaf, and Mung Bean Flour on the Quality of Wet Noodles" by Wafiyah, Eko Basuki, and Siska Cicilia. The study originally had six treatments, but in this analysis only three treatments were used that were considered most representative of the effect of mung bean flour substitution on noodle protein content. The treatments used included MB2 (50:10), MB4 (30:30), and MB6 (10:50) for combinations of mocaf and mung bean flour substitution. The observational data showed an increase in protein content as the proportion of mung bean flour increased and a decrease in protein contribution as the percentage of mocaf increased. This pattern was entirely consistent with the characteristics of the constituent ingredients.

Based on the three treatments tested (MB2, MB4, and MB6), the average protein content of the noodles reached 6.25% with a standard deviation of 2.15%. This average value was obtained from a simple calculation using three protein content data, namely 4.16% (MB2), 6.13% (MB4), and 8.45% (MB6). The increase in protein content was calculated based on the change in value between the treatment with the lowest and highest proportion of mung bean flour. In the MB2 formulation, the protein content reached 4.16%, while in MB6 the protein content reached 8.45%. The difference between these two values was the basis for calculating the percentage increase.

The percentage increase is calculated using the following formula:

$$\text{Percentage increase} = \frac{\textit{Final protein content} - \textit{Initial protein content}}{\textit{Initial protein content}} \times 100\ \%$$

By comparing the initial protein content and the final protein content, we obtain:

$$\frac{8.45 - 4.16}{4.16} \times 100\,\% = 103.1\%$$

These results show that increasing the proportion of mung bean flour from 10% to 50% causes an increase in protein content of ±103%. Conversely, a decrease in the proportion of mocaf from 50% to 10% also resulted in the same pattern of protein content increase, indicating that the higher the composition of mung bean flour, the higher the protein content produced, and a decrease in the composition of mocaf flour contributes significantly to the increase in noodle protein content.

Fuzzification

Fuzzification is the process of converting definite-valued inputs into linguistic variables through membership functions to obtain membership degrees that are then used in the rule base of a fuzzy system (Qothrunnada *et al.*, 2024). The fuzzification stage is carried out by identifying fuzzy variables with different numbers of variables on the input and output sides, namely two input variables and one output variable. The two input variables are the percentage of mocaf and mung bean flour substitution in noodles. Meanwhile, the output variable is the protein content in noodles. The fuzzy sets of mocaf and mung bean flour variables are low, medium, and high, while those of protein content are low, medium, and high.

Table 2 Variable input

Function	Variable	Fuzzy set	Universe set	Domain
Input	Mung Bean Flour	Few	10-50	[10-10-15-30]
		Medium		[10-30-50]
		High		[30-45-50-50]
	Mocaf	Few	10-50	[10-10-15-30]
		Medium		[10-30-50]

		High		[30-45-50-50]

Table 3 Variable output

Function	Variable	Fuzzy set	Universe set	Domain
Output	Protein Content	Low	4.16-8.45	[4.16-4.16-6.13]
		Medium		[4.16-6.13-8.45]
		High		[6.13-8.45-8.45]

Rules in fuzzy logic are a set of guidelines that connect input variables with output variables. These rules help address uncertainty in data and facilitate information based on combinations of input variable values. Fuzzy logic facilitates the formation of relationships between input and output variables through 'if–then' inference rules. These rules reflect the general definition of the Mamdani method, where the IF part contains conditions from input variables based on their membership degrees, while the THEN part states the consequences in the form of fuzzy outputs. This process allows the model to map changes in the flour ratio to protein content more smoothly and flexibly than linear mathematical methods. In this study, three combinations of rules were used to create different fuzzy rules.

Table 4 Rules base noodle

Code	***Rules***
[R1]	IF mung bean flour is few AND mocaf is high THEN the protein content is low
[R2]	IF mung bean flour is medium AND mocaf is medium THEN protein content is medium
[R3]	IF mung bean flour is high AND mocaf is few THEN the protein content is high

In general, fuzzy modeling in continuous input domains usually involves more rules in order to describe variations and nonlinear relationships in greater detail. The more complex the input variables (e.g., continuous), the greater the number of rules that are formed (Kastina & Silalahi, 2016). Although the secondary data used in this study actually covered more than three combinations of ingredient proportions, only three main conditions were selected for modeling purposes because they were considered the most representative and capable of describing gradual pattern changes. However, in this study, the number of rules was limited to only three because the relationship between the proportions of mocaf and mung beans to protein content showed a fairly clear and monotonous pattern. In other words, changes in protein content can be explained gradually through three main conditions that represent.

Based on Table 1, the three representative conditions selected were mocaf and mung bean ratios of 50:10, 30:30, and 10:50. An increase in the proportion of mung beans causes an increase in protein content, while an increase in mocaf decreases it, and a balanced combination produces a medium value. In addition, the characteristics of the ingredients do show a relatively clear relationship, where mung beans are a source of protein and mocaf has lower protein content, so the three rules are considered sufficient to represent the main pattern without adding complexity to the model.

Fuzzy Mamdani Design

1. **Input Variables: Mocaf Substitution and Mung Bean Flour**

   The crucial input variables in the fuzzy logic-based noodle quality control system are the Mocaf Substitution Variable and the mung bean Flour Substitution Variable. These two variables represent the proportion of non-wheat raw material mixtures, namely Modified Cassava Flour (Mocaf) and mung bean flour, which are used to replace some of the wheat flour in the noodle dough formulation. The quantitative values of these input variables serve as the basis for predicting and determining their effect on the output variable, namely the protein content of the noodle product. Within the fuzzy system framework, each input variable is translated into a fuzzy set through the fuzzification process. The substitution proportion is represented in the form of linguistic membership functions, such as low, medium, and high, which indicate the level of substitution proportion of each flour in the total dough composition. This fuzzy approach was chosen because the relationship between the variation in the proportion of substitute flour and the protein content of noodles is complex, non-linear, and contains uncertainties that are difficult to explain explicitly through conventional mathematical calculations.

The Fuzzy Logic design applied is the Mamdani Method, which is known as an intuitive and commonly used inference method. After the fuzzification process, the system will proceed to the Fuzzy Inference stage by applying a knowledge base consisting of a number of IF-THEN rules. These rules are in the form of implications (cause and effect) with antecedents in the form of conjunctions (AND) processed using the Minimisation operator (Min) to obtain the degree of membership of the inference results for each rule. Next, the system performs Rule Composition by combining the consequences of all activated rules, where this combination is in the form of Maximum (Max). The application of the Min-Max operator is very characteristic of the Mamdani method and is suitable for sets of rules that are independent (Adha *et al*., 2022). Each substitution level, through the calculated membership degree, will directly affect the shape and position of the fuzzy set output, which will then be processed at the Defuzzification stage to obtain a crisp protein content value.

With this inference mechanism, the fuzzy system can link the formulation characteristics with the desired output results. Overall, the proportions of both ingredients are used as input data in the fuzzy system to determine the relationship between changes in the composition of raw materials and the protein content of the noodle product. Any change in the input variable values will affect the output values in accordance with the established fuzzy logic rules, enabling the system to provide more adaptive and realistic decision- making results.

The attraction between fuzzy mechanisms and the formulation data becomes more apparent when the input values of each ingredient are integrated into the model. Based on the mocaf and mung bean flour input data from the study by Wafiyah *et al*. (2025), both ingredients have a maximum limit of 50%. The input values range from 10% to 50% with a midpoint of 30%. This range is used to form a fuzzy set through the calculation of the appropriate formula. The application of fuzzy logic allows for analysis of the uncertainty of protein content that arises due to differences in the ratio between mocaf and mung bean flour. Using the Mamdani fuzzy logic approach, the two inputs are processed into representative fuzzy values, which are then used in the inference and defuzzification processes to obtain more accurate results.

$$\mu SEDIKIT[x] = \begin{cases} 0, & x \le a \\ \dfrac{x-a}{b-a}, & a < x \le b \\ 1, & b < x < c \\ \dfrac{d-x}{d-c}, & c < x \le d \\ 0, & x > d \end{cases}$$

$$\mu SEDANG[x] = \begin{cases} 0, & x \le a \\ \dfrac{x-a}{b-a}, & a < x \le b \\ \dfrac{c-x}{c-b}, & b < x \le c \\ 0, & x > c \end{cases}$$

$$\mu BANYAK[x] = \begin{cases} 0, & x \leq a \\ \dfrac{x-a}{b \quad a}, & a < x \leq b \\ 1, & b < x \leq c \\ \dfrac{d-x}{d-c}, & c < x \leq d \\ 0, & x > d \end{cases}$$

Based on the figure above, the fuzzy membership function with domain [a, b, c, d] for the linguistic variables few and high and domain [a, b, c, d] for the linguistic variable medium describes the relationship between input values and membership levels for certain categories that are vague (fuzzy). The variables few and high have a trapezoidal shape, which means that both sets have areas with full membership ($\mu = 1$) in certain ranges, as well as ascending and descending areas that show the transition from not included to fully included, or vice versa. Meanwhile, the medium variable has a triangular shape, reflecting that the maximum membership value only occurs at one point (the apex of the triangle), while the values to the left and right of that point have linearly decreasing membership. The trapezoidal shape of few and high is suitable for describing extreme conditions that have a stable range, while the triangular shape of medium reflects a middle condition that is relative and transitions smoothly between the two extreme categories.

$$\mu SEDIKIT[x] = \begin{cases} 0, & x \leq 10 \\ \dfrac{x-10}{15 \quad 10}, & 10 < x \leq 15 \\ 1, & 15 < x \leq 30 \\ \dfrac{30-x}{30-15}, & 30 < x \leq 30 \\ 0, & x > 30 \end{cases}$$

$$\mu SEDANG[x] = \begin{cases} 0, & x \leq 10 \\ \dfrac{x-10}{30-10}, & 10 < x \leq 30 \\ \dfrac{50-x}{50-30}, & 30 < x \leq 50 \\ 0, & x > 50 \end{cases}$$

$$\mu BANYAK[x] = \begin{cases} 0, & x \leq 30 \\ \dfrac{x-30}{45-30}, & 30 < x \leq 45 \\ 1, & 45 < x \leq 50 \\ \dfrac{50-x}{50-45}, & 45 < x \leq 50 \\ 0, & x > 50 \end{cases}$$

Based on the figure above, the fuzzy membership functions for the linguistic variables few, medium, and high have been determined with more specific numerical domains to describe the quantity levels in the fuzzy system. The variable few with domain [10, 10, 15, 30] has a trapezoidal shape, which means that this function starts with a membership value of zero at $x \leq 10$, increases linearly from 10 to 15, then reaches full membership value ($\mu = 1$) in the range $15 \leq x \leq 30$, and finally decreases back to zero after $x > 30$. This shape indicates that the range between 15 and 30 is an area with a full confidence level that a value belongs to the 'little' category, while values below 10 or above 30 have a very small probability. For the medium variable, the domain used is [10, 30, 50] with a triangular shape, where the membership value increases linearly from 0 at $x = 10$ to the peak of full membership ($\mu = 1$) at $x = 30$, then decreases back to 0 at $x = 50$. This triangular shape conceptually represents conditions that lie between two extreme categories (few and high), where values around 30 are considered most representative of the 'medium' category. The triangular shape is very effective for describing central categories, as it provides a smooth gradation between two opposing conditions.

Meanwhile, the variable high with domain [30, 45, 50, 50] also has a trapezoidal shape. This function has a value of zero for x ≤ 30, then increases linearly from 30 to 45, and reaches a maximum value of μ = 1 between 45 and 50. Values above 50 still have full membership in the ‘many’ category. Interpretively, this shape shows that after a value passes a certain threshold (around 45), the fuzzy system completely considers the condition to be ‘many’, without any decrease in membership value. Overall, the combination of these three membership functions forms a complementary system: few and high act as extreme limits with a stable range (due to their trapezoidal shape), while medium acts as a transitional bridge that describes the area of uncertainty or balance between the two. Thus, this membership function formulation is capable of representing real-world phenomena that are gradual and lack clear boundaries, in accordance with the basic principles of fuzzy logic in accommodating ambiguity and linguistic assessments quantitatively.

Example Calculation

For example an input value of mung bean flour = 30 and MOCAF = 30, the degree of membership for each category is calculated as follows:

- For few
  Because x = 30 is at the end of the trapezoid (decreasing from 1 to 0 in the range 15–30), then:
  $$\mu SEDIKIT(30) = \frac{30-30}{30-15} = 0$$
- For medium
  Since x = 30 is the peak of the triangle (the midpoint of the domain [10,30,50]), then:
  $$\mu SEDANG(30) = 1$$
- For high
  Since x = 30 is at the starting point of the increase (30-45), then:
  $$\mu BANYAK(30) = \frac{30-30}{45-30} = 0$$

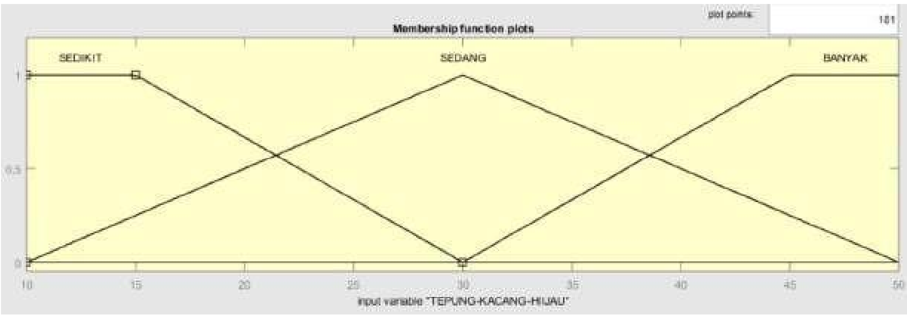

Figure 1 Membership function of mung bean flour input variable

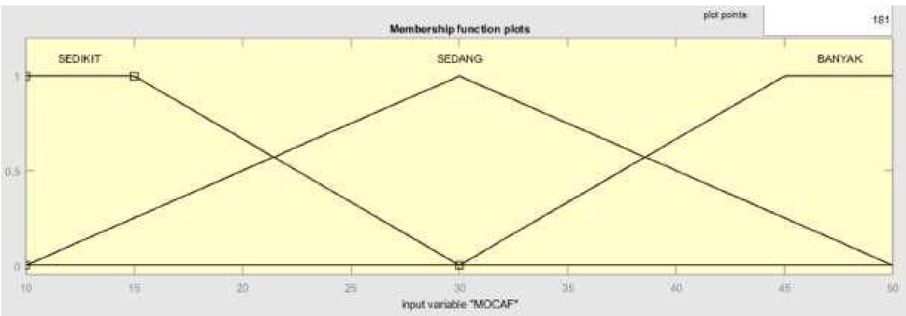

Figure 2 Membership function of mocaf input variables

2. Defuzzification

Defuzzification is an important process in fuzzy logic systems that serves to convert fuzzy values into real values. In the context of noodle production, this stage plays a role in decision-making related to product quality, raw material proportions, and production process parameters. For example, when determining the composition of wheat flour, mocaf, and mung bean flour, fuzzy systems can help handle uncertainties arising from variations in materials and process conditions. Thus, the results of defuzzification provide more accurate decisions that are in line with actual conditions in the field.

For the defuzzification stage, there are five methods that can be used, namely the Centroid, Bisector, Mean of Maximum (MOM), Smallest of Maximum (SOM) and Largest of Maximum (LOM) methods (Teti *et al*., 2024). However, some commonly used defuzzification methods include centroid, bisector, and mean of maxima. In the application of fuzzy systems to determine protein content in noodle production, the centroid method is used.

The centroid method was chosen because it produces the most representative output value from the fuzzy set formed, where this method produces a weighted average value of all possible outputs. This value is taken as the centre point of the fuzzy region (centroid) to then obtain a crisp solution that can be used immediately (Sinaga *et al*. 2023). For example, when determining the optimal protein content from the substitution of mocaf and mung bean flour, the fuzzy system will evaluate the input data from various predefined ingredient combination rules. The fuzzy evaluation results are then converted into a single value through a defuzzification process, thereby obtaining the final protein content estimate that is closest to the ideal condition in wet noodles.

The application of defuzzification in the noodle production process not only improves the accuracy and efficiency of decision making, but also supports the development of more innovative product formulations. By analysing data and integrating the results of defuzzification, manufacturers can find a balanced combination of ingredients in terms of nutritional value and sensory characteristics, thereby meeting consumer preferences and maintaining competitiveness in the food industry.

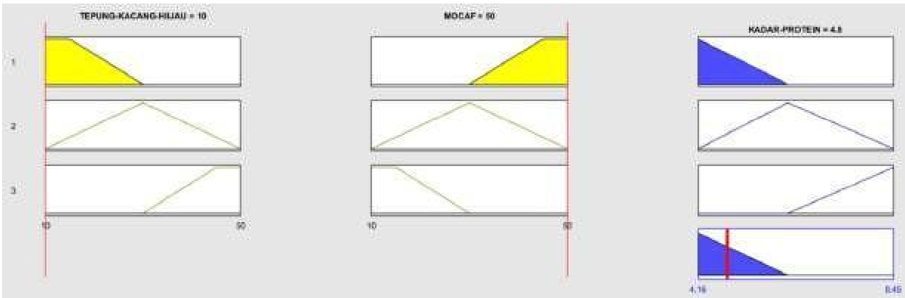

Figure 3 Results of the first rule defuzzification

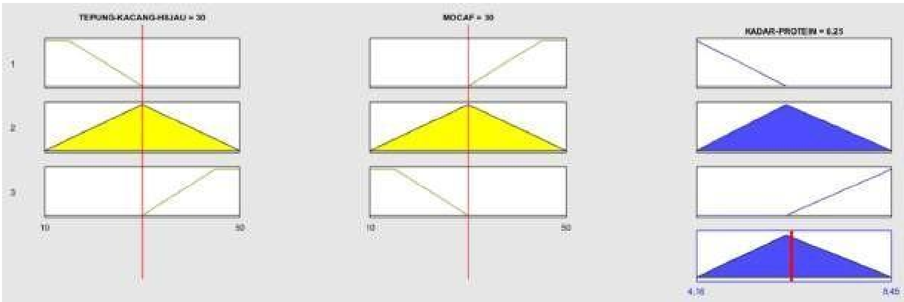

Figure 4 Results of the second rule defuzzification

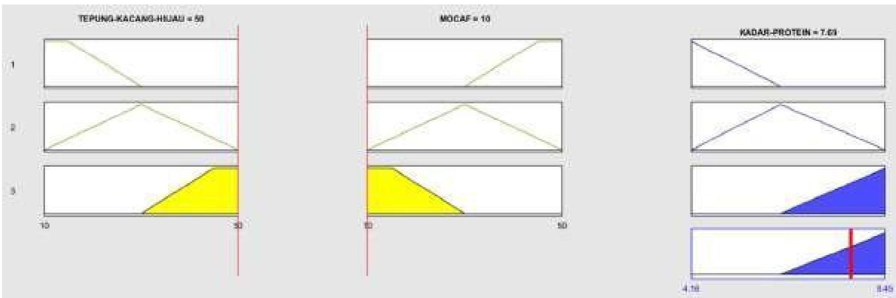

Figure 5 Results of the third rule defuzzification

Example Calculation

For example, an input value of mung bean flour = 30 and MOCAF = 30, the defuzzification calculation using the centroid method is calculated as follows:

$$Z = \frac{\sum_{4.16}^{8,45} = \mu'(x)x.dx}{\sum_{4,16}^{8,45} = \mu'(x)dx}$$

$$Z \approx 6.13\%$$

Based on the results of the rules viewer and the calculations from the defuzzification formula, various combinations of mocaf and mung bean flour inputs produced different protein levels in the noodles. The combination of 50% mocaf and 10% mung beans in rule viewer 1 produced a protein level of 4.16%, reflecting the influence of the low-protein mocaf on the total composition. In rule viewer 2, a combination of 30% of each ingredient resulted in a protein content of 6.13%, indicating an increase in protein as the proportion of mung beans increased, while in rule viewer 3, a combination of 50% mocaf and 10% mung beans resulted in an output of 8.45%, showing another variation in the effect of flour composition. All these values are the results of defuzzification, where the fuzzy logic system converts linguistic values into crisp outputs that represent the estimated protein content of noodles according to the ratio of flour used. Furthermore, to further understand the relationship between the two input variables and the protein content of noodles, a surface viewer was used to visualise the defuzzification results. In the context of fuzzy logic systems, the defuzzification surface is an important visualisation to help understand the process of changing fuzzy values into definite output values. This surface is usually obtained by plotting the output values against various variations in input values, making it easier to observe the relationships and interactions between factors that influence the production process.

In noodle production, defuzzification surface visualisation can show how changes in the proportions of raw materials such as wheat flour, mocaf, and mung bean flour affect output values, such as protein content or final noodle quality. From the observations on the defuzzification surface, it can be seen that an increase in the percentage of mung bean flour tends to increase the protein content of the noodles, while an increase in the proportion of mocaf has the opposite effect, namely decreasing the protein content. This visualisation not only serves as a decision-making tool, but is also useful for identifying the optimal combination of ingredients and process parameters to produce the best quality noodle products.

Overall, the results of the fuzzy logic system show that the proportion of raw materials has a significant effect on the protein content of noodles. Using the fuzzy approach, the complex and non-linear relationship between mocaf and mung bean flour can be modelled more realistically. This proves that the fuzzy logic method is capable of providing adaptive and accurate predictions of product quality, while also helping producers determine the most suitable ingredient composition to achieve a balance between the nutritional value and sensory characteristics of wet noodles.

3. **Surface of defuzzification results**

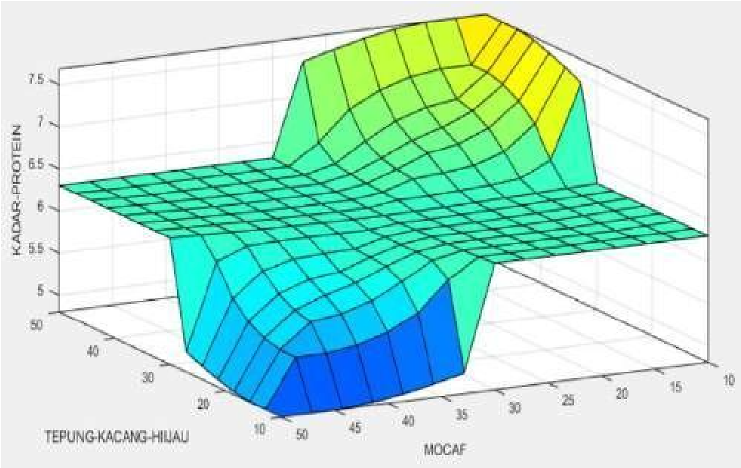

Figure 6 Surface of defuzzification results

From the surface pattern formed, it illustrates the interactive relationship between the proportion of mung bean flour and mocaf to the protein content of the product. The surface pattern formed shows that an increase in mung bean flour consistently contributes to an increase in protein content. This is in line with the characteristics of mung bean flour, which has a relatively high protein content of around 20–24%. This increase is most evident when mocaf is at low to medium levels, so that the protein contribution from mung bean flour becomes more dominant.

Conversely, the addition of mocaf did not show a significant increase in protein content. Under some conditions, the protein content tended to decrease when mocaf was added in high amounts without being balanced with mung bean flour. This condition can be explained by the much lower protein content of mocaf (around 1–2%) and its role in forming the texture and gluten-free characteristics of the product, rather than as a source of protein.

These results are consistent with fuzzy system inferences, which indicate that the highest protein content is achieved with a combination of high mung bean flour and low–medium mocaf. Thus, the optimal formulation for increasing the protein content of noodles is to increase the proportion of mung bean flour, while mocaf is used in lower amounts to maintain product texture.

4. **Data Validation**

Table 6 Comparison of Protein Content Between The Results and Wafiyah *et al*. (2025)

Treatment	Protein Content (%)	
	Wafiyah, *et al* (2025)	Result
MB2	4.16	4.16
MB4	6.13	6.13
MB6	8.45	8.45

Validation was performed by comparing the protein values calculated using the fuzzy inference system (FIS) with the results of the study using reference data from Wafiyah *et al*. (2025). Based on Table 6, the three treatments (MB2, MB4, and MB6) showed identical protein values between the study results and the comparative data. Treatment MB2 had a protein value of 4.16%, MB4 had 6.13%, and MB6 had 8.45%, all of which were the same as the values in the previous study. This consistency confirms that the calculation method used is capable of consistently reproducing data trends.

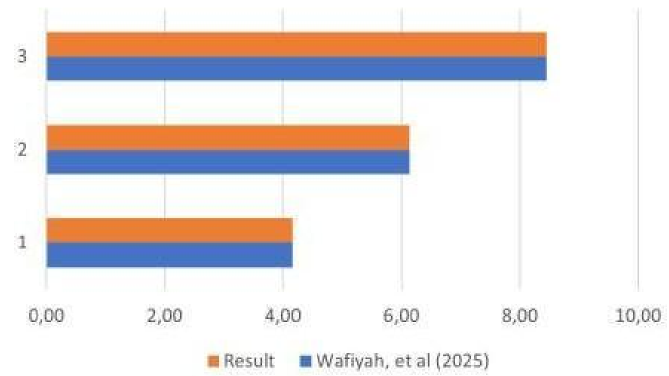

Figure 7 Comparison of protein values between the results and Wafiyah *et al*. (2025)

The visualization in the form of a bar chart shows that the values of the two data sources almost completely overlap, indicating that there is no significant difference between the research results and the reference data. In addition, simple regression analysis shows a very strong linear relationship between the two data sets, with a coefficient of determination value of $R^2 = 0.9978$, indicating that almost all of the variation in the calculation results can be explained by the reference data.

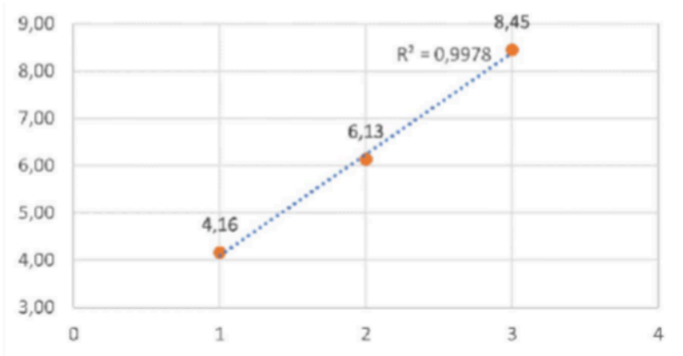

Figure 8 Linear relationship with R^2 value

Additional quantitative validation using RMSE and MAPE also supports these results. RMSE = 0% and MAPE = 0% values were obtained because all data points had zero differences between the research results and the reference values. This shows that there were no absolute errors or percentage errors in the data produced. Overall, the combination of visualization, regression analysis, and RMSE and MAPE calculations proves that the analysis method used is highly accurate and reliable in estimating the protein content in each treatment.

CONCLUSION

Based on the results of the design and analysis using the Mamdani fuzzy logic system on the effect of mocaf flour and mung bean flour substitution on noodle protein content, it can be concluded that the fuzzy model is able to accurately describe the non-linear relationship between the two ingredients. The modeling results show that an increase in the use of mung bean flour consistently increases the protein content of noodles, while a high proportion of mocaf only contributes a very small amount of protein. The defuzzification values for the three treatments (MB2, MB4, and MB6) are also in line with the research data of Wafiyah *et al.* (2025), namely 4.16%, 6.13%, and 8.45%. This consistency is reinforced by RMSE and MAPE values of 0% and a coefficient of determination $R^2 = 0.9978$, indicating excellent model accuracy. Therefore, the Mamdani fuzzy method has been proven effective in predicting protein content change patterns in noodle formulations with local flour substitution, especially when the available data is limited.

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