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Analysis of the Effect of Protein Content and Preheating Temperature on the Hardness of SPC Biscuits Using the Fuzzy Logic Method

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This study aimed to analyze and model the non-linear effect of protein content and preheating temperature on the hardness of Soy Protein Concentrate (SPC)-based biscuits using the Sugeno fuzzy logic method. A descriptive quantitative approach was employed, utilizing the Sugeno-type Fuzzy Inference System (FIS) designed and implemented using MATLAB software. The inputs were protein concentration (7-16%) and preheating temperature (70-90°C), with biscuit hardness (747.5-2176.5 gf) as the output. The system successfully mapped the complex interactions through nine fuzzy *if-then* rules. The results showed that increasing protein content generally increases hardness, particularly at higher preheating temperatures. However, excessive heating at medium protein content led to a decrease in hardness due to structural degradation. The defuzzification surface indicated that the preheating temperature has a relatively stronger influence on the final hardness than protein content. The developed fuzzy model provides accurate and interpretable predictions (e.g., 11.5% protein and 80°C yields a medium hardness of 1.45 x 10^3 gf), proving its effectiveness as an adaptive decision-support tool for optimizing high-protein biscuit production.

Keywords: Fuzzy Logic, SPC Biscuits, Hardness, Protein Content, Preheating Temperature.

INTRODUCTION

In the food industry, product texture is one of the most decisive attributes that determines both quality and the level of consumer acceptance. Biscuits, as one of the most popular and widely consumed food products, must not only offer good flavor but also possess an appropriate hardness level that matches consumer preferences (El-Gohery, 2021). The formulation of high-protein biscuits using Soy Protein Concentrate (SPC) has emerged as an innovation aimed at improving the nutritional value of the product. However, increasing protein content often alters the structural properties of the dough, resulting in a harder texture that can reduce consumer preference if not properly optimized (Khairina *et al.,* 2025).

In addition to formulation, processing factors such as preheating temperature play a crucial role in determining the final characteristics of biscuits. Preheating treatment can affect protein denaturation and starch gelatinization, which in turn influence pore formation, brittleness, and hardness. Improper temperature control may lead to excessively hard or fragile textures, ultimately lowering the sensory quality and overall product acceptance (Lasaji *et al.,* 2024). Therefore, the relationship between protein content, preheating temperature, and biscuit hardness is complex, involving non-linear interactions that require advanced modeling techniques to accurately describe.

The fuzzy logic method offers an effective approach to model systems that involve uncertainty and imprecision, such as those commonly encountered in food formulation and processing. This system translates linguistic variables such as “high,” “medium,” or “low” into mathematical representations that can be processed through a set of inference rules. In this context, the Sugeno fuzzy logic model is known for its capability to produce numerical outputs that can be directly applied for prediction and optimization purposes. Unlike the Mamdani model, which produces linguistic outputs through defuzzification, the Sugeno approach utilizes linear or constant functions at the output stage, resulting in more precise and computationally efficient predictions (Agrahar-Murugkar *et al.,* 2020). The Sugeno fuzzy logic approach has shown high flexibility in food quality modeling. It allows researchers and industry practitioners to map complex relationships between formulation parameters such as protein concentration and preheating temperature into mathematical models that can predict biscuit hardness accurately. This method also reduces the need for extensive experimental trials by providing quantitative predictions of quality attributes. Furthermore, fuzzy-based approaches can represent the variability and uncertainty commonly present in food data, offering a more realistic modeling framework for texture prediction (Pavani *et al.,* 2023).

Based on these considerations, this study aims to analyze and model the effect of protein content and preheating temperature on the hardness of SPC-based biscuits using the Sugeno fuzzy logic method. The developed model is expected to provide accurate and interpretable predictions that support formulation and process optimization in high-protein biscuit production. Moreover, the findings are anticipated to contribute to the development of efficient and adaptive decision-support systems in the food industry, particularly in the formulation of plant-protein-based bakery products.

METHODS

Research Approach

This study employs a descriptive quantitative approach by applying the Sugeno-type fuzzy logic method to model the relationship between protein content and preheating temperature on the hardness of SPC (Soy Protein Concentrate) biscuits. The Sugeno model was selected because it provides stable numerical outputs and is effective in handling nonlinear relationships and uncertainties within food processing data. This approach allows linguistic variables—such as “low,” “medium,” and “high”—to be translated into mathematical forms through processes of fuzzification, rule base construction, inference, and defuzzification. Through a literature review, the researcher strengthens the theoretical foundation, examines findings from previous studies, and deepens the understanding of key concepts related to Fuzzy Logic (Gusti *et al.,* 2025).

Data Collection

This study utilizes both secondary and primary data. Secondary data were obtained through a literature review of scientific journals, books, and relevant publications to strengthen the theoretical foundation of the Sugeno fuzzy inference system and support the research analysis. Primary data were sourced from experimental data published by Khairina *et al.* (2025), consisting of 10 samples (n = 10) with three main variables: SPC protein content (7.00% – 16.00%), preheating temperature (preheat) 70°C – 90°C, and biscuit hardness measured using a Texture Analyzer with a compression method in gram-force (gf). In the Sugeno fuzzy modeling, protein content and preheat temperature serve as input variables, while biscuit hardness serves as the output variable. All data were processed in MATLAB through fuzzification, rule base construction, Sugeno inference, and defuzzification, resulting in predicted biscuit hardness values based on variations in protein content and preheating temperature. The integration of experimental data with the Sugeno fuzzy model has proven effective in handling vague or uncertain data, particularly for qualitative or subjective food parameters such as biscuit hardness (Garg *et al.,* 2025).

Data Analysis

Fuzzy logic is an approach to problem solving in control systems that can be applied to various types of systems, ranging from simple and small systems to embedded systems, computer networks, multi- channel systems, workstation-based data acquisition systems, and other control systems. This methodology can be implemented through hardware, software, or a combination of both. More specifically, fuzzy logic is an extension of multivalued logic that focuses on approximate reasoning rather than seeking absolutely correct results (Harliana and Rahim, 2017).

There are two main types of fuzzy inference methods that are the most influential, namely the Mamdani method and the Sugeno method (or Takagi-Sugeno-Kang/TS). The Sugeno Fuzzy Inference System (FIS) enhances traditional fuzzy systems by incorporating simple mathematical functions to improve computational precision and efficiency. This approach offers three key advantages: (1) high computational efficiency, (2) excellent performance when integrated with optimization and adaptive methods, particularly in dynamic nonlinear environments, and (3) ease of use in mathematical analysis (Cahyani and Ikhsan, 2024).

The Sugeno FIS model was developed using MATLAB R2015b equipped with the Fuzzy Logic Toolbox. The construction of the model followed the standard fuzzy system framework, beginning with the definition of input and output variables, followed by fuzzification, rule base formation, inference processing, and final defuzzification. Two variables were defined as inputs: protein concentration (X_1) and preheating temperature (X_2), both of which significantly influence biscuit hardness. Each input was represented by three linguistic terms, Few, Medium*,* and High, to capture the uncertainty and gradation that typically appear in food processing operations. The output variable, biscuit hardness (Y), was also categorized into three levels, Few, Medium, and High, based on the empirical hardness distribution within the dataset.

Triangular membership functions were chosen for all fuzzy sets because of their simplicity, ease of computation, and suitability for problems involving limited data. The ranges for each membership function were determined directly from the experimental data, such as defining "Few" protein between 7–11.5%, "Medium" between 7–16%, and "High" between 11.5–16%. Similar ranges were assigned for temperature and output hardness. The membership values for each experimental condition were calculated manually and subsequently validated using graphical plots generated in MATLAB. These membership shapes allowed the model to represent gradual transitions between states rather than abrupt classifications.

The fuzzy rule base consisted of nine rules representing all combinations of the three protein levels and three temperature levels. Each rule encoded empirical knowledge derived from the observed trends in biscuit hardness. Typical examples include: "IF protein level is Few AND temperature is Few THEN hardness is Few" and "IF protein level is High AND temperature is High THEN hardness is High." The rules were designed to reflect the physical behavior of the system, such as increased hardness at higher protein levels or moderate hardness at mid-range heating. The Sugeno model assigns a linear function to each rule's consequent, expressed as $z_i = p_i X_i + q_i X_2 + r_i$, allowing smooth interpolation within the input domain.

The inference mechanism used the Sugeno weighted-average approach, where the firing strength of each rule was determined by the minimum operator applied to the membership degrees of both inputs. The overall system output was computed as the weighted average of all rule consequents. This defuzzification method ensured computational efficiency and produced continuous output surfaces suitable for prediction tasks. The entire system was implemented through MATLAB's Fuzzy Logic Designer, which enabled precise tuning of membership functions, rule inspection, and model simulation.

To ensure that the model generalizes well beyond the training data, a systematic validation procedure was conducted. The dataset was divided into 70% training data and 30% testing data. Model performance was evaluated using standard regression-based metrics, including the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2). These metrics were selected to measure both the accuracy and consistency of prediction errors. Finally, the performance of the Sugeno FIS model was compared with two alternative modeling approaches—Multiple Linear Regression (MLR) and a Backpropagation Neural Network (BPNN)—to determine whether the fuzzy approach provided superior predictive capability, especially under nonlinear and small-sample conditions.

Through data analysis this research aims to demonstrate the effectiveness of the Fuzzy Logic approach in predictive modeling of organoleptic attributes. The results of this implementation are expected to provide valuable insights into how Fuzzy Logic can be utilized as a predictive modeling tool that is more accurate and data-driven.

RESULTS AND DISCUSSION

Data Collection

The data obtained consists of data from ten samples, including the protein content, temperature, and hardness of SPC (Soy Protein Concentrate) biscuit products, which can be seen in Table 1.

Table 1. Average hardness values of high-protein biscuits

Sample (Run)	Protein Concentration (%)	Temperature (°C)	Hardness (gf)
Run 1	8,32	72,93	1185,07
Run 2	11,50	80,00	1548,44
Run 3	11,50	80,00	1349,33
Run 4	11,50	80,00	1159,07
Run 5	16,00	80,00	1654,32
Run 6	11,50	90,00	1057,73
Run 7	7,00	80,00	747,56
Run 8	11,50	80,00	857,14
Run 9	11,50	70,00	932,50
Run 10	14,68	87,07	2176,49

Raw data (Khairina*et al.* 2025)

Computational Analysis using MATLAB

Input Variable

The input variables are factors that influence the output variables. There are two input variables: Protein Level and Temperature. These two input variables are grouped into three fuzzy sets: few, medium, and high. This categorization is done to accommodate uncertainties in the data.

Table 2. Variable input

Function	Variable	Fuzzy set	Universe set	Domain
Input	Protein level	Few	7 - 16	[7-11,5]
		Medium		[7-11,5-16]
		High		[11,5-16]
	Temperature	Few	70 - 90	[70-80]
		Medium		[70-80-90]
		High		[80-90]

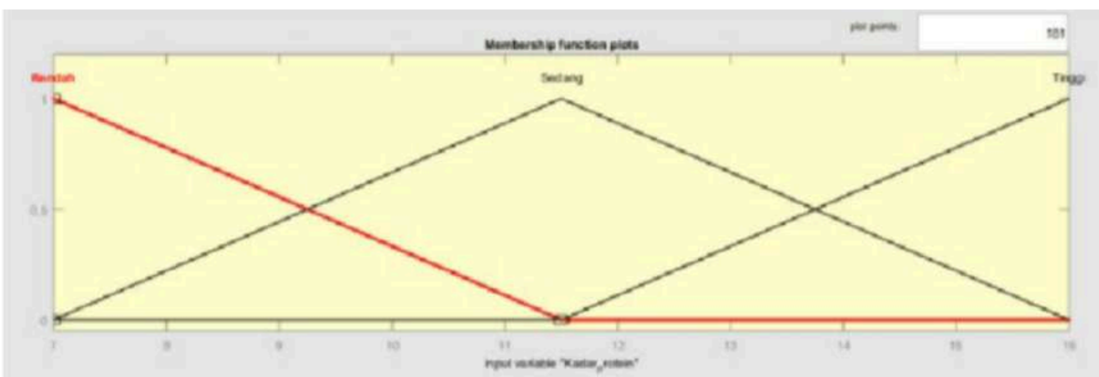

Figure 1. Membership function plots for input variable protein level

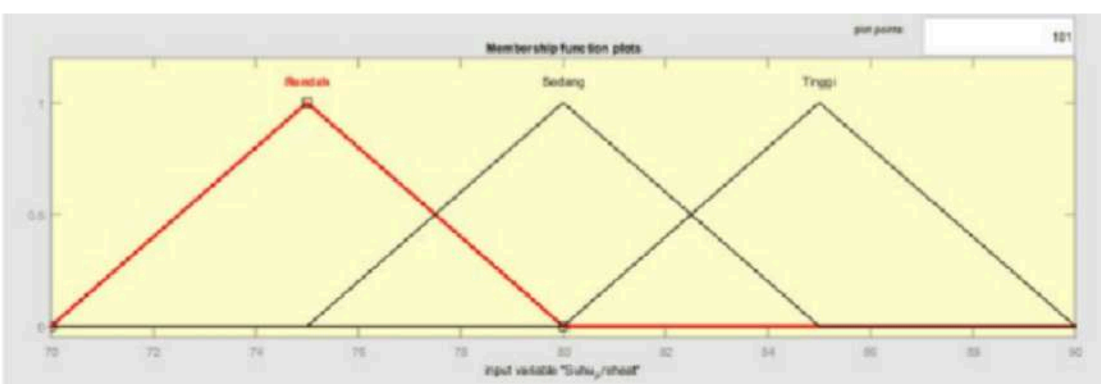

Figure 2. Membership function plots for input variable preheating temperature

Output Variable

The output variables represent the factors affected by the input variables, serving as the results to be predicted or analyzed. In this study, the output variable refers to the hardness attribute of SPC Biscuits ,which is classified into three fuzzy categories: few, medium, high.

Table 3. Variable output

Function	Variable	Fuzzy set	Domain
Output	Hardness	Few	[747,5]
		Medium	[1462]
		High	[2176,5]

Rules

Fuzzy Inference System (FIS) was developed to predict the hardness of biscuits based on two input variables: protein concentration (CP) and preheat temperature (SP). These parameters were selected because both have a significant influence on the physical characteristics of the final product, particularly its hardness. In a fuzzy system, the relationship between input and output variables is defined through a set of fuzzy rules expressed in *if–then* statements, which represent the knowledge or interaction patterns among variables. These rules serve as the foundation for decision-making under conditions of uncertainty or qualitative data. By defining three fuzzy sets for each input variable (*low*, *medium*, and *high*), a total of nine rule combinations were generated to describe the possible interactions between protein concentration and preheat temperature affecting biscuit hardness.

	Protein Level (X_1)	Preheating Temperature (X_2)	Hardness
1	Few	Few	Few
2	Few	Medium	Few
3	Few	High	Medium
4	Medium	Few	Few
5	Medium	Medium	Medium
6	Medium	High	High
7	High	Few	Medium

Table 4. Fuzzy rules

No	Input		Output

8	High	Medium	High
9	High	High	High

The fuzzy rules were formulated in the form of *if–then* statements that describe the logical relationships among variables based on the observations from experimental data. In this study, each input variable was divided into three fuzzy sets (*low*, *medium*, and *high*). Consequently, nine rule combinations (3 × 3) were established to represent all possible interactions between protein concentration and preheat temperature affecting biscuit hardness. The determination of each rule was based on the tendency of hardness values obtained from the actual data presented in Table 4.

In general, the analysis showed that increasing protein concentration tends to increase the hardness value, particularly when accompanied by higher preheat temperatures. However, under conditions of medium protein concentration and high preheat temperature, a slight decrease in hardness was observed, which is presumably due to excessive protein denaturation that weakens the matrix structure.

The resulting fuzzy rules can be explained as follows:

- When CP is low and SP is low, hardness tends to be classified as *low*, since both protein content and thermal energy are insufficient to form a strong solid structure.
- The combination of low CP with medium or high SP still results in *low* hardness, indicating that higher temperature cannot compensate for the low protein content.
- At medium CP and medium SP, hardness increases to a *medium* level, representing an optimal balance between protein concentration and thermal treatment.
- When CP is high with medium to high SP, hardness significantly increases and is categorized as *high*, consistent with the strengthening of the gluten network due to higher protein levels.
- Conversely, medium CP combined with high SP produces *lower* hardness, possibly caused by structural degradation from excessive heating.

Thus, the fuzzy system effectively captures the nonlinear relationship among protein concentration, preheat temperature, and product hardness. Each established rule reflects the empirical behavior of food materials under varying process conditions, suggesting that the fuzzy model can serve as a decision-support tool to determine the optimal combination of parameters for achieving the desired biscuit texture.

Protein Concentration Input Variable

$$Few[x_1] = \begin{cases} 1; x \leq a \\ \dfrac{b-x}{b-a};\ a \leq x \leq b \\ 0; x \geq b \end{cases}$$

$$\mu Medium[x_1] = \begin{cases} 0; x \leq a \text{ atau } x \geq c \\ \dfrac{x-a}{b-a};\ a \leq x \leq b \\ \dfrac{c-x}{c-b};\ b \leq x \geq c \end{cases}$$

$$\mu High[x_1] = \begin{cases} 0; x \leq b \\ \dfrac{x-b}{c-b};\ b \leq x \leq c \\ 1; x \geq c \end{cases}$$

$$Few[x_1] = \begin{cases} 1; x \le 7 \\ \frac{11,5-x}{11,5-7}; 7 \le x \le 11,5 \\ 0; x > 11,5 \end{cases} = \begin{cases} 0 & ; x \le 7 \\ \frac{11,5-x}{4,5} & ; 7 < x < 11,5 \\ 0 & ; x \ge 11,5 \end{cases}$$

$$\mu Medium[x_1] = \begin{cases} 0 & ; x < 7 \text{ atau } x \ge 16 \\ \frac{x-7}{11,5-7}; & 7 \le x \le 11,5 \\ \frac{16-x}{16-11,5}; & 11,5 \le x \ge 16 \end{cases} = \begin{cases} 0 \; ; x < 7 \text{ atau } x > 16 \\ \frac{x-7}{4,5} & ; 7 < x < 11,5 \\ \frac{16-x}{4,5} & ; 11,5 < x > 16 \end{cases}$$

$$\mu\ High\ [x_1] = \begin{cases} 0 & ; x \le 11,5 \\ \frac{x-11,5}{16-11,5} & ; 11,5 \le x \le 16 \\ 1 & ; x \ge 16 \end{cases} = \begin{cases} 0 & ; x < 11,5 \\ \frac{x-11,5}{4,5} & ; 11,5 < x < 16 \\ 1 & ; x \ge 16 \end{cases}$$

Protein content is one of the important factors affecting biscuit hardness, as it plays a role in the formation of the gluten network and how protein interacts with starch during the heating process. According to research (Khairina et al., 2025), the protein content in SPC biscuit samples ranges from 7% to 16%. To convert this value into a fuzzy linguistic form, a fuzzification process was carried out using a triangular membership function that divides the protein content range into three categories: low (7–11.5%), medium (11.5–16%), and high (11.5–16%). For example, if the protein content is 11.5%, this data is in the middle of the range, so the largest membership level is in the medium category with a medium μ value = 1, while low μ and high μ = 0. If the protein content is 9%, then this data is included in the low category with low μ = (11.5 – 9) / (11.5 – 7) = 0.56, and medium μ = 1 – 0.56 = 0.44. On the other hand, if the protein content is 14%, this data is included in the high category with high μ = (14 – 11.5) / (16 – 11.5) = 0.56, and medium μ = 0.44. This manual calculation shows how fuzzy logic transforms numerical data into a flexible linguistic form to describe uncertain conditions.

The results of the protein content fuzzification process were used in conjunction with the temperature variable (70–90 °C) to form an inference rule. The combination of 11.5% protein content and 80 °C temperature resulted in a hardness value of 1.45×10^3 gf, which is classified as medium. This value is consistent because the protein content of 11.5% has undergone partial denaturation, forming a matrix network that is strong enough without being too hard. Analytically, increasing protein content has a positive correlation with increasing biscuit hardness up to an optimum point, after which the hardness will decrease due to excessive denaturation that weakens the matrix structure (Lasaji et al., 2023).

This is in line with research by Agrahar-Murugkar et al. (2020) which found that high protein content increases density and decreases porosity in flour-based products. In fuzzy logic, this phenomenon is explained through nonlinear inference rules, where increasing protein content does not always result in a linear increase in hardness. Thus, the results of manual calculations of protein content indicate that the fuzzy logic system is able to effectively map the complex relationship between protein content and biscuit hardness. These results support a realistic quantitative approach to controlling high-protein product formulations, while reducing the need for repeated testing in the food industry.

Furthermore, recent studies reinforce that the interaction between protein and starch has a decisive influence on the structural and textural properties of biscuits. According to Zhang et al. (2025), protein–starch interactions affect starch crystallinity and gel formation, determining product density and hardness. Similarly, Liu et al. (2022) observed that increasing protein content significantly raises biscuit hardness and thickness due to enhanced gluten development, whereas excess protein can lead to brittleness.

Dai (2024) also emphasized that optimizing protein modification through preheating or enzymatic treatment can improve dough stability and prevent excessive hardening. Meanwhile, Mashau (2024) demonstrated that enriching biscuits with plant proteins enhances nutritional quality but requires formulation adjustments to maintain acceptable hardness and sensory properties.

These findings align with the fuzzy-based model analysis, where the nonlinear categorization of protein levels effectively captures complex interactions within the dough matrix. Therefore, the fuzzy logic framework not only represents numerical transitions but also models biochemical interactions occurring between proteins and starch during baking. This validates the system's ability to provide realistic, data- driven predictions and process optimizations for high-protein biscuit formulations.

Temperature Input Variable

$$\mu Few[x_2] = \begin{cases} 1; x \leq a \\ \dfrac{b-x}{b-a}; \ a < x < b \\ 0; x \geq b \end{cases}$$

$$\mu Medium[x_2] = \begin{cases} 0; x \leq a \ atau \ x \geq c \\ \dfrac{x-a}{b-a}; \ a \leq x \leq b \\ \dfrac{c-x}{c-b}; b \leq x \geq c \end{cases}$$

$$\mu High[x_2] = \begin{cases} 0; x < b \\ \dfrac{x-b}{c-b}; \ b < x < c \\ 1; x \geq c \end{cases}$$

$$\mu\ Few\ [x_2] = \begin{cases} 1 & ; x \leq 70 \\ \dfrac{80-x}{80-70} & ; 70 < x < 80 \\ 0 & ; x \geq 80 \end{cases} = \begin{cases} 1 & ; x \leq 70 \\ \dfrac{80-x}{10} & ; 70 \leq x \leq 80 \\ 0 & ; x \geq 80 \end{cases}$$

$$\mu\ Medium\ [x_2] = \begin{cases} 0 & ; x \leq 70 \ atau \ x \geq 90 \\ \dfrac{x-70}{80-70} & ; 70 < x < 80 \\ \dfrac{90-x}{90-80} & ; 80 \leq x \leq 90 \end{cases} = \begin{cases} 0 & ; x \leq 70 \ atau \ x \geq 90 \\ \dfrac{x-70}{10} & ; 70 < x < 80 \\ \dfrac{90-x}{10} & ; 80 \leq x \leq 90 \end{cases}$$

$$\mu\ High\ [x_2] = \begin{cases} 0 & ; x < 80 \\ \dfrac{x-80}{90-80} & ; 80 \leq x \leq 90 \\ 1 & ; x \geq 90 \end{cases} = \begin{cases} 0 & ; x < 80 \\ \dfrac{x-80}{10} & ; 80 < x < 90 \\ 1 & ; x \geq 90 \end{cases}$$

According to Khairina et al. (2025), the increase in biscuit hardness is influenced by the natural properties of protein, which can be modified through structural changes using a preheating treatment. The preheating process itself is an initial heating process that raises the temperature from normal conditions to a specific desired level (Wahono et al., 2016). This process plays an important role in altering the protein structure, which ultimately affects the final texture of the food product. In the context of a fuzzy logic system, the preheating temperature is used as one of the input variables to predict the hardness level of the product.

Fuzzy logic can transform numerical data into linguistic forms that resemble human reasoning, such as categorizing values into “low,” “medium,” or “high” (Fauzan et al., 2025). The initial stage of this system is called fuzzification, which is the process of converting numerical or crisp input data into degrees of membership within a fuzzy set (Fatkhurrozi et al., 2024). In this study, temperature values were classified into three linguistic sets: Few, Medium, and High. This classification aims to qualitatively represent temperature conditions so that they can be processed using a flexible fuzzy logic approach that mimics human reasoning patterns. The temperature range used, from 70°C to 90°C, represents the operational conditions of the soybean protein preheating process as described by Khairina et al., (2025).

The results show that each temperature has a different degree of membership for each category. A temperature of 70°C belongs entirely to the low category (μFew = 1), while 75°C lies between low and medium (μFew = 0.5; μMedium = 0.5). At 80°C, the membership shifts completely to medium (μMedium = 1), while 85°C falls between medium and high (μMedium = 0.5; μHigh = 0.5). Finally, at 90°C, the membership value belongs entirely to the high category (μHigh = 1). These results indicate that the temperature values change gradually from low to high, consistent with the characteristics of a fuzzy system.

Deffuzification

The defuzzification process is the final stage in a fuzzy inference system that serves to convert the system output in the form of fuzzy sets into crisp outputs. In this study, defuzzification was used to determine the hardness value of SPC biscuits based on the effects of protein content and pre-baking temperature. The defuzzification method used is centroid or centre of gravity, which mathematically finds the weighted average value of all degrees of membership resulting from fuzzy inference. This method produces more stable and representative output values than other methods because it considers the entire membership distribution (Saatchi *et al.*., 2024).

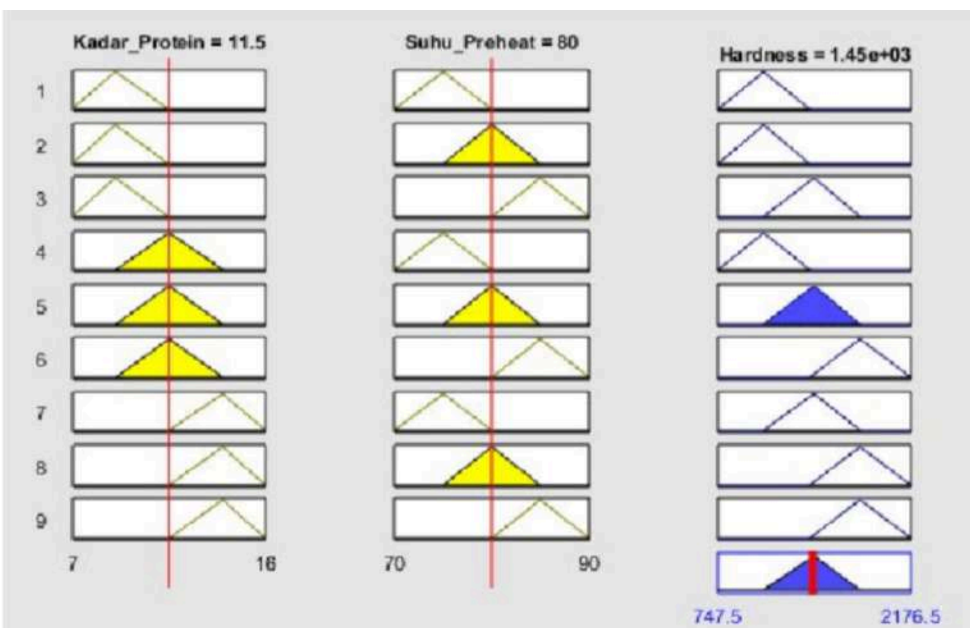

Figure 3. Defuzzification of the rules results

Figure 4 shows the defuzzification results of the fuzzy system at a protein content of 11.5% and a preheating temperature of 80 °C, which produces a hardness value of 1.45×10^3. This value is the single output of the centroid calculation process from all active rules in the input combination. This display shows how the fuzzy system combines the effects of various rules, such as rules with ‘low’, “medium”, and ‘high’ outputs, into a single value that reflects the actual conditions. This defuzzification result value indicates a medium level of hardness, which is logical because under conditions of relatively high protein but low heating temperature, the dough structure has not undergone maximum protein denaturation. This result is in line with the findings of Khairo and Sitepu (2024), who explain that the centroid method produces balanced defuzzification values, because the position of the output point is determined by the accumulation of all membership degrees from the active rules.

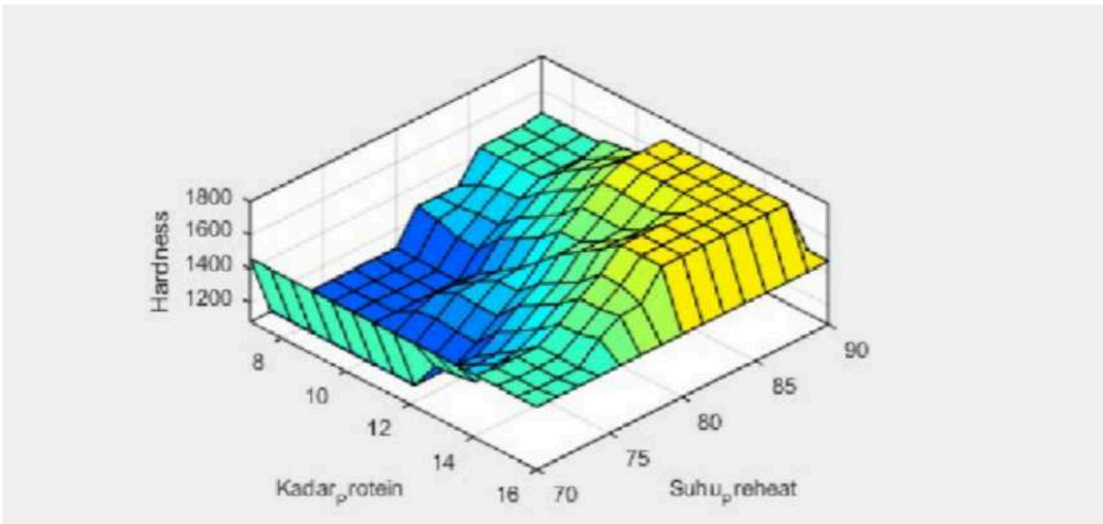

Figure 4. Surface of defuzzification results

Figure 5 shows the defuzzification surface in the form of a three-dimensional graph that shows the relationship between protein content and preheating temperature on biscuit hardness. The surface shows a continuous and non-linear increase in hardness; the higher the protein content and pre-heating temperature, the higher the hardness value predicted by the fuzzy system. The steeper gradient of the surface towards temperature indicates that pre-heating temperature has a stronger influence on the increase in hardness than protein content. The smooth surface shape indicates the ability of the centroid method to produce proportional and stable outputs to input variations. This pattern is consistent with the results of Mada *et al.*., (2022) study, which reported that the centroid method produces a smooth output surface and is responsive to interactions between variables in the Mamdani system.

The Mamdani fuzzy model used is capable of representing the relationship between protein content, preheating temperature, and biscuit hardness in a logical and stable manner. The defuzzification values in Figure 4 reflect a single output for specific input conditions, while the surface in Figure 5 shows a smooth increase in hardness as protein content and temperature increase. The pattern formed shows that the centroid method produces outputs that are proportional and continuous to input variations. These results are in line with the research by Mada *et al.*., (2022) and Lima *et al.*., (2025), which explains that the centroid method in the Mamdani system provides the most stable and realistic defuzzification results for physical process- based prediction models.

CONCLUSION

The non-linear relationship between protein content and preheating temperature on the hardness of Soy Protein Concentrate (SPC) biscuits is effectively modeled and analyzed using the Sugeno fuzzy logic method. The developed Fuzzy Inference System (FIS), which was implemented and processed using MATLAB, accurately maps the complex interactions between the input variables across the range of 7–16% protein and 70–90°C temperature. Biscuit hardness demonstrates a general non-linear increase as both protein content and preheating temperature are elevated. This model successfully captured the complex empirical findings, articulated through nine distinct fuzzy rules, including the anomalous behavior where moderate protein concentration combined with high heat can result in decreased hardness, likely due to excessive protein denaturation that compromises the structural matrix. Furthermore, defuzzification results utilizing the *centroid* method indicate that the preheating temperature exerts a relatively stronger influence on the final product hardness compared to the protein concentration. Ultimately, by providing stable and interpretable predictive outputs (e.g., 11.5% protein and 80°C predicts a hardness of 1.45 x 10^3 gf), the fuzzy logic approach is validated as an accurate and adaptive decision support tool for optimizing the formulation and industrial production parameters of high-protein, plant-based biscuits.

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