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The Effect of Temperature, Weight, and Roasting Time on the Roasted Level of Coffee Beans Using Fuzzy Logic

Fannan Cakti Wibisono[1*]
[1]Food Quality Assurance Supervisor, College of Vocational Studies, IPB University
[1]horusfannan@apps.ipb.ac.id

Nuriah Nurani Muhsin[2], Farida Fadhilatun Nisa[3], Cut Mesya Meuthia[4], Muhammad[5], Putri Alya Faisal[6], Amanda Catur Sukmarani[7], Daffa Zulqisthi[8], Muhammad Faiz Assariy[9], Chika Hayya Sabillah[10], Lukie Trianawati[11*]
[23456711]Food Quality Assurance Supervisor, College of Vocational Studies, IPB University
[8910]Computer Engineering Technology, College of Vocational Studies, IPB University
[2]nuriahmuhsin@apps.ipb.ac.id, [3]faridafadhilatun@apps.ipb.ac.id, [4]mesyameuthia@apps.ipb.ac.id, [5]balahmarmuhammad@apps.ipb.ac.id, [6]502211877606alya@apps.ipb.ac.id, [7]amandacatursukmarani@apps.ipb.ac.id, [8]zulqs@apps.ipb.ac.id, [9]faizmuhammad@apps.ipb.ac.id, [10]chikahayya_asabillah@apps.ipb.ac.id, [11]mrrlukietrianawati@apps.ipb.ac.id

Abstract

This study examines the effect of temperature, roasting time, and coffee bean weight on the maturity level of roasted coffee beans, utilizing fuzzy logic to model and predict optimal roast outcomes. Coffee bean roasting level, a critical factor in determining flavor, is assessed using Mamdani-type fuzzy logic, which takes three input parameters—temperature, time, and weight—divided into ranges for specific roast outcomes. Case study parameters, including a coffee bean weight of 450 grams, roasting time of 39 minutes, and temperature of 130°C, were analyzed to classify the roast maturity. The fuzzy logic output indicates that this specific case falls within the medium roast level by the similarity of centroid between moment calculation and matlab calculation is 10,7, demonstrating the model's capability to provide precise roast classifications. This structured approach to evaluating coffee roasting parameters contributes to enhancing consistency and quality in the coffee industry, highlighting the potential of fuzzy logic for robust decision support in coffee quality control.

Keywords: fuzzy logic, coffee roasting, mamdani method, roast maturity, quality control.

INTRODUCTION

Contemporary society has witnessed a notable upsurge in coffee consumption, with individuals from diverse age groups frequenting coffee shops and cafes to partake in this beverage. In this current era coffee is a global beverage. Two common types of coffee products are instant coffee and ground coffee. Instant coffee is a dehydrated form of coffee that dissolves readily in hot water, leaving no residue. Ground coffee, such as *kopi tubruk*, is brewed with water and sugar, producing a beverage with coffee grounds (Damayanti *et al.*, 2023).

The coffee industry is currently striving to improve the quality of its products to meet increasingly high consumer demand (Sasongko and Rivai 2018). One important aspect in maintaining coffee quality is controlling the processing process, including roasting. The quality of coffee is greatly influenced by various factors, one of which is the maturity level of the coffee beans. Coffee beans that are perfectly ripe will produce a better taste compared to coffee beans that are not yet or are too ripe, in another research conducted by (Marhaenanto *et al.*, 2015) it is said that despite a significant rise in coffee bean production in Indonesia, the quality of the processed coffee remains a concern. The lack of standardized post-harvest practices, particularly in the roasting process, hinders the production of high-quality roasted coffee. There is a pressing need for more research on optimal roasting profiles and the development of suitable instruments to evaluate the degree of roast.

One of the physical signs of coffee roasting is a change in the color of the beans from green to brown or light to dark (Winarto and Wirawati 2023). This process is the result of complex chemical changes, including decomposition of organic compounds due to heat (Sukainah *et al.,* 2023). However, visually determining the maturity level of coffee beans is often difficult and subjective. Therefore, a more objective system is needed to determine the maturity level of coffee beans. This is in accordance with the opinion of (Edvan *et al.*, 2016) who state that roasting is the process by which the flavor and aroma of coffee beans are developed. When coffee beans exhibit a high degree of uniformity in terms of size, specific gravity, texture, moisture content, and chemical composition, the roasting process becomes relatively easier to control. However, the reality is that coffee beans exhibit significant variations, rendering the roasting process an art that demands skill and experience to meet consumer demands.

Temperature, roasting time, and coffee bean quantity are three primary variables that significantly influence the flavor and maturity level of roasted coffee (Alam *et al.*, 2022). Suboptimal temperatures, either too high or too low, insufficient or excessive roasting times, and varying coffee bean quantities can result in unpredictable and subpar maturity levels and flavors (Ariyanto *et al.,* 2024). Consequently, the precise selection of these variables is crucial for achieving the desired level of coffee bean maturity (Bi *et al.*, 2023).

Fuzzy logic is a fundamental component of soft computing. It serves as a method to map real-world problems from input to desired output. Fuzzy logic has proven to be a valuable tool for decision support systems across various domains (Rifanti *et al.*, 2023). Consequently, by leveraging fuzzy logic, a system can be constructed to predict the maturity level of roasted coffee based on coffee bean quantity, temperature, and roasting time values.

METHODS

The initial step in developing a fuzzy system involves identifying the variables required for problem analysis and final value calculation. These variables are categorized into input and output variables. Each input and output variable is associated with multiple fuzzy sets (Rumalowak *et al.*, 2023). Fuzzy sets exist within a specific range of values, determining the mathematical equations used to obtain fuzzy membership values as output (Rifanti *et al.*, 2023). The method used in this research is a literature study aimed to find information of correlation between time, temperature and weight variables and how it affects the level of roasted coffee bean by means of qualitative descriptive from secondary data. The input and output gathered from various sources, one specifically used from (Klaidaeng *et al.,* 2023). As for the output was taken from (Pristianto *et al.,* 2016). The method is chosen in hope that the information gathered will be more reliable (Ridwan *et al.,* 2021).

To acquire the output desired from the initial input, Mamdani method is used, also known as the MIN-MAX method, similarly to (Abrori and Prihamayu 2015). To obtain an output involves four stages, firstly both input and output variables are partitioned into one or more fuzzy sets, each characterized by specific linguistic terms. Subsequent to the definition of fuzzy sets, an appropriate implication function is chosen to map the input and output spaces. The MIN operator is a commonly employed implication function in Mamdani systems. The next step involves composing the fuzzy rules, which combine fuzzy sets and logical operators to represent linguistic knowledge. The MAX operator is frequently used as an inference method to aggregate the outputs of individual rules. The final stage, defuzzification, transforms the fuzzy output set into a crisp numerical value. The centroid method, which calculates the center of gravity of the fuzzy set, the method used as it is widely adopted and recommended for defuzzification technique.

RESULTS AND DISCUSSION

Fuzzy logic can be used to help organize and control the coffee roasting process by considering many factors and calculating the right parameters to achieve optimal roasting results (Roziqin *et al*., 2024). Fuzzy logic is very suitable for determining the roasted level of coffee beans because of its ability to handle uncertainty. Fuzzy logic is an effective method for mapping input space to output space with continuous values. Its main advantage lies in its ability to use language-based reasoning, so that its design does not require complicated mathematical equations to control an object. The application of fuzzy logic allows coffee producers to produce products with consistent characteristics and flavors. In addition, this approach can help reduce time and costs in the roasting process.

Literature Study Data

As suggested by Anisa *et al*. (2017), the roasting process governs the developmental progression of volatile compounds, consequently leading to varying complexities in coffee aroma across different roast degrees and conditions. The degree of roasting is regulated by roasting time and temperature, ensuring that the time-temperature combination is adequate for the necessary chemical reactions to occur without charring the beans and compromising the beverage's flavor. Conversely, Putri *et al*. (2023) assert that coffee varietals possess distinct weights, which can influence the roasting time required for the beans to reach maturity. In line with the correlation between variables and output, Bastian *et al.,* (2021) suggest to determine the maturity level, fuzzy logic is to be employed using input data such as roasting time, temperature, and coffee bean weight, with the output being the desired maturity level. The variables and parameters for each input are determined through a literature review, considering the fixed value ranges for coffee bean weight, roasting time, and roasting temperature as shown in *Table 1*. There are three output parameters: light roast, medium roast, and dark roast (Nugroho *et al.*, 2022). The respective value ranges for these parameters are 0-8, 5-14, and 8-16.

Table 1.Linguistic Input Parameters (X)

Weight (grams)	**Time (minutes)**	**Temperature** (°C)
Light (250 – 500)	Short (25 – 30)	Low (120 – 135)
Medium (501 – 750)	Medium (31 – 35)	Medium (136 – 150)
Heavy (751 – 1.000)	Long (36 – 42)	High (151 – 165)

Case Study

The case in this study has a weight criterion with a value of 450 grams, a time criterion with a value of 39 minutes, and a temperature criterion with a value of 130°C which will then be assessed to determine the level of ripeness of the coffee produced. Roasting has an important role in determining the color and taste of coffee products, and can be used as a basis for simple classification (Sirappa *et al.*, 2024). Therefore, determining the level of ripeness of coffee needs to be considered to get good quality coffee.

Determining Input and Output Variables

The fuzzification stage is then carried out to obtain an atomic fuzzy proposition, namely a fuzzy set (A) based on the obtained linguistic variables (X) as shown in *Figure 1* to *Figure 5*.

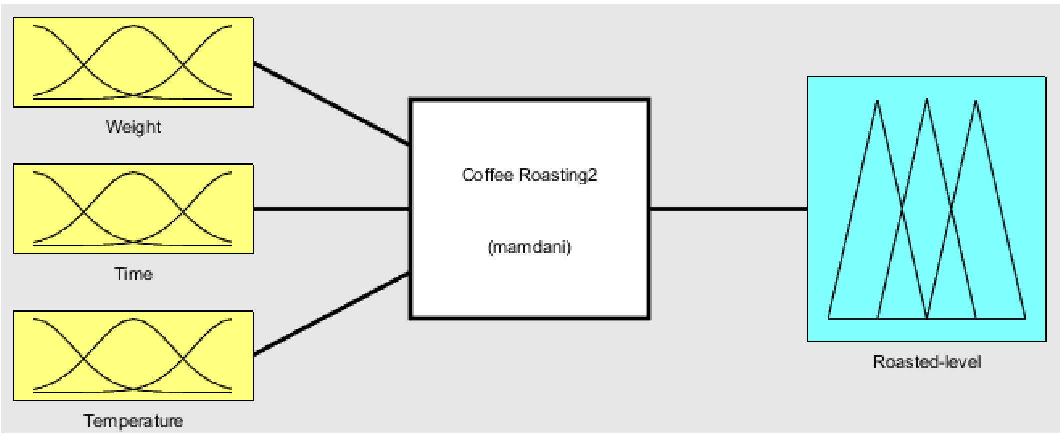

Figure 1. Fuzzy Logic Model for Roasted Coffee Level

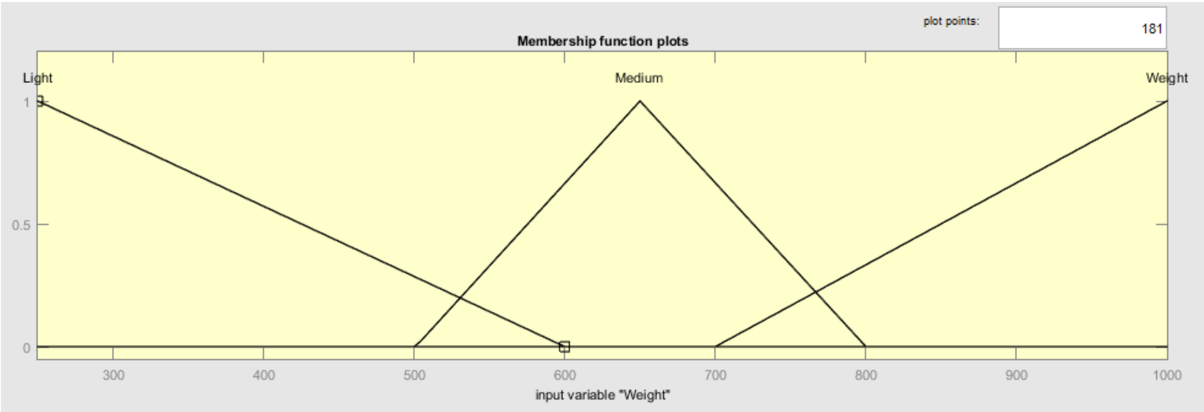

Figure 2. Fuzzy Logic Membership Plot Input Variable Weight

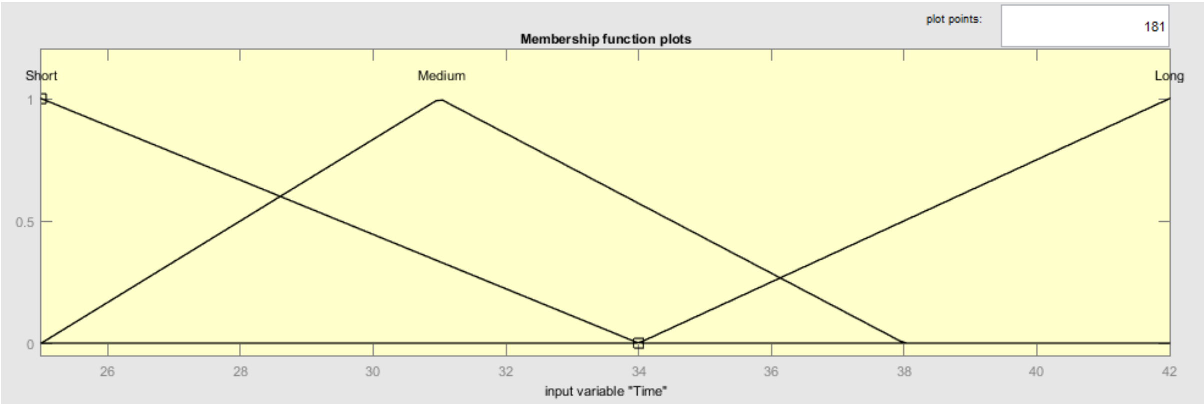

Figure 3. Fuzzy Logic Membership Plot Input Variable Time

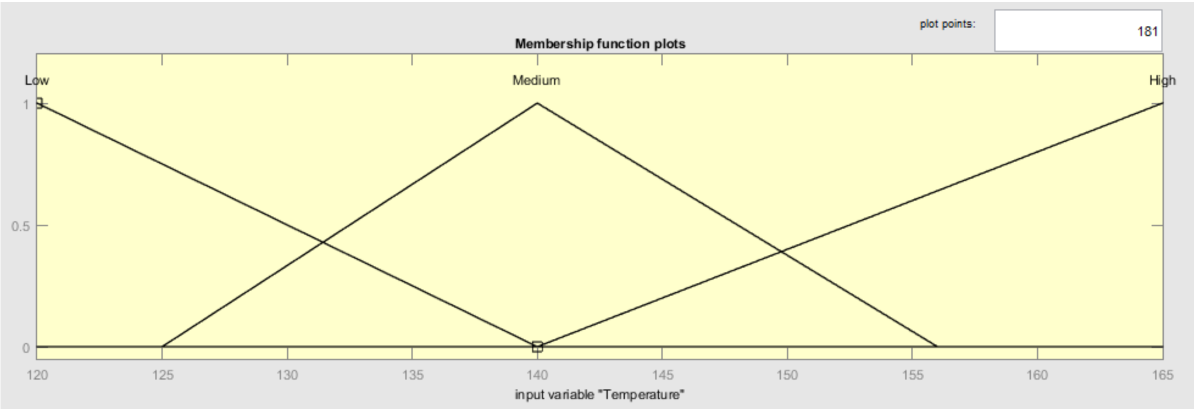

Figure 4. Fuzzy Logic Membership Plot Input Variable Temperature

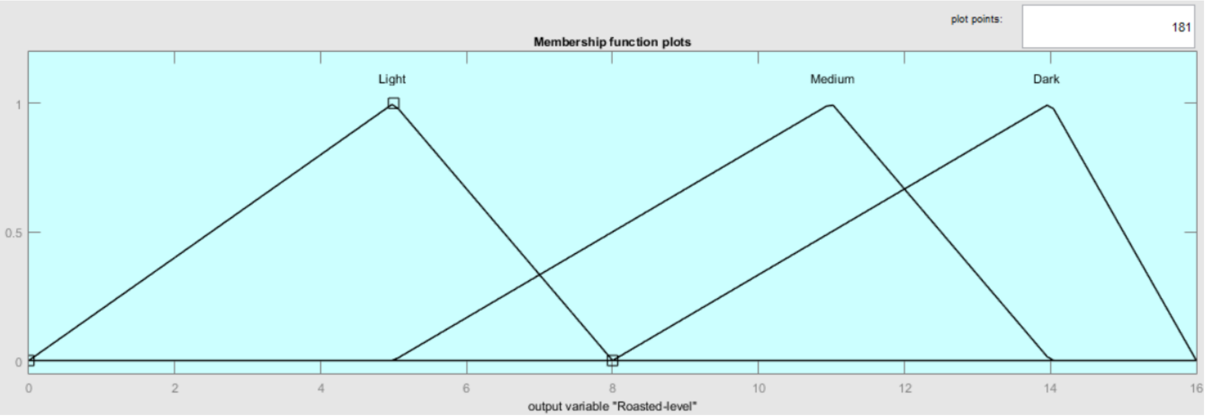

Figure 5. Fuzzy Logic Membership Plot Output Maturity Level/Roasted-level

Building Fuzzy Membership Set

Fuzzy membership set is a continuation from the input and output variables to determine the membership from data input and output. Using the concept of thinking and fuzzy sets in mapping input space to output space is an appropriate application of fuzzy logic. Fuzzy logic utilizes membership degrees from 0 to 1 to handle imprecision and data limitations (Yulianto *et al.*, 2023).

Weight Input Membership Set

The first input to the weight variable contains three fuzzy parameters, namely light, medium and weight. The three parameters were processed to get the midpoint by forming a triangle in the MATLAB application, the light parameter had a midpoint of 250, the medium parameter had a midpoint of 650, and the weight parameter had a midpoint of 1000.

$$\mu Light = \begin{cases} 0,\ x \leq 250 \\ \dfrac{600 - x}{600 - 250},\ 250 \leq x \leq 600 \\ 0,\ x \geq 600 \end{cases}$$

The light parameter is divided into three parts which can be used as a formula, namely first in the left area with ranges 0-249 the membership classified as 0, second in the peak area with range 250, and finally on the right with ranges 251-600 the membership will gradually decreasing until 0.

$$\mu Medium = \begin{cases} 0,\ x \leq 500\ or\ x \geq 800 \\ \dfrac{x - 500}{650 - 500},\ 500 \leq x \leq 650 \\ \dfrac{800 - x}{800 - 650},\ 650 \leq x \leq 800 \end{cases}$$

The medium parameter is divided into three parts which can be used as a formula, namely first in the peak area with range 650, and on ranges of left 500-649 and right 651-800, the membership will gradually increasing to 1.

$$\mu Weight = \begin{cases} 0, \ x \leq 700 \\ \frac{x - 700}{1000 - 700}, \ 700 \leq x \leq 1000 \\ 0, \ x \geq 1000 \end{cases}$$

The weight parameter is divided into three parts which can be used as a formula, namely first in the left area with ranges 700 and below will achieve membership of 0, second in the peak area with range 1000, and finally on the right with ranges 1001 and above will achieve membership of 0. Based on the case study above, the input of weight is 450 grams included in the right side of light range. So the formula and calculation results used are as follows:

$$\frac{\text{c - x}}{\text{c - b}} = \frac{600 - 450}{600 - 250} = 0{,}43$$

Time Input Membership Set

The second input to the time variable contains three fuzzy parameters, namely short, medium, and long. The three parameters were processed to get the midpoint by forming a triangle in the MATLAB application, the short parameter had a midpoint of 25, the medium parameter had a midpoint of 34, and the long parameter had a midpoint of 42.

$$\mu Short = \begin{cases} 0, \ x \leq 25 \\ \frac{34 - x}{34 - 25}, \ 25 \leq x \leq 34 \\ 0, \ x \geq 34 \end{cases}$$

The short parameter is divided into three parts which can be used as a formula, namely first in the left area with numbers 0-24 the membership classified as 0, second in the peak area with range 25, and finally on the right with ranges 26-34 the membership will gradually decreasing until 0.

$$\mu Medium = \begin{cases} 0, \ x \leq 25 \ or \ x \geq 38 \\ \frac{x - 25}{38 - 25}, \ 25 \leq x \leq 38 \\ \frac{38 - x}{38 - 25}, \ 25 \leq x \leq 38 \end{cases}$$

The medium parameter is divided into three parts which can be used as a formula, namely first in the peak area with range 34, and on ranges of left 25-33 and right 35-38, the membership will gradually increasing to 1.

$$\mu Long = \begin{cases} 0, \ x \leq 34 \\ \frac{x - 34}{42 - 34}, \ 34 \leq x \leq 42 \\ 0, \ x \geq 42 \end{cases}$$

The long parameter is divided into three parts which can be used as a formula, namely first in the left area with range 34 and below will achieve membership of 0, second in the peak area with range

42, and finally on the right with ranges 43 and above will achieve membership of 0. Based on the case study above, the input of time is 39 minutes included in the left side of long range. So the formula and calculation results used are as follows:

$$\frac{x - a}{b - a} = \frac{39 - 34}{42 - 34} = 0{,}63$$

Temperature Input Membership Set

The first input to the temperature variable contains three fuzzy parameters, namely low, medium and high. The three parameters were processed to get the midpoint by forming a triangle in the MATLAB application, the low parameter had a midpoint of 120, the medium parameter had a midpoint of 140, and the high parameter had a midpoint of 165.

$$\mu Low = \begin{cases} 0, \; x \leq 120 \\ \frac{140 - x}{140 - 120}, \; 120 \leq x \leq 140 \\ 0, \; x \geq 140 \end{cases}$$

The low parameter is divided into three parts which can be used as a formula, namely first in the left area with range 0-119 the membership classified as 0, second in the peak area with range 120, and finally on the right with ranges 121-140 the membership will gradually decreasing until 0.

$$\mu Medium = \begin{cases} 0, \; x \leq 125 \; or \; x \geq 156 \\ \frac{x - 125}{156 - 125}, \; 125 \leq x \leq 156 \\ \frac{156 - x}{156 - 125}, \; 125 \leq x \leq 156 \end{cases}$$

The medium parameter is divided into three parts which can be used as a formula, namely first in the peak area with range 140, and on ranges of left 125-139 and right 140-156, the membership will gradually increasing to 1.

$$\mu High = \begin{cases} 0, \; x \leq 140 \\ \frac{x - 140}{165 - 140}, \; 165 \leq x \leq 140 \\ 0, \; x \geq 165 \end{cases}$$

The high parameter is divided into three parts which can be used as a formula, namely first in the left area with ranges 140 and below will achieve membership of 0, second in the peak area with range 165, and finally on the right with range 166 and above will achieve membership of 0. Based on the case study above, the temperature input is 130 degrees Celsius where the input intersects two lines, low and medium. The input is included in the right side of the low range and the left side of the medium range. So the formula and calculation results used are as follows:

$$\text{Low} \; \frac{c - x}{c - b} = \frac{140 - 130}{140 - 120} = 0{,}5$$

$$\text{Medium } \frac{x - a}{b - a} = \frac{130 - 125}{156 - 125} = 0{,}16$$

Roasted Level Output Membership Set

The output to the time variable contains three fuzzy parameters, namely light, medium, and dark. The output of three parameters forms a triangle in the MATLAB application, the light parameter had a midpoint of 0, the medium parameter had a midpoint of 8, and the dark parameter had a midpoint of 16.

$$\mu Light = \begin{cases} 0, \; x \leq 0 \; or \; x \geq 8 \\ \frac{x - 0}{8 - 0}, \; 0 \leq x \leq 8 \\ \quad x = 5 \\ \frac{8 - x}{8 - 0}, \; 0 \leq x \leq 8 \end{cases}$$

The light parameter is divided into three parts which can be used as a formula, namely first in the left area with range 0-4, second in the peak area with range 5, and finally on the right 6-8.

$$\mu Medium = \begin{cases} 0, \; x \leq 5 \; or \; x \geq 14 \\ \frac{x - 5}{14 - 5}, \; 5 \leq x \leq 14 \\ \quad x = 11 \\ \frac{14 - x}{14 - 5}, \; 5 \leq x \leq 14 \end{cases}$$

The medium parameter is divided into three parts which can be used as a formula, namely first in the left area with range 5-10, second in the peak area with range 11, and finally on the right 12-14.

$$\mu Dark = \begin{cases} 0, \; x \leq 8 \; or \; x \geq 16 \\ \frac{x - 8}{16 - 8}, \; 8 \leq x \leq 16 \\ \quad x = 14 \\ \frac{16 - x}{16 - 8}, \; 8 \leq x \leq 16 \end{cases}$$

The dark parameter is divided into three parts which can be used as a formula, namely first in the left area with range 8-13, second in the peak area with range 14, and finally on the right 15-16.

Determining Rules of Fuzzy Operators

The Fuzzy IF-THEN Rules process involves a fuzzy logic evaluation of each point within the membership function (Buana 2017) similarly to (Arini 2024) statement, namely that Fuzzy logic operates by mapping inputs to outputs using IF-THEN rules. Its functioning principle is to elucidate the relationship between the mapped input and output. This mapping process is carried out by a "black box" component situated between the input and output. To implement a Fuzzy Inference System (FIS), all rules must be predefined, as FIS can accommodate numerous rules that can be arranged flexibly to generate conclusions.

There are several functions to describe the membership degree of a fuzzy set. These include the AND operator, which corresponds to the intersection of sets. The resulting predicate of this operation uses the AND operator, selecting the lowest membership value of each element in the involved sets ($\mu A \cap B = \min(\mu A(x), \mu B(y))$). The OR operator, on the other hand, corresponds to the union of sets. The resulting predicate of this operation uses the OR operator, selecting the highest membership value of each element in the involved sets ($\mu A \cup B = \max(\mu A(x), \mu B(y))$). The NOT operator corresponds to the complement of a set, producing the opposite of the original set ($\mu A' = 1 - \mu A(x)$) (Pratama *et al.,* 2024).

Table 2. Fuzzy Rules

No	Input			Output
	Weight	Time	Temperature	Roasted-level
1	Light	Short	Low	Light
2	Light	Short	Medium	Light
3	Light	Short	High	Medium
4	Light	Medium	Low	Light
5	Light	Medium	Medium	Medium
6	Light	Medium	High	Dark
7	Light	Long	Low	Medium
8	Light	Long	Medium	Dark
9	Light	Long	High	Dark
10	Medium	Short	Low	Light
11	Medium	Short	Medium	Medium
12	Medium	Short	High	Dark
13	Medium	Medium	Low	Light
14	Medium	Medium	Medium	Medium
15	Medium	Medium	High	Dark
16	Medium	Long	Low	Medium
17	Medium	Long	Medium	Dark
18	Medium	Long	High	Dark
19	Weight	Short	Low	Light
20	Weight	Short	Medium	Medium
21	Weight	Short	High	Dark
22	Weight	Medium	Low	Medium
23	Weight	Medium	Medium	Dark
24	Weight	Medium	High	Dark
25	Weight	Long	Low	Medium
26	Weight	Long	Medium	Dark
27	Weight	Long	High	Dark

As shown in Table 2, the fuzzy rule base employs "AND" rules, requiring three inputs to be considered. Since the desired output is "dark," twenty one rules were identified. Due to the use of "AND" rules, the minimum membership degree is 0,16 as shown in the calculation above.

Analyse of Response

Decision making is a form of selection from various alternative actions that may be chosen, which process through certain mechanisms, with the hope that it will produce the best decision. The preparation of a decision model is a way to develop logical relationships underlying the decision problem into a mathematical model, which reflects the relationship between the factors involved (Sutisna and Basjaruddin 2015). Matlab is an application used to obtain data conformity between input image data and output data after several training tests (Sadli 2018).

Figures 6, 7 and 8 show the response graph of roasting coffee beans to the level of maturation of coffee beans with respect to temperature, time and weight.

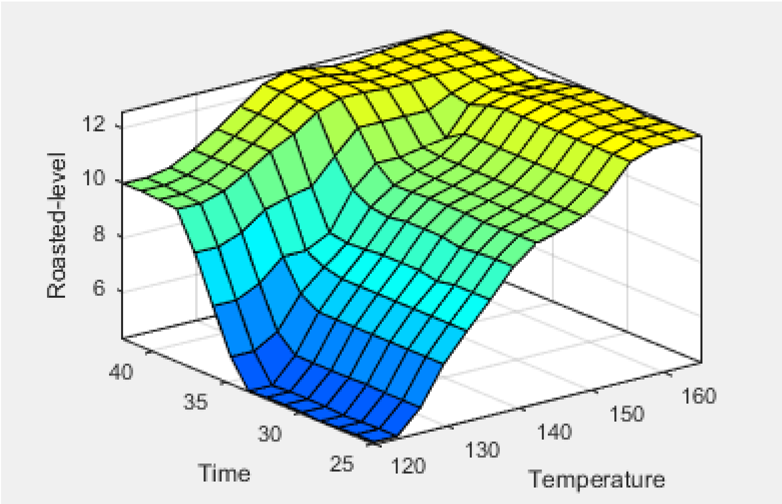

Figure 6. Graph of coffee roasting response to temperature and time

From *Figure 6*, it proves that the fuzzy logic built by the coffee bean roasting element control system is said to be in accordance with the expertise of an operator when roasting. For example, when the coffee beans are at maturity level 6, it means that the coffee beans are still at the light level. While the time is under 35 minutes and the roasting temperature is at 120-130 °C. While at 40 minutes and 160°C roasted level will reach 12. However, if the time is 40 minutes but the temperature is 150°C, the roasted level will be at 10.

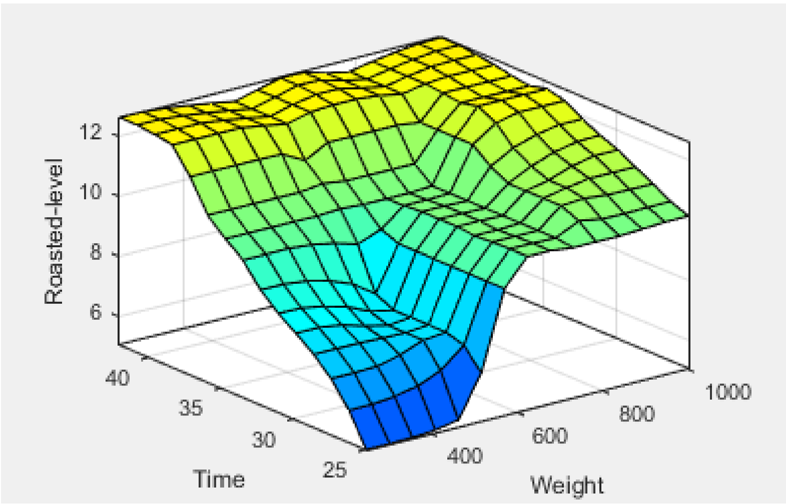

Figure 7. Graph of coffee roasting response weight and time

In *Figure 7*, the graph of coffee roasting response to weight and time, for example, when the coffee beans are at roasted level 8, it means that the coffee beans are still at the light-medium level. While the time is under 30 minutes and the roasting weight is at 400-600 gr. While at the roasting weight is at 800-1000 gr the roasted level will be at 12.

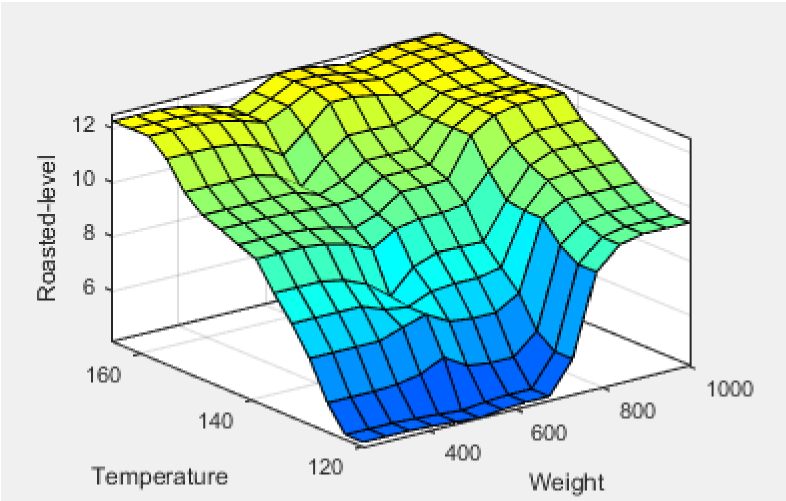

Figure 8. Graph of coffee roasting response temperature and weight

In *Figure 8*, the graph of coffee roasting response to temperature and weight, for example, when the coffee beans are at roasted level 10, it means that the coffee beans are at the medium level. While at a temperature of 140 °C and the weight of coffee is at 600-800 gr, the roasted level is obtained 6. While at a weight of 800-1000 gr it is at a temperature of 160 °C with a roasted level of 12.

Implication Function

The implication function is a logical structure consisting of a collection of functions that require data in the form of fuzzy logic figures, linguistic input parameters (X), input and output membership, and response graphs (Naufal and Muttofar 2024). Fuzzy logic is a branch of artificial intelligence for building intelligent systems, which are designed using the mamdani method (Yulmaini 2015). Fuzzy logic offers an intuitive approach to determining fuzzy decision-making systems through if-then rules. In the Mamdani method, the implication function applied is min. The Mamdani method has several processes in its process, namely forming fuzzy sets, determining implication functions, rule composition, and defuzzification (Suprianto and Agustin 2022).

The stages of this process are entering firm values, fuzzification, fuzzy rule base towards inference and firm output, namely defuzzification (Suprianto and Agustin 2022). The application of the implication function is carried out by providing an intuitive way of determining a fuzzy decision system. In this research the author uses fuzzy logic data and graphs which are then used to analyze the implication function as a whole.

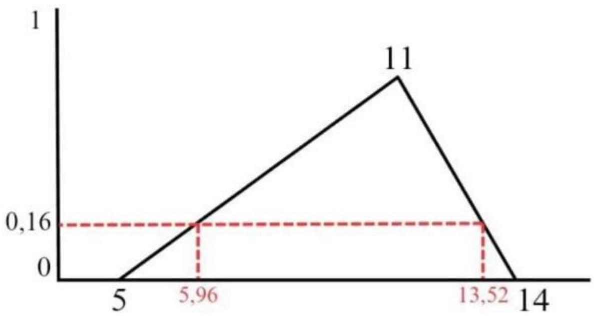

Figure 9. Process area medium implication values

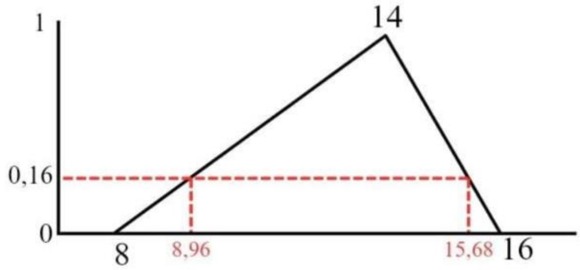

Figure 10. Process area dark implication values

$$(X1)\ 0{,}16 = \frac{x_1-5}{11-5} \rightarrow 0{,}96 = x_1 - 5 \rightarrow x = 5{,}96$$

$$(X2)\ 0{,}16 = \frac{14-x_2}{14-11} \rightarrow 0{,}48 = 14 - x_2 \rightarrow x = 13{,}52$$

$$(X3)\ 0{,}16 = \frac{x_3-8}{14-8} \rightarrow 0{,}96 = x_3 - 8 \rightarrow x = 8{,}96$$

$$(X4)\ 0{,}16 = \frac{16-x_4}{16-14} \rightarrow 0{,}32 = 16 - x_4 \rightarrow x = 15{,}68$$

Defuzzification

Defuzzification is a crucial process in fuzzy logic systems that converts fuzzy results into clear data that may be used for analysis decision. According to the diagram, a fuzzy logic system takes inputs with a high degree of accuracy and produces output in the form of fuzzy input. However, in order for the output to be presented in a clear and concise manner, defuzzification must be carried out in order to obtain more precise and lucid results (Zadeh 2018).

One common method of defuzzification is the use of the centroid. The centroid is calculated by considering the area under the curve of the membership function of the fuzzy set. Defuzzification also plays a significant role in enhancing the effectiveness of fuzzy logic systems across various applications, such as automatic control and recommendation systems. By calculating a representative crisp value, decision-makers can more easily interpret the results and take appropriate actions. The accuracy of the outcomes from the defuzzification process can directly influence the performance of fuzzy systems in real-world situations, making it an indispensable component in the development of fuzzy-based technologies (Driankov *et al.*, 2019).

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