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Implementation of Mamdani Fuzzy Logic for Determining Bread Doneness Based on Temperature and Time

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Abstract

This study proposes a classification model of bread doneness using a Mamdani Fuzzy Inference System (FIS) based on the nonlinear interaction between baking temperature and time. Conventional threshold-based baking approaches often fail to represent gradual transitions in doneness levels, limiting their adaptability in intelligent oven systems. The proposed model utilizes two input variables—oven temperature (150–230 °C) and baking time (5–40 minutes)—and produces a normalized doneness output categorized as underbaked, properly baked, and overbaked. Fuzzy rules were formulated based on thermal baking characteristics, and the inference process was implemented through fuzzification, minimum operator rule evaluation, maximum aggregation, and centroid defuzzification. Both direct mathematical calculations and MATLAB Fuzzy Logic Toolbox simulations were conducted to validate the model. For a test case of 190 °C and 18 minutes, the system generated a defuzzified value of 66.6, corresponding to the properly baked category. The results demonstrate consistent output behavior and stable classification performance. The proposed model provides an interpretable and computationally efficient decision framework that can serve as a foundational component for intelligent baking systems.

Keywords: Mamdani Fuzzy Inference System; Bread Doneness; Temperature–Time Interaction; Intelligent Oven; Decision Model.

INTRODUCTION

Bread is a widely consumed food product, and its final quality is strongly influenced by baking parameters, particularly oven temperature and baking time. Variations in these two parameters directly affect the color, texture, moisture content, and sensory characteristics of bread.(Astuti, 2015) reported that variations in baking temperature have a significant effect on the production results of sweet bread. In addition, (Kusnandar et al., 2022) emphasized that thermal conditions during the baking process play an important role in determining the final quality of bread products.

Besides temperature, baking time is also an important factor in determining the level of bread doneness. A baking time that is too short may result in undercooked bread, while excessive baking time may cause the bread to become overcooked. (Ayu Paramita et al., 2023) explained that the interaction between temperature and processing time significantly affects bread production results. Similarly, (Hidayat et al., 2023) showed that variations in processing conditions contribute to differences in the final quality of bread. These findings confirm that temperature and time are the main variables that determine the level of bread doneness during the baking process.

Previous studies have examined the influence of baking temperature and baking time on the final quality of bread. However, most of these studies focus primarily on experimental analysis of baking parameters or general quality evaluation, rather than developing a computational model that can be integrated into an automated baking system. In addition, studies that utilize a fuzzy logic–based approach to classify bread doneness as part of a smart oven control mechanism are still limited. Therefore, there is a need for a systematic decision-making model that can represent the relationship between temperature and baking time and support automated control in a smart oven system.

One approach that can be used to handle uncertainty in decision-making systems is fuzzy logic, particularly the Fuzzy Mamdani method. This method has been widely applied in various studies because it can represent human reasoning through linguistic rules and membership functions. Study (Surohadi et al., n.d.) applied the Fuzzy Mamdani method to predict production quantities in the industrial sector and showed that this approach can produce decisions that are more adaptive to changes in input variables. In addition, study (Karima & Rahman, 2024) implemented Fuzzy Mamdani in a production recommendation system and proved that this method is effective in generating systematic rule-based decisions. The Fuzzy Mamdani method works through the stages of fuzzification, rule base formation, inference, and defuzzification to produce outputs that are flexible to variations in input values. Therefore, this study aims to develop a classification model for bread doneness using the Fuzzy Mamdani method with oven temperature and baking time as input variables.

METHODS

This study uses a quantitative approach based on intelligent system modeling by applying a Mamdani-type Fuzzy Inference System to determine the level of bread doneness based on oven temperature and baking time parameters. This approach was chosen because fuzzy logic is capable of handling uncertainty and linguistic representation in decision-making processes that are nonlinear and uncertain (FIBRIAYORA et al., 2019) In the context of intelligent systems, the Fuzzy Inference System (FIS) is widely used for control and classification systems because of its flexibility in modeling complex relationships between variables (Cateni & Coll, 2012).

The research design consisted of several stages, including determining input and output variables, defining membership functions, constructing the rule base, performing the inference process, and conducting defuzzification (Mogharreban & DiLalla, 2006). he input variables used in this study were oven temperature with a range of 150–230 °C and baking time with a range of 5–40 minutes. These ranges were determined based on the general characteristics of the baking process, which is influenced by heat distribution and heating duration that affect the physical and color changes of bakery products (Purlis, 2010). The output variable was the level of bread doneness, which was classified into three linguistic sets: undercooked, properly cooked, and overcooked, to represent the doneness condition in a gradual and interpretable manner.

The research procedure began with a literature study of scientific journals and previous studies related to the application of Mamdani fuzzy logic in temperature control systems, decision-making, and intelligent systems(Aguilar et al., 2012). The literature study served as a conceptual foundation for determining the fuzzy model structure, variable parameters, and inference methods used (Pedrycz, 1996) The Fuzzy Inference System model was then designed using the MATLAB Fuzzy Logic Toolbox as the simulation tool because it allows comprehensive visualization of membership functions, rule bases, and defuzzification processes (Ramya et al., 2014a).

The temperature and time ranges were determined based on common bread-baking practices and literature indicating that sweet bread is generally baked at temperatures of 160–220 °C for 10–30 minutes (Silva et al., 2022; Siskawardani et al., 2021). To provide flexibility and allow overlap in the fuzzy system, the temperature range was set at 150–230 °C and the time range at 5–40 minutes (Pranata Putri et al., 2026). The output variable representing bread doneness was normalized on a scale of 0–100 to simplify the inference and defuzzification processes and to produce more representative system outputs.

The triangular membership functions were used in this research because they have a simple structure, are computationally efficient, and are widely applied in Mamdani fuzzy inference systems (Khairuddin et al., 2021). The parameter values for each linguistic variable were determined through a review of several previous studies related to bread baking characteristics and the influence of temperature and baking time on the final doneness of bread.

The temperature variable was categorized into three levels: low, medium, and high, with parameters (150,150,180), (170,195,220), and (200,230,230). These ranges were selected to represent baking temperature conditions commonly reported in the literature, where variations in temperature influence the physical and quality changes of bread during the baking process (Silva et al., 2022).

Similarly, the baking time variable was divided into three categories: short (5,5,15), optimal (10,20,30), and long (25,40,40). These intervals were chosen to reflect baking durations that are commonly applied in sweet bread production and have been shown to influence the chemical and physical characteristics of bread (Siskawardani et al., 2021).

The output variable represents the level of bread doneness and was normalized on a scale from 0 to 100. It was divided into three categories: undercooked (0,0,50), cooked (40,70,90), and overcooked (80,100,100) to represent the gradual transition of doneness conditions. Overlapping areas between adjacent membership functions were intentionally included to allow the fuzzy system to capture gradual changes in input values and to avoid abrupt transitions in the output.

The fuzzy rule base consists of nine rules and was developed using a knowledge-based approach derived from literature on bread baking processes and thermal behavior during baking. These rules reflect commonly accepted baking principles, where lower temperatures combined with shorter baking durations tend to produce undercooked bread, while higher temperatures and longer baking durations increase the level of doneness and may result in overbaked conditions. The rule combinations were therefore constructed to represent these logical relationships between temperature, baking time, and bread doneness (Silva et al., 2022; Siskawardani et al., 2021).

The rule base was constructed in the form of IF–THEN rules that describe the relationship between temperature, time, and bread doneness. The combination of three linguistic sets for each input variable resulted in nine fuzzy rules representing expert knowledge in the baking process. The rule-based reasoning approach in Mamdani fuzzy systems has been proven effective in knowledge-based control systems because it integrates linguistic logic with mathematical inference processes (Moewes & Kruse, 2012).

The data collection technique used in this study was a literature review and system simulation approach. The data consisted of conceptual parameters of oven temperature and baking time adjusted to the general characteristics of the bread-baking process. The simulation approach was chosen because it allows controlled, efficient, and structured testing of intelligent system models before real-world implementation (Cauvain, 2015).

Data analysis was carried out through four main stages in the Mamdani Fuzzy Inference System: fuzzification, implication, aggregation, and defuzzification. In the fuzzification stage, crisp values of temperature and time were converted into membership degrees for each fuzzy set (Mada et al., 2022). The inference process used the Mamdani method with the minimum operator (AND) and maximum aggregation, followed by defuzzification using the centroid method. The model was implemented using the MATLAB Fuzzy Logic Toolbox for visualization, rule construction, and system response simulation.

The implementation of the fuzzy inference system model in this study was carried out using the MATLAB Fuzzy Logic Toolbox to build the Mamdani FIS structure, define triangular membership functions, construct the rule base, and perform simulation and output analysis (Manara et al., 2006). The use of MATLAB in fuzzy-based intelligent system research is widely adopted because it provides an accurate, robust, and user-friendly computational environment for testing fuzzy inference models (Ramya et al., 2014b).

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RESULTS AND DISCUSSION

FUZZY MODEL IMPLEMENTATION RESULTS

1. Membership Function Suhu

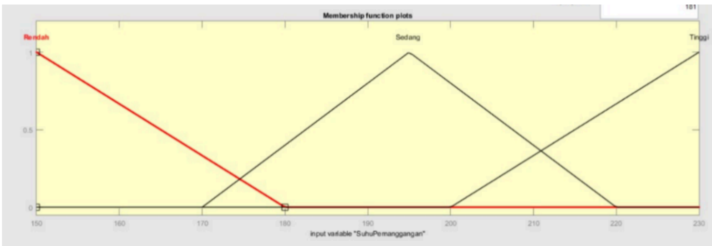

Figure 1. Membership Function Suhu

The graph shows the membership functions of the temperature variable within the range of 150–230 °C, which are divided into three categories: low, medium, and high. Overlap between the sets can be observed, allowing gradual value transitions. This overlap is important to prevent abrupt output changes when small variations in temperature occur. The membership functions for each category are defined as follows:

$$\mu_{rendah}(x) = \begin{cases} 1, & x \leq 150 \\ \dfrac{180 - x}{180 - 150}, & 150 < x < 180 \\ 0, & x \geq 180 \end{cases}$$

$$\mu_{Sedang}(x) = \begin{cases} 0, & x \leq 170 \; atau \; x \geq 220 \\ \dfrac{x - 170}{195 - 170}, & 170 < x < 196 \\ \dfrac{220 - x}{220 - 195}, & 195 \leq x < 220 \end{cases}$$

$$\mu_{Tinggi}(x) = \begin{cases} 0, & x \leq 200 \\ \dfrac{x - 200}{230 - 200}, & 200 < x < 230 \\ 1, & x \geq 230 \end{cases}$$

2. Membership Function Waktu

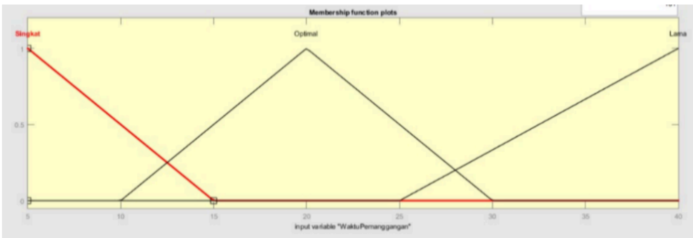

Figure 2. Membership Function Waktu

The figure shows the membership functions of the time variable within the range of 5–40 minutes. The short, optimal, and long categories are designed with a continuous distribution so that the system can represent variations in baking duration realistically. The membership functions for each category are defined as follows:

$$\mu_{Singkat}(x) = \begin{cases} 1, & x \le 15 \\ \dfrac{15 - x}{15 - 5}, & 5 < x < 15 \\ 0, & x \ge 15 \end{cases}$$

$$\mu_{Optimal}(x) = \begin{cases} 0, & x \le 10 \; atau \;\; x \ge 30 \\ \dfrac{x - 10}{20 - 10}, & 10 < x < 20 \\ \dfrac{30 - x}{30 - 20}, & 20 \le x < 30 \end{cases}$$

$$\mu_{Lama}(x) = \begin{cases} 0, & x \le 25 \\ \dfrac{x - 25}{40 - 25}, & 25 < x < 40 \\ 1, & x \ge 40 \end{cases}$$

3. Membership Function Tingkat Kematangan

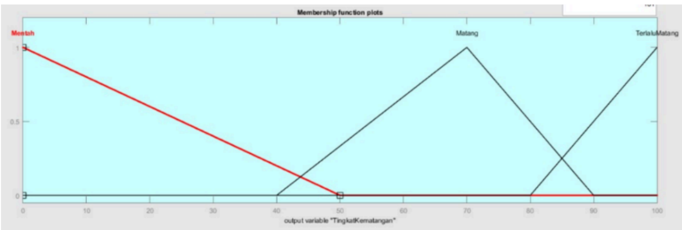

Figure 3. Membership Function Tingkat Kematangan

The graph shows the membership functions of the bread doneness level on a scale of 0–100. The distribution of the undercooked, cooked, and overcooked categories is constructed based on a normalization principle so that the defuzzification results can be directly interpreted as a relative doneness level. The membership functions for each category are defined as follows:

$$\mu_{Mentah}(x) = \begin{cases} 1, & x \le 0 \\ \dfrac{50 - x}{50 - 0}, & 0 < x < 50 \\ 0, & x \ge 50 \end{cases}$$

$$\mu_{Matang}(x) = \begin{cases} 0, & x \le 40 \; atau \;\; x \ge 90 \\ \dfrac{x - 40}{70 - 40}, & 40 < x < 70 \\ \dfrac{90 - x}{90 - 70}, & 70 \le x < 90 \end{cases}$$

$$\mu_{Terlalu\ Matang}(x) = \begin{cases} 0, & x \le 80 \\ \dfrac{x - 80}{100 - 80}, & 80 < x < 100 \\ 1, & x \ge 100 \end{cases}$$

FUZZIFICATION RESULTS

In the fuzzification stage, crisp input values in the form of temperature and baking time are converted into membership degrees for each fuzzy set. In this test, a temperature of 190 °C and a baking time of 18 minutes were used. For the temperature variable, the value of 190 °C lies within the interval 170–195, so it belongs to the **medium** category with the following membership function:

$$\boldsymbol{\mu_{Sedang}(190) = \frac{190 - 170}{195 - 170} = \frac{25}{20} = 0.8}$$

Meanwhile, the membership degrees for the **low** and **high** categories are equal to 0 because the value lies outside the active domain of those functions. For the time variable, the value of 18 minutes lies within the interval 10–20, so it belongs to the **optimal** category with the following membership function:

$$\mu_{Optimal}(18) = \frac{18 - 10}{20 - 10} = \frac{8}{10} = 0.8$$

INFERENCE RESULTS

The inference process in the fuzzy system is carried out using the Mamdani method with the MIN operator as the implication function and the MAX operator as the aggregation method between rules. The rule base consists of nine rules, which are combinations of the three temperature sets and the three baking time sets, as shown in Table 1:

Tabel 1. Rule Base

No	Suhu Pemanggangan	Waktu Pemanggangan	Tingkat Kematangan
1	Rendah	Singkat	Mentah
2	Rendah	Optimal	Mentah
3	Rendah	Lama	Matang
4	Sedang	Singkat	Matang
5	Sedang	Optimal	Matang
6	Sedang	Lama	Terlalu Matang
7	Tinggi	Singkat	Matang
8	Tinggi	Optimal	Terlalu Matang
9	Tinggi	Lama	Terlalu Matang

In the test case with a temperature of 190 °C and a baking time of 18 minutes, the following results were obtained:

$$\mu_{Sedang}(190) = 0.8$$

$$\mu_{Optimal}(18) = 0.8$$

Based on the rule base, the active rule combination is:
IF Suhu Sedang AND Waktu Optimal THEN Kematangan Matang

The firing strength (α) value is calculated using the MIN operator:

$$\alpha = \min(\mu_{Sedang}(190), \mu_{Optimal}(18))$$

$$\alpha = \min(0.8, 0.8) = 0.8$$

The firing strength value is then used in the implication stage to modify the output membership function according to the Mamdani method using the minimum operator. Mathematically, the output membership function after implication can be expressed as follows:

$$\mu'_{Matang}(z) = min(\mu_{Matang}(z), 0.8)$$

The Cooked fuzzy set is defined as a triangular membership function with parameters (40, 70, 90). Mathematically, the membership function can be expressed as::

$$\mu_{Matang}(z) = \begin{cases} 0, & z \leq 40 \; atau \; z \geq 90 \\ \dfrac{z-40}{70-40}, & 40 < z \leq 70 \\ \dfrac{90-z}{90-70}, & 70 < z < 90 \end{cases}$$

To determine the clipping domain limits, the value α = 0.8 is substituted into the equations of each side of the triangular membership function of the Cooked set.

For the rising edge (40 ≤ z ≤ 70):

$$\frac{z-40}{70-40} = 0.8$$

$$\boldsymbol{z = 64}$$

For the falling edge (70 ≤ z ≤ 90):

$$\frac{90-z}{90-70} = 0.8$$

$$\boldsymbol{z = 74}$$

Thus, the output membership function after implication has a maximum height of 0.8 and forms a flat region within the interval 64 ≤ z ≤ 74. Geometrically, the resulting implication curve forms a trapezoidal shape over the domain 40 ≤ z ≤ 90.

Since only one rule is active in this case, the aggregation process using the maximum operator produces a function identical to the implication result. This aggregated function is then used in the defuzzification stage to obtain a crisp value using the centroid method..

DEFUZZIFICATION RESULTS

The defuzzification stage is carried out to obtain a crisp value from the aggregated output membership function. In this study, the centroid (center of gravity) method is used because this method considers the entire area of the inference curve, providing a more accurate representation of the distribution of membership degrees.

The output membership function of the cooked category before the implication process is a triangular function with parameters (40, 70, 90). Based on the previous inference results, a firing strength value of α = 0.8 was obtained. Therefore, the output membership function is clipped at a height of 0.8, forming a trapezoidal curve over the domain 40 ≤ z ≤ 90, with a flat region in the interval 64 ≤ z ≤ 74. Mathematically, the output membership function after implication can be expressed as follows:

$$\mu(z) = \begin{cases} 0, & z \leq 40 \; atau \; z \geq 90 \\ \dfrac{z-40}{70-40}, & 40 < z < 64 \\ 0.8, & 64 \leq z \leq 74 \\ \dfrac{90-z}{90-70}, & 70 < z < 90 \end{cases}$$

The crisp value is determined using the centroid method equation.

$$\boldsymbol{z^* = \frac{\int z\mu(z)dz}{\int \mu(z)dz}}$$

The calculation is performed by dividing the area into three parts, namely the left triangle (40–64), the rectangular section (64–74), and the right triangle (74–90). The total area (A) is obtained by summing the integral values of the output membership functions in each interval. Mathematically, the total area can be expressed as follows:

$$\boldsymbol{A} = \int_{\mathbf{40}}^{\mathbf{90}} \boldsymbol{\mu(z)dz}$$

Since the output membership function after implication consists of several linear segments within different domains, the integral evaluation is carried out separately for each interval. In the first interval ($40 \le z \le 64$), the membership function forms an increasing line segment, so the area is calculated as follows:

$$A_1 = \int_{40}^{64} \frac{z-40}{30} dz$$

$$A_1 = \frac{1}{30} \int_{40}^{64} (z-40)dz$$

$$A_1 = \frac{1}{30} \left[\frac{(z-40)^2}{2} \right]_{40}^{64}$$

$$A_1 = \frac{1}{30} \cdot \frac{24^2}{2}$$

$$\boldsymbol{A_1} = \mathbf{9.6}$$

In the second interval ($64 \le z \le 74$), the membership function has a constant value of 0.8, so the area of this section is calculated as follows:

$$A_2 = \int_{64}^{74} 0.8\, dz$$

$$A_2 = 0.8(74-64)$$

$$\boldsymbol{A_2} = \mathbf{8}$$

In the third interval ($74 \le z \le 90$), the membership function forms a decreasing line segment, so the area is calculated as follows:

$$A_3 = \int_{74}^{90} \frac{90 - z}{20} dz$$

$$A_3 = \frac{1}{20} \int_{74}^{90} (90 - z) dz$$

$$A_3 = \frac{1}{20} \left[90z - \frac{z^2}{2} \right]_{74}^{90}$$

$$A_3 = \frac{128}{20}$$

$$\boldsymbol{A_3 = 6.4}$$

Thus, the total area of the implication result is obtained as follows:

$$A = A_1 + A_2 + A_3$$

$$\boldsymbol{A = 9.6 + 8 + 6.4 = 24}$$

Next, the moment value is calculated using Equation (10), which represents the centroid method. The moment is obtained by multiplying the output variable zzz by the output membership function value at each interval, then integrating over the corresponding domain. Mathematically, the moment can be expressed as follows:

$$\boldsymbol{M = \int_{40}^{90} z\, \mu(z) dz}$$

Since the output membership function after implication consists of several linear segments within different domains, the moment calculation is carried out separately for each interval.

In the first interval (40 ≤ z ≤ 64), the result is obtained as follows:

$$M_1 = \int_{40}^{64} \frac{z - 40}{30} z\, dz$$

$$M_1 = \frac{1}{30} \int_{40}^{64} (z^2 - 40z) dz$$

$$M_1 = \frac{1}{30} \left[\frac{z^3}{3} - 20z^2 \right]_{40}^{64}$$

$$\boldsymbol{M_1 = 531.2}$$

In the second interval (64 ≤ z ≤ 74), since the membership function has a constant value of 0.8, the moment value is calculated as follows:

$$M_2 = \int_{64}^{74} 0.8z\, dz$$

$$M_2 = 0.8\left[\frac{z^2}{2}\right]_{64}^{74}$$

$$\boldsymbol{M_2 = 552}$$

In the third interval ($74 \leq z \leq 90$), the result is obtained as follows:

$$M_3 = \int_{74}^{90} \frac{90 - z}{20} z\, dz$$

$$M_3 = \frac{1}{20}\int_{74}^{90} (90z - z^2)dz$$

$$M_3 = \frac{1}{20}\left[45z^2 - \frac{z^3}{3}\right]_{74}^{90}$$

$$\boldsymbol{M_3 = 518.4}$$

The total moment value is then obtained by summing all moment contributions in each interval, resulting in the following momentum value:

$$M = M_1 + M_2 + M_3$$

$$\boldsymbol{M = 531.2 + 552 + 518.4 = 1601.6}$$

Based on all the calculations of area and moment described previously, the total area is A = 24 and the total moment is M = 1601.6. Using the centroid method, the crisp output value of the system is calculated as follows:

$$\boldsymbol{z^* = \frac{M}{A} = \frac{1601.6}{24} = 66.73}$$

This value indicates that the bread doneness level lies in the range of 66–67 on the output domain, which corresponds to the “Matang” (properly baked) category. The result is consistent with the previously activated fuzzy rules, namely the combination of Medium temperature and Optimal time, indicating that the inference and defuzzification processes have been carried out consistently.

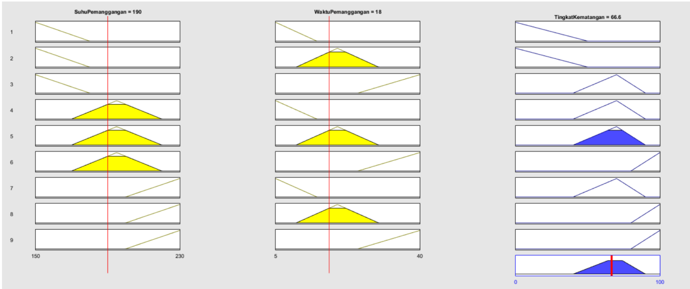

Figure 4. Hasil Perhitungan Matlab

The figure above shows the simulation results using the Rule Viewer with an example input of temperature 190 °C and baking time 18 minutes. Based on the activated fuzzy rules, the system produces a defuzzification value of 66.6, which falls into the partially baked category.

The rule activation indicates that the combination of medium temperature and optimal time provides the dominant contribution to the baked category. This shows that the model successfully represents the logical relationship between thermal parameters and the bread doneness level.

If the temperature is reduced to 160 °C with a baking time of 10 minutes, the output value falls below 50 and is categorized as underbaked. Conversely, at a temperature of 220 °C and a baking time of 35 minutes, the output value increases above 85 and approaches the overbaked category.

SYSTEM RESPONSE SURFACE ANALYSIS

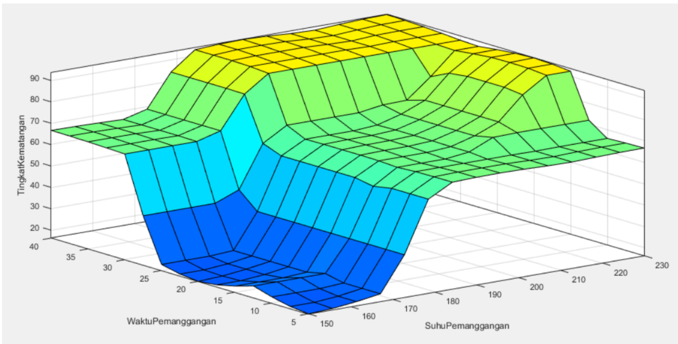

Figure 5. Surface Matlab

The figure shows the three-dimensional relationship between temperature, baking time, and bread doneness level. In the temperature range of 150–170 °C with a duration of 5–15 minutes, the output values are at a low doneness level, representing the underbaked condition.

An increase in temperature and baking time results in a progressive increase in the doneness value. The color gradient from blue to green to yellow indicates that the system provides a continuous response to changes in the input variables. At temperatures above 200 °C and baking times longer than 25 minutes, the doneness level approaches the maximum value and can be classified as overbaked.

The relatively smooth response surface without discontinuities indicates that the Mamdani fuzzy model with the centroid defuzzification method is able to produce stable and consistent outputs that correspond well with the thermal characteristics of the bread baking process.

DISCUSSION

The research results were obtained through the implementation of a Mamdani-type Fuzzy Inference System using the MATLAB Fuzzy Logic Toolbox with two input variables, namely oven temperature and baking time, and one output variable representing the bread doneness level on a scale of 0–100. The visualization of the membership functions shows that each input variable is divided into three overlapping linguistic categories. The overlap among these sets allows the system to produce gradual value transitions so that small changes in temperature or time do not cause discrete output changes. This is important for representing real baking conditions, which are continuous and do not have rigid boundaries between doneness levels.

The rule base consists of nine IF–THEN rules representing the relationship between temperature, time, and bread doneness level. These rules were constructed based on the thermal logic of the baking process, where heat intensity and exposure duration work simultaneously in determining the level of doneness. The combination of medium temperature and optimal time produces the "properly baked" category, while the combination of high temperature and long baking time produces the "overbaked" category. This rule structure shows that the system does not rely on a single parameter but rather on the interaction of both parameters simultaneously.

The simulation was conducted using an example input of 190 °C temperature and 18 minutes of baking time. The inference results show that the defuzzification value falls within the properly baked category, approximately in the range of 66–70. The dominant rule activation comes from the combination of medium temperature and optimal time, which has the highest membership degree during the fuzzification process. Additional testing shows that a temperature of 160 °C with a baking time of 10 minutes produces a value below 50, which falls into the underbaked category, while a temperature of 220 °C with a baking time of 35 minutes produces a value above 85, which falls into the overbaked category. These results indicate the consistency of the system in responding to variations in input parameters according to baking logic.

The three-dimensional response surface analysis shows a non-linear relationship between temperature, time, and bread doneness level. The resulting surface is smooth and does not show discontinuities, indicating that the Mamdani method with centroid defuzzification is capable of producing a stable and continuous classification system. Theoretically, the baking process involves heat transfer mechanisms through conduction and convection as well as Maillard reactions influenced by heating intensity and duration. These relationships are not simply linear, making the fuzzy approach more suitable than fixed-threshold methods, which tend to be rigid.

This research successfully addresses the formulated problem, namely how to develop a structured computational model to classify bread doneness levels based on the combination of temperature and baking time. Unlike previous studies that only analyzed parameter effects experimentally, this research integrates both variables into a rule-based inference system processed mathematically. Therefore, this study not only explains the relationships between variables but also provides a decision-support system framework that can be further developed.

The contribution of this research lies in the development of a Mamdani fuzzy logic–based classification model capable of systematically representing the non-linear relationship between temperature and time. The resulting model has the potential to be integrated into automatic oven systems or artificial intelligence–based bakery production systems to support more adaptive and consistent product quality control. However, this model is still limited to two main parameters and does not yet consider other factors such as oven humidity, bread size, or dough composition. Therefore, further research is needed to improve the complexity and validity of the system under real conditions.

CONCLUSION

This study successfully developed a classification model for bread doneness levels based on a Mamdani-type Fuzzy Inference System by utilizing oven temperature and baking time as the main input variables. The model was designed using triangular membership functions and nine expert knowledge–based rules representing the relationship between heat intensity and heating duration on bread doneness levels.

The simulation results show that the system is capable of producing stable, continuous, and consistent outputs in response to variations in input parameters. The combination of medium temperature and optimal baking time produces the properly baked category, while simultaneous increases in temperature and baking time increase the tendency toward overbaking. The implementation of the centroid defuzzification method allows the system to produce representative crisp values on a 0–100 scale without discontinuities.

Conceptually, this study demonstrates that the Mamdani fuzzy approach is effective in representing the non-linear relationship between temperature and time in the baking process. The main contribution of this research lies in the formulation of a structured computational model that can be used as a decision-support system for quality control in the baking process. The developed model has the potential to be integrated into automatic oven systems or artificial intelligence–based bakery production systems to improve production consistency and efficiency.

However, this study is still limited to two main parameters and does not yet consider other factors such as oven humidity, internal heat distribution, bread size, or dough composition. Further research is required to perform experimental validation under real conditions and to integrate additional parameters in order to improve the accuracy and generalization of the model.

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