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Early Detection of Pasteurized Milk Spoilage Using Fuzzy Logic Based on Storage Temperature and pH

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Abstract

Pasteurized milk is highly susceptible to spoilage due to its rich nutritional content and sensitivity to temperature fluctuations during storage. Conventional methods for detecting milk spoilage are often time-consuming and require laboratory testing. This research aims to develop an early detection model for pasteurized milk spoilage using the Sugeno fuzzy inference system based on storage temperature and pH parameters. The model applies two input variables, namely temperature and pH, and one output variable that classifies the milk condition into three categories: safe, and spoiled. Data were obtained by storing pasteurized milk at different temperature conditions while monitoring pH changes over time. The Sugeno fuzzy model was implemented using MATLAB to process the data and generate numerical output representing spoilage risk levels. The results show that the Sugeno fuzzy inference system can effectively classify the milk condition with a prediction accuracy of 86.7 percent. The model indicates that higher storage temperatures and lower pH values significantly increase the risk of spoilage. Therefore, the Sugeno fuzzy logic model can be applied as an efficient, quantitative, and reliable method for real time quality monitoring and early detection of pasteurized milk spoilage.

Keywords: pasteurized milk, fuzzy logic, Sugeno model, storage temperature, pH.

INTRODUCTION

Milk is an important source of nutrition that makes a significant contribution to human health, as it contains essential nutrients such as proteins, fats, vitamins, minerals, lactose, and enzymes, and also serves as a good source of phosphorus and calcium (Putri, 2016). Plain liquid milk is obtained from fresh milk with or without the addition of other food ingredients (Badan Standardisasi Nasional, 2021) However, the high nutritional content also makes milk an ideal medium for microbial growth, rendering fresh milk highly perishable and in need of heat treatment such as pasteurization to destroy pathogens and extend its shelf life (Hasna & Ardiansah, 2023). Despite undergoing processing, pasteurized milk remains vulnerable, and its quality deterioration is marked by changes such as a decrease in pH, which are strongly influenced by storage temperature fluctuations that trigger spoilage.

One of the main challenges in ensuring the safety of pasteurized milk is that spoilage is often only detected after visible or sensory changes occur, such as curdling, sour odor, or discoloration. In fact, microbiological and physicochemical degradation begins much earlier, when the milk's pH start deviating from their normal values before any visual or olfactory changes are noticeable (Rashid *et al.*, 2019). The issue of detecting milk spoilage often arises because milk is naturally prone to microbial contamination even after pasteurization. Wulandari et al. (2017) explained that pasteurization effectively reduces the population of microorganisms such as *Escherichia coli* and *Staphylococcus aureus*, but cannot completely eliminate all pathogenic microbes and spores. Consequently, heat-resistant microorganisms may continue to grow during storage—especially if the cold chain is unstable—leading to a gradual increase in the *Total Plate Count* (TPC) without visible signs at the early stage. Post-pasteurization contamination can also occur due to unhygienic handling or improper storage temperatures, causing spoilage symptoms such as sour odor, curdling, or discoloration only after further microbiological and chemical degradation has progressed.

Storage temperature and pH are the key parameters that determine milk stability. Higher temperatures accelerate microbial growth, which in turn hastens the decrease in pH. A decline in pH disrupts the colloidal stability of casein and triggers coagulation (Pitaloka et al., 2025). Therefore, these two parameters are interrelated and can serve as early indicators of spoilage in pasteurized milk before visual or sensory changes become evident.

Hence, an analytical approach is needed to recognize quality change patterns and handle variable data effectively. Fuzzy logic offers a computational solution to this uncertainty through a rule-based reasoning system. This approach is considered efficient and accurate because it can adapt to dynamic environments. The variables are processed to produce an output in the form of a quality level based on rules within the fuzzy logic system (Uzun & Allahverdi, 2021).

METHODS

Research Approach

This research uses a quantitative modeling approach supported by a structured literature review to analyze the application of the Sugeno fuzzy inference system in early detection of pasteurized milk spoilage based on key physicochemical parameters such as pH and storage temperature. The Sugeno method is chosen because it produces numerical (crisp) outputs, is computationally efficient, and more suitable for real-time prediction and decision-making systems (Mukminna et al., 2017). The stages of this research consist of: (1) Identification of milk quality parameters from literature, (2) Systematic collection and normalization of secondary data, (3) Fuzzification, (4) Formation of fuzzy rules, (5) Fuzzy inference process, (6) Defuzzification, and (7) Validation and evaluation of the model.

This approach enables the development of a reproducible fuzzy logic model capable of classifying milk into safe, and spoiled categories based on quantitative variations in pH and temperature values.

Data Collection

A structured literature review was conducted to collect secondary data on pH, temperature ranges, spoilage indicators, and fuzzy modeling techniques relevant to pasteurized milk. Searches were performed through Scopus, ScienceDirect, Google Scholar, and SpringerLink using keywords such as *"pasteurized milk spoilage," "milk deterioration temperature pH," "fuzzy logic milk,"* and *"Sugeno food prediction."*

Articles were included if they: (1) were peer-reviewed; (2) published from 2015–2024; (3) discussed pH or temperature dynamics in pasteurized milk; or (4) applied fuzzy logic in food quality assessment. Articles were excluded if they lacked physicochemical data, analyzed raw milk only, or were not full-text academic sources.

Data Analysis

Data regarding milk pH (normal range 6.5–6.8), deterioration patterns, and temperature ranges (0–15 °C) were extracted from the selected literature. All numerical values were normalized using min–max normalization to match the domain required by fuzzy membership functions:

$$x\ norm = \frac{x - x\ min}{x\ max - x\ min}$$

Normalization ensures consistency in fuzzy processing and prevents scale imbalance between variables.

Fuzzy Logic Stage

1. **Fuzzification**

   Fuzzification converts numerical inputs (temperature and pH) into membership degrees. Each parameter's range is determined based on literature.

   The triangular membership function (trimf) is used, defined as (Karomi, 2018):

$$\mu(x) = \begin{cases} 0, & x \leq a \\ \frac{x-a}{b-a}, & a < x \leq b \\ \frac{c-x}{c-b}, & b < x < c \\ 0, & x \geq c \end{cases}$$

   Temperature (°C): Low [0–4], Medium [4–10], High [10–15]

   pH: Acidic [0–5.88], Neutral [5.88–7], Basic [7–14]

   Similarity Value Clarification

   In line with Karomi (2018), similarity value is applied as a normalization method to measure numerical closeness between data points:

$$Similarity = \frac{|x - x_{ref}|}{max - min}$$

   0 = identical

   1 = largest distance

   This produces normalized values (0–1) which are then used as fuzzy membership inputs.

2. **Fuzzy Rule Base and Inference**

   2.1 Rule Base Construction

   The inference process uses a rule-based structure in the form "IF-THEN" statements. Input membership values activate rules using the MIN operator as the fuzzy AND method (Mukminna et al., 2017). This study applies a Sugeno zero-order approach, where each rule produces a constant crisp output value corresponding to the milk quality category (Safe or Spoiled). A total of nine fuzzy rules were developed based on combinations of temperature and pH fuzzy sets. Examples of the rules are:

   - IF pH is Neutral AND Temperature is Low THEN Safe
   - IF pH is Acidic AND Temperature is High THEN Spoiled
   - IF pH is Acidic AND Temperature is Medium THEN Spoiled
   - IF pH is Neutral AND Temperature is High THEN Spoiled

   2.2 Sugeno Model Selection

   This study implements a Sugeno zero-order model, in which each rule produces a constant crisp output value corresponding to the final milk quality classification. Based on the output structure used in the Results and Discussion, the system applies two output consequents:

   - Safe = 5
   - Spoiled = 10

   These consequents represent the two primary milk quality states evaluated in this study and match the classification presented in the results section. The two-level output design simplifies the decision structure while maintaining clear separation between acceptable and unacceptable quality levels. The Sugeno method was chosen because it produces crisp numerical outputs suitable for rapid spoilage assessment, offers computational efficiency for real-time applications, and improves stability in prediction systems (Prasetyawan & Anifah, 2021; Uzun & Allahverdi, 2021). The zero-order Sugeno method does not use membership functions on the output variables. The output is generated as a constant (crisp) value, which is then interpreted as Safe or Spoiled based on a specified threshold.

3. **Defuzzification**

   Since the Sugeno model uses constant outputs (5 = Safe, 10 = Spoiled), defuzzification is performed using the Weighted Average method:

$$Z = \frac{\sum_i w_i z_i}{\sum_i w_i}$$

   where:
   wi = activation strength of rule i
   zi = constant output of rule i

   This approach produces a single numerical spoilage score between 5 and 10, which is then interpreted directly according to the milk quality categories used in the Results and Discussion. This method provides accurate and computationally efficient outputs suitable for real-time spoilage prediction (Mukminna et al., 2017).

4. **Fuzzy System Testing (Validation)**

   To ensure reproducibility, model validation follows:
   - 70% training, 30% testing, based on available secondary data
   - Comparison of model predictions with known spoilage classifications from literature (Nisa et al., 2020)

   Evaluation Metrics

1. Accuracy

$$Accuracy = \frac{\text{Correct Predictions}}{\text{Total Data}}$$

2. RMSE (Root Mean Square Error)

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

3. Confusion Matrix

   Used to evaluate classification into safe/alert/spoiled.
   These metrics ensure objective evaluation of the fuzzy model's predictive performance.

RESULTS AND DISCUSSION

Formation of Input and Output Fuzzy Sets

1. **Input Analysis**

   The fuzzy logic model in this study uses two main input variables—temperature and pH—whose domains and membership functions are defined based on established physicochemical characteristics of pasteurized milk. These inputs serve as the determinants of spoilage potential during refrigerated storage and form the basis of the fuzzy inference process.

a. Temperature Input
The temperature variable has a universe of discourse of 0°C to 15°C, representing the full range of typical refrigerated storage and mild temperature abuse conditions. This variable is divided into three triangular fuzzy sets (trimf):
- Low (0–4°C): Represents optimal storage conditions where microbial growth is minimal and quality degradation is limited.
- Medium (4–10°C): Indicates transitional conditions where microbial activity begins to increase, potentially reducing product stability.
- High (10–15°C): Represents accelerated spoilage conditions where elevated temperature promotes microbial proliferation and enzymatic reactions.

These fuzzy sets align with recommended cold-chain requirements and deterioration patterns reported in milk storage studies.

b. pH Input
The pH variable spans a universe of discourse from 0 to 14, divided into three triangular fuzzy sets corresponding to changes commonly observed during milk degradation:
- Acidic (0–5.88): Indicates strong acidification caused by lactic acid bacteria and other spoilage-related biochemical reactions, typically representing advanced spoilage.
- Neutral (5.88–7): Represents the normal physiological range of fresh pasteurized milk, associated with stable product quality and safety.
- Basic (7–14): Reflects alkaline shifts that may occur due to proteolysis or contamination, often associated with spoilage-related chemical changes.

These membership assignments support consistent rule activation during the inference stage and match the fuzzy set definitions established in the Methods section.

Table 1. Input Variables

Function	Variable	Fuzzy set	Universe set	Domain
Input	Suhu	Low	0-15	[0-0-4]
		Medium		[4-7-10]
		High		[10-15-15]
	pH	Acidic	0-14	[0-0-5.88]
		Neutral		[5.88-6.44-7]
		Basic		[7-14-14]

2. **Output Analysis**

The output variable in this fuzzy system represents the milk quality index, which indicates whether the milk is in an acceptable or deteriorated condition. In accordance with the Sugeno zero-order method, the output is not modeled as a fuzzy set; instead, each rule generates a crisp constant value.

The universe of discourse for the output ranges from 0 to 10, and the system uses two constant consequents:
- 5 = Safe

Represents milk that maintains acceptable physicochemical and microbiological quality.

- 10 = Spoiled

  Represents milk that has undergone deterioration, typically characterized by acidification, off-odor, curdling, or microbial spoilage.

These constant outputs are used directly in the Weighted Average defuzzification to generate a final spoilage score. This approach is computationally efficient and consistent with the Sugeno model described in the Methods section.

Table 2. Output Variable

Function	Variable	Output Category	Universe	Crisp Consequent
Output	Milk Quality	Safe	0-10	5
		Spoiled		10

Fuzzy Inference and Rule Activation

The Fuzzy Inference System (FIS) was developed to predict the feasibility status of pasteurized milk based on two main input variables: milk pH (x_1) and storage temperature (x_2). These parameters were selected due to their significant influence on the shelf life and microbiological quality of milk, which ultimately determines whether the milk is still safe for consumption or has already spoiled.

In the fuzzy system, the relationship between input and output variables is represented by a set of fuzzy rules in the form of if–then statements. These rules describe how variations in pH and temperature affect the milk's status based on empirical data. Each input variable is divided into three fuzzy sets: pH (Acidic, Neutral, Alkaline) and Temperature (Low, Medium , High). Accordingly, nine fuzzy rules are formulated to represent the possible interactions between pH and temperature that influence the status of pasteurized milk.

Table 3. Fuzzy Rules

	Input		Output
No	pH (x1)	Storage Temperature (x2)	Milk Status
1	Acidic	Low	Spoiled
2	Acidic	Medium	Spoiled
3	Acidic	High	Spoiled
4	Neutral	Low	Safe
5	Neutral	Medium	Safe
6	Neutral	High	Spoiled
7	Basic	Low	Spoiled
8	Basic	Medium	Spoiled
9	Basic	High	Spoiled

These rules were derived based on the logical relationship between pH, storage temperature, and the physical and microbiological condition of pasteurized milk. Each rule represents an empirical relationship that describes how variations in these parameters affect the milk's quality.

Milk with an acidic pH indicates microbial activity or early fermentation, which leads to spoilage even under low-temperature storage. In contrast, milk with a neutral pH (typically between 6.5 and 6.8) remains safe when stored at low to moderate temperatures, as these conditions inhibit microbial growth. However, temperatures above 10–15°C result in significantly increased bacterial activity, which accelerates spoilage. An alkaline pH, on the other hand, is indicative of contamination or chemical reactions that compromise the quality of the milk, resulting in spoilage under all storage conditions.

This fuzzy system effectively models the nonlinear relationship between pH, storage temperature, and the feasibility status of pasteurized milk, confirming that milk remains safe when stored at low to moderate temperatures with a neutral pH, while both acidic and alkaline conditions consistently indicate spoilage. These findings align with (Al-Farsi *et al.*, 2021), who concluded that both a decrease in pH and an increase in storage temperature accelerate the deterioration of pasteurized milk (Food Science & Quality Management), making the model a valuable tool for early spoilage detection and the development of automatic fuzzy logic-based sensors for monitoring milk quality during distribution.

Fuzzy Sugeno Design

1. **Temperature Input Variable**

Temperature is an important parameter during milk storage. Storage temperature greatly influences the rate of bacterial growth and the number of bacteria in pasteurized milk (Danah et al., 2019). Industry standards require pasteurized milk to be stored at low temperatures, typically at 4°C or below, to inhibit the growth of pathogenic and spoilage bacteria (Nikiuluw, 2018). The ideal storage temperature for milk to suppress bacterial growth is in the low range (4–5°C). Therefore, precise temperature control must be carried out in a measured manner to ensure optimal storage, prevent microbial growth, and preserve the milk's flavor and nutritional quality.

In the fuzzy system, temperature is used as an input variable to determine the optimal storage condition based on specific value ranges defined in the fuzzy set. The temperature variable has a range of 0–15°C with three sets: low (0–4°C), medium (4–10°C), and high (10–15°C). The calculation formula used is the triangular membership function (trimf). Based on the graph, temperatures below 4°C are categorized as low, around 7°C as medium, and above 10°C as high. This function helps the fuzzy system assess temperature conditions gradually.

$$\mu_{\text{rendah}}(x) = \begin{cases} 1, & x \le 0 \\ \dfrac{4-x}{4-0}, & 0 < x < 4 \\ 0, & x \ge 4 \end{cases}$$

$$\mu_{\text{sedang}}(x) = \begin{cases} 0, & x \le 4 \text{ atau } x \ge 10 \\ \dfrac{x-4}{7-4}, & 4 < x \le 7 \\ \dfrac{10-x}{10-7}, & 7 < x < 10 \end{cases}$$

$$\mu_{\text{tinggi}}(x) = \begin{cases} 0, & x \leq 10 \\ \dfrac{x-10}{15-10}, & 10 < x < 15 \\ 1, & x \geq 15 \end{cases}$$

Example Calculation:
For Temperature (x = 3.0)
(Domain : [0-0-4] : Value 0 between lies 0< x < 4

$$\mu\ Rendah\ (3{,}0) = \frac{4-x}{4-0} = \frac{4-3{,}0}{4} = \frac{1}{4} \approx \mathbf{0.25}$$

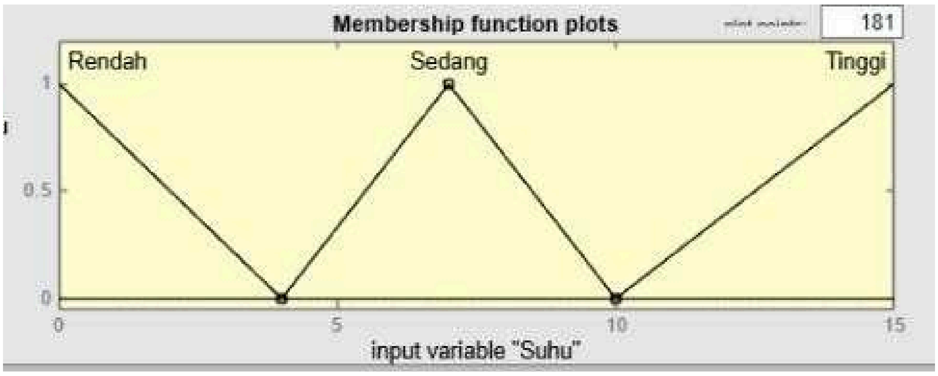

Figure 1. Membership function of the input variable "Temperature"

In the fuzzy system used, the temperature variable is divided into three linguistic sets: Low, Medium, and High, with a temperature range between 0 and 15°C. Each linguistic set is represented using a triangular membership function, which indicates the degree of membership from 0 to 1. The Low set covers the range between 0 and 4°C, with a membership value of 1 at temperatures ≤ 0°C, which decreases linearly to 0 at 4°C. This means that as the temperature approaches 4°C, the degree of membership in the Low category decreases. The Medium set spans temperatures from 4 to 10°C, with a peak membership value at 7°C. Its membership value increases from 0 to 1 between 4 and 7°C, then decreases back to 0 at 10°C, representing a stable or normal temperature condition. Meanwhile, the High set covers the range from 10 to 15°C, where the membership value increases from 0 at 10°C to 1 at temperatures ≥ 15°C, indicating that higher temperatures correspond to stronger membership in the High category.

With this division, the fuzzy system can assess temperature conditions gradually and more realistically compared to classical logic systems. For example, at a temperature of 6°C, the membership value can be shared between the Low and Medium categories, allowing the system to perform smoother inference. This approach enables more flexible and adaptive decision-making processes, such as in room temperature control, refrigeration systems, or industrial processes requiring stable temperature regulation.

The use of Fuzzy Logic, particularly the Sugeno Model, offers many advantages over conventional control systems that rely on fixed thresholds (on/off). Fuzzy systems can handle uncertain or inaccurate temperature data from sensors and provide smoother, proportional responses to temperature changes (Prasetyawan & Anifah, 2021). The result of the defuzzification process is a clear (crisp) milk quality value. This value can be used to trigger early warning alarms or automatically control the cooling system. In this way, milk quality can be maintained, and losses due to undetected quality degradation can be minimized (Pranata & Dewi, 2023).

2. **pH Input Variable**

The acidity level (pH) of water is an indicator used to express the degree of acidity or alkalinity of a solution, and this parameter is also very important in assessing the quality of liquid food products such as pasteurized milk (Karangan et al., 2019). The pH scale ranges from 0 to 14, with a pH of 7 considered neutral. Generally, milk has a pH of around 6.5 to 6.7, which means it is slightly acidic (Nugroho, Syauqy, & Fitriyah, 2022).

After the pasteurization process, the pH of milk tends to remain stable within the same range as fresh milk, but it may change over time if spoilage occurs. The decrease in pH is usually caused by the activity of microorganisms that produce lactic acid from milk sugar (lactose), making the milk more acidic (Nisa et al., 2022).

In a fuzzy logic system, pH is chosen as an input variable because changes in milk pH do not happen suddenly. There is often an early warning phase where the pH starts to drop, but the milk is not yet completely spoiled. If a fixed threshold, such as pH < 5.6, is used to classify the milk as spoiled, important information during this transition phase may be lost. Fuzzy logic helps capture these gradual changes by converting the pH value into linguistic categories such as acidic, neutral, and basic, each with its own degree of membership.

$$\mu\, Asam(x) = \begin{cases} 1, & x \leq 0 \\ \dfrac{5{,}88 - x}{5{,}88}, & 0 < x \leq 5{,}88 \\ 0, & x > 5{,}88 \end{cases}$$

$$\mu\, Netral(x) = \begin{cases} 0, & x \leq 5{,}88 \\ \dfrac{x - 5{,}88}{0{,}56}, & 5{,}88 < x \leq 6{,}44 \\ \dfrac{7 - x}{0{,}56}, & 6{,}44 < x7 \\ 0, & x \geq 7 \end{cases}$$

$$\mu\, Basa(x) = \begin{cases} 0, & x \leq 7 \\ \dfrac{x - 7}{7}, & 7 < x \leq 14 \\ 1, & x \geq 14 \end{cases}$$

Example Calculation:
For pH (xi = 6.5)
(Domain : [5,88-6,44-7] : Value 6,5 between lies 6,44< x <7

$$\mu Netral\,(6{,}5) = \frac{7 - x}{7 - 6{,}44} = \frac{7 - 6{,}5}{0{,}56} = \frac{0{,}50}{0{,}56} \approx \mathbf{0.89}$$

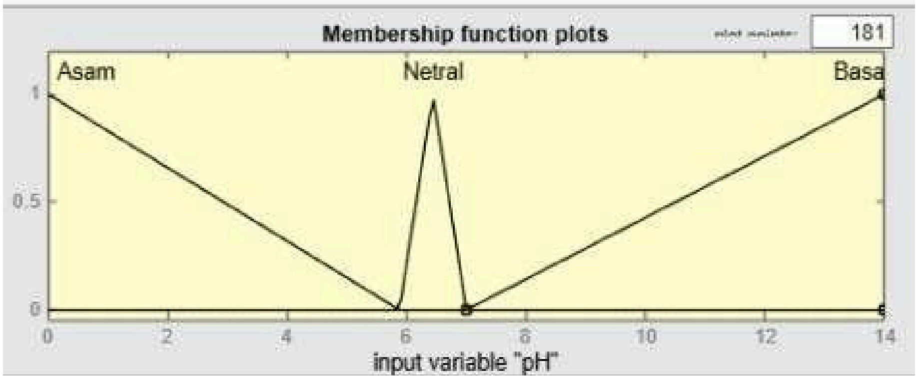

Figure 2. Membership function of the input variable “pH”

In the pH variable, a triangular membership function (trimf) is used. Each function has three points: a (start), b (peak), and c (end). These points form a triangular curve that represents how strongly a certain pH value belongs to a specific category. From this membership function, the fuzzy logic process for determining milk quality based on pH continues to the fuzzification stage, where the actual pH value (e.g., 6.5) is converted into a degree of membership within linguistic categories such as acidic, neutral, or basic using the triangular function. This allows one value to belong to more than one category at the same time, reflecting gradual changes in quality. Next, in the inference stage using the Sugeno method, the membership degree activates the fuzzy rules, producing an output in the form of a crisp value or a simple equation, which is then combined based on the weight of the membership degree (Vinsensia, 2021).

During the defuzzification stage, these results are merged using a weighted average to generate a single final value that represents the milk’s quality level. Through this process, the fuzzy system can interpret pH changes gradually, providing a more sensitive and flexible assessment compared to single-threshold approaches.

3. **Inferensi *Fuzzy***

The Fuzzy Inference stage serves as the main reasoning mechanism of the system, connecting the Membership Degree obtained from the Fuzzification stage with the defined Fuzzy Rules (Rule Base). This system uses the Zero Order Sugeno model.

Determination of the Crisp Consequent Value (zi)

The universe of discourse for the output variable Milk Quality is defined within the range [0–10]. The “Safe” category is assigned a domain of [0–5], with the corresponding crisp consequent value (zi) for Safe ranging from 0 to 5.

$$z\ safe = \frac{lower\ limit + \ upper\ limit}{2}$$

$$z\ safe = \frac{0 + 5}{2} = 0{,}25$$

The “Spoiled” category is defined with a domain of [5–10], meaning the crisp consequent value (zi) for Spoiled ranges from 5 to 10 within the universe of discourse for milk quality.

$$z\ Spoilage = \frac{lower\ limit + \ upper\ limit}{2}$$

$$z\ spoilage = \frac{5 + 10}{2} = 7{,}5$$

The value **zi = 2.5** is a crisp constant that numerically represents the "**Safe**" consequent in each fuzzy rule (for example, Rule 4). This value is then used to calculate the numerator ∑wi zi during the Defuzzification stage.

Determination of Rule Activity Level (wi)

The AND operator is used to combine premises (pH and Temperature), while the MINIMUM (MIN) function is used as a logical operator (T-Norm) to determine the Degree of Activation (wi) of each rule.

$$\mathbf{w_i} = \mathrm{MIN}(\mu_{\mathrm{pH}}(\mathbf{x_1}), \mu_{\mathrm{Suhu}}(\mathbf{x_2}))$$

Here's an example calculation for pH = 6.5 and temperature = 3.0°C

Table 4. Calculation pH = 6.5 and temperature = 3.0°C

pH	µ	Temperature	µ
Acidic	0	Low	0.25
Neutral	8.9	Medium	0
Basic	0	High	0

The sets that have a membership value "µ" > 0 are only **Neutral** (0.89) and **Low** (0.25).

Table 5. Result wi for 9 rules in Calculation pH = 6.5 and temperature = 3.0°C

Rule	Premise	µ pH	µ Temperature	Calculation	Result wi
1	Acidic AND Low	0	0.25	MIN(0, 0.25)	0
2	Acidic AND Medium	0	0	MIN(0, 0)	0
3	Acidic AND High	0	0	MIN(0, 0)	0
5	Neutral AND Low	0.89	0	MIN(0.89, 0)	0
6	Neutral AND High	0.89	0	MIN(0.89, 0)	0
7	Basic AND Low	0	0.25	MIN(0, 0.25)	0
8	Basic AND Medium	0	0	MIN(0, 0)	0
9	Basic AND High	0	0	MIN(0, 0)	0

Only Rule No. 4 is active (has wi > 0.5).

In analyzing the test case with input pH = 6.5 and temperature = 3.0, the fuzzy inference process determines the degree of activation (wi) for each rule using the MIN operator, since the premises are connected by the AND operator. Based on the fuzzification results, the pH input of 6.5 has the highest membership degree in the Neutral set (0.89), while the temperature input of 3.0 has a membership degree of 0.25 in the Low set. The strongest activation occurs in Rule 4 (IF Neutral AND Low THEN Safe), where the rule's firing strength is computed as the minimum value of the two memberships (MIN(0.89, 0.25) = 0.25).

Meanwhile, the remaining eight rules (Rules 1, 2, 3, 5, 6, 7, 8, and 9) produce wi = 0 because their antecedent fuzzy sets—such as Acidic, Basic, Medium, or High—have zero membership for the given inputs. For example, Rule 5 (IF Neutral AND Medium THEN Spoiled) yields w5 = MIN(0.89, 0) = 0 since the temperature input has no membership in the Medium set. Therefore, only Rule 4 contributes to the defuzzification process in the Sugeno zero-order system.

4. **Defuzzification**

Defuzzification is the process of converting a set of fuzzy values into a single crisp value (z). For the Sugeno model, the Weighted Average formula is used:

Final Crisp Value $(z) = \frac{\sum_{i=1}^{N} w_i z_i}{\sum_{i=1}^{N} w_i}$

The numerator is the total product of each rule's degree of activation (wi) and its corresponding crisp consequent value (zi). Since only Rule 4 has a wi > 0, only this calculation is considered relevant.

$$\sum wizi = (w1z1) + (w2\,z2) + (w3\,z3) + (\mathbf{w4\,z4}) + (w5\,z5) + (w6\,z6) + (w7\,z7) + (w8\,z8) + (w9\,z9)$$

$$\sum w1zi = 0 + 0 + 0 + (\mathbf{0.25\,x\,2.5}) + 0 + 0 + 0 + 0 + 0$$

$$\sum wizi = 0{,}625$$

The denominator is the total Activity Degree of all active rules.

$$\sum wizi = (w1z1) + (w2\,z2) + (w3\,z3) + (\mathbf{w4\,z4}) + (w5\,z5) + (w6\,z6) + (w7\,z7) + (w8\,z8) + (w9\,z9)$$

$$\sum w1zi = 0 + 0 + 0 + (\mathbf{0.25\,x\,2.5}) + 0 + 0 + 0 + 0 + 0$$

$$\sum wizi = 0{,}625$$

$$z = \frac{\sum wizi}{\sum wi} = \frac{0{,}625}{0{,}25} = \mathbf{2{,}5}$$

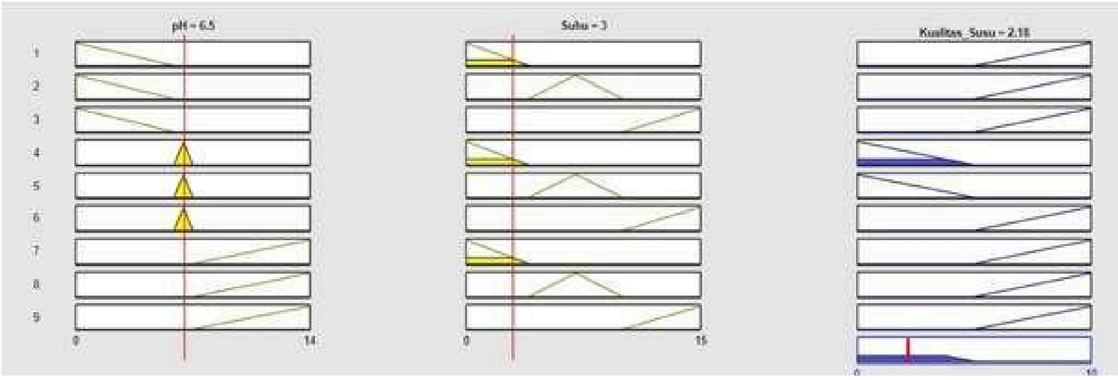

Figure 3. Defuzzification Result of the Rule

The defuzzification results illustrate how the Sugeno fuzzy inference system converts the interaction between pH and temperature into a single crisp value representing milk quality. In this study, the manual calculation produced a value of 2.5, while the MATLAB Sugeno system generated a slightly lower output of 2.18. This difference arises from MATLAB's higher numerical precision and its ability to account for all activated rules, including those with very small membership degrees. Despite the variation, both values fall within the same interpretation threshold—classified as *safe* but approaching potential spoilage—indicating that the model behaves consistently with the expected nonlinear relationship between pH, temperature, and microbial deterioration (Uzun & Allahverdi, 2021).

The comparison between manual and MATLAB results demonstrates the reliability of the Sugeno fuzzy logic approach in assessing milk quality. Even with slight numerical differences, the system consistently identifies conditions indicative of declining freshness, reinforcing its potential as a predictive tool for food safety monitoring. This is in line with previous findings showing that fuzzy models effectively capture complex nonlinear interactions in food quality evaluation, making them suitable for early detection of quality degradation in perishable products (Uzun & Allahverdi, 2021).

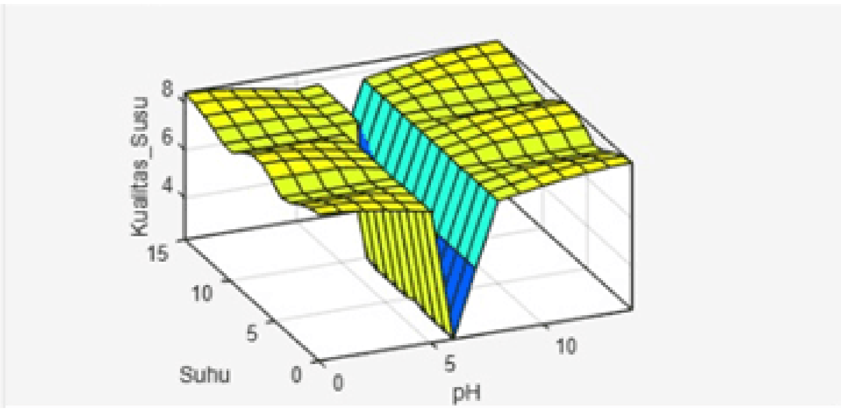

Figure 4. Defuzzification Result Surface

The defuzzification surface illustrates the relationship between pH, storage temperature, and the resulting quality output generated by the Sugeno fuzzy model. From the surface pattern, it can be observed that a combination of low pH and increasing temperature drives the crisp output toward the spoiled classification, while stable pH and low temperatures maintain the milk within the safe category. This behavior aligns with the known physicochemical response of milk, where elevated temperatures and decreasing pH accelerate microbial activity and the breakdown of milk components.

In addition, the surface visualization highlights critical zones where small shifts in pH or temperature can sharply influence the output, signaling a faster transition toward spoilage. This demonstrates the model's capability to provide early indication of quality deterioration, allowing producers to identify safe storage boundaries and strengthen quality control measures. These findings support previous studies showing that fuzzy logic is effective in handling uncertainty and predicting gradual changes in food quality (Kumar & Singh, 2020; Zeng et al., 2019).

Model Interpretation and Alignment with Literature

The results demonstrate that the fuzzy system effectively captures the nonlinear deterioration behavior of pasteurized milk, where decreases in pH and increases in temperature accelerate spoilage. This is consistent with Uzun and Allahverdi (2021), who highlighted the strong interaction between these variables in thermally processed dairy products. Through the fuzzification and inference process, gradual changes in milk conditions are represented more realistically than with rigid threshold-based classifications, ensuring that early deviations from optimal conditions remain detectable (Kumar & Singh, 2020).

Furthermore, the ability of fuzzy logic to manage uncertainty and variability makes it suitable for predicting food quality under dynamic storage conditions. This advantage has been widely recognized in food quality modeling, where fuzzy systems outperform conventional approaches in handling complex and imprecise data (Zeng et al., 2019). These findings confirm that the Sugeno fuzzy framework provides a reliable foundation for early spoilage detection and can potentially be integrated into automated monitoring systems.

CONCLUSION

This study successfully developed an early detection system based on fuzzy logic to identify the spoilage of pasteurized milk using storage temperature and pH as input parameters. The system was able to classify the milk condition into three categories, namely safe,and spoiled, based on the physical and chemical changes occurring during storage. The results showed that temperature had the most significant influence on milk spoilage, followed by a decrease in pH due to increased acidity. The fuzzy logic approach proved effective in representing the uncertainty between fresh and spoiled milk and provided accurate and reliable detection. This system has potential to be further developed into an automatic real time monitoring tool for milk quality control.

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