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Development of a Fuzzy Logic Control System for the Noodle Dough Sheeting Process

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ABSTRACT

The process of dough sheeting is the most crucial step in the production of noodles. In the food industry, the sheeting process of noodle dough is important because it specifically aims to improve the quality and efficiency of noodle production. This study provides a background on the mechanical sheeting process on the mechanical sheeting process used in the food industry, highlighting its significance in shaping, and flattening dough for various goods, particularly noodles. The research identifies several challenges in the current noodle dough sheeting procedures, like uneven dough thickness, surface crack and stickiness. The study formulates a problem statement, emphasizing the need for an accurate and controlled sheeting environment to address these challenges. The proposed solution is to develop and implement a fuzzy logic control system for noodle dough sheeting. The study aims to identify critical parameters influencing dough sheeting and implement fuzzy-rule-base in monitoring the dough sheeting process using identified critical parameters. The amount of flour can be adjusted by the fuzzy control system (software) created in this study, depending on the input parameters, which include surface cracks and dough thickness. The results demonstrated that an ideal dough sheeting method is achieved by implementing a fuzzy system. This research contributes to the advancement of noodle production by introducing a fuzzy logic control system in the development of the dough sheeting process. The findings offer practical insights for small and medium-sized enterprises (SMEs), noodle manufacturers, and sheeting machine manufacturers, paving the way for more efficient and higher-quality noodle production in the culinary sector.

1. INTRODUCTION

A mechanical process called sheeting is used in the food industry, especially in baking and pastry preparation, to shape and flatten dough or pastry into a thin, even layer of a specific thickness and shape. The dough or pastry is passed through a sequence of rollers that exert pressure and gradually reduce the consistency of the

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finished product to the desired thickness. Adjustments can be made to sheet thickness, roller pressure, and other factors depending on the desired outcome.

Dough's behaviour during sheeting is primarily influenced by its viscoelastic characteristics, which are largely determined by the gluten protein. As a structural component binding starch grains together, gluten has both viscous and elastic properties. Particularly in steps such as mixing, resting, and sheeting, gluten depolymerizes and reforms during noodle processing, thereby directly affecting dough strength and final noodle texture. Noodles produced from inadequate gluten formation may lack the appropriate elasticity and stiffness (Liu et al., 2023).

Due to their nutritional value, sensory appeal, and convenience, noodles have become a staple food item worldwide (Li et al., 2014). Following the bread industry, the noodle industry has become the second-largest segment in global food processing (Heo et al., 2013). Noodle dough contains a lower water content (28–38%) compared to bread dough (40–55%), resulting in a denser texture that necessitates distinct handling techniques (Ross, 2006). The sheeting process is important in the production phases, as it directly influences the strength of the final product and aids the development of the gluten network, which in turn affects the dough's rheological properties (Song et al., 2019).

Traditional noodle production relies heavily on skilled manual expertise. However, as the modern food sector grows, the global food market is becoming increasingly diverse, and consumers are paying particular attention to the quality of the food they consume, including, but not limited to, its appearance and flavour. As a result, to increase the quality of the noodles, the science of making noodles must be valued more highly than expertise. The number of studies examining how processing variables affect noodle processing and product quality is growing (Liu et al., 2021).

Despite breakthroughs, several challenges persist in the dough sheeting method, including inconsistent sheet thickness, surface cracking, and excessive dough stickiness. These factors impact production stability and noodle quality (Mahadevappa et al., 2017; Chakrabarti-Bell et al., 2010). Uneven thickness, for instance, affects cooking time and noodle appearance, while stickiness can lead to operational inefficiencies and equipment malfunctions (S. Liu et al., 2019).

To address these challenges, this study proposes the development of a fuzzy logic management system for the noodle-making process, specifically involving dough sheeting. The system utilizes key input parameters, namely dough thickness and surface cracks, to evaluate dough condition. Based on these inputs, it adjusts an output parameter, which is the rate of flour addition, in real-time to maintain optimal dough quality. The fuzzy-rule-based approach is expected to simplify production control, reduce human intervention, and ensure more consistent product quality.

This study builds on parameters from Mahadevappa et al. (2017) and focuses on small and medium-sized enterprises (SMEs) involved in noodle production. By integrating fuzzy logic into the sheeting process, the research aims to offer practical solutions for quality control, cost reduction, and machine optimization, thereby advancing automation in food manufacturing.

2. LITERATURE REVIEW

2.1 Fuzzy logic in food processing

Many new technologies, such as artificial intelligence (AI), robots, and the Internet of Things (IoT), have transformed the food production process, particularly in quality monitoring and process control (Akyazi et al., 2020; Mavani et al., 2021). Fuzzy logic is one of these technologies that has shown promise because it can handle uncertainty and make decisions like a person.

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Mavani et al. (2021) reviewed AI applications in food operations, highlighting the use of fuzzy logic, expert systems, artificial neural networks (ANN), and machine learning. These methods have been employed to enhance regularity and reduce the need for human intervention in food drying, quality control, and sensory analysis. Fuzzy logic is becoming increasingly common because it can enhance the dependability of dough-based processes, such as noodle-making, while ensuring the quality of the finished product and minimizing waste.

Recent research has illustrated the growing significance of fuzzy-based decision-making methodologies in the food sector. Singh et al. (2024) utilised a fuzzy analytical hierarchy process (FAHP) to rank obstacles to the adoption of big data analytics in the food supply chain, demonstrating the efficacy of fuzzy methodologies for managing complex, uncertain, and qualitative variables in food manufacturing contexts.

2.2 Noodle dough process

Noodles are extensively consumed throughout Asia and are gaining popularity globally due to their convenience and texture (Li et al., 2014). The production process comprises stages such as mixing, resting, sheeting, and cutting, with sheeting being crucial for shaping the dough and improving the gluten structure (Song et al., 2019).

Noodle dough demonstrates viscoelastic characteristics, functioning as both a solid and a liquid due to its gluten network, which enables stretching and recovery throughout processing (Liu et al., 2019). The dough's rheological properties, such as elasticity and extensibility, affect its performance during sheeting and the resultant quality of the noodles (Ross, 2006). Recent research has shown that processing parameters, such as rolling speed and resting time, have a significant effect on dough rheology and gluten development (Liu et al., 2021; Liu et al., 2023).

Innovative methods, like non-contact ultrasonics (Kerhervé et al., 2019) and vacuum mixing (Liu et al., 2017), have been investigated to assess or enhance dough consistency. Nonetheless, real-time control continues to pose a difficulty, particularly for SMEs, underscoring the potential of fuzzy logic in this domain.

2.3 Parameters for noodle dough sheeting process

Identifying the correct input parameters that accurately represent the state of the dough and the appropriate control actions are necessary to utilize fuzzy logic in noodle dough sheeting. This study is based on Mahadevappa et al. (2017) and aims to investigate three key factors: dough thickness, surface cracks, and flour addition.

(i) Dough thickness is a critical quality factor during the sheeting process. Inconsistent thickness can impact cooking uniformity, texture, and the final product's appearance.

(ii) Surface cracks: Cracks on the surface indicate that the gluten network did not form correctly or that excessive stress was applied during the rolling process. Cracks can result in product rejection or reduced consumer appeal.

(iii) Flour addition: Adding flour is a common way to adjust the stickiness and workability of dough. However, adding flour manually is not always accurate and depends significantly on the person's knowledge.

A fuzzy logic system can transform expert opinions into control actions based on established rules and regulations. As an example:

(i) IF Dough thickness is Thick AND Surface Cracks are Medium, THEN Flour Addition is Medium.

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(ii) IF Dough Thickness is Medium AND Surface Crack is High THEN Flour Addition is High.

These language rules enable the system to handle uncertain situations, making the process of making noodles more consistent and of higher quality. This is especially helpful for small businesses that want to automate their processes without incurring significant expenses.

2.4 Applications of fuzzy logic in noodle dough sheeting

Food manufacturers are increasingly utilizing fuzzy logic to manage uncertain or qualitative inputs, particularly in dough handling, where elasticity, stickiness, and surface flaws are difficult to quantify. Previous studies focused mainly on thickness control; however, recent research has highlighted the use of fuzzy-based adaptive decision-making approaches to enhance robustness across diverse processing conditions (Singh et al., 2024). Noodle dough sheeting requires uniform thickness and surface quality; however, dough rheology makes this challenging. Traditional control systems often fail to solve these concerns. However, fuzzy logic can adapt to such unpredictability by utilizing expert-derived rules. Previous research on fuzzy logic in similar circumstances has shown its potential to improve noodle dough sheeting operations.

3. RESEARCH METHODOLOGY

The approach used to create a fuzzy logic control system for the noodle dough sheeting process covers data collection, the fuzzy inference system (FIS) architecture, and the fundamental fuzzy logic elements of defuzzification, rule base, and fuzzification.

3.1 Applications of fuzzy logic in noodle dough sheeting

This study focuses on key parameters such as dough thickness and surface defects, which are critical in the noodle dough lamination process. These parameters were identified based on experimental insights by Mahadevappa et al. (2017) and were subsequently evaluated to align with the simulation environment and control objectives. Table 1 illustrates the fundamental input variables that are implemented within the system.

Table 1: Parameters for noodle dough sheeting process

Criteria	Parameters
Input	Dough thickness
	Surface cracks
Output	Addition of flour

Source: Adapted from Mahadevappa et al. (2017)

3.2 Fuzzy logic system

Fuzzy logic, introduced by Zadeh (1965), offers a practical approach to managing uncertainty in complex systems. It is founded on fuzzy sets, wherein an element's membership varies from 0 to 1. A fuzzy set A is defined as:

$$A = \{x, \mu_A(x) | x \in U\} \quad (1)$$

where $\mu_A(x)$ is the Membership Function (MF) of x in A. The membership functions used in this work comprise triangular and trapezoidal shapes, which are frequently employed in process control systems.

3.3 Fuzzy inference system

Fuzzy logic is used by a fuzzy inference system (FIS) to connect input values to output replies. Fuzzification, fuzzy rule base, inference engine, and defuzzification are the four main parts that make it up.

3.3.1. Fuzzification

During this phase, crisp (precise) inputs are converted into fuzzy values. This transformation utilizes membership functions to assess the degree of membership for each input. A triangular membership function (MF) is defined by three parameters (a, b, and c), where a < b < c as shown in Equation (2). On the other hand, a trapezoidal membership function involves four parameters (a, b, c, and d), where a < b < c ≤ d as represented in Equation (3). Both Equation (2) and Equation (3) are adapted from (Zimmermann, 2001).

$$Trampmf(x; a, b, c) = \begin{cases} 0, & x < a \\ (x - a) / (b - a), & a \le x \le b \\ (c - x) / (c - b), & b \le x \le c \\ 0, & c < x \end{cases} \tag{2}$$

$$Trampmf(x; a, b, c, d) = \begin{cases} 0, & x < a \\ (x - a) / (b - a), & a \le x \le b \\ 1, & b \le x \le c \\ (c - x) / (c - b), & c \le x \le d \\ 0, & d \le x \end{cases} \tag{3}$$

3.3.2. Fuzzy rule-based

IF-THEN logic is used to structure fuzzy rules. Every rule establishes a connection between the fuzzy sets of input and output. Here is an example of a fuzzy rule format using IF-THEN logic:

$$R_i\text{: IF } x \text{ is } A_i \text{ and } y \text{ is } B_i \text{ THEN } z \text{ is } C_i \text{ (for } i = 1,2, \ldots, k) \tag{4}$$

where k denotes the number of rules, R_i denotes the rule number, A_i and B_i denote the fuzzy sets, x and y denote the antecedent variables (inputs) in the fuzzy system, while z denotes the consequent (output) variable (Akgun et al., 2012; Tosun et al., 2011)

3.3.3. Inference engine

The inference engine assesses all rules and produces fuzzy results. Mamdani-type inference was implemented using the max-min composition method. This involves identifying the lowest degree of membership across inputs and taking the highest among all rules.

3.3.4. Defuzzification.

Defuzzification is the process of converting fuzzy outputs into crisp values, which are plain and distinct. In this investigation, we implemented the centroid of area (COA) method, which is defined as the point at which the area under the output membership function curve is balanced. It denotes the average value of the output distribution.

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$$Z_{COA} = \frac{\int \mu_A(z) z \, dz}{\int \mu_A(z) \, dz} \quad (5)$$

3.4 Mamdani fuzzy model

The Mamdani fuzzy model is utilized for its interpretability and common application in process control. It employs fuzzy sets in both the antecedent and consequent components of the rules. The max-min approach for rule assessment and COA for defuzzification ascertains the ultimate result.

3.5 Fuzzy set theory

In fuzzy set theory, membership values between 0 and 1 can be used to describe uncertainty. In systems with incomplete or unclear data, such as those used in the noodle dough sheeting process, this flexibility helps individuals make informed decisions.

3.6 Model validation and comparative consideration

We used MATLAB to simulate the proposed fuzzy logic control system and assessed the logical consistency and stability of the output responses across different input combinations. Many early fuzzy control studies use this evaluation method based on simulations, especially when real-time industrial data isn't readily available.

While comparing simulations with other smart methods, such as artificial neural networks (ANN) or adaptive neuro-fuzzy inference systems (ANFIS), could provide more performance information, this study does not include such comparisons. This is mainly because there aren't enough labelled industrial datasets available to train data-driven models.

However, future research should compare the proposed system with ANNs or ANFIS and test it with real production data to assess its robustness and scalability.

4. FINDING AND DISCUSSION

The results of the MATLAB simulation show that the fuzzy logic control system optimizes the process of sheeting the noodle dough.

4.1 Fuzzy logic implementation

To effectively implement the system, five simulation stages were conducted by the four primary components of fuzzy logic, as outlined in the research methodology.

Step 1: **Definition of linguistic variables and membership functions**

Two input variables (dough thickness and surface crack) and one output variable (flour adjustment) were defined. Table 2 summarizes the fuzzy sets, membership types, and their respective ranges.

Table 2: Linguistic values, fuzzy numbers, and range

Type	Variable	Linguistic Value	Fuzzy Number	Range
Input	Dough Thickness	Thin	(5, 7, 10)	

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		Medium	(8, 15, 20)	[5, 45]
		Thick	(17, 24, 32, 45)	
Input	Surface Crack	Low	(0.08, 0.15, 0.20)	[0.08, 0.5]
		Medium	(0.18, 0.25, 0.35, 0.45)	
		High	(0.40, 0.47, 0.50)	
Output	Flour Adjustment	Low	(0, 5, 10)	[0, 65]
		Medium	(8, 20, 30)	
		High	(25, 45, 65)	

Source: Developed by the author based on system requirements and simulation setup in MATLAB, with reference to Mahadevappa et al. (2017).

The range of each variable was adapted from Mahadevappa et al. (2017) and refined to suit the system constraints and MATLAB simulation setup. The fuzzy numbers, used to represent linguistic terms through triangular and trapezoidal membership functions, were developed by the author based on these adaptations for practical inference.

Step 2: **Development of membership functions**

The degree of membership for each variable was represented using trapezoidal and triangular membership functions, as indicated below:

(i) Dough Thickness: Thin (Triangular), Medium (Triangular), Thick (Trapezoidal)

(ii) Surface Crack: Low (Triangular), Medium (Trapezoidal), High (Triangular)

(iii) Flour Adjustment: Low (Triangular), Medium (Triangular), High (Triangular)

The classifications originate from the three membership function graphs (Fig 2 to Fig 4) created using the fuzzy numbers and ranges outlined in Table 2. The graphs presented (Fig 2, 3, and 4: Dough Thickness, Surface Crack, and Flour Adjustment) illustrate the construction of the fuzzy sets and clearly show the membership functions associated with each linguistic term.

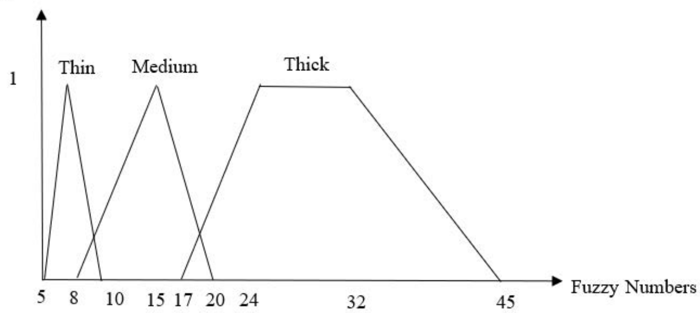

Fig 1. The membership graph of dough thickness

Fig 1 illustrates the membership functions for dough thickness, constructed based on the mathematical expressions provided in Equations (6) to (8). These equations represent specific membership functions derived from substituting the corresponding a, b, c, and d values that were acquired from Table 2. The formulation of these equations was based on the generic formulations for triangular and trapezoidal membership functions, which are shown in Equations (2) and (3).

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$$\mu_{thin}(x) = \begin{cases} x/7; & x \le 7 \\ (10-x)/3; & 7 \le x \le 10 \\ 0; & \text{otherwise} \end{cases} \tag{6}$$

$$\mu_{medium}(x) = \begin{cases} (x-8)/7; & 8 \le x \le 15 \\ (20-x)/5; & 15 \le x \le 20 \\ 0; & \text{otherwise} \end{cases} \tag{7}$$

$$\mu_{thick}(x) = \begin{cases} (x-17)/7; & 17 \le x \le 24 \\ 1; & 24 \le x \le 32 \\ (45-x)/13; & 32 \le x \le 45 \\ 0; & \text{otherwise} \end{cases} \tag{8}$$

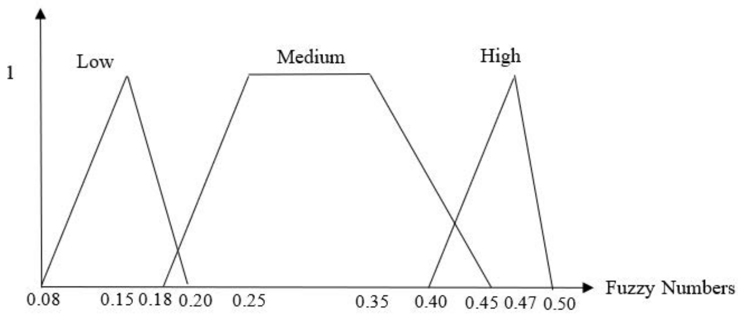

Fig 2. The membership graph of the surface crack

Fig 2 illustrates the membership functions for the surface crack, where triangular shapes represent Low and High, while a trapezoidal shape depicts Medium. The functions derived from membership function equations (9) to (11) were developed utilizing the fuzzy numbers and ranges presented in Table 2.

$$\mu_{low}(x) = \begin{cases} (x-0.08)/0.07; & 0.08 \le x \le 0.15 \\ (0.20-x)/0.05; & 0.15 \le x \le 0.20 \\ 0; & \text{otherwise} \end{cases} \tag{9}$$

$$\mu_{medium}(x) = \begin{cases} (x-0.18)/0.07; & 0.18 \le x \le 0.25 \\ 1; & 0.25 \le x \le 0.35 \\ (0.45-x)/0.1; & 0.35 \le x \le 0.45 \\ 0; & \text{otherwise} \end{cases} \tag{10}$$

$$\mu_{high}(x) = \begin{cases} (x-0.40)/0.07; & 0.40 \le x \le 0.47 \\ (0.50-x)/0.03; & 0.47 \le x \le 0.50 \\ 0; & \text{otherwise} \end{cases} \tag{11}$$

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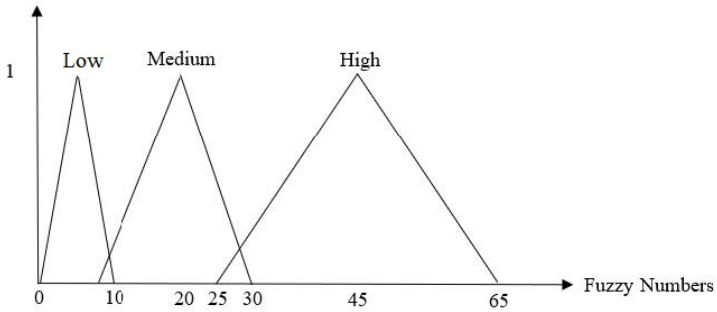

Fig 3. The membership graph of the addition of flour

The triangular membership functions for the linguistic terms Low, Medium, and High represent the addition of flour in Fig 3. These were developed based on fuzzy data from Table 2 and membership function equations (12) to (14).

$$\mu_{low}(x) = \begin{cases} x/5; & 0 \le x \le 5 \\ (10-x)/5; & 5 \le x \le 10 \\ 0; & \text{otherwise} \end{cases} \tag{12}$$

$$\mu_{medium}(x) = \begin{cases} (x-8)/12; & 8 \le x \le 20 \\ (30-x)/10; & 20 \le x \le 30 \\ 0; & \text{otherwise} \end{cases} \tag{13}$$

$$\mu_{high}(x) = \begin{cases} (x-25)/20; & 25 \le x \le 45 \\ (65-x)/20; & 45 \le x \le 65 \\ 0; & \text{otherwise} \end{cases} \tag{14}$$

Step 3: Fuzzy rule base

The fuzzy IF-THEN rules in Table 3 were developed using the relationships seen in the membership function graphs (Fig 1-3). These rules were created by examining the overlapping regions between input variables (Dough Thickness and Surface Crack) and their impact on the output variable (Flour Adjustment), which ensured logical coherence with the fuzzified data. There were nine rules made to cover all the potential combinations of the three input language phrases for each variable (3 Dough Thickness × 3 Surface Crack = 9 combinations).

Table 3: Fuzzy IF-THEN rules

No	Rule
1	IF Dough Thickness is Thin AND Surface Crack is Low THEN Flour Addition is Low
2	IF Dough Thickness is Thin AND Surface Crack is Medium THEN Flour Addition is Low
3	IF Dough Thickness is Thin AND Surface Crack is High THEN Flour Addition is Medium
4	IF Dough Thickness is Medium AND Surface Crack is Low THEN Flour Addition is Low
5	IF Dough Thickness is Medium AND Surface Crack is Medium THEN Flour Addition is Medium

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6	IF Dough Thickness is Medium AND Surface Crack is High THEN Flour Addition is High
7	IF Dough Thickness is Thick AND Surface Crack is Low THEN Flour Addition is Low
8	IF Dough Thickness is Thick AND Surface Crack is Medium THEN Flour Addition is Medium
9	IF Dough Thickness is Thick AND Surface Crack is High THEN Flour Addition is High

Step 4: System implementation using MATLAB

The Fuzzy Logic Toolbox in MATLAB was employed to implement the fuzzy logic control system. A Mamdani-type fuzzy inference system (FIS) was created, which comprises one output variable (Flour Adjustment) and two input variables (Dough Thickness and Surface Crack). The following components were incorporated into the design process:

(i) FIS Designer: Utilised to establish the structure and type of the system.

(ii) Membership Function Editor: Utilised to create and modify the input/output membership functions by predefined ranges and fuzzy numbers.

(iii) Rule Editor: Implemented to input the nine fuzzy IF-THEN rules from Table 3.

(iv) Rule Viewer: Enabled the observation of the system's response in response to various input combinations.

(v) Surface Viewer: Displayed the broad input-output relationship in a 3D surface plot.

This MATLAB implementation helped the construction and testing of the fuzzy logic system, ensuring consistent and logical output responses.

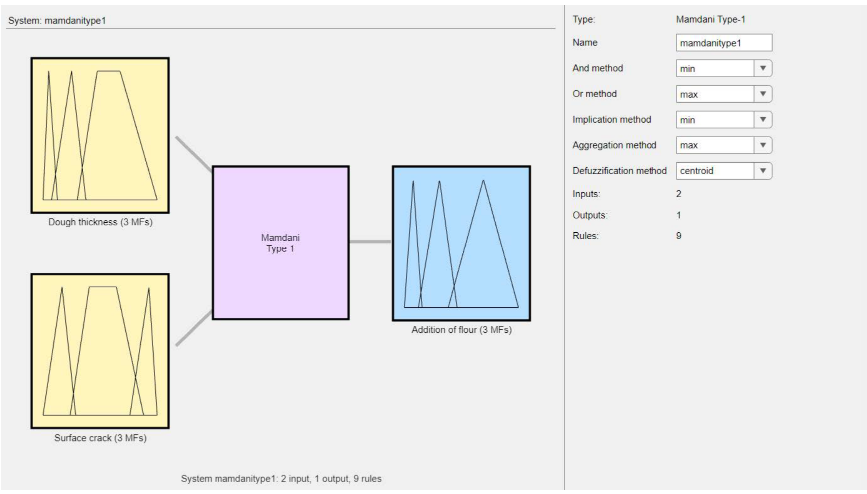

Fig 4. Fuzzy inference system interface input and output

Fig 4 displays the fuzzy inference system (FIS) designed using MATLAB's FIS Designer. It is a Mamdani-type system with two input variables, Dough Thickness and Surface Crack, each defined by three membership functions. The output variable, the Addition of Flour, also comprises three membership functions.

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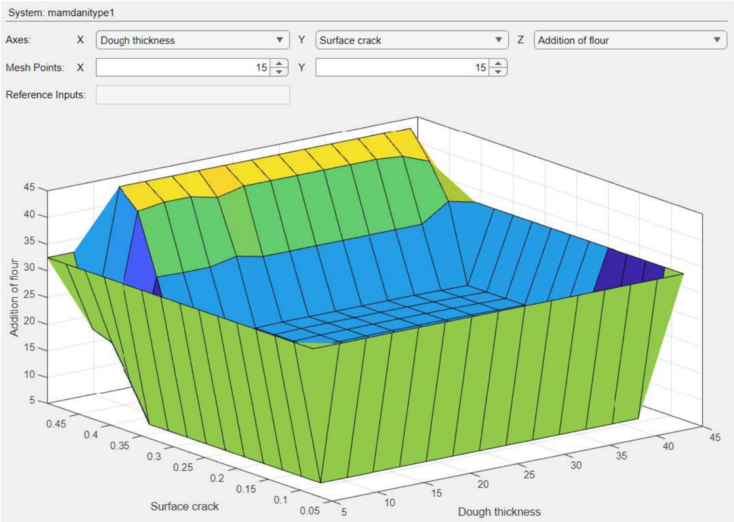

Fig 5. Control surface for inputs and outputs

Fig. 5 illustrates the output surface generated using the Surface Viewer. It visualizes how different combinations of input variables influence the output. The surface demonstrates a smooth transition of flour adjustment levels in response to the fuzzy rules and membership functions established earlier.

Step 5: Results and discussion

System performance was assessed using specified input combinations and inference procedures. Select output samples are in Table 4. The fuzzy inference engine in MATLAB calculated flour adjustments based on rules and membership functions to get these outcomes.

Table 4: Inference Results

Sample	Dough Thickness (mm)	Surface Crack	Flour Adjustment (g)
1	20	0.35	19.2
2	7	0.14	5.01
3	45	0.50	32.5
4	39	0.09	5.02

As shown in Table 4, the flour adjustment values reflect logical trends, higher values are produced for thicker dough and more severe cracks, while lower inputs yield smaller adjustments. This demonstrates consistency with the fuzzy rule base.

The results show that the fuzzy logic control system can give consistent and appropriate flour adjustment values for different types of dough. These results agree with those of Mahadevappa et al. (2017), who showed that fuzzy logic works for noodle dough sheeting. Adaptive fuzzy tuning has also been shown to improve system robustness across different processing conditions (Singh et al., 2024). The current system modifies the fuzzy rule base and membership ranges to better fit the dough properties used in this study, resulting in more accurate, context-specific flour adjustments than those reported by Mahadevappa et al. (2017). The fuzzy logic system can handle gradual changes in dough properties while maintaining smooth, reliable control. This differs from classical PID or standard rule-based controllers, which struggle with

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nonlinear and uncertain inputs. This shows how fuzzy logic can help with the unpredictability of real-world food processing operations. The system shows that it can handle uncertainty and gradual changes in dough characteristics by simultaneously combining dough thickness and surface cracks.

This directly addresses the original research goal: to use smart decision-making to improve the process of rolling out noodle dough. The fuzzy logic approach is better at handling nonlinearity and uncertainty than traditional PID or rule-based controllers. It is a new way to control real-time dough processing for small and medium-sized businesses. The inferred output values indicate that the system responds smoothly, suggesting that fuzzy logic is a good choice for food processing applications where precise mathematical modelling is difficult. In general, the proposed system has significant promise as a reliable decision-support tool for improving process consistency.

These findings are important because they apply to modern food processing systems in 2025. This shows how useful fuzzy logic can be in smart food manufacturing, helping maintain quality and making it easier for companies to adopt Industry 4.0. As the industry moves increasingly toward automation and smart manufacturing, there is a greater need for control systems that can adapt and operate reliably even when input conditions are unclear. The suggested fuzzy logic control system is a useful solution because it enables real-time decision-making without requiring exact mathematical models. This makes it a good fit for food production settings where material properties are always changing.

Moreover, the fuzzy inference system's smooth control surface shows that the model is stable and consistent. This behaviour shows that the system could make operations more efficient, reduce production variability, and lessen the need for human judgement, which would help bring Industry 4.0 ideas to food manufacturing.

This study is limited to simulation-based evaluation using predefined input ranges and rule sets, even though it works well. Future research might enhance the model by integrating additional input variables, such as dough moisture content and temperature, and by validating the system using actual industrial data. Future work should include validation with real industrial data and comparative analysis against other intelligent systems, such as ANN or ANFIS, to evaluate performance and scalability. The proposed method could be even more useful and reliable if it were combined with sensor-based monitoring systems.

In conclusion, the proposed fuzzy logic control system shows great promise as a smart decision-making tool for optimizing flour adjustments during noodle dough sheeting. The system helps make dough processing operations more flexible, stable, and efficient by handling uncertainty effectively and integrating multiple input factors.

5. CONCLUSIONS AND RECOMMENDATIONS

This research effectively developed a fuzzy-logic-based system to determine optimal flour modifications during noodle dough preparation, utilising two input variables: dough thickness and surface cracks. The system used triangular and trapezoidal membership functions, along with a Mamdani-type fuzzy inference mechanism, to convert expert knowledge into 9 logical IF-THEN rules. The Fuzzy Logic Toolbox in MATLAB made it easier to design, test, and validate systems.

The inference results showed that the outputs were consistent and made sense, as people would expect. This shows that the fuzzy logic method is reliable and useful for dough processing operations. These results are important for today's food manufacturing, where automation and flexible decision-making are becoming increasingly important, especially in 2025 and beyond. The system can help people rely less on their own judgment, make processes more consistent, and help people adopt smart manufacturing ideas.

For future research, the system could be improved by adding more input variables, such as the dough's moisture content or the mixing time, to better show how different dough properties can vary. It is best to

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test it with real industrial data to ensure it is robust and can grow. Also, comparing this system to other smart systems, such as neural networks or adaptive neuro-fuzzy inference systems (ANFIS), could help us learn how to improve its performance and use it in real-world settings.

In conclusion, the proposed fuzzy logic control system is a reliable, flexible, and useful approach to improving the mixing of flour when making noodle dough. Its ability to work with automated processes and its potential to handle more complex inputs make it a promising tool for smart food processing applications.

Overall, this study shows that fuzzy logic can handle uncertainty and variability in dough processing, which is a step toward smarter, more consistent, and automated food production. By using these smart systems, businesses can improve the quality of their products and rely less on people to make decisions. This will lead to the next generation of automated food production.

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7. CONFLICT OF INTEREST STATEMENT

The authors declare that this research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

8. AUTHORS' CONTRIBUTIONS

Suzanawati Abu Hasan: conceptualized the study, designed the fuzzy logic control system for the noodle dough sheeting process, supervised the overall research work, and critically revised the manuscript. **Aina Irsalina Itqan Rosli:** conducted the data collection, developed, and implemented the fuzzy logic model, performed simulations and analysis, and prepared the initial draft of the manuscript. **Teoh Yeong Kin:** contributed to the methodology formulation, system validation, and analysis of the fuzzy control results. **Diana Sirmayunie Mohd Nasir:** assisted in result interpretation, manuscript editing, and refinement of the discussion section. All authors read and approved the final manuscript.

9. REFERENCES

Akgun, A., Sezer, E. A., Nefeslioglu, H. A., Gokceoglu, C., & Pradhan, B. (2012). An easy-to-use MATLAB program (MamLand) for the assessment of landslide susceptibility using a Mamdani fuzzy algorithm. *Computers & Geosciences*, *38*(1), 23–34. https://doi.org/10.1016/J.CAGEO.2011.04.012

Akyazi, T., Goti, A., Oyarbide, A., Alberdi, E., & Bayon, F. (2020). A guide for the food industry to meet the future skills requirements emerging with industry 4.0. *Foods*, *9*(4), 492. https://doi.org/10.3390/foods9040492

Chakrabarti-Bell, S., Bergström, J. S., Lindskog, E., & Sridhar, T. (2010). Computational modeling of dough sheeting and physical interpretation of the non-linear rheological behavior of wheat flour dough. *Journal of Food Engineering*, *100*(2), 278–288. https://doi.org/10.1016/J.JFOODENG.2010.04.010

Heo, S., Lee, S. M., Bae, I. Y., Park, H.-G., Lee, H. G., & Lee, S. (2013). Effect of Lentinus edodes β-Glucan-enriched materials on the textural, rheological, and oil-resisting properties of instant fried noodles. *Food and Bioprocess Technology*, *6*(2), 553–560. https://doi.org/10.1007/s11947-011-0735-z

Kerhervé, S. O., Guillermic, R. M., Strybulevych, A., Hatcher, D. W., Scanlon, M. G., & Page, J. H. (2019). Online non-contact quality control of noodle dough using ultrasound. *Food Control*, *104*, 349–357. https://doi.org/10.1016/J.FOODCONT.2019.04.024

Li, M., Zhu, K. X., Peng, J., Guo, X. N., Amza, T., Peng, W., & Zhou, H. M. (2014). Delineating the protein changes in Asian noodles induced by vacuum mixing. *Food Chemistry*, *143*, 9–16. https://doi.org/10.1016/J.FOODCHEM.2013.07.086

Liu, R., Zhang, Y., Wu, L., Xing, Y., Kong, Y., Sun, J., & Wei, Y. (2017). Impact of vacuum mixing on protein composition and secondary structure of noodle dough. *LWT - Food Science and Technology*, *85*, 197–203. https://doi.org/10.1016/J.LWT.2017.07.009

Liu, S., Li, Y., Obadi, M., Jiang, Y., Chen, Z., Jiang, S., & Xu, B. (2019). Effect of steaming and defatting treatments of oats on the processing and eating quality of noodles with a high oat flour content. *Journal of Cereal Science*, *89*, 102794. https://doi.org/10.1016/J.JCS.2019.102794

Liu, Shuyi, Jiang, Y., Xu, B., & Jiang, S. (2023). Analysis of the effect of rolling speed on the texture properties of noodle dough from water-solid interaction, development of gluten network, and bubble distribution. *Food Chemistry*, *404*, 134359. https://doi.org/10.1016/J.FOODCHEM.2022.134359

Liu, Shuyi, Liu, Q., Li, X., Obadi, M., Jiang, S., Li, S., & Xu, B. (2021). Effects of dough resting time on the development of gluten network in different sheeting directions and the textural properties of noodle dough. *LWT*, *141*, 110920. https://doi.org/10.1016/J.LWT.2021.110920

Mahadevappa, J., Groß, F., & Delgado, A. (2017). Fuzzy logic based process control strategy for effective sheeting of wheat dough in small and medium-sized enterprises. *Journal of Food Engineering*, *199*, 93–99. https://doi.org/10.1016/J.JFOODENG.2016.12.013

Mavani, N. R., Ali, J. M., Othman, S., Hussain, M. A., Hashim, H., & Rahman, N. A. (2021). Application of Artificial Intelligence in food industry—a Guideline. *Food Engineering Reviews 2021 14:1*, *14*(1), 134–175. https://doi.org/10.1007/S12393-021-09290-Z

Ross. (2006). Sheeting characteristics of salted and alkaline Asian noodle doughs: Comparison with Lubricated Squeezing Flow Attributes. *Cereal Foods World*, *51*(5), 191–196. https://doi.org/10.1094/CFW-51-0191

Singh J, Kumar R, Kumar V, Chatterjee S. (2024). Exploring the dynamics of bigdata adoption in the Indian food industry with fuzzy analytical hierarchical process. *British Food Journal*, *126*(6), 2310–2327. https://doi.org/10.1108/BFJ-01-2024-0012

Song, M., Liu, C., Hong, J., Li, L., Zheng, X., Bian, K., & Guan, E. (2019). Effects of repeated sheeting on rheology and glutenin properties of noodle dough. *Journal of Cereal Science*, *90*, 102826. https://doi.org/10.1016/J.JCS.2019.102826

Tosun, M., Dincer, K., & Baskaya, S. (2011). Rule-based Mamdani-type fuzzy modelling of thermal performance of multi-layer precast concrete panels used in residential buildings in Turkey. *Expert*

Systems with Applications, *38*(5), 5553–5560. https://doi.org/10.1016/J.ESWA.2010.10.081

Zadeh, L. A. (1965). Fuzzy sets. *Information and Control*, *8*(3), 338-353.

Zimmermann, H.-J. (2001). *Fuzzy Set Theory—and Its Applications*. Springer Netherlands. https://doi.org/10.1007/978-94-010-0646-0