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Fuzzy Expert System for Melamine Moulding Compound Dye Feasibility Identification: A Case study on Plastic Industry

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Abstract

This study develops and evaluates an explainable zero order Fuzzy Sugeno expert system for assessing the feasibility of Melamine Moulding Compound (MMC) dyes in the melamine industry. The objective is to support consistent dye assessment by converting expert knowledge of boiling point, processing time, and injection pressure into a structured decision model. Each input variable is represented by low, medium, and high fuzzy sets, while four domain experts contributed to the definition and review of the membership ranges, rule base, and feasibility outcomes. The model contains 27 rules with singleton consequents of 10, 20, and 30 for not feasible, conditionally feasible, and feasible decisions, respectively, with midpoint decision boundaries of 15 and 25. The model was evaluated using 23 historical process profiles and classified 10 samples as not feasible (43.48%), 8 as conditionally feasible (34.78%), and 5 as feasible (21.74%). MMC103, with a boiling point of 165 °C, processing time of 65 seconds, and pressure of 55 bar, activated eight rules and produced a Sugeno score of 26.67, resulting in a feasible classification. A ±5% sensitivity analysis with 10,000 random perturbations produced MMC103 scores from 25.86 to 27.29 and retained its feasible classification in all runs, while overall class stability across the 23 profiles reached 98.86%. Sugeno classifications agreed with Mamdani inference for 20 of 23 profiles and with a crisp rule baseline for 18 profiles. By combining expert knowledge formalization, sensitivity evaluation, comparative analysis, and web implementation, this study provides an explainable and traceable decision support approach for MMC dye feasibility assessment in melamine production.

Keywords: Dye Feasibility, Expert System, Fuzzy Sugeno, Melamine Moulding Compound, Web-based Application.

1. Introduction

The production of melamine-based tableware necessitates consistent material selection, as the visual quality and processing stability of the final product are influenced by the compatibility between Melamine Moulding Compound (MMC) and the dye employed during manufacturing [1], [2], [3]. MMC serves as the primary compound in the forming process of melamine products. To achieve tableware with diverse and appealing colors, dye materials must be incorporated with MMC under appropriate process conditions. An incompatible dye or unsuitable processing environment may compromise the stability of the molding process and the overall quality of the finished product [3], [4]. Consequently, the feasibility of dyes must be evaluated prior to their routine application in production [5].

In the melamine industry, the suitability of an MMC dye is commonly evaluated through several production-related parameters [6], [7], [8]. This study concentrates on three key parameters pertinent to the dye evaluation process: boiling point, processing time, and injection pressure. The boiling point reflects the dye's thermal tolerance during production. Processing time indicates the duration necessary for proper mixing of the dye with MMC. Injection pressure describes the condition required during the molding process. These parameters are not always interpreted in a straightforward binary manner, as their values may overlap across low, medium, and high assessment levels. Consequently, decisions regarding feasibility may become inconsistent if based solely on manual judgment. The primary concern addressed herein is the difficulty in accurately determining the feasibility of MMC dyes when the measured values of boiling

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point, processing time, and pressure vary among different dye samples. In practical scenarios, production personnel may receive new dye samples from procurement teams or suppliers. Each sample must undergo testing prior to approval for production use. However, manual assessments can be subjective, depending on the evaluator's interpretation of the parameter values. This situation underscores the necessity for a decision support mechanism capable of translating expert knowledge into a measurable and reproducible decision-making process.

Expert systems have been extensively utilized to support decision-making processes such as assessment, recommendation, prediction, diagnosis, and feasibility analysis [9], [10], [11]. These systems are particularly effective when decisions depend on expert knowledge and structured rules. Numerous prior studies have demonstrated that expert systems can assist users in data interpretation, case classification, and decision production with increased consistency [12], [13], [14]. Additionally, fuzzy expert systems are appropriate for addressing problems involving uncertainty, gradual membership, and linguistic categories [15], [16]. This characteristic is especially pertinent to the feasibility assessment of MMC dyes, where parameters such as boiling point, processing time, and pressure may not be categorically distinct.

Among the fuzzy inference methods, the Sugeno model is suitable for this research as it yields a crisp output through weighted average defuzzification [17], [18]. This feature facilitates the expression of the feasibility result as a numerical score that can be mapped into a definitive decision class [17], [19]. In this study, the Fuzzy Sugeno model incorporates three input variables: boiling point, processing time, and pressure. Each variable is characterized by three fuzzy sets—low, medium, and high. The rule base comprises 27 rules derived from expert knowledge. The output classes are categorized as not feasible, conditionally feasible, and feasible. This structure enables the system to process measured dye parameters and generate a feasibility score that supports decision-making within the context of melamine production.

Furthermore, this research develops a web-based Fuzzy Sugeno application to facilitate easier access and utilization of the feasibility identification process. The application enables users to manage fuzzy variable ranges, output classes, and rule base data. It also allows users to input measured process parameters, execute the Fuzzy Sugeno inference process, view the resulting score and classification, and save the feasibility history. The web-based implementation is significant as it transforms the proposed model into a practical tool suitable for deployment in a production environment, beyond mere manual calculation models [20], [21], [22].

Considering these aspects, the objective of this study is to design and evaluate a Fuzzy Sugeno expert system for assessing the feasibility of MMC dyes within the melamine industry. The contribution of this research lies in formalizing expert knowledge into a structured fuzzy rule base, generating a measurable feasibility score, and implementing the model through a web-based application. The study is guided by several research questions that address the development, evaluation, and implementation of the proposed Fuzzy Sugeno expert system. First, the study examines how expert knowledge concerning boiling point, processing time, and injection pressure can be represented through complete fuzzy membership functions and a zero order Sugeno rule base for MMC dye feasibility assessment. It then evaluates how closely the feasibility classifications produced by the proposed model correspond with historical process profiles and available expert assessments. The study also compares the Sugeno model with Mamdani inference and a crisp rule baseline in terms of classification results, interpretability, and inference time. In addition, the robustness of the model is examined by assessing the stability of the generated feasibility decisions when the membership breakpoints are perturbed by plus or minus 5%. Finally, the study evaluates whether the web application provides acceptable functional performance, response time, usability, and security for controlled use in an industrial environment.

2. Literature Review

2.1. Fuzzy Expert Systems

An expert system stores knowledge from a domain expert and applies it to help solve a specific decision problem [9], [23], [24]. In a fuzzy expert system, the rules can handle vague or overlapping conditions rather than only true or false conditions an expert system captures knowledge from a domain specialist and utilizes it to assist in resolving specific decision-making issues [15], [25]. In a fuzzy expert system, the rules are capable of managing ambiguous or overlapping conditions, rather than solely binary true or false states [26], [27], [28]. This capability holds particular significance in manufacturing, where process measurements frequently evolve gradually [9], [25]. A dye sample is not invariably entirely acceptable or entirely unacceptable; it often resides within a continuum between these states, and the system should be capable of representing such partial conditions not always fully acceptable or fully unacceptable. It may sit between these states, and the system should be able to show that partial condition.

2.2. Fuzzy Sugeno Inference

Sugeno fuzzy inference employs rules where the antecedent is fuzzy and the consequent is crisp. In a zero-order Sugeno model, the consequent is represented as a constant [18], [29], [30]. This study utilizes constants 10, 20, and 30 to indicate not feasible, conditionally feasible, and feasible categories, respectively. The methodology is practical for a web application due to its computational simplicity and ease of explanation. Each active rule possesses a firing strength, a consequent value, and a contribution to the final score. The final Sugeno score is calculated by dividing the sum of weighted consequents by the sum of firing strengths. This design enhances the transparency of the model. The production manager can assess the input memberships, active rules, and the final score without the necessity of reviewing program code.

2.3. Dye Feasibility in Melamine Production

Melamine-based materials are influenced by heat, curing, and processing conditions [31]. In manufacturing practice, it is essential that the dye is compatible with the MMC material and the molding process. The specific parameters utilized in this study include boiling point, processing time, and pressure. These three parameters provide a comprehensive evaluation of whether the dye can be processed without introducing unacceptable production risks. Consequently, the decision is modeled as a fuzzy multi-parameter feasibility problem.

2.4. Research Gap and Contribution

Previous studies have applied fuzzy inference to manufacturing control, risk assessment, diagnosis, and other decision problems. However, the use of fuzzy reasoning in a new industrial setting is not sufficient by itself to establish a scientific contribution. The present study therefore evaluates the knowledge base and its behavior rather than presenting the Sugeno method as a new algorithm. The research gap concerns the formalization of MMC dye feasibility using the combined evidence of boiling point, processing time, and injection pressure, together with an explicit rule trace, boundary sensitivity analysis, and a web implementation that preserves the calculation history. This position defines the study as an applied knowledge engineering and evaluation contribution.

3. Methodology

The study adopts an applied system development methodology (figure 1). Knowledge was gathered from the dye feasibility process utilized within the melamine industry. The production manager supplies expert judgment. The system receives numerical test results following the completion of physical testing. It does not replace laboratory or shop floor testing; rather, it supports decision-making once measurements such as boiling point, processing time, and pressure are obtained.

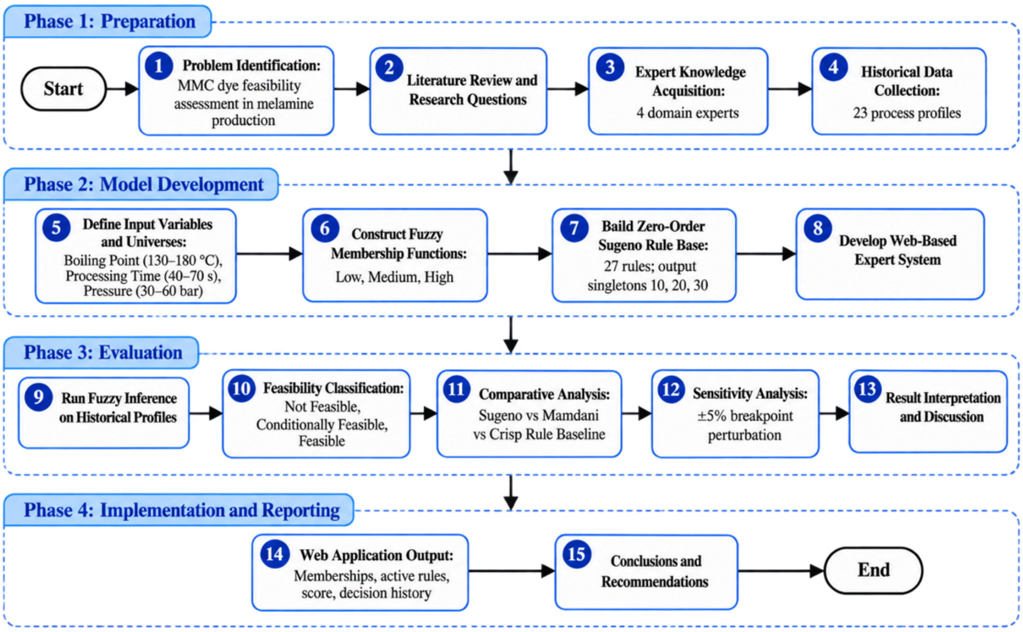

Figure 1. Research workflow

3.1. Expert Panel and Knowledge Acquisition

The knowledge acquisition process involved four domain experts shown in table 1. E1 was a production manager with 11 years of professional experience and 9 years of MMC dye assessment experience. E2 and E3 were process engineers with 17 and 14 years of professional experience and 16 and 14 years of MMC dye assessment experience, respectively. E4 was a quality specialist with 8 years of professional experience and 6 years of MMC dye assessment experience. The panel therefore represented 45 person years of MMC dye assessment experience. E1 supplied the initial ranges and rule consequents, E2 and E3 performed technical reviews, and E4 reviewed outcome consistency from a quality perspective.

Table 1. Expert Panel

No	Expert	Role	Professional experience	MMC assessment experience	Contribution
1	E1	Production manager	11 years	9 years	Initial ranges and rules
2	E2	Process engineer	17 years	16 years	Technical review
3	E3	Process engineer	14 years	14 years	Technical review
4	E4	Quality specialist	8 years	6 years	Outcome validation

To reduce circular validation, model development and outcome validation should be separated. E2, E3, and E4 should classify the historical profiles independently and without access to the Sugeno outputs. A unanimous decision should be accepted directly. A two out of three majority should define the reference decision when one expert disagrees. Cases with three different decisions should be resolved in a documented consensus meeting. Raw agreement and Fleiss kappa should be reported after the independent ratings are complete.

3.2. Fuzzy Sugeno Model Construction

Table 2 presents fuzzy membership functions. For each input variable x, the validated universe is represented by four coordinates, L, a, b, and U. L and U are the lower and upper validated limits, a is the upper end of the low core, and b is the medium peak and the start of the medium to high transition. The 3 membership functions form a complete partition within the validated universe.

$$\Omega_{BP} = [130,180], \qquad \Omega_T = [40,70], \qquad \Omega_P = [30,60] \tag{1}$$

$$v \in \{BP, T, P\}, \qquad (l_v, a_v, b_v, u_v) \tag{2}$$

Table 2. Fuzzy membership functions

No	Variable	Unit	Validated universe (L,U)	Low core upper point (a)	Medium peak (b)	Upper limit (U)	5% shift
1	Boiling point	degrees	130 to 180 °C	150 °C	160 °C	180 °C	2.5
2	Processing time	seconds	40 to 70 s	50 s	60 s	70 s	1.5
3	Pressure	bar	30 to 60 bar	40 bar	50 bar	60 bar	1.5

Low Membership function: This left shoulder function eliminates gaps at the lower end of each validated universe.

$$\mu_{v,\mathrm{Low}}(x) = \begin{cases}1, & l_v \le x \le a_v\\ \frac{b_v - x}{b_v - a_v}, & a_v < x < b_v\\ 0, & b_v \le x \le u_v\end{cases} \quad (3)$$

Medium Membership function: This triangular function represents the gradual transition between low and high process conditions.

$$\mu_{v,\mathrm{Med}}(x) = \begin{cases}0, & l_v \le x \le a_v\\ \frac{x - a_v}{b_v - a_v}, & a_v < x \le b_v\\ \frac{u_v - x}{u_v - b_v}, & b_v < x \le u_v\end{cases} \quad (4)$$

High Membership function: This right shoulder function reaches full membership at the upper validated limit.

$$\mu_{v,\mathrm{High}}(x) = \begin{cases}0, & l_v \le x \le b_v\\ \frac{x - b_v}{u_v - b_v}, & b_v < x \le u_v\end{cases} \quad (5)$$

$$\mu_{v,\mathrm{Low}}(x) + \mu_{v,\mathrm{Med}}(x) + \mu_{v,\mathrm{High}}(x) = 1, \qquad x \in \Omega_v \quad (6)$$

$$x \notin \Omega_v \Rightarrow D = \text{Outside validated range} \quad (7)$$

Complete partition property (Equation 6) This equation directly addresses the reviewer concern about zero membership gaps within the validated range, and out of range handling (Equation 7) Inputs outside the expert validated ranges should be referred for expert review rather than extrapolated. With three inputs and 3 membership categories per input, the complete rule base comprises 3 x 3 x 3 = 27 rules, as shown in figure 2. To ensure conciseness of the manuscript, table 3 displays the same rule base in the form of a matrix. Each row specifies the boiling point and processing time, while the three pressure columns indicate the respective outcomes for low, medium, and high pressure.

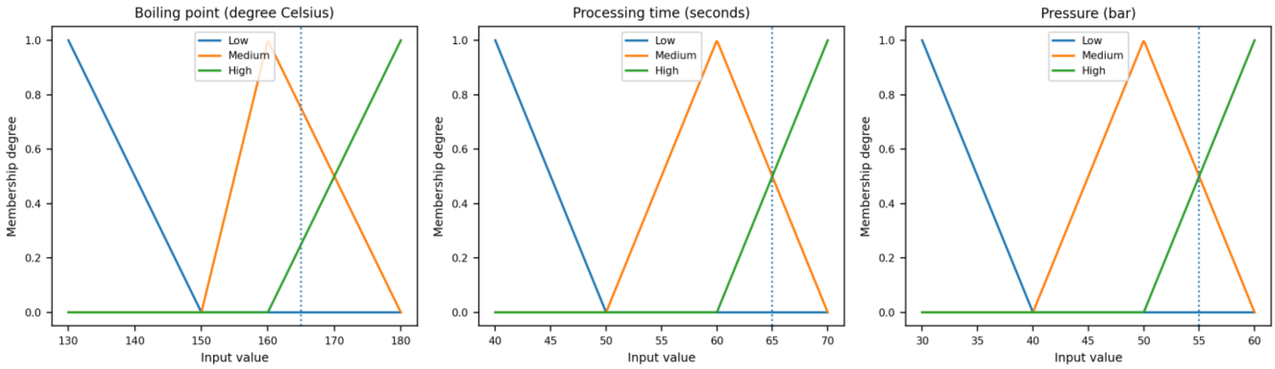

Figure 1. The vertical dotted line marks the MMC103 input value in each parameter.

Table 3. Compact representation of the 27 rule Sugeno knowledge base

Boiling point	Processing time	Pressure = Low	Pressure = Medium	Pressure = High
Low	Low	Bad	Bad	Bad
Low	Medium	Bad	Bad	Bad
Low	High	Bad	Bad	Bad
Medium	Low	Bad	Bad	Quite feasible
Medium	Medium	Bad	Quite feasible	Feasible
Medium	High	Bad	Quite feasible	Feasible
High	Low	Bad	Quite feasible	Quite feasible
High	Medium	Bad	Feasible	Feasible
High	High	Quite feasible	Feasible	Feasible

The firing strengths are fuzzy rule activation degrees rather than probabilities. Because several overlapping rules may be active at the same time, their sum is not restricted to 1. The weighted average denominator normalizes the combined contribution. If every firing strength is multiplied by the same positive constant, that constant cancels from the numerator and denominator and the final score does not change. The output class and sugeno singleton values are shown in table 4. The midpoint boundaries follow from (10 + 20)/2 = 15 and (20 + 30)/2 = 25. An affine recoding K prime = aK + b produces Z prime = aZ + b, so an equivalent scale such as 0, 1, and 2 preserves the ordering when its boundaries are transformed in the same manner. For each input x, the low membership diminishes linearly from 1 to 0 within the low support interval, the high membership increases linearly from 0 to 1 within the high support interval, and the medium membership attains its maximum at the lower boundary of the high support interval.

Table 4. Output classes and Sugeno singleton values

No.	Output class	Singleton value	Decision rule
1	Not feasible	10	Z <= 15
2	Conditionally feasible	20	15 < Z <= 25
3	Feasible	30	Z > 25

The functions are deliberately designed to be straightforward, as the production expert rules are linguistic in nature; furthermore, the primary objective is to facilitate explainable feasibility identification rather than black-box prediction.

$$\alpha_r = \min\left\{\mu_{BP,A_i}(BP), \mu_{T,B_j}(T), \mu_{P,C_k}(P)\right\} \tag{8}$$

$$Z = \frac{\sum_{r=1}^{27} \alpha_r K_r}{\sum_{r=1}^{27} \alpha_r} \tag{9}$$

The firing strengths are rule activation degrees rather than probabilities; therefore, their sum is not required to equal one. The denominator in the weighted average normalizes the combined rule contributions. The singleton consequents 10, 20, and 30 form an equally spaced ordinal scale for not feasible, conditionally feasible, and feasible outcomes. Accordingly, the midpoint values of 15 and 25 are used as the decision boundaries. The complete inference procedure used to process the three input variables and determine the MMC dye feasibility class is summarized in Algorithm 1 For each of the 27 rules, the firing strength is calculated using the minimum operator. The resulting firing strengths are combined with their corresponding Sugeno singleton consequents, and the final score is obtained using weighted average defuzzification.

Algorithm 1. Fuzzy Sugeno Inference for MMC Dye Feasibility Assessment

```
Input:
   BP = boiling point
   T  = processing time
   P  = injection pressure
Output:
   Z = Sugeno feasibility score
   C = feasibility class

1:  Define the validated input ranges:
      BP ∈ [130, 180]
      T  ∈ [40, 70]
      P  ∈ [30, 60]
2:  If BP, T, or P is outside its validated range, then
      Return "Outside validated range"
   End If
3:  Calculate the low, medium, and high membership degrees
   for BP, T, and P.
4:  Set total_firing_strength = 0
   Set weighted_sum = 0
5:  For each rule r = 1 to 27 do
      Calculate:
         αr = min(μBP,Ai(BP), μT,Bj(T), μP,Ck(P))
      Assign:
```

```
        Kr = 10 for Not Feasible
        Kr = 20 for Conditionally Feasible
        Kr = 30 for Feasible
      Calculate:
        wr = αr × Kr
      Update:
        total_firing_strength =
          total_firing_strength + αr

        weighted_sum =
          weighted_sum + wr
    End For
6:  If total_firing_strength = 0, then
      Return "No valid inference"
    End If
7:  Calculate:
      Z = weighted_sum / total_firing_strength
8:  If Z ≤ 15 then
      C = "Not Feasible"
    Else if 15 < Z ≤ 25 then
      C = "Conditionally Feasible"
    Else
      C = "Feasible"
    End If
9:  Store memberships, active rules, firing strengths,
    rule consequents, final score, and decision history.

10: Return Z and C
```

The operator 'min' is employed for AND aggregation within the antecedent of each rule. The final score Z is calculated as the weighted average of all rule consequents, where alpha_r represents the firing strength of rule r and z_r denotes the zero-order consequent constant associated with the rule. The comprehensive rule base comprises 27 rules, as depicted in table 5. The rule base is deliberately conservative. A low boiling point invariably results in infeasibility, as weak thermal tolerance should not be remedied solely through adjustments in time or pressure.

Table 5. Fuzzy Sugeno rule base for MMC dye feasibility

No.	Rule	Statement	K
1	R1	If boiling point is low, processing time is low, and pressure is low, then the dye is not feasible.	10
2	R2	If boiling point is low, processing time is low, and pressure is medium, then the dye is not feasible.	10
3	R3	If boiling point is low, processing time is low, and pressure is high, then the dye is not feasible.	10
4	R4	If boiling point is low, processing time is medium, and pressure is low, then the dye is not feasible.	10
5	R5	If boiling point is low, processing time is medium, and pressure is medium, then the dye is not feasible.	10
6	R6	If boiling point is low, processing time is medium, and pressure is high, then the dye is not feasible.	10
7	R7	If boiling point is low, processing time is high, and pressure is low, then the dye is not feasible.	10
8	R8	If boiling point is low, processing time is high, and pressure is medium, then the dye is not feasible.	10
9	R9	If boiling point is low, processing time is high, and pressure is high, then the dye is not feasible.	10
10	R10	If boiling point is medium, processing time is low, and pressure is low, then the dye is not feasible.	10
11	R11	If boiling point is medium, processing time is low, and pressure is medium, then the dye is not feasible.	10
12	R12	If boiling point is medium, processing time is low, and pressure is high, then the dye is conditionally feasible.	20
13	R13	If boiling point is medium, processing time is medium, and pressure is low, then the dye is not feasible.	10
14	R14	If boiling point is medium, processing time is medium, and pressure is medium, then the dye is conditionally feasible.	20
15	R15	If boiling point is medium, processing time is medium, and pressure is high, then the dye is feasible.	30
16	R16	If boiling point is medium, processing time is high, and pressure is low, then the dye is not feasible.	10
17	R17	If boiling point is medium, processing time is high, and pressure is medium, then the dye is conditionally feasible.	20
18	R18	If boiling point is medium, processing time is high, and pressure is high, then the dye is feasible.	30
19	R19	If boiling point is high, processing time is low, and pressure is low, then the dye is not feasible.	10
20	R20	If boiling point is high, processing time is low, and pressure is medium, then the dye is conditionally feasible.	20
21	R21	If boiling point is high, processing time is low, and pressure is high, then the dye is conditionally feasible.	20
22	R22	If boiling point is high, processing time is medium, and pressure is low, then the dye is not feasible.	10
23	R23	If boiling point is high, processing time is medium, and pressure is medium, then the dye is feasible.	30
24	R24	If boiling point is high, processing time is medium, and pressure is high, then the dye is feasible.	30
25	R25	If boiling point is high, processing time is high, and pressure is low, then the dye is conditionally feasible.	20

No.	Rule	Statement	K
26	R26	If boiling point is high, processing time is high, and pressure is medium, then the dye is feasible.	30
27	R27	If boiling point is high, processing time is high, and pressure is high, then the dye is feasible.	30

3.3. Historical profile dataset and Calculation

The computational evaluation used 23 populated historical MMC dye profiles, identified as MMC101 through MMC123 shown on table 6. The profiles cover boiling points from 130 to 180 degrees Celsius, processing times from 40 to 70 seconds, and pressures from 30 to 60 bar. The dataset includes lower and upper limits, internal breakpoints, overlap values, and mixed process conditions. MMC124 was excluded because it contained no measurements. Reference decisions were available for MMC101, MMC102, and MMC103. The remaining profiles were processed by the frozen fuzzy model but were not used to claim overall accuracy because independent reference decisions were not yet available.

Table 6. Calculated Results

Sample	Boiling point	Processing time	Pressure	Sugeno score	Calculated feasibility
MMC101	160	60	50	20.00	Conditionally feasible
MMC102	130	40	30	10.00	Not feasible
MMC103	**165**	**65**	**55**	**26.67**	**Feasible**
MMC104	135	50	45	10.00	Not feasible
MMC105	135	45	45	10.00	Not feasible
MMC106	150	65	50	10.00	Not feasible
MMC107	150	55	45	10.00	Not feasible
MMC108	145	50	35	10.00	Not feasible
MMC109	140	70	35	10.00	Not feasible
MMC110	145	65	60	10.00	Not feasible
MMC111	160	65	50	20.00	Conditionally feasible
MMC112	155	65	55	17.50	Conditionally feasible
MMC113	180	65	55	30.00	Feasible
MMC114	175	60	40	10.00	Not feasible
MMC115	180	50	50	20.00	Conditionally feasible
MMC116	170	70	60	30.00	Feasible
MMC117	170	65	55	27.50	Feasible
MMC118	155	60	60	20.00	Conditionally feasible
MMC119	175	50	55	18.33	Conditionally feasible
MMC120	155	50	45	10.00	Not feasible
MMC121	165	65	50	23.33	Conditionally feasible
MMC122	180	40	60	20.00	Conditionally feasible
MMC123	165	60	55	26.67	Feasible

The output variables are presented in table 6. The 'not feasible' class denotes a dye that should not be employed. The 'conditionally feasible' class signifies a dye that may require further evaluation or limited application. The 'feasible' class indicates a dye that is acceptable for production, based on the three evaluated parameters. The figure 3 shows that 5 of the 23 dye samples, representing 21.74% of the total, were classified as feasible. Although this was the smallest class, it indicates that the system applied a selective decision process and assigned the feasible status only to samples that met the required combination of boiling point, processing time, and pressure. This result reflects the conservative nature of the Fuzzy Sugeno model in supporting dye acceptance decisions.

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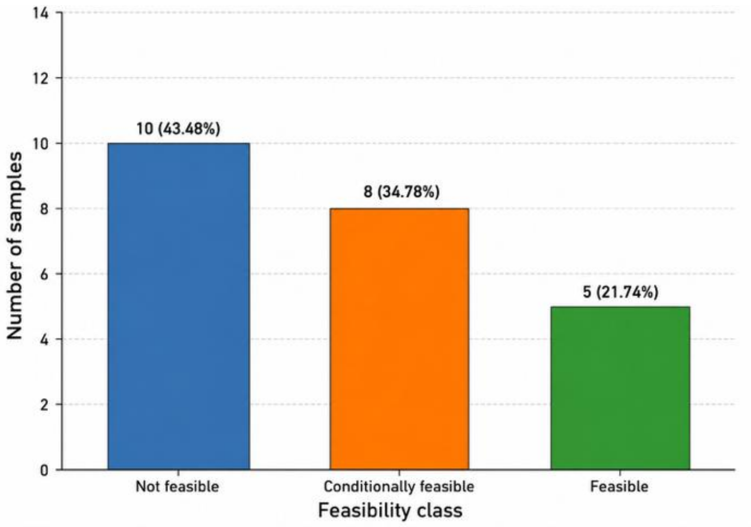

Figure 2. Class Distribution

3.4. Use Case Diagram

The use case diagram was revised to focus solely on the software functions required by the Fuzzy Sugeno expert system (figure 4). The production manager has the ability to sign in, maintain the fuzzy knowledge base, register samples, input measured parameters, execute identification procedures, view the score and classification, and save the feasibility history. Procurement personnel or suppliers are not permitted to modify the fuzzy model. They are displayed exclusively as parties that submit dye samples and receive the feasibility decision.

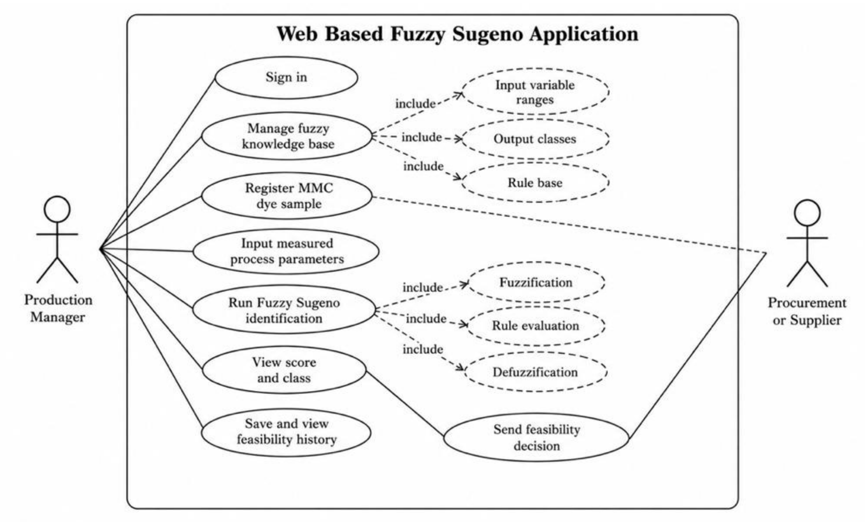

Figure 3. Use case diagram for the web-based Fuzzy Sugeno application.

3.5. Web application architecture and safe scope statement

The application follows a layered structure consisting of a browser interface, a PHP application and validation layer, a Sugeno inference module, and a MySQL data layer. The proposed database structure includes users, roles, fuzzy variables, membership parameters, output singletons, rules, dye samples, measurements, inference results, model versions, rule traces, and audit logs. The current study verifies functional behavior but does not describe the prototype as production ready until the source code and deployment are checked for password hashing, prepared statements, server-side validation, output encoding, Cross Site Request Forgery protection, secure session handling, role-based authorization, HTTPS, login throttling, least privilege database access, and audit logging.

3.6. Evaluation Procedure

The evaluation employed two methods of assessment. Initially, a manual rule trace was compared with the system output for the MMC103 example. Subsequently, black box testing was utilized to verify whether the application's functionalities corresponded with the anticipated behavior [8], [9]. The testing concentrated on sign-in, fuzzy set management, output class management, rule management, sample input, inference calculation, result display, and feasibility history.

4. Results and Discussion

The revised Sugeno model was applied to 23 historical process profiles, as shown in table 7. Ten profiles were classified as not feasible, eight as conditionally feasible, and five as feasible. The results cover all three output classes and include several profiles near membership or decision boundaries. This class distribution demonstrates computational coverage but should not be interpreted as classification accuracy because only three profiles currently have independent reference decisions.

Table 7. Sugeno results for the 23 historical profiles

No	Sample	Boiling point	Time	Pressure	Sugeno score	Sugeno class	Active rules	Sensitivity stability
1	MMC101	130	40	30	10.00	Not feasible	1	100.00%
2	MMC102	160	60	50	20.00	Conditionally feasible	1	99.79%
3	MMC103	165	65	55	26.67	Feasible	8	100.00%
4	MMC104	135	50	45	10.00	Not feasible	2	100.00%
5	MMC105	135	45	45	10.00	Not feasible	2	100.00%
6	MMC106	150	65	50	10.00	Not feasible	2	100.00%
7	MMC107	150	55	45	10.00	Not feasible	4	100.00%
8	MMC108	145	50	35	10.00	Not feasible	1	100.00%
9	MMC109	140	70	35	10.00	Not feasible	1	100.00%
10	MMC110	145	65	60	10.00	Not feasible	2	100.00%
11	MMC111	160	65	50	20.00	Conditionally feasible	2	99.98%
12	MMC112	155	65	55	17.50	Conditionally feasible	8	100.00%
13	MMC113	180	65	55	30.00	Feasible	4	100.00%
14	MMC114	175	60	40	10.00	Not feasible	2	99.79%
15	MMC115	180	50	50	20.00	Conditionally feasible	1	100.00%
16	MMC116	170	70	60	30.00	Feasible	2	100.00%
17	MMC117	170	65	55	27.50	Feasible	8	100.00%
18	MMC118	155	60	60	20.00	Conditionally feasible	2	100.00%
19	MMC119	175	50	55	18.33	Conditionally feasible	4	100.00%
20	MMC120	155	50	45	10.00	Not feasible	4	100.00%
21	MMC121	165	65	50	23.33	Conditionally feasible	4	94.20%
22	MMC122	180	40	60	20.00	Conditionally feasible	1	100.00%
23	MMC123	165	60	55	26.67	Feasible	4	80.08%

4.1. Sugeno Calculation for MMC103

MMC103 had a boiling point of 165 degrees Celsius, a processing time of 65 seconds, and a pressure of 55 bar. The boiling point memberships were 0.00 for low, 0.75 for medium, and 0.25 for high. Processing time and pressure each had memberships of 0.00 for low, 0.50 for medium, and 0.50 for high. Eight rules were active. Their firing strengths summed to 3.00 and their weighted consequent contributions summed to 80.00. The final score was therefore $Z = 80.00/3.00 = 26.67$, which exceeded the revised feasible boundary of 25. The aggregate firing strength of 3.00 is valid because firing strengths are not probabilities. The overlapping input sets activate several nonexclusive rules. Weighted average defuzzification normalizes the combined rule contribution through the denominator. MMC103 was accepted because all three variables avoided the low region and the active feasible rules contributed most of the weighted numerator. MMC103 was selected as the exemplar due to its activation of both medium and high fuzzy sets. The measured values are presented in table 8.

Table 8. MMC103 input values

No.	Parameter	Input Value	Low	Medium	High	Dominant Fuzzy
1	Boiling point	165 °C	0.00	0.75	0.25	Medium > High
2	Processing time	65 seconds	0.00	0.50	0.50	Medium = High

3	Pressure	55 bar	0.00	0.50	0.50	Medium = High

The resulting memberships are presented in table 9. All low memberships are zero, indicating that none of the parameters reside within the poor process region. The sample activates both medium and high memberships for each parameter, as the measured values lie within the overlap between the medium and high sets. Since all low memberships are zero, only rules that integrate medium and high conditions are operational. The computation of active rules is illustrated in table 10.

Table 9. MMC103 membership values

No.	Variable	Set	Membership degree
1	Boiling point	Low	0.00
2	Boiling point	Medium	0.75
3	Boiling point	High	0.25
4	Processing time	Low	0.00
5	Processing time	Medium	0.50
6	Processing time	High	0.50
7	Pressure	Low	0.00
8	Pressure	Medium	0.50
9	Pressure	High	0.50

Table 10. Active rule calculation for MMC103

Rule	Boiling point	Processing time	Pressure	alpha	K	alpha K
R14	Medium	Medium	Medium: Conditionally feasible (z=20)	0.50	20	10.00
R15	Medium	Medium	High: Feasible (z=30)	0.50	30	15.00
R17	Medium	High	Medium: Conditionally feasible (z=20)	0.50	20	10.00
R18	Medium	High	High: Feasible (z=30)	0.50	30	15.00
R23	High	Medium	Medium: Feasible (z=30)	0.25	30	7.50
R24	High	Medium	High: Feasible (z=30)	0.25	30	7.50
R26	High	High	Medium: Feasible (z=30)	0.25	30	7.50
R27	High	High	High: Feasible (z=30)	0.25	30	7.50
Total				**3.00**		**80.00**

The final score is Z = 80.00 / 3.00 = 26.67. According to table 3, MMC103 is classified as feasible because the score exceeds 20 but does not surpass 30. This determination is supported by six of the eight active rules, which contribute 60.00 of the 80.00 weighted numerator. The remaining 20.00 derives from quite feasible rules, while no adverse rules are active since none of the parameters fall into the low fuzzy set. This outcome indicates that feasibility depends on consistent medium-to-high compatibility across boiling point, processing time, and pressure. The sample passes because all three parameters avoid low regions and pressure and processing time activate high states simultaneously, rather than due to a single dominant parameter. This insight supports production decisions by explaining MMC103's acceptance within overlapping ranges.

Aggregate firing strength:

$$\sum_{r=1}^{27} \alpha_r = 4(0.50) + 4(0.25) = 3.00 \tag{10}$$

Weighted consequent sum:

$$\sum_{r=1}^{27} \alpha_r \, K_r = 80.00 \tag{11}$$

MMC Sugeno score:

$$Z = \frac{80.00}{3.00} = 26.67 \tag{12}$$

MMC103 Final decision:

$$Z = 26.67 > 25 \Rightarrow Class(Z) = \text{Feasible} \tag{13}$$

The total firing strength is 3.00, with a weighted consequent sum of 80.00, resulting in a final score of Z = 26.67. Since this score falls within the range of 20 to 30, MMC103 is considered feasible. Six rules contribute 60.00 to the numerator, two conditionally feasible rules add 20.00, and no rules indicate 'Not feasible."

4.2. Sensitivity analysis

Across all 23 profiles, the overall class stability was 98.86 percent. Eighteen profiles retained their baseline class in every random perturbation. MMC121 and MMC123 were the most sensitive profiles, with stability rates of 94.20 percent and 80.08 percent. These results in table 11 show that interior cases are stable, while profiles close to the decision boundary require closer expert review.

Universe width and five percent perturbation:

$$W_v = u_v - l_v, \qquad \Delta_v = 0.05W_v \tag{14}$$

Variable specific perturbations:

$$\Delta_{BP} = 2.5^{\circ C}, \qquad \Delta_T = 1.5\text{s}, \qquad \Delta_P = 1.5\text{bar} \tag{15}$$

Table 11. Sensitivity Analysis

Sensitivity scenario	MMC103 score	Class	Interpretation
Baseline breakpoints	26.67	Feasible	Reference configuration
All internal breakpoints shifted downward by 5%	27.29	Feasible	Class unchanged
All internal breakpoints shifted upward by 5%	25.82	Feasible	Class unchanged
10,000 random perturbations	25.86 to 27.29	Feasible in 100% of runs	Mean 26.68; StDev σ 0.30

4.3. Comparison with alternative decision methods

The Mamdani comparison indicates that the two fuzzy methods usually produce the same class, but Mamdani classified MMC103, MMC117, and MMC123 as conditionally feasible while Sugeno classified them as feasible. The crisp baseline differed more often because it discarded partial membership and selected only one rule. These comparisons in Table 12 demonstrate methodological behavior rather than predictive superiority. A conclusion about accuracy requires independent reference labels for the complete dataset.

Table 12. The Comparison of Sugeno with alternative decisions methods

Comparison	Same class	Agreement	Different or limited cases
Sugeno versus Mamdani	20 of 23	86.96%	MMC103, MMC117, and MMC123
Sugeno versus crisp dominant rule	18 of 23	78.26%	MMC103, MMC112, MMC117, MMC118, and MMC123
Sugeno versus independent reference labels	3 of 3 currently labeled	100% on labeled subset	Insufficient for overall accuracy

4.4. Main Feasibility Findings

MMC103 is classified as feasible because all three measured parameters avoid the low fuzzy regions. Processing time and pressure have equal medium and high memberships, while boiling point is predominantly medium with partial high membership. The final decision therefore reflects the combined contribution of the three process variables rather than a single dominant measurement. The second finding indicates that the model maintains transparency of expert reasoning. The system displays the membership degree of each parameter, the activated rules, the rule consequent, and the final score. This approach is more informative than a binary yes or no label, as it enables the production manager to elucidate the rationale behind the dye's acceptance. The third finding is that the rule base exhibits a conservative behavior. A low boiling point consistently yields an infeasible result. Neither high pressure nor extended processing time can compensate for a low boiling point. This aligns with the expert opinion that thermal tolerance is a fundamental prerequisite for dye feasibility in MMC production.

4.5. Deployment

The primary user of the system is the production manager. Procurement departments or suppliers submit dye samples and receive feasibility information after the system generates a result. The application stores fuzzy variables, output classes, rules, input sample data, Sugeno calculation results, and feasibility history. The public login page for the application is accessible at https://fuzzysugeno.gejur.id/login.php. The research additionally yielded a web-based Fuzzy Sugeno application. This application is accessible via the login page specified in the methodology. It was constructed to enable the production manager to oversee the fuzzy knowledge base, input dye sample values, execute the Sugeno calculation, and review previous feasibility results. Figure 5 through figure 8 display the interface, which has been recreated in English at a standard resolution of 1600 by 900 pixels. User data are obscured with asterisks (****) to ensure privacy protection.

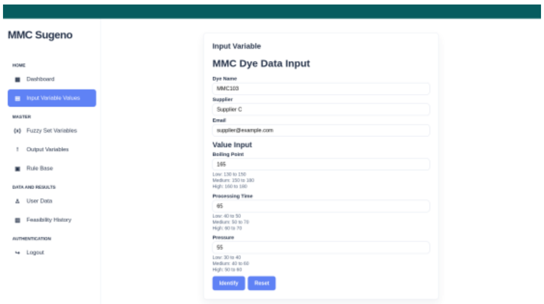

Figure 4. MMC dye input interface for boiling point, processing time, and pressure.

Figure 5. Fuzzy set variable management interface.

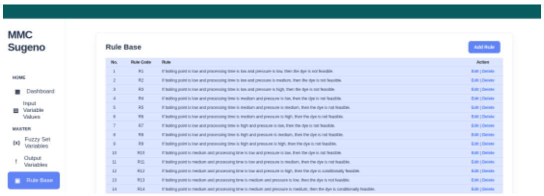

Figure 6. Rule base management interface.

Figure 7. Fuzzy Sugeno result interface for MMC103.

The interface facilitates the decision-making process in a straightforward manner. The production manager initially logs in, accesses the input page, inputs the dye information and three measured values, and subsequently executes the identification process. The knowledge base pages enable the manager to review the input ranges, output classes, and rules. The result page displays the calculation trace. The history page archives the results to allow for the review of prior dye decisions at a later time.

4.6. System Functional Testing

The black box testing presented in table 13 demonstrates that the application supports the anticipated user flow. The findings do not assert statistical validity, as the study did not utilize an extensive historical dataset. The evaluation confirms that the system accurately implements the expert rules and presents the calculations in a manner accessible for inspection by the production manager.

Table 13. Black box test summary

No.	Function	Expected behavior	Result
1	Sign in	Registered user can access the application	Valid
2	Input fuzzy variable ranges	User can review and maintain boiling point, processing time, and pressure ranges	Valid
3	Output classes	User can review not feasible, conditionally feasible, and feasible classes	Valid
4	Rule base	User can review and maintain 27 Sugeno rules	Valid
5	Dye sample input	User can enter dye name, supplier, email, boiling point, processing time, and pressure	Valid
6	Sugeno calculation	System displays membership values, active rules, score, and class	Valid
7	Feasibility history	System stores and displays previous results	Valid
8	User privacy in manuscript figures	User records in the interface figure are masked with ****	Valid

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4.7. Discussion

The results show that the revised Sugeno model can produce all three feasibility classes across varied combinations of boiling point, processing time, and injection pressure. The rule base is deliberately conservative. Low boiling point conditions produce not feasible outcomes in all nine related rules, which prevents favorable time or pressure values from fully compensating for weak thermal tolerance. The historical profile analysis also demonstrates why a fuzzy model can provide more information than a crisp rule lookup. Profiles such as MMC103, MMC112, MMC117, and MMC123 activate several rules because their measurements belong partly to more than one linguistic state. Sugeno inference retains these partial conditions in the weighted score. The crisp baseline discards this information, which explains its lower agreement with the Sugeno classifications.

Sensitivity analysis provides a separate view of robustness. MMC103 remained feasible under all tested breakpoint perturbations, but MMC123 was less stable because its score was close to the boundary between conditionally feasible and feasible. The model should therefore present the numeric score and active rule trace rather than only the class label. A profile close to 15 or 25 should receive additional expert attention. The current study does not yet establish overall predictive accuracy because 20 profiles lack independent reference outcomes. It also does not evaluate production defects, color stability, batch consistency, or long-term acceptance. Method agreement cannot replace validation against independent expert consensus or documented production outcomes. The web implementation similarly requires measured performance, usability, and security evidence before it can be described as ready for production deployment [32], [33], [34].

5. Conclusion

This study developed an explainable zero order Sugeno expert system for MMC dye feasibility assessment using boiling point, processing time, and injection pressure. The revised model defines complete membership partitions, a 27-rule knowledge base, singleton consequents of 10, 20, and 30, and midpoint decision boundaries at 15 and 25. When applied to 23 historical process profiles, the model produced 10 not feasible, 8 conditionally feasible, and 5 feasible classifications. MMC103 produced a score of 26.67 and remained feasible under all plus or minus 5 percent sensitivity scenarios. Across all profiles, class stability was 98.86 percent. Sugeno agreed with Mamdani on 86.96 percent of profiles and with a crisp rule baseline on 78.26 percent. These results support the internal consistency and interpretability of the model within the evaluated ranges, but they do not yet establish overall predictive accuracy because independent reference decisions are complete for only three profiles. The web application demonstrates the intended inference and record keeping functions, but quantitative performance, usability, and security verification are still required. The proposed system should therefore be treated as a transparent decision support prototype rather than a replacement for physical testing or expert responsibility. Although the present study evaluates 23 historical samples, further external validation using additional production batches, other manufacturing facilities, and long-term quality outcomes remains necessary.

6. Declarations

6.1. Author Contributions

Conceptualization: J.W., S.F.W., S.A.S., and F.K.; Methodology: J.W., S.A.S., A.A.K., and N.S.; Software: J.W., S.A.S., N.S.; Validation: J.W., S.F.W., and H.B.; Formal Analysis: J.W., S.A.S., and F.K.; Investigation: S.F.W., and A.A.K.; Resources: J.W.; Data Curation: J.W., S.A.S.; Writing Original Draft Preparation: J.W., and F.K.; Writing Review and Editing: J.W., S.F.W., and H.B.; Visualization: J.W., and N.S.; All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data from this study are available upon request from the corresponding author.

6.3. Funding

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6.4. Institutional Review Board Statement

Ethical Clearance: 0129-RD-LPPM/UMN/I/2023

6.5. Informed Consent Statement

Informed consent was obtained from all participants in the study. Before data collection, the research team explained the purpose of the study and data confidentiality. A consent statement is considered valid as a form of informed consent because all participants approved the process consciously and voluntarily.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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