

Original Article

Damage Risk Assessment of Lightweight Steel Roof Trusses using a Mamdani Fuzzy Inference System

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Abstract - Assessing the damage risk of Lightweight Steel Roof Trusses (LSRT) is essential for disaster prevention and structural safety, especially given their vulnerability to structural and degradation factors. This study aims to develop a Mamdani Fuzzy Inference System (FIS) model for assessing the damage risk of LSRT amidst the uncertainties and nonlinearity intrinsic to the system. The methodology involves establishing fuzzy variables, such as technical structural factors, loading conditions, and degradation states, as well as developing membership functions and linguistic rules. It uses the Min implication, Max aggregation, and Centroid defuzzification for inferring a measurable level of risk. The experimental results show that the FIS model performance demonstrates high efficacy, with a sensitivity and precision of 90.00% each and an overall accuracy of 88.57%. The FIS model has a Mean Absolute Percentage Error (MAPE) of 15.13%, a Root Mean Square Error (RMSE) of 8.92, and a Relative RMSE of 16.42%. The MAPE presents "good" predictive performance, and the Relative RMSE is in a "sufficient" range. These results demonstrate that the FIS model serves as a highly effective initial screening tool for identifying truss risk levels, especially for civil engineers. However, it may need to be improved for high-precision mitigation strategies.

Keywords - Damage risk assessment, Lightweight Steel Roof Trusses, Mamdani Fuzzy Inference System, Predictive accuracy metrics, Uncertainty Modeling.

1. Introduction

The present era of civil engineering construction across the world market is witnessing a substantial increase in the adoption of cold-formed steel, often referred to as light steel, especially for roof trusses. Lightweight Steel Roof Truss (LSRT) has become widely used for homes, industries, and factories as the main roof structure in Indonesia. Most property developers and self-builders are adopting these systems in their new buildings. At present, homeowners associate steel with 'modern' and 'clean' material when compared to wood [1].

The fast development of LSRT is determined by a reasonable approach with regard to performance benefits (e.g., high structural resistance-to-weight ratios, economy, and time saving due to pre-fabrication) [2]. LSRT facilitates significantly reduced construction timelines. Research indicates that lightweight steel has been shown to accelerate construction periods by up to 47% and reduce cost by 13.5% as compared with conventional timber [3]. Moreover, these systems possess an enormous potential from the environmental perspective since they present a low carbon footprint and a high recycling possibility, which is in line with

current sustainability criteria [4, 5]. This trend is in line with global practice in countries like New Zealand, where the absence of conventional timber supply has accelerated migration to light steel framing [6].

Given the attractive and promising techno-economic advantages and the rapid application of LSRT in tropical countries like Indonesia, its adoption is often evidenced by an alarming structural failure rate. LSRT structures have a 20%-30% higher failure rate during extreme wind events compared to timber structures. Although LSRT is still 25-35% cheaper than superior-quality timber, the limited availability of "Class 1" timbers has caused a massive shift to steel systems in areas where the labor force does not have formal specialized training [7]. Such market pressure, combined with the 40% deviation in terms of engineering requirements for residential projects, particularly with respect to missing lateral bracing, has an increased potential for LSRT failures [8]. Such systemic failures usually occur in the form of catastrophic buckling and high flexural deformations rather than local failures of members [9, 10]. Thus, the difference between theoretical analysis and on-site construction underscores the need for more advanced evaluation means in terms of structural damage reliability.



The failure of LSRT systems is a result of the complex interactions between structural vulnerability and degradation factors, which destabilize the assembled structure. Structural vulnerability is due to inadequate steel thickness, disproportionately large spans, and connection defects, particularly the self-drilling screws from which the required quantity was not applied, causing joint failure when subjected to risky loads [11]. In addition, the systems often fail due to roof tile overloads not meeting the design and having no intrinsic capacity for extreme wind and seismic loads [12-14]. These mechanical issues are worsened by degradation factors, including the insidious process of corrosion at drill-hole interfaces [15], increased precipitation load as a result of climate change, and insufficient site supervision and human resources [16]. Therefore, developing a well-founded methodology for the assessment of structural damage risk in these complex failure pathways is substantial. Such a study would enhance public confidence in current structural safety and mitigate economic impacts.

At present, the risk evaluation of structural damage like LSRT still relies heavily on visual inspection and subjective qualitative assessment. This dependence on the inspector's subjective experience and technical training causes high uncertainty and less structured results [17]. Numerous inspection reports in the field are condemned for being too pessimistic or based on vague assumptions, where there is a propensity for premature intervention and misjudgment of dangerous structural risk [18]. The challenge of assessing structural damage risk is in the handling of multivariate uncertainties, which comprise technical factors together with non-technical aspects, such as material properties, geometric features, and loading conditions, which could increase the probability of structural failure by over 30% [19, 20].

According to Hazır and Ulusoy [21], additional potential causes of uncertainty are currently being neglected in project management models, which mostly center on the unpredictable, dangerous structural risk. On the other hand, traditional structural analysis actions are basically deterministic when practicing fixed load and resistance factors [22]. Often, the stochastic nature of environmental loads as well as the effect of human error during construction are not captured by these models and can instead be modeled with some single deterministic value [23, 24]. This means that there is still a lack of research on LSRT-specific thorough multivariate uncertainties and consideration of human and organizational aspects in risk assessments.

Analysis of multivariate uncertainties and consideration of human and organizational aspects can be accomplished by new soft computing algorithms. Currently, there are several studies that use fuzzy systems for risk assessment purposes, such as fuzzy inference systems with various approaches [25-27], Fuzzy Multi-Attribute Decision Making (FMADM) [28], and Adaptive Neuro Fuzzy Inference System (ANFIS) [29],

[30]. Their use in the full risk assessment of LSRT is still underresearched, and also, integrated models tailored to Indonesia's tropical climate remain scarce. At present, the use of soft computing algorithms like fuzzy membership using Fuzzy Inference Systems (FIS) models is proven to be able to manage imprecise, subjective, and interacting variables in several engineering applications [31]. Therefore, the FIS approach is a potential tool for evaluation over various multivariable interactions like LSRT damage risk, which have not yet been developed.

The use of the FIS model in the assessment of damage risk in recent complex and multivariable structural engineering problems reveals that the Mamdani FIS has inherently proved with greater success than those using Sugeno and Tsukamoto techniques [32]. The Mamdani FIS is often preferred for its high interpretability as well as the ability to utilize qualitative human expertise through human-centric logic.

Unlike Sugeno's system, which is based on constants (or linear functions), or the monotonicity characteristic of Tsukamoto, which uses linear outputs, Mamdani uses a fuzzy rule base (fuzzy sets for input and output) so that the analysis can express more diverse non-linear membership functions concerning the "gray areas" of degradation in structures. Also, due to the native transparency of regulations in the Mamdani approach, civil engineers are able to manually audit "IF-THEN" rules through natural language, which is indispensable for safety in a regulated sector, where there is no room for error, and will need decades of historical data to understand diverse phenomena as an accurate risk-mitigating strategy.

Based on the above explanation, the aim of this research is to address the existing gaps in structural safety by formulating a Mamdani FIS model for assessing damage risk in LSRT under multiparameter uncertainties. The study responds to the need to move away from deterministic approaches that do not consider complex non-linear interactions among structural variables and to the absence of comprehensive models facilitating expedited field-based assessments.

This study uses FIS to accommodate the uncertainty that was a major finding in previous research [17-20]. Far from detection, the system becomes an essential mitigation mechanism during pre-installation and forensic damage investigations, ensuring safety remains a focus throughout the building's life. This paper has two major contributions: first, it introduces a risk detection system with very high accuracy that can predict potential failures in advance, and second, it provides the underlying decision-making framework suitable for incorporation in software tools to enable field technicians to replace subjective judgements with objective, evidence-based evaluations.

2. Methods

The present study is employing mixed methods of research, utilizing both qualitative and quantitative methods to converge conceptual structural understanding and numerical verification. By combining these methods, this research greatly improves the precision and reliability of risk assessment [33] and assists decision makers in making better decisions regarding structural safety, especially when facing the uncertainty embedded in field inspections [17].

A systematic review of literature and the Indonesian standard SNI ('Standar Nasional Indonesia') [34] was the first step in the qualitative research process. To augment this stage, ten purposeful professionals with expertise in the LSRT building industry were surveyed using semi-structured interviews. Through this approach, the most significant variables that controlled structural failure and damage were defined as a conceptual foundation. Then, ten experts who were part of the interview participated in a Focus Group Discussion (FGD) to confirm these variables. Following a comprehensive evaluation of the variables and putting up extensive feedback, they came up with the "IF-THEN" rule base by their invaluable skills that govern the Mamdani FIS model.

The following step employed quantitative methods based on field inquiry and measurement, which attempted to confirm the FIS model's accuracy. There were thirty-five LSRT cases across Java Island in Indonesia that were collected throughout six months of investigation. These cases were both collapsed and non-collapsed structures to allow for a variety of data from real-world damage percentages as a test set. The computational basis of the research was based on general FISs' inference flow, which was performed in MATLAB software to facilitate complex, computationally intensive stages.

The detailed proposed approaches are systematically constituted of seven consecutive stages, ranging from the classification of variables to comprehensive performance testing, as follows:

2.1. Stage 1: Identification of Fuzzy Variables

By means of fuzzy reasoning, variables were determined and classified into two primary effects on damage risks: factors related to structural vulnerability and degradation factors. The structural factors were categorized into (1) technical aspects, such as thinness of steel, span length, and connection type, and (2) load aspects due to other factors like wind and roof loads. Degradation factors included environmental and human elements; these were corrosion resistance, rainfall intensity, and human resources competency.

The identified factors were the input variables of the FIS, and the level of damage risk constituted the output. These

variables were assigned specific units and appropriate limits, which are derived from references in the Indonesian SNI standard and expert judgment. For instance, the thickness of the lightweight steel varies between 0.6 mm and 1 mm, and the wind load condition is limited to the range of 150 km/hr. These fuzzy variables are in Table 1.

Table 1. Fuzzy variables

Factors	Fuzzy Variables	Unit	Lower limit	Upper limit
Structural vulnerabilities	Thickness of lightweight steel	mm	0.6	1
	Span length	m	6	16
	Connection type	-	0	10
	Roof load	kg/m ²	1	50
	Wind load	km/h	0	150
Degradation	Corrosion resistance	g/m ²	70	150
	Intensity of rain	mm/h	1	20
	Human resource competencies	-	0	10

2.2. Stage 2: Fuzzy Set and Membership Function Determination

After determining the fuzzy variables, Stage 2 governed fuzzy sets and membership functions for each variable. This research utilized a trapezoidal membership function as shown in Figure 1, with four parameters, such as a (minimum value), b, c, and d (maximum value). This function was chosen, as it is fair for each element in the given domain to be considered equally throughout its span of membership values. The membership function is represented by Equation (1).

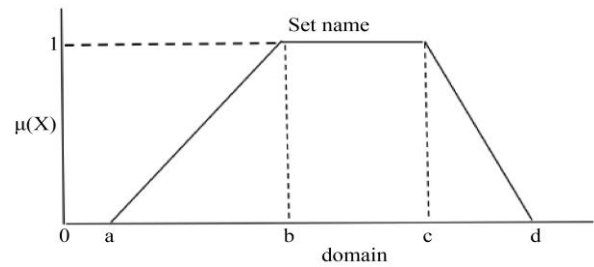


Fig. 1 Trapezoidal function

$$\mu_A[x] = \begin{cases} 0; & x \leq a \text{ or } x \geq d \\ \frac{x-a}{b-a}; & a \leq x \leq b \\ 1; & b \leq x \leq c \\ \frac{d-x}{d-c}; & x \geq d \end{cases} \quad (1)$$

2.3. Stage 3: Knowledge Base Generation

Stage 3 involved generating knowledge bases, being the FIS structure for rule development. Two different FIS models

were first designed: one for structural vulnerability factors and the other for degradation factors. The structural risk model takes information about the technical and load elements as inputs, whereas the degradation model consists of corrosion resistance, intensity of rain, and human competent input; both are thematically synthesized to obtain an overall damage risk.

The rule base was a set of "IF-THEN" rules derived from the expert FGD. These rules characterized the logical relationship between input features and the resulting risk levels. Since such rules were based on expert professional experience, they assisted in the reduction of uncertainties found in standard deterministic evaluations. The picture of the FIS used for rules development is displayed in Figure 2.

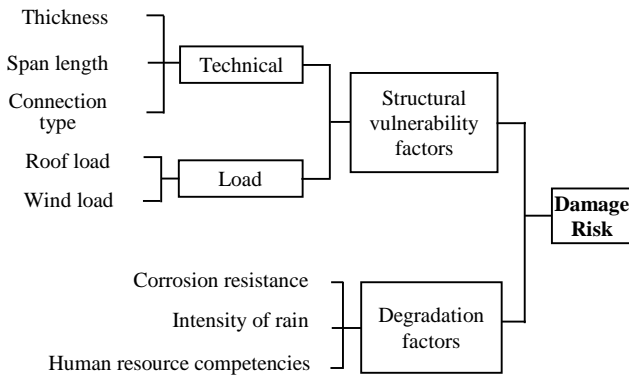


Fig. 2 FIS structure for rule development

2.4. Stage 4: Application of the Implication Function

The fourth stage comprised fuzzy set operations and the implication function to determine membership values. The "and" operator, which represents the intersection of the sets, was used in this method to determine the "fire strength" (α) of each rule. To assess these rules, Mamdani FIS employed the "min" function. To determine the fire strength, this applied the "and" operator as shown in Equation (2).

$$\alpha_k = \min(\mu_{A1}(x_1), \mu_{A2}(x_2), \dots, \mu_{An}(x_n)) \quad (2)$$

Where α_k is the fire strength of the k-rule, $\mu_A(x_i)$ is the value of x_i 's membership in the A set, and n is the number of input variables in the k-th rule.

In order to assess the membership value of the k-th rule, the "min" function was utilized, employing the Mamdani FIS. The formula is in Equation (3).

$$\mu_{Bk}(z) = \min(\alpha_k, \mu_B^{(k)}(z)) \quad (3)$$

Where $\mu_{Bk}(z)$ is the membership value of z in the output set B in the k-th rule, and $\mu_B^{(k)}(z)$ is the consequent membership function of the k-th rule.

2.5. Stage 5: Aggregation of Fuzzy Rules

Stage 5 encompassed the aggregation of these fuzzy rules using the maximum function, as given in Equation (4). This process sequentially combined the results of the rules to create a single fuzzy output distribution. The aggregation started with the second rule and continued until the final rule in the set was processed.

$$\mu_B(z) = \max(\mu_{B1}(z_1), \mu_{B2}(z_2), \dots, \mu_{Bm}(z_m)) \quad (4)$$

2.6. Stage 6: Defuzzification

The defuzzification process was described in Stage 6, where the results of the fuzzy inference were transformed into crisp numerical values. In this investigation, the Centroid (or "center of gravity") approach was utilized. This approach was definitely selected because it was able to capture the complete distribution of the output membership degrees and produce more balanced and stable risk measure values. Equation (5) shows the formula for this Centroid calculation.

$$z^* = \frac{\int z\mu(z)dz}{\int \mu(z)dz} \quad (5)$$

Where z^* is the crisp output, z is the output variable, and $\mu(z)$ is the fuzzy output's membership value at z

2.7. Stage 7: Performance Testing

The last stage, Stage 7, was a detailed experimental comparison to assess the effectiveness of the FIS model. The thirty-five cases collected across Java Island in Indonesia were the data collected for this numerical and categorical testing. Quantitative testing consists of comparing the real-world damage percentages with the risk levels estimated by the FIS model.

The indicators of numerical outputs' accuracy were determined by Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE), encompassing Relative RMSE. These indicators are calculated using the following Equations (6)-(8) [35].

$$MAPE = \frac{100\%}{N} \left(\sum_{i=1}^N \left(\frac{y_i - z_i}{y_i} \right) \right) \quad (6)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (y_i - z_i)^2}{N}} \quad (7)$$

$$RMSE_{Rel} = \left(\frac{RMSE}{\text{mean}(y)} \right) 100\% \quad (8)$$

Where N =number of cases, y_i =true condition, and z_i =FIS model output

The analysis of the indicators was performed using two methods, numerical testing and categorical testing, to give a statistical measure of how well the fuzzy model fits the observed field data. Numerical testing was conducted by

comparing the damage percentages in real cases with the risk levels as output from the FIS model. Categorical testing was conducted by comparing the damage categories (collapse vs. non-collapse) from real cases with the converted FIS model output. Since the FIS output was a percentage, a threshold of 50% was applied: Risk values below 50% were categorized as “Not Collapse,” while values of 50% or higher were categorized as “Collapse.”

Finally, the model performance was summarized using a confusion matrix that tracked with the true-false condition: “True Positive,” “True Negative,” “False Positive,” and “False Negative.” A positive condition indicated a roof collapse, and a negative condition indicated a roof non-collapse. Figure 3 shows the confusion matrix.

	FIS Collapse	FIS Not Collapse
Facts Collapse	True Positive (TP)	False Negative (FN)
Facts Not Collapse	False Positive (FP)	True Negative (TN)

Fig. 3 Confusion matrix

From this matrix in Figure 3, five key indicators were calculated to determine the model’s reliability: Sensitivity, Specificity, Precision, F1 score, and overall Accuracy, as shown in Equations (9)-(13) [36-38].

$$Sensitivity = \frac{TP}{TP + FN} \times 100\% \tag{9}$$

$$Specificity = \frac{TN}{TN + FP} \times 100\% \tag{10}$$

$$Precision = \frac{TP}{TP + FP} \times 100\% \tag{11}$$

$$F1\ score = 2 \left(\frac{(precision)(sensitivity)}{precision + sensitivity} \right) \tag{12}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100\% \tag{13}$$

3. Results

3.1. FIS Modeling

The first stage of the Mamdani FIS modeling was to determine the appropriate fuzzy variables. Based on the factor identification results (Table 1), a separate fuzzy set was defined for each variable using trapezoidal membership functions, as shown in Equation (1). The particular setting for these sets, including the input parameters in Table 2 and output data in Table 3, describes the four sensitive parameters (a, b, c, and d) explaining each of the functions. Practical validity justified by experts was carried out in an FGD to maintain logic consistency while concurrently matching the variable setting of the fuzzy sets to the Indonesian SNI Standard.

Table 2. Fuzzy variables for input

Factors	Variables	Set	Parameters			
			a	b	c	d
Structural vulnerability (Technical)	Thickness of lightweight steel	Thin	0.00	0.00	0.60	0.75
		Medium	0.65	0.75	0.75	0.85
		Thick	0.75	1.00	1.20	1.20
	Span length	Short	0	0	6	9
		Medium	7	9	9	11
		Long	9	12	16	16
	Connection type	Weak	0	0	3	5
		Medium	3	5	5	7
		Strong	5	7	10	10
Structural vulnerability (Load)	Roof load	Light	1	1	5	25
		Medium	5	25	25	45
		Weight	25	45	50	50
	Wind load	Low	0	0	25	75
		Medium	25	75	75	125
		High	75	125	150	150
Degradation	Corrosion resistance	Low	50	50	70	100
		Medium	70	100	100	130
		High	100	130	170	170
	Intensity of rain	Light	0	0	2	10
		Medium	2	10	10	18
		High	10	18	20	20
	Human resource competencies	Low	0	0	3	5
		Medium	3	5	5	7
		High	5	7	10	10

After defining the fuzzy sets, the “IF-THEN” rules were generated from a knowledge base comprising five different functional groups. These groups managed the determination of (1) Technical factor values, (2) Load factor values, (3) Structural factor values, (4) Degradation factor values, and (5) the final damage risk levels. For the technical and load parameters used in this study, there were twenty-four rules to obtain technical factor outputs (Table 4), combined with eight rules dedicated only to the load factor outputs (Table 5). This rule-based model guaranteed a systematic transition from linguistic variables to effective assessments of risk.

Table 3. Fuzzy variables for output

Variables	Set	Parameters			
		a	b	c	d
Technical, Load, Degradation	Low	0	0	0.3	0.5
	Medium	0.3	0.5	0.5	0.7
	High	0.5	0.7	1	1
Risk	Very low	0	0	10	30
	Low	10	30	30	50
	Medium	30	50	50	70
	High	50	70	70	90
	Very high	70	90	100	100

Table 4. Rule basis for technical factors

No.	Input			Output
	Thickness	Span length	Connection type	Technical Factors
1.	Thin	Short	Strong	Medium
2.	Thick	Medium	Low	Low
3.	Thick	Short	Strong	Strong
4.	Thick	Long	Strong	Strong
5.	Medium	Short	Medium	Strong
6.	Thin	Medium	Medium	Low
7.	Thin	Short	Medium	Medium
8.	Thick	Medium	Medium	Medium
9.	Medium	Short	Low	Medium
10.	Medium	Short	Strong	Strong
11.	Thick	Short	Low	Medium
12.	Thick	Short	Medium	Strong
13.	Thin	-	Low	Low
14.	Thin	Medium	Strong	Medium
15.	Medium	Medium	Low	Medium
16.	Medium	Medium	Strong	Strong
17.	Thick	Medium	Strong	Strong
18.	Thin	Long	Medium	Low
19.	Thin	Long	Strong	Medium
20.	Medium	Long	Low	Low
21.	Medium	-	Medium	Medium
22.	Medium	Long	Strong	Medium
23.	Thick	Long	Low	Low
24.	Thick	Long	Medium	Medium

Table 5. Rule basis for load factor outputs

No.	Input		Output
	Roof Load	Wind Load	Load Factors
1.	Light	High	High
2.	Light	Low	Low
3.	Weight	-	Low
4.	Medium	Medium	Medium
5.	Light	Medium	Medium
6.	Weight	Medium	Low
7.	Medium	High	High
8.	Medium	Low	Low

Combining both technical and load factors altogether, the study obtained 7 rules of structural factor outputs (Table 6). Similarly, as before, the outputs of the degradation factor were produced via a 24-rule overall rule base (Table 7). Nine rules for both structural and degradation factors were used to generate the damage risk outputs (Table 8). These rules have been implemented in the FIS model and then validated by comparison with 35 cases of evaluation. These cases comprised LSRT structures collected across Java Island in Indonesia, with true conditions of fifteen non-collapse and twenty collapse structures, all experiencing strong wind, earthquakes, or hard rain.

Table 6. Rule basis for structural factor outputs

No.	Input		Output
	Technical Factors	Load Factors	Structural Factors
1.	Low	High	Medium
2.	Low	Low	Low
3.	Strong	-	High
4.	Medium	High	High
5.	Medium	Medium	Medium
6.	Medium	Low	Medium
7.	Low	Medium	Medium

Table 7. Rule basis for degradation factor outputs

No.	Input			Output
	Corrosion resistance	Intensity of rain	Human resource competencies	Degradation Factors
1.	Low	High	Low	High
2.	Low	Light	Low	Medium
3.	High	High	High	Low
4.	High	Light	High	Low
5.	-	Medium	Medium	Medium
6.	Medium	High	Low	High
7.	Low	Light	Medium	Medium
8.	Low	Light	High	Low
9.	Medium	Light	Low	Low
10.	Medium	Light	Medium	Medium
11.	Medium	Light	High	Low
12.	High	Light	Low	Medium
13.	High	Light	High	Low

14.	Low	Medium	Low	High
15.	Low	Medium	High	Low
16.	Medium	Medium	-	Medium
17.	High	Medium	Low	Medium
18.	High	Medium	High	Low
19.	Low	High	Medium	High
20.	Low	High	High	High
21.	Medium	High	Medium	High
22.	Medium	High	High	Medium
23.	High	High	Low	Medium
24.	High	High	Medium	Medium

In general, the process of FIS modeling began with the fuzzification of the inputs through membership values computation in Equation (1). Subsequently, the fire strength for each rule was computed by means of Equation (2), and then the fuzzy output membership values were derived using Equation (3). After fuzzy output composition was performed as given by Equation (4), the damage risk levels obtained were processed through a defuzzification operation using the Centroid method of defuzzification on Equation (5). These findings are presented as percentages in Table 9.

Table 8. Rule basis for risk damage

No.	Input		Output
	Structural Factors	Degradation Factors	Damage Risk
1.	Low	High	Very Low
2.	High	Low	Very High
3.	Low	Low	High
4.	High	Medium	Low
5.	Medium	Medium	Medium
6.	Low	Medium	High
7.	Medium	High	High
8.	Medium	Low	Low
9.	High	High	High

3.2. Performance Testing

The model’s performance was tested on numerical and categorical assessments by comparing the “True Condition” versus the "FIS Model Outputs," as shown in Table 10. To make possible the categorical classification, the numerical outputs of FIS were transformed into “collapse” or “non-collapse” by a defined threshold of $\theta = 50\%$. This binary simplification enabled a direct comparison of predicted risk with observed structural appearance.

Table 9. Fuzzy inference system modeling results based on thirty-five evaluation cases

# Cases	Input								Output FIS
	Light steel thickness (mm)	Span distance (m)	Types of connections	Roof load (kg/m ²)	Wind load (km/hr)	Corrosion (gr/m ²)	Int. rain (mm/h)	HR Competencies	(z) (%)
1	1.00	10	2	37.5	75	100	18	5	56.55
2	0.75	6	4	37.5	120	100	20	5	62.12
3	1.00	6	3	1.6	10	100	0	5	49.48
4	1.00	10	7	40	10	100	0	8	45.21
5	1.00	10	7	37.5	10	100	0	7	48.78
6	1.00	8	8	1.6	150	100	20	5	58.3
7	0.75	8	5	40	10	100	20	5	64.8
8	1.00	10	3	40	20	70	20	5	59.8
9	1.00	12	5	37.5	10	100	20	5	65.7
10	0.75	8	5	37.5	10	70	20	5	64.8
11	0.75	8	3	1.6	150	100	20	5	58.6
12	0.75	8	5	37.5	10	100	20	5	64.8
13	1.00	10	3	45	10	100	10	5	52.7
14	0.75	10	3	37.5	15	70	16	5	60.1
15	0.70	10	5	37.5	10	100	20	5	66.5
16	0.75	7	7	37.5	10	100	10	6	47.34
17	0.85	10	8	40	10	100	0	8	45.7
18	0.7	10	7	37.5	10	90	10	7	47.5
19	0.75	8	6	37.5	10	70	0	8	39.88
20	0.75	7	7	37.5	10	100	10	6	47.34
21	1.00	10	8	37.5	15	100	10	7	44.5
22	0.75	8	5	1.6	10	90	0	0	41.38
23	1.00	11	6	37.5	15	70	15	6	54.1
24	0.75	8	6	37.5	17	60	10	8	42.25
25	0.75	6	4	37.5	120	100	20	5	62.12

26	0.85	10	8	40	10	100	10	8	44.9
27	1.00	10	7	40	10	100	0	8	45.21
28	1.00	10	5	37.5	15	100	0	8	40.42
29	0.75	10	5	37.5	10	90	0	7	44.19
30	0.75	8	5	37.5	10	70	20	5	64.75
31	0.75	8	3	1.6	150	100	20	5	58.53
32	0.75	8	5	40	10	100	20	5	64.76
33	1.00	10	2	37.5	150	100	18	5	61.11
34	0.75	8	3	1.6	150	100	20	5	58.53
35	1.00	10	2	37.5	150	75	18	5	60.77

Table 10. Numerical and categorical performance test results

#Cases	True Condition		FIS Model Outputs		y _i - z _i (%)	Comparison Status
	y _i (%)	Category	z _i (%)	Category		
1	60	collapse	56.55	collapse	3.45	correct
2	75	collapse	62.12	collapse	12.88	correct
3	65	collapse	49.48	not collapse	15.52	incorrect
4	30	not collapse	45.21	not collapse	15.21	correct
5	35	not collapse	48.78	not collapse	13.78	correct
6	35	not collapse	58.3	collapse	23.30	incorrect
7	70	collapse	64.8	collapse	5.20	correct
8	70	collapse	59.8	collapse	10.20	correct
9	75	collapse	65.7	collapse	9.30	correct
10	70	collapse	64.8	collapse	5.20	correct
11	60	collapse	58.6	collapse	1.40	correct
12	75	collapse	64.8	collapse	10.20	correct
13	65	collapse	52.7	collapse	12.30	correct
14	70	collapse	60.1	collapse	9.90	correct
15	75	collapse	66.5	collapse	8.50	correct
16	55	collapse	47.34	not collapse	7.66	incorrect
17	40	not collapse	45.7	not collapse	5.70	correct
18	45	not collapse	47.5	not collapse	2.50	correct
19	30	not collapse	39.88	not collapse	9.88	correct
20	35	not collapse	47.34	not collapse	12.34	correct
21	40	not collapse	44.5	not collapse	4.50	correct
22	37	not collapse	41.38	not collapse	4.38	correct
23	40	not collapse	54.1	collapse	14.10	incorrect
24	35	not collapse	42.25	not collapse	7.25	correct
25	65	collapse	62.12	collapse	2.88	correct
26	40	not collapse	44.9	not collapse	4.90	correct
27	45	not collapse	45.21	not collapse	0.21	correct
28	40	not collapse	40.42	not collapse	0.42	correct
29	45	not collapse	44.19	not collapse	0.81	correct
30	70	collapse	64.75	collapse	5.25	correct
31	60	collapse	58.53	collapse	1.47	correct
32	70	collapse	64.76	collapse	5.24	correct
33	60	collapse	61.11	collapse	1.11	correct
34	60	collapse	58.53	collapse	1.47	correct
35	60	collapse	60.77	collapse	0.77	correct

Table 10 presents a comparison of FIS model predictions to observed structural states in the real world. The categorical status of “collapse” or “non-collapse” according to $\theta = 50\%$ threshold was obtained within the FIS model. In contrast, real-world states observed were investigated directly in the field of damaged areas promptly after extreme wind, earthquake, or hard rain occurred. The numerical performance of the model was evaluated by Equations (6)-(8). These provide an MAPE of 15.13%, an RMSE of 8.92, and an $RMSE_{Rel}$ of 16.42%. The FIS model yields favorable results with MAPE lower than 20% and $RMSE_{Rel}$ in the "sufficient" (10-20%) level. These measures indicate that the model represents a viable tool for initial damage assessment, but further refinement is needed to ensure high accuracy in terms of mitigation decision-making.

Following multiple categorical evaluations were performed to determine sensitivity, specificity, precision, and accuracy, using Equations (9)-(13). The results are a sensitivity of 90.00%, a specificity of 86.67%, a precision of 90.00%, an F1 score of 0.9, and an overall accuracy of 88.57%. The high sensitivity and F1 scores indicate an acceptable ability to detect SLRT damage. However, the specificity results suggest the necessity of further enhancement to minimize false-positive predictions and suppress false alarms. Ultimately, the FIS-based model serves as a very reliable way to identify complex truss risk profiles,

as shown by the research results. This important early-stage evaluation provides civil engineers with the information they need to make decisions. This makes structures much safer and makes better use of resources during the early stages of planning and managing the design and construction process.

3.3. Comparative Evaluation with Other Methods

For the comparison with the other evaluation method, the Centroid method of defuzzification used in this FIS was evaluated with four different methods, which are Bisector, Smallest of Maximum (SOM), Mean of Maximum (MOM), and Largest of Maximum (LOM). Also, these four methods are quite popular as defuzzification methods. The results are shown in Table 11, showing that the Centroid method performed best across all indicators. The Centroid method proved to be the best defuzzification method in this study, producing the lowest RMSE value of 8.92 and the highest classification accuracy of 88.57%. Its ability to calculate the center of gravity across the entire membership function area allows the model to generate highly refined and precise risk values compared to other methods. This superior performance is further evidenced by the F1-score of 0.90, indicating an optimal balance between damage detection sensitivity and field category prediction accuracy. Therefore, this method is the most reliable approach for use as a standard in objective safety audits of light steel structures.

Table 11. Comparison of the results of the Centroid, Bisector, SOM, MOM, and LOM methods

Metric	Defuzzification Methods				
	Centroid	Bisector	SOM	MOM	LOM
MAPE (%)	15.13%	15.45%	17.80%	16.50%	15.90%
RMSE (Absolute)	8.92	9.12	11.2	10.5	9.85
Relative RMSE (%)	16.42%	16.80%	20.60%	19.30%	18.15%
Accuracy	88.57%	85.71%	80.00%	82.86%	85.71%
Sensitivity (Recall)	90.00%	85.00%	80.00%	80.00%	85.00%
Specificity	86.67%	86.67%	80.00%	86.67%	86.67%
Precision	90.00%	89.47%	84.21%	88.89%	89.47%
F1-Score	0.90	0.87	0.82	0.84	0.87

3.4. Field Validation & Case Studies

Field validation demonstrated that the multilevel fuzzy inference system achieved very high classification accuracy in detecting actual damage risks in lightweight steel structures. The numerical prediction results consistently reflected real-world conditions at the study site, with the predicted risk level directly proportional to the actual damage level across the 35 tested cases. The use of degradation variables such as corrosion rate and rainfall intensity proved crucial in objectively reflecting the decline in structural capacity. The consistent alignment of the True Condition (VI) value with the numerical outputs strengthened the model's effectiveness as a reliable structural audit tool for identifying building vulnerability levels. The synergy between technical parameters and environmental conditions within the model

ensured a comprehensive risk assessment based on the physical facts found on-site.

The 35 evaluated case studies demonstrated clearly how the interaction between input variables determines the ultimate stability of the roof truss system under various load scenarios. Cases with long spans and extreme wind loads were still detected as having a significant risk of damage even though the materials used met the maximum thickness specifications. Conversely, case studies of buildings with minimal loads and supported by competent human resources demonstrated a consistent reduction in the risk of damage. The decision-making logic in this system proved highly sensitive to small parameter changes, enabling detailed differentiation of structural vulnerability levels in each case. The study

concluded that a hierarchical approach to data processing is highly effective for modeling the complexity of real-world structural failures based on the specific characteristics of each building.

4. Discussion

4.1. Sensitivity & Uncertainty Analysis

The numerical evaluation of the Mamdani FIS model demonstrates good conformity with acceptable engineering criteria, consistent with a prior study [35]. The Mean Absolute Percentage Error (MAPE) of 15.13% is considered the "good" forecasting category (10%-20%). This shows that the fuzzy rules are able to accurately grasp the risk factors' central tendency. Although the Relative RMSE value of 16.42% is deemed "adequate," it still indicates that this FIS model is slightly more sensitive to outlying or extreme loading conditions than normal states. This figure of the Relative RMSE is very crucial for the case of LSRT, in which nonlinear deterioration in structures may cause a rapid change of risk level. In general, these numerical evaluations validate the use of the FIS model for preliminary LSRT structural testing. They also offer a mathematically justifiable foundation to detect preliminary LSRT structure risk, which necessitates urgent professional inspection.

In the case of roof trusses, sensitivity is used to indicate how well the model can predict which truss will become hazardous. Mamdani FIS has a sensitivity of 90.00% in detecting truss damage. More specifically, the FIS model is able to identify 90% of the LSRTs that are truly damaged or high-risk. These findings correspond to the study conducted by Ashwini et al. [39] that suggested fuzzy systems are very suitable for modeling physical defects of structural members when using linguistic rules and fuzzy sets with vague information. This high sensitivity of 90.00% will make catastrophic "misses" less likely, so this represents a significant advantage for safety-critical infrastructure. However, a limitation of this approach is the frequent occurrence of overlapping byproducts of high sensitivity.

Specificity explains the FIS model's ability to correctly recognize or classify healthy or "safe" trusses. A result of 86.67% indicates that the FIS is quite effective at recognizing when a roof truss is actually fine and does not require necessary maintenance or false alarms. In this study, approximately 13% of safe trusses might have been incorrectly flagged as risky (false positives), which is relatively low for a fuzzy logic application. Previous studies, such as those by Naser and Alavi [35], emphasize that specificity is crucial in structural health monitoring to maintain the credibility of the monitoring system among stakeholders. While this result is strong, the inherent limitation of Mamdani systems, being "black boxes" of expert subjectivity, means that specificity can fluctuate significantly depending on the expert's conservative or aggressive bias during the rule-development phase. Consequently, it is

imperative to enhance the specificity of technical decision-making in order to enhance its efficacy.

Precision focuses on the "Damage Risk" alarm's reliability. Precision indicates the occurrence with which the FIS's prediction that an LSRT is at risk is accurate. A score of 90.00% indicates that there is a 90% chance that an LSRT is truly damaged when the FIS system reports it is. This accords with the findings of Akinoso et al. [36], who found that hybrid fuzzy models provide higher accuracy in estimating construction risk than traditional deterministic methods. The disadvantage is that Mamdani precision is highly dependent on the degree of change in the input variables, but the advantage is that it lessens "alarm fatigue" for engineers. For example, forecast accuracy may drastically decrease with low-resolution data [37].

The F1 score designates the harmonic mean of sensitivity and precision. In the risk analysis of LSRT, balancing between sensitivity and precision metrics is essential to prevent incorrect classification, which directly influences failure risk assessments. The analysis demonstrates that sensitivity and precision are both high (90%), but the F1 score of 0.45 is a mathematical abnormality. This type of variance typically indicates that the dataset exhibits a very imbalanced class structure. Naser and Alavi [35] state that this phenomenon frequently occurs in the literature of structural health monitoring as one of the key challenges. The main reason is that when the "minority class" is rare, average measurements might not accurately represent a system's actual usefulness. Therefore, while the model of Mamdani FIS provides appropriate transparency, this result signifies that data balancing techniques should be applied to improve rare-event recognition, as suggested by a previous study [38].

Accuracy provides a total correct prediction for the whole data of observed LSRT, combining both safe and damage rates together. With an accuracy of 88.57%, the FIS model could be useful to assess the damage risk of LSRT constructions under conditions of uncertainty, as the correct determination is made nearly 89 times out of 100. This finding confirms that inclusion of a nonlinear relationship between structural and environmental variables makes fuzzy-based system assessments often better than the usual linear models. Therefore, such findings are in line with several engineering applications [36]. However, accuracy sometimes leads to a misleading risk assessment, whether safe or unsafe in all cases; its main drawback is that it gives equal weight to false positives and false negatives. Because a missed risk (false negative) is far more expensive than a false alarm (false positive), this lack of distinction might not be in line with engineering priorities [35].

4.2. Integration with BIM/Digital Twins

The results reveal that the FIS model proves to be an excellent screening device in determining roof truss risk levels

at this early stage of construction management, during planning and design. Modulating these systematic risk responsibilities is one of the key challenges in contemporary civil engineering to guarantee that equivocal physical weaknesses are resolved well ahead of actual building. This FIS model proves to be a key factor in improving the effectiveness of resource allocation in disaster mitigation efforts by identifying high-risk components early. Overall, this data-based approach serves as an important cornerstone in the success of civil engineering interventions leading towards better sustainability and resiliency of infrastructure for disaster events through prevention and management.

Integrating the results of this fuzzy inference system with Building Information Modeling (BIM) technology, or Digital Twins, opens up significant opportunities for real-time structural health management. By integrating fuzzy output into BIM object parameters, each light steel frame component can dynamically display its health status based on input data, such as corrosion rates or additional loads in the field. This enables facility managers to visually identify critical, high-risk areas within the digital model before conducting time-consuming physical inspections. This synergy transforms static audit data into spatial information, facilitating more targeted and efficient preventive maintenance planning.

Within a digital twins framework, results from case studies covering various load and degradation scenarios can be used as a knowledge base for predicting future failures. Integrating IoT sensors that transmit real-time wind load or rainfall intensity data into a multi-level fuzzy system will enable continuous risk monitoring within the building's digital twin. When the system detects parameter changes that lead to an increased risk of damage, the digital twin can provide automated early warnings to stakeholders based on proven decision-making logic for each case. This approach ensures that structural integrity is constantly monitored in a digital ecosystem that is responsive to changing real-world environmental and operational conditions.

5. Study Limitations and Future Research Directions

Although the Mamdani FIS model shows accurate applicability for early risk assessment in 88.57%, a few intrinsic limitations exist. Based on the "sufficient" state, which resulted in the Relative RMSE of 16.42%, the FIS model is more sensitive to outliers than steady-state averages. This is extremely essential for LSRT since nonlinear degradation in SLRT can cause risk levels to change suddenly. In addition, the FIS model's specificity is inherently limited by the subjectivity of expert rule specification. The F1 score suggests a major class imbalance in the datasets, making it questionable whether state-of-the-art metrics truly capture system performance when dealing with rare damage occurrences. Finally, the model is not entirely consistent with

the priorities of safety-critical engineering, where a missed detection is significantly more critical than a false positive.

These limitations can be lightened by scaling out research on existing data balancing model improvement mechanisms, such as synthetic oversampling, developing a more prominent rare-event detection reliability of the models, and addressing the F1 score anomalies. It is also suggested that the combination of hybrid machine learning systems with fuzzy logic can decrease the effects of experts' subjectivity, which may help improve system performance against extreme outliers or harsh loading conditions. Finally, future versions of the model should address the design of cost-sensitive objective functions that exclusively penalize false negatives in order to better approximate safety-critical structural engineering standards.

6. Conclusion

Development of a Mamdani FIS for damage risk of LSRT monitoring in the presence of uncertainty shows that it works very well to monitor the health of structures, but also in uncertain ones. This makes it a very useful first step for figuring out the risk level of roof trusses for achieving a primary objective of modern civil engineering and ensuring the efficacy of technical interventions. The performance in terms of classification of the model is a sensitivity of 90.00%, a precision of 90.00%, and an accuracy of 88.57%. These large values indicate that the FIS is efficient in identifying most of the critical damage states and ensuring a fair identification of most structural risks. Furthermore, the specificity of 86.67% indicates that the system is still quite successful in detecting healthy trusses. An F1 score of 0.45, however, is a very telling sign of class imbalance or how difficult it can be to balance precision and sensitivity on this particular dataset. This suggests that the model is really good at discovering risks, but the trade-off between its true positive rate and its prediction reliability requires further adjustment to achieve optimal performance.

The performance of the model (15.13% MAPE, 8.92 RMSE, and 16.42% Relative RMSE) is within "good" to "sufficient" predictive power criteria in terms of numerical accuracy for civil engineering-based modeling. The MAPE of 15.13% (less than 20%) indicates that the FIS model is feasible to estimate the initial damage, as it can reflect the nonlinear interactions of the structural factors. As the Relative RMSE falls in the "sufficient" category (10–20%), this would imply that the model is a good framework to identify risk patterns; however, further improvement should be obtained to enable high-precision automated decision-making for mitigation. In conclusion, this Mamdani FIS presents a well-defined, expert knowledge-based model that maps raw structural data to safety-critical evaluation. This work has provided a foundational basis for hybrid monitoring systems with more sophisticated features.

Conflicts of Interest

The authors declare that the study was conducted in the absence of any personal or commercial relationships that could be considered potential conflicts of interest.

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