COMPUTATIONAL EPISTEMIC UNCERTAINTY MODELING OF SINGLE EDGE CRACKED PLATES USING THE FUZZY FINITE ELEMENT METHOD (FUZZYFEM)

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ABSTRACT

This study investigates the analysis of a two-dimensional (2D) single-edge crack plate using the Fuzzy Finite Element Method (FuzzyFEM), incorporating uncertainties inherent in engineering systems. Addressing critical engineering challenges, such as damage progression or loading effects from real-world conditions, requires consideration of uncertainty as an unavoidable factor. These uncertainties arise from incomplete data, conflicting information, and subjective interpretations, necessitating systematic approaches to mitigate material failure in engineering applications. The primary objective of this research is to evaluate the application of FuzzyFEM while accounting for epistemic uncertainties associated with single-edge crack plates. Accurately modeling these uncertainties is crucial for improving the reliability of structural assessments. To achieve this, a fuzzy system is proposed as an effective approach. Unlike conventional statistical methods, fuzzy system theory is a non-probabilistic technique well-suited for handling uncertainty when data is limited. The methodology begins with fuzzification, where crisp inputs are transformed into fuzzy values, followed by a core mapping process. At the mapping stage, a hybrid approach integrating fuzzy systems with the finite element method is employed. The extension principle method is used to numerically process fuzzy inputs, allowing for systematic uncertainty quantification. The results of this study, presented in figures and tables, demonstrate the efficiency and reliability of the proposed FuzzyFEM approach. By incorporating fuzzy logic into finite element analysis, this method provides a more comprehensive framework for addressing uncertainties in structural integrity assessments, offering valuable insights for engineering applications.

Keywords: *Epistemic Uncertainty, Stress Intensity Factor, Linear Elastic Fracture Mechanics, Fuzzy Finite Element Method (FuzzyFEM).*

1. INTRODUCTION

An uncertainty is defined as a gradual assessment of the truth content of a proposition, doubt arises as to whether the truth content may be stated with sufficient accuracy using each of the data models in all cases. Also, uncertainties are defined as the vagueness and lack of the information or data, [5]. The element of uncertainty is one of the biggest challenges in the field of engineering. In general, uncertainty can divide into three types, which are stochastic uncertainty, epistemic uncertainty and error [3]. Stochastic uncertainty is due to variations in the system. For the epistemic uncertainty, it exists as a result of incomplete information, ignorance and lack of knowledge caused by the lack of experimental data. When compare to the error, this uncertainty is the uncertainty that can be identified due to the imperfections in the modelling and simulation. For

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a several decades ago, uncertainty is modelled according to the theory of probability. Probability method is very effective in solving the problem of stochastic uncertainty, but this method is not suitable to be used to solve problem involving the lack of data. Some scholars hold that the use of non-probability methods is most appropriate to interpret the uncertainty compared to statistical approach when deal with the lack of data. The interval analysis [6] convex modelling [9] and fuzzy set theory [7] the main categories of non-probabilistic methods. Specifically, fuzzy system is a system to be precisely defined and it applied all the theories that use the basic concept of fuzzy set theory. Fuzzy set theory offers significant advantages over fuzzy probability theory by preserving the intrinsic randomness of physical variables without requiring the modeling of probability density functions [4]. The justification for fuzzy system theory lies in the complexity of real-world phenomena, which often defy precise explanation and description. As knowledge-based or rule-based systems, fuzzy models have been widely applied across various domains. A general theory of epistemic random fuzzy sets has been developed to facilitate reasoning with both fuzzy and crisp evidence, providing a unified approach to handling uncertainty in various applications.

Similarly, the Finite Element Method (FEM) has become a powerful tool for solving complex scientific and engineering problems by discretizing material structures into finite elements. In conventional FEM, system parameters such as geometry, material properties, external loads, and boundary conditions are treated as crisp values with well-defined properties. However, in practical applications, these parameters often contain vague, imprecise, and incomplete information due to inherent uncertainties in material behavior and loading conditions. By integrating fuzzy set theory with FEM, the limitations of conventional FEM in dealing with uncertainty can be addressed. The use of epistemic random fuzzy sets allows FEM to incorporate imprecise and uncertain information into the modeling process, enhancing its ability to represent real-world complexities. This integration provides a more realistic and flexible approach to engineering analysis, ensuring more reliable and robust predictions despite the presence of uncertainty in material properties and system parameters.

Fuzzy Finite Element Method approach (FuzzyFEM) is present to deal with the uncertainty and it is the merger method of fuzzy approach with the conventional Finite Element Method (FEM). In this approach, FEM serves as the foundational method, while fuzzy set theory is integrated to handle uncertainty in input parameters. By utilizing fuzzy logic, FuzzyFEM effectively maps imprecise input data to corresponding output responses, enhancing the reliability and robustness of engineering simulations under uncertain conditions. This integration provides a systematic methodology for managing uncertainties in material properties, boundary conditions, and loading scenarios, making it a valuable tool for complex engineering applications, [10]. This study contributes to the field by implementing the Fuzzy Finite Element Method (FuzzyFEM) in the analysis of structural problems under uncertainty, with a specific focus on a single-edge crack plate. The originality of this work lies in the representation of crack length and other influencing parameters as fuzzy variables, thereby illustrating the effectiveness of FuzzyFEM in addressing uncertainties within fracture mechanics.

2. PRELIMINARIES

In the following paragraphs, some of the notation, definition and preliminaries which are used further in this paper discuss in this section.

Definition 1:

A fuzzy set is a generalization of a classical set that allows the membership function to take any value in the unit interval [0,1]. A fuzzy number is convex normalized fuzzy set of the real line such that [12]:

$$\mu_A = X \to [0,1] \tag{1}$$

Definition 2:

This research used the triangular membership function to represent the fuzzy number. Define an arbitrary triangular fuzzy number as $\tilde{A} = [a_L, a_N, a_R]$. The fuzzy number $\tilde{A}$ is said to be triangular fuzzy number when the membership given by Equation (2):

$$\mu_{\tilde{A}} = \begin{cases} 0, & x \le a_L \\ \dfrac{x-a_L}{a_N-a_L}, & a_L \le x \le a_N \\ \dfrac{a_R-x}{a_R-a_N}, & a_N \le x \le a_R \\ 0, & x \ge a_R \end{cases} \quad (2)$$

This triangular fuzzy number $\tilde{A}=[a_L, a_N, a_R]$ can be transformed into interval form by using β-cut as Equation (3).

$$\tilde{A}=[a_L+(a_N-a_L)\beta, a_R-(a_R-a_N)\beta] \quad (3)$$

3. FUZZY SYSTEM THEORY

The fuzzy system theory applied all the theories that use the basic concept of fuzzy set theory. The word fuzzy is defined as blurred, imprecisely defined, confused or vague. The simple justification for fuzzy system theory is the real world is too complicated for precise explanation and description to be obtained. Therefore, fuzziness must be introduced to obtain a reasonable model and finally to explain the overall of some problem in many fields in world. This justification characterized the unique feature of fuzzy system theory and justifies the presence of fuzzy system theory as an independent branch in engineering. In general, a good engineering theory should be capable of making use of all available information or data effectively. Basically, there are three types of fuzzy system that are commonly used by many researchers which are pure fuzzy system, Takagi-Sugeno-Kang fuzzy system and finally is fuzzy system with fuzzifier and defuzzifier.

For this paper, the fuzzy system with fuzzifier and defuzzifier are applied. The basic configuration for this fuzzy system is shown in Figure 1. The fuzzifier is the process to transform the real set input into fuzzy set input whereas the defuzzifier is process to transform the fuzzy set output into real set output. An important impact of fuzzy system theory is it provides a systematic approach for transforming a knowledge base into a nonlinear mapping and this finally can be applied in many engineering problems. The main process in applied the fuzzy finite element method is known as mapping process. The term mapping here means that the logical relationship between two or more entities. In this study, the fuzzy inputs are numerically integrated based on extension principal method.

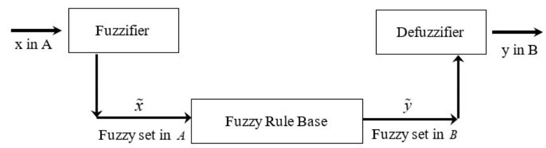

Figure 1: Basic configuration of fuzzy system with fuzzifier and defuzzifier

4. FUZZY FINITE ELEMENT METHOD (FuzzyFEM)

The Fuzzy Finite Element Method (FuzzyFEM) integrates fuzzy logic with the conventional Finite Element Method (FEM) to effectively address uncertainties in engineering analysis. As depicted in Figures 2 and 3, this methodology consists of four key stages: fuzzification, mapping, β-cut level processing, and defuzzification. The process begins with fuzzification, where crisp input values are transformed into fuzzy representations to account for uncertainties in material properties, geometry, boundary conditions, and loading [11]. To model these uncertainties, triangular fuzzy numbers are employed to define fuzzy membership functions.

The mapping stage applies fuzzy inputs to the FEM model using the β-cut method, with the vertex method commonly utilized to implement the extension principle. This approach integrates interval arithmetic with β- cut method, enabling the transformation of multiple fuzzy inputs into fuzzy outputs through binary combinations of input parameters. By systematically incorporating fuzzy logic into FEM, FuzzyFEM offers a robust framework for uncertainty quantification in complex engineering problems, enhancing the accuracy and reliability of computational analyses.

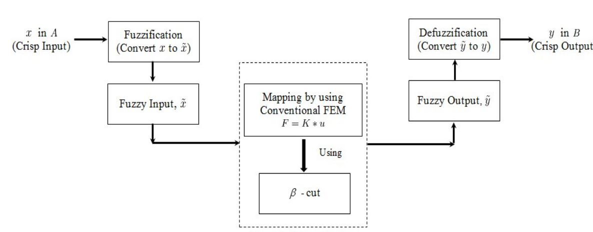

Figure 2: FuzzyFEM Flowchart

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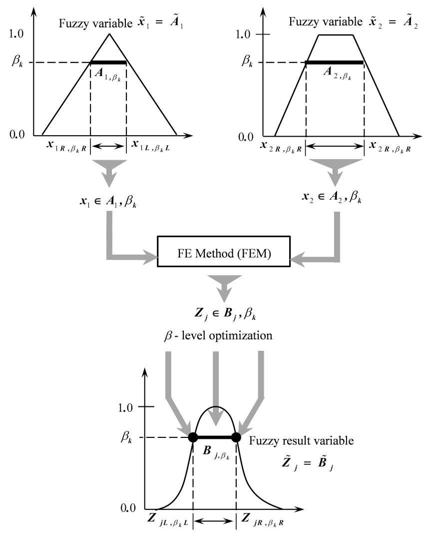

Figure 3: Fuzzy structural analysis with FEM as a mapping model, numerical solution by β-level method

In the FuzzyFEM framework, the final stage entails the defuzzification process, which converts fuzzy outputs into precise numerical values. This study employs the center of gravity (COG) method, a widely accepted technique that determines the centroid of the membership function to derive a representative crisp output. Various defuzzification approaches exist, including the center of area, mean of maximum, and fuzzy clustering methods; however, the COG method is preferred due to its effectiveness in handling uncertainty and its ability to provide a balanced and well-defined output. Following the fuzzy mapping process, new probability distributions for the fuzzy outputs are generated, ensuring a structured transformation of the uncertain parameters.

Defuzzification is an essential step in this process, as it facilitates the conversion of the fuzzy stress intensity factor (SIF) into a deterministic value, thereby enhancing the interpretability and applicability of the results. Given that fuzzy outputs inherently contain epistemic uncertainty, the defuzzification process is crucial for obtaining meaningful numerical representations of the membership functions, allowing for more precise and reliable analysis.

In this study, the defuzzification process is applied at each finite element node to determine the maximum output parameter. This approach ensures that the computational model accurately captures the variations and uncertainties present within the fuzzy domain, ultimately leading to a more comprehensive assessment of the system's behaviour. Additionally, the implementation of defuzzification at the nodal level enhances the precision of the finite element analysis, providing refined insights into stress distribution and structural performance. The results obtained through this defuzzification process contribute to a more accurate interpretation of the fuzzy-based finite element model, supporting informed decision-making in engineering applications. A detailed discussion of the findings and their implications is provided in the subsequent section.

4. RESULT AND DISCUSSION ON ILLUSTRATIVE SINGLE CRACK PLATE

4.1 A single edge crack plate by considering four fuzzy variables

The material used in this research as the experimental sample is a non-ferrous metal type, namely aluminum alloy 2024-T351. This material is widely used in the field of structure, aircraft assembly, watch component construction, hydraulic and piston valve parts, gear and shaft, orthopedic equipment and others. In this study, three parameters that are Young's modulus, E, Poisson ratio, v and Density, ρ of aluminum alloys 2024-T351, are used as non-fuzzy parameters. The geometry used in this study is based on the stress analysis of crack handbook as shown in Figure 4 [8].

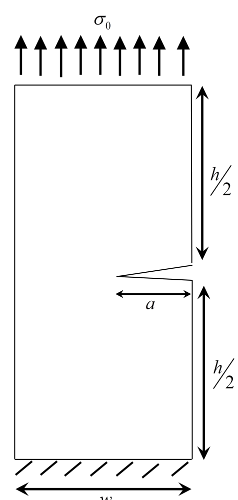

Figure 4: Model geometry of the present idealization with the boundary condition

From analytical aspect, the stress intensity factor under mode I can be obtained by using the Equation (4).

$$K_I = \sigma\sqrt{\pi a}Y\left(\frac{a}{w}\right) \quad (4)$$

the geometry function $Y\left(\frac{a}{w}\right)$ in Equation (4) can be calculated by using the Equation (5)

$$Y\left(\frac{a}{w}\right) = 1.122 - 0.231\left(\frac{a}{w}\right) + 10.55\left(\frac{a}{w}\right)^2 - 21.7\left(\frac{a}{w}\right)^3 + 30.382\left(\frac{a}{w}\right)^4 \quad (5)$$

where a is the crack length, w is width of the geometry, π is the constant with the value 3.1415927 and σ is the applied stress. Tada et. al (2000) stated that the best calculation of stress intensity factor (SIF) will be obtained using ratio for the geometry function ratio, $\left(\frac{a}{w}\right)$ is less than 0.06. In this research, small and large value of geometry function ratio are considered. The fuzzy value of crack length, a is represent in a triangular fuzzy number in form as a $\tilde{A} = \left[a_L + (a_N - a_L)\beta, a_R - (a_R - a_N)\beta\right]$.

Figure 5 presents the triangular membership function of the stress intensity factor (SIF), where fuzzification is applied exclusively to the tensile load (P). The resulting membership function exhibits slight deviations from the ideal triangular shape typically associated with fuzzy numbers. In this analysis, Young's Modulus (E) and other parameters are treated as crisp inputs, while fuzzification is applied systematically to individual variables. This structured approach facilitates a comprehensive evaluation of the SIF, ensuring accuracy in the uncertainty assessment. The implementation of fuzzification in this study enhances the representation of epistemic uncertainty within the finite element model. By systematically incorporating uncertainty into the analysis, the model achieves a more refined understanding of variability in SIF values. Furthermore, the fuzzification process aligns with the six-sigma concept, contributing to improved precision and reliability in the numerical results. These findings highlight the effectiveness of the fuzzy approach in addressing uncertainties and enhancing the robustness of computational modeling techniques.

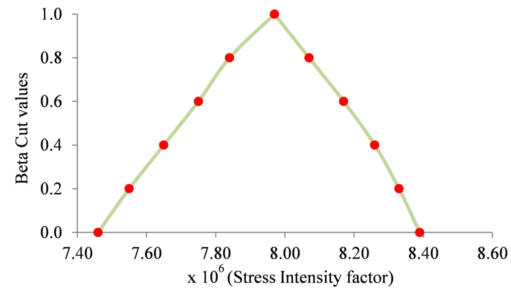

Figure 5: SIF fuzzy output with fuzzified on tensile load (P) only

Figure 6 illustrates the triangular membership function of the stress intensity factor (SIF) with fuzzification applied to two variables: tensile load (P) and Poisson's ratio (v). The resulting graph does not exhibit a perfectly straight triangular shape, as expected for a fuzzy number, and appears slightly skewed to the right. This asymmetry suggests that the interaction between the two fuzzified variables introduces additional uncertainty into the system. A notable characteristic of this membership function is its increased width compared to the graph generated with only one fuzzy input. The broader distribution indicates a higher degree of uncertainty in the SIF values, as more variability is introduced when multiple parameters are fuzzified simultaneously.

This phenomenon highlights the influence of incorporating multiple fuzzy variables in the analysis, emphasizing the need for careful consideration when selecting parameters for fuzzification. In contrast, other variables in the model are treated as crisp inputs, ensuring a controlled and systematic approach to evaluating the effects of fuzzification. The increased width of the membership function provides valuable insight into the impact of uncertainty propagation in the finite element analysis, offering a more comprehensive understanding of the system's behaviour. This analysis contributes to a more robust assessment of the structural response under uncertain conditions.

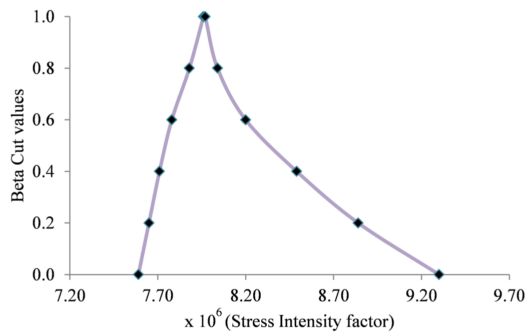

Figure 6: SIF fuzzy output with fuzzified on tensile load (P) and Poisson Ratio (v)

Figure 7, illustrates the triangular membership function of SIF with fuzzified Tensile load (P), Poisson ratio (v) and geometry function ratio $\left(\frac{a}{w}\right)$. The shape of this membership is skew to the right and the width of the membership function graph are wider compared to membership function in Figure 6. By using the concept of six sigma the accuracy of the fuzzy output is high compare to fuzzified one or two variables.

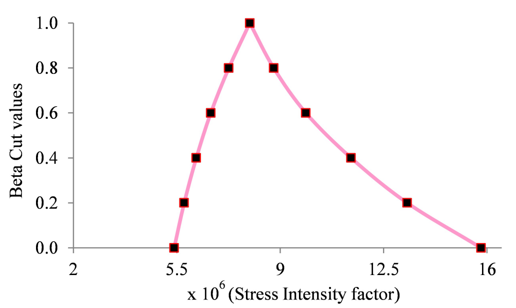

Figure 7: IF fuzzy output with fuzzified Tensile Load (P), Poisson Ratio (v) and Geometry Function Ratio (a/w)

Figure 8 illustrates the triangular membership function of the Stress Intensity Factor (SIF), where four input variables have been fuzzified, while Young's modulus (E) and plate thickness (T) remain as crisp inputs. Unlike a perfectly linear triangular shape, the membership function exhibits slight curvature, reflecting the influence of multiple fuzzified variables. Additionally, the width of the triangular membership function is broader compared to cases with fewer fuzzy inputs, indicating increased uncertainty in the system.

By keeping Young's modulus (E) and plate thickness (T) as deterministic inputs, the analysis maintains a structured approach, ensuring the effects of fuzzification are systematically evaluated. The broader distribution suggests greater variability in SIF values due to the propagation of uncertainty from multiple sources. Once the fuzzy output of the SIF is obtained, the final stage of the FuzzyFEM process, known as defuzzification, is performed to transform the fuzzy output into a precise numerical value for further analysis.

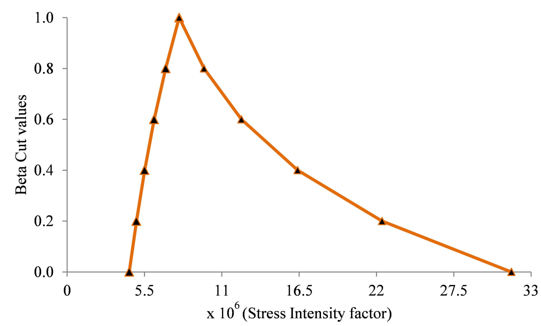

Figure 8: Fuzzy output with fuzzified all fuzzy input except Young's modulus (E) and thickness (T)

4.2 Defuzzification of Fuzzy Output to Crisp Output

Defuzzification is performed on the membership function of each finite element node to obtain the maximum value for each output parameter. Proposed FuzzyFEM approach revealed an important issue when the triangular membership function plot SIF fuzzy output with fours fuzzy number. Figure 9 shown the triangular membership function graph skew to the left with the minimum of fuzzy SIF value is $4.42 \times 10^6\ Pa\ (44.2\ MPa)$ and maximum of fuzzy value is $3.16 \times 10^7\ Pa\ (31.6\ MPa)$. Although the range between the minimum and maximum is only approximately $5.6\ MPa$, this does not produce a major uncertainty.

Even though it shows a small range of uncertainty, but it is crucial when analyze with critical SIF. The critical SIF, KI_c for Aluminum Alloy 2024-T351 is $26\ MPa$. By referring to COG value in Figure 9 is shown the SIF crisp value (deterministic value). The deterministic SIF value is 1.37 × 107 Pa (13.7MPa) in which it is not exceeded the critical SIF, that shows a safe structure. However, the upper bounds (maximum fuzzy SIF value) exceed the critical SIF that indicates a significant value for unstable maximum stress as shown in Region Z in Figure 9. Thus, the fracture of the material and structural component could occur.

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This result demonstrates the importance of a non-probabilistic analysis in the context of fatigue problems to avoid structural failure and potentially harmful consequences. Hence, an implementation of a non-probabilistic FuzzyFEM design is advisable in practical cases.

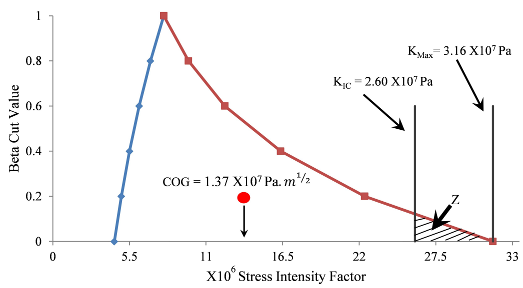

Figure 9: SIF fuzzy output with fuzzified all fuzzy input except (E)

4.3 Effect on Fuzzy SIF with Different Number of Fuzzy Variables

This study analyzes the impact of varying fuzzy input variables on uncertainty, measured through percentage error. An increase in fuzzy inputs amplifies uncertainty, reflected in higher percentage errors. Percentage error quantifies the deviation between analyzed results and true values, arising from factors such as human error, estimation approximations, and measurement limitations. It is calculated by determining the absolute error (difference between observed and true values), normalizing it by the true value to obtain the relative error, and multiplying by 100 to express it as a percentage. This metric provides critical insight into the accuracy of the analysis.

Table 1 presents the percentage error for the Stress Intensity Factor (SIF) output based on the varying number of fuzzy input variables considered in this study. The results indicate that the percentage error remains relatively low when one or two fuzzy inputs are incorporated. This suggests that fuzzifying one or two input variables using the FuzzyFEM approach yields results that closely align with those obtained from the deterministic Finite Element Method (FEM) in terms of percentage error. It is generally accepted that a percentage error below 10% signifies strong agreement between the two methods. However, when three or four fuzzy input variables are introduced, the percentage error exceeds 10%.

From the perspective of error analysis, this increase in percentage error indicates a reduced level of agreement and, consequently, a slight decline in output analysis efficiency, as higher percentage errors correspond to greater levels of uncertainty.

Table 1: Comparison of K_I for analytical (FEM) and different fuzzy input considered in this research

Fuzzy Input	Error (%)
One fuzzy input	0.37
Two fuzzy inputs	3.26
Three fuzzy inputs	17.44
Four fuzzy inputs	22.20

This study applies the Six Sigma (6σ) concept, covering 99.73% of the normal distribution, to evaluate the efficiency of FuzzyFEM. Results indicate that models incorporating three and four fuzzy input variables yield the best agreement and accuracy, as wider triangular membership functions enhance the representation of uncertainty. The Six Sigma approach, widely used in quality control, validates the effectiveness of this method in minimizing defects in materials and processes. Key factors influencing FuzzyFEM efficiency include the number of fuzzy input variables and the width of the membership function. The study considers four fuzzy variables tensile load (P), Poisson's ratio (v), crack length (a), and the geometry function ratio. As the number of fuzzy inputs increases, uncertainty representation improves, resulting in a more conservative and precise stress intensity factor (SIF) analysis.

Figures 10 and 11 illustrate the triangular membership function graphs of the fuzzy stress intensity factor (SIF) for both small and large geometry function ratios. The analysis is classified into three cases: Case A, Case B, and Case C. In Case A, four input variables are fuzzified, while in Case B and Case C, three and two fuzzy variables are considered, respectively. This classification demonstrates that increasing the number of fuzzy inputs introduces greater uncertainty, resulting in a wider membership function for the fuzzy output. Consequently, the broader distribution leads to a more conservative and accurate analysis.

This section focuses on the effect of varying the number of fuzzified variables, particularly in relation to the width of the triangular membership function and the six-sigma concept. The findings highlight that Young's modulus (E) is the only parameter that cannot be effectively fuzzified, as it does not significantly influence the final fuzzy output. Despite variations in the range of Young's modulus as a fuzzy number, the resulting output remains largely unchanged, with only minor deviations observed.

The application of the fuzzy approach in this study confirms that epistemic uncertainty associated with Young's modulus does not pose a significant issue compared to other variables. This suggests that uncertainties in Young's modulus have a minimal impact on the overall fuzzy output, reinforcing the robustness of the FuzzyFEM method in handling uncertainty while maintaining analytical reliability. These findings provide valuable insights into the role of different parameters in uncertainty modeling, ensuring that key variables contributing to structural behaviour are appropriately accounted for in engineering analyses.

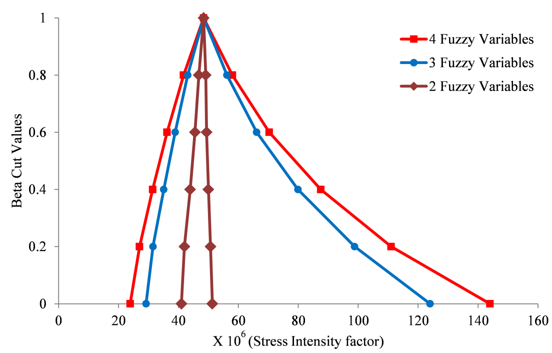

Figure 10: Fuzzy SIF with different fuzzy variables and large $\left(\frac{a}{w}\right)$

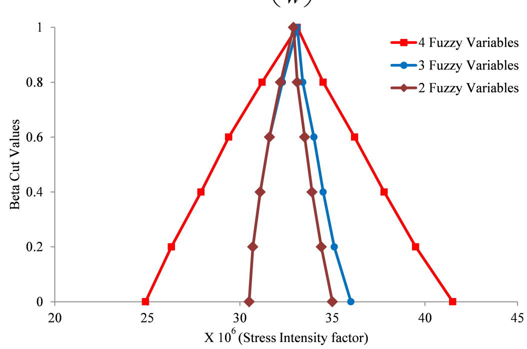

Figure 11: Fuzzy SIF with different fuzzy variables and small $\left(\frac{a}{w}\right)$

5. CONCLUSION

The findings of this study highlight the effectiveness of the Fuzzy Finite Element Method (FuzzyFEM) in addressing epistemic uncertainties in structural analysis, particularly in the context of single-edge crack plates. The results, presented through figures and tables, demonstrate that FuzzyFEM not only yields reliable estimations of stress intensity factors (SIF) and crack propagation zones but also provides a conservative approach compared to traditional deterministic methods. This conservatism is particularly beneficial in engineering design, where safety margins are critical.

A notable strength of the FuzzyFEM approach lies in its minimal dependency on extensive datasets. By leveraging expert knowledge, inductive logic, and optimization techniques like genetic algorithms, the method effectively constructs membership functions that encapsulate uncertainty. This feature is particularly advantageous when empirical data is limited or costly to obtain. However, a critical observation from this study is that while FuzzyFEM is powerful in handling uncertainty, its effectiveness is highly sensitive to the number and nature of fuzzy parameters. As the number of uncertain inputs increases, so does computational complexity, which may limit its practicality in large-scale systems without sufficient computational resources. Furthermore, defining appropriate membership functions requires careful judgment and expertise—introducing a degree of subjectivity that, if not managed properly, could compromise the quality of results.

Another limitation is that the method, while conservative, may yield overly cautious estimates under certain scenarios, potentially leading to overdesign. Therefore, integrating fuzzy analysis with probabilistic techniques or sensitivity analyses could enhance robustness and provide a more balanced perspective in future work. This study supports the application of FuzzyFEM as a promising tool for structural integrity assessments under uncertainty. Its ability to model epistemic uncertainty without requiring exhaustive datasets makes it a practical choice in many real-world engineering problems. Nonetheless, careful parameter selection, expert judgment, and future integration with hybrid uncertainty quantification methods are essential to maximize its potential. Future work could also explore real-time implementation in dynamic systems or structural

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health monitoring applications to further validate its applicability.

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