Analysis and Performance Comparison of Fuzzy Inference Systems in Handling Uncertainty: A Review

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Abstract—**Uncertainty is an inevitable characteristic in human life and systems, posing challenges in decision-making and data analysis. Fuzzy theory emerges to address this uncertainty by describing variables with vague or uncertain values, one of which is the Fuzzy Inference System (FIS). This research analyzes and compares the performance of FIS from previous studies as a solution to manage uncertainty. FIS allows for flexible and responsive representations of truth levels using human-like linguistic rules. Common FIS methods include FIS-M, FIS-T, and FIS-S, each with different inference and defuzzification approaches. The findings of this research review, referencing previous studies, indicate that the application of FIS in various contexts such as prediction, medical diagnosis, and financial decision-making, yields very high accuracy levels up to 99%. However, accuracy comparisons show variations, with FIS-M tending to achieve more stable accuracy based on the referenced studies. The accuracy difference among FIS-M studies is not significantly different, only around 7.55%. Meanwhile, FIS-S has a wider accuracy range, from 81.48% to 99% (17.52%). FIS-S performs best if it can determine influencing factors well, such as determining constant values in its fuzzy rules. Additionally, the performance comparison of FIS can also be influenced by other factors such as data complexity, variables, domain, membership functions (curves), fuzzy rules, and defuzzification methods used in the study. Therefore, it is important to consider these factors and select the most suitable FIS method to manage uncertainty in the given situation.**

Keywords—Fuzzy Inference System; Tsukamoto; Sugeno; Mamdani; Uncertainty.

I. INTRODUCTION

Uncertainty is an inevitable phenomenon in human life, especially within systems, whether in small-scale or complex-scale systems [1], [2]. In various contexts, humans are often faced with situations where the available information is not clear or certain enough to make the right decisions. The concept of uncertainty cannot be represented in a crisp or binary manner, such as in the case of "black" or "white". Instead, these variables may have fuzzy or uncertain values, such as "low", "medium", or "high" [3], [4], [5], [6], [7], [8]. This is the basis of fuzzy theory, where membership concepts can be used to describe how close or far a value is from a truth [9], [10].

This phenomenon poses significant challenges, both in scientific and practical domains, as decisions made must consider the level of uncertainty inherent in the available data or information [11]. In the scientific domain, uncertainty is not only an integral part of the observation and measurement process but also a major challenge that must be overcome in data analysis and interpretation [12], [13], [14], [15]. Although the measurement tools used are becoming more sophisticated, there is still a level of uncertainty associated with the measurement results. This uncertainty can be caused by various factors, including instrument imperfections, natural variability, or other factors that are difficult to measure accurately [16], [17]. The problem lies in human's ability to understand and accurately estimate this level of uncertainty. When not managed properly, uncertainty can lead to incorrect or unreliable conclusions from the data [18], [19]. This can result in errors in decision-making, inaccurate theory development, or even misinterpretations of observed phenomena.

Therefore, managing uncertainty is key to ensuring that conclusions drawn from scientific data can be more accurate and useful. This involves the use of appropriate statistical methods, one of which is fuzzy logic, which is used to estimate and measure uncertainty as accurately as possible [20], [21], [22]. Recognizing uncertainty is not only an important first step but also a critical element in the scientific research process that can ensure the validity and reliability of results [23], [24].

On the other hand, in practical applications, uncertainty can arise in many contexts. In addressing the challenges of this uncertainty, Fuzzy Inference Systems (FIS) emerge as an intriguing solution due to their ability to confront data variability using linguistically defined rules. FIS enables a more flexible representation of truth levels compared to traditional Boolean logic [25], [26], utilizing fuzzy set concepts and linguistic rules to generate adaptive and responsive outputs, even in situations where input data is incomplete or ambiguous.

In the real world, FIS is applied in various contexts of uncertainty, such as system control [27], weather prediction [28], [29], [30], [31], financial decision-making [32], [33], risk analysis [34], traffic control [35], [36], [37], medical diagnosis [38], [39], and many more. These studies certainly have different impressions when discussing the application of FIS. Therefore, this paper aims to review and provide an understanding of the concept of FIS and its application in managing uncertainty. Through detailed analysis, this paper also aims to identify existing research gaps and present new contributions in this field. Thus, the main contribution of this research is to analyze and compare the performance of FIS in addressing uncertainty, as well as to provide new insights for the future development and application of FIS.

II. Basic Concept of FIS

FIS is a computational system that utilizes the principles of fuzzy logic to make decisions [40]. Fuzzy logic [41] comes along with 2 other methods of uncertainty, namely certainty factor (CF) [42], [43] and probability. This system models the human decision-making process by considering the uncertainty and ambiguity in input data. FIS consists of several main components, namely fuzzy sets, membership functions, fuzzy rules, fuzzy inference, fuzzification, rule evaluation, aggregation, and defuzzification. Fuzzy sets represent concepts that are less precise, membership functions determine the degree of membership of elements in those sets, and fuzzy rules capture expert knowledge or heuristic information. Fuzzy inference involves determining crisp output values from fuzzy input values based on fuzzy rules through the process of fuzzification, rule evaluation, aggregation, and defuzzification [44]. FIS itself has several types, namely Mamdani type (FIS-M), Tsukamoto type (FIS-T) [45], and Sugeno type (FIS-S) [46], [47], [48]. The general architecture of FIS is shown in Fig. 1.

A. FIS-M

FIS-M involves a series of steps to compute the output based on input data [43], [58]. These steps include determining fuzzy rules, fuzzifying inputs, combining inputs according to rules, determining rule consequences, combining these consequences to obtain an output distribution, and finally, reassigning the output if a crisp output is required.

The process begins by creating fuzzy rules, which are linguistic statements that determine how the system should classify inputs or control outputs. Fuzzification then maps input data to fuzzy values using fuzzy membership functions on input variables. Fuzzy combination operators, such as "AND" and "OR," are used to evaluate fuzzy rules. The consequences of the rules are determined by combining fuzzified inputs and intersecting the output membership function at the strength of the rule.

The outputs from multiple rules are then combined into a single fuzzy output distribution, usually using fuzzy "OR" operators. Finally, the defuzzification stage is used to convert the fuzzy output distribution into a single crisp output value [59]. This can be done using techniques such as the Center of Gravity Method or Centroid Method. The illustration of machine inference in FIS-M is shown in Fig. 2.

B. FIS-T

FIS-T operates based on a series of fuzzy rules supported by monotonic logic. These rules use fuzzy sets with monotonic membership functions to describe the outcomes of each IF-THEN rule [60]. The first stage in FIS-T is fuzzification, which is the process of converting crisp values into fuzzy values using fuzzy curves. Several types of curves can be applied in this stage, such as triangular membership curves, rising linear membership curves, falling linear membership curves, shoulder membership curves, and others [61]. After the input values become fuzzy values in each formed fuzzy set, they will then enter the Inference System stage. In this stage, fuzzy rules in the form of IF-THEN statements are used to draw conclusions based on fuzzy set theory [27]. Basic logic operators like AND, OR, and NOT are applied to the rules. The AND operator obtains the minimum element (Equation (1)), the OR operator finds the maximum element (Equation (2)), and the NOT operator subtracts 1 from the fuzzy element (Equation (3)) [62], [63]. After the inference stage, it will proceed to the defuzzification stage. This stage is the final process of converting fuzzy output into crisp values [64], [65], [66]. In this stage, the weighted average (WA) method can be used, which calculates the weighted sum of fuzzy output values divided by the sum of weights. The WA formula is shown in Equation (4). Meanwhile, the illustration of machine inference in FIS-T is shown in Fig. 3.

$$\mu A \cap B = MIN(\mu A[x], \mu B[x]) \quad (1)$$

$$\mu A \cup B = MAX(\mu A[x], \mu B[x]) \quad (2)$$

$$\mu A' = 1 - \mu A[x] \quad (3)$$

$$Z = \frac{\sum_{i=1}^{n} w_i X_i}{\sum_{i=1}^{n} w_i} \quad (4)$$

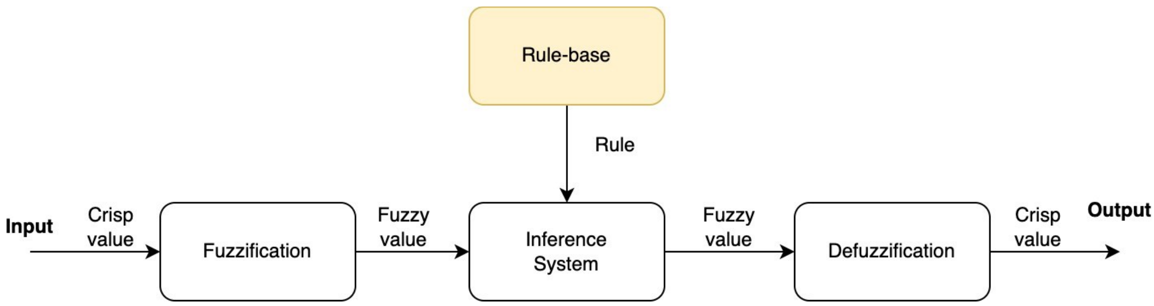

Fig. 1. General architecture of FIS Method [27], [49], [50], [51], [52], [53]

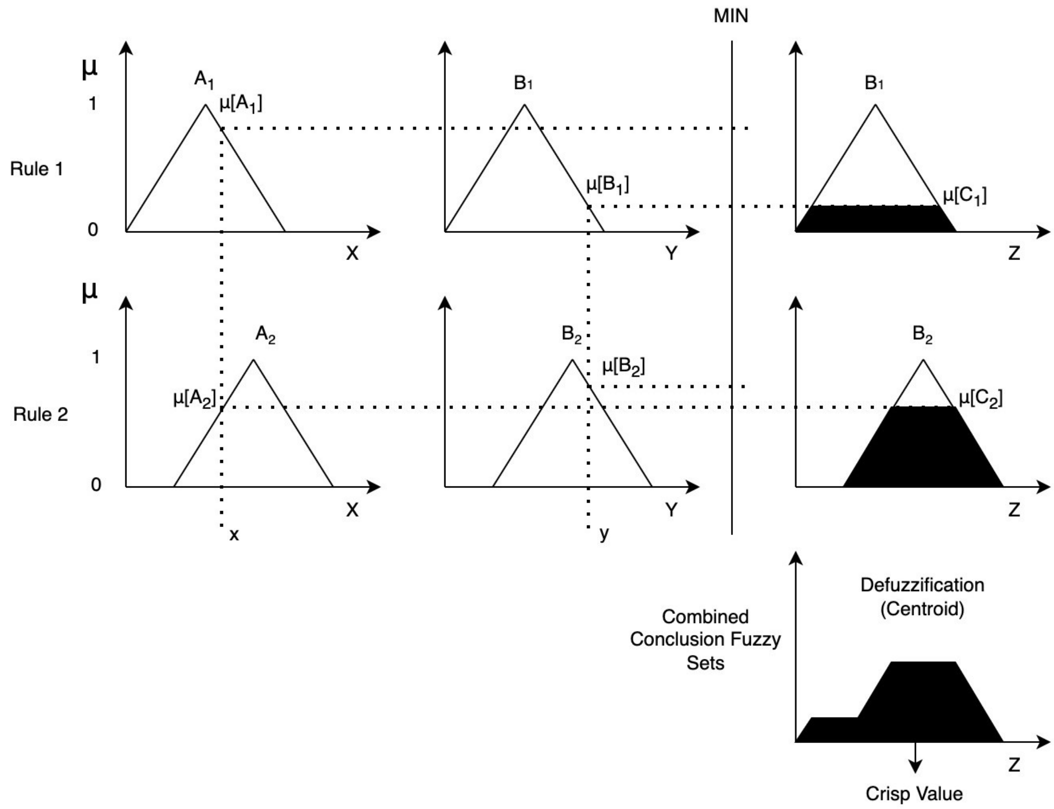

Fig. 2. Machine Inference in FIS-M [54], [55], [56], [57]

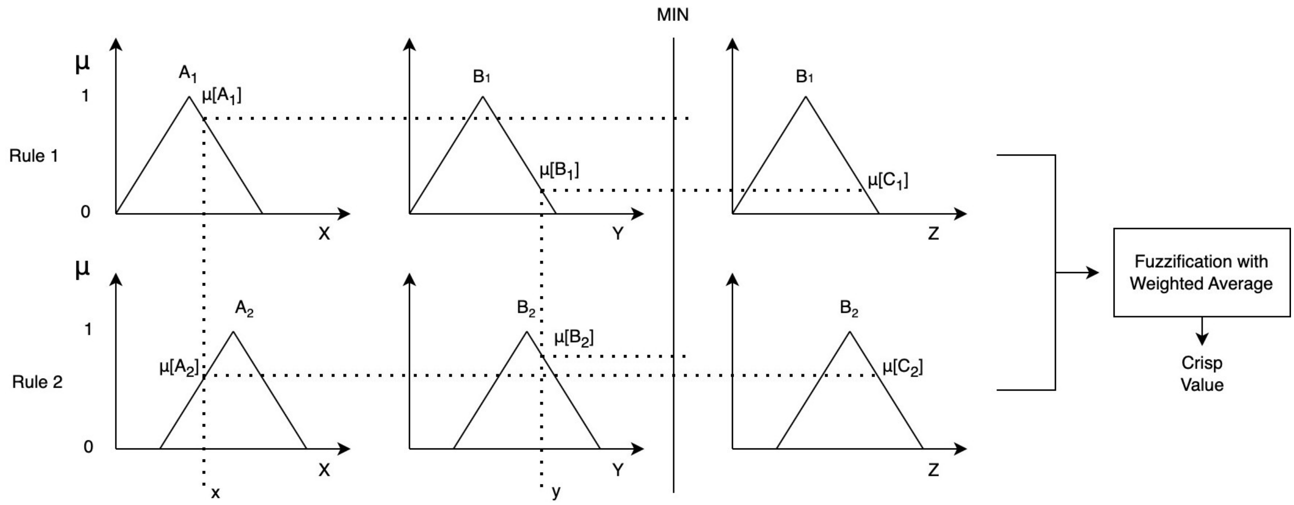

Fig. 3. Machine Inference in FIS-T [44], [61], [67], [68], [69]

C. FIS-S

FIS-S is one of the methods in FIS used to generate output based on a series of fuzzy rules [70]. This FIS was developed by Takagi-Sugeno-Kang (TSK) in 1985 [71], [72]. The basic concept in FIS-S is fuzzy rules used to link inputs to outputs. Each rule in FIS-S has the form "IF ... THEN ..." [73], where the given inputs will produce a specific output according to the specified mathematical function [71]. The main difference from FIS-M lies in the form of the consequence of these rules. In FIS-S, the output consequence is calculated by multiplying each input by a certain constant, then summing them up to produce a crisp value as the output. Rules in FIS-S generally have simple mathematical forms, such as: **IF input1 is A AND input2 is B THEN output = ax + by + c**. Where A and B are membership functions for each input, while a, b, and c are constants that need to be determined [74], [75], [76]. These constant values determine how much influence each input has on the output. The process of determining these constant values can be done through mathematical modeling, simulation, or optimization using special algorithms. FIS-S has the advantage of producing concrete and more easily interpretable outputs, but determining optimal constant values for each rule is a major challenge in this type [77]. The proper adjustment of constants can affect the overall performance and accuracy of the system. The illustration of machine inference in FIS-S is shown in Fig. 4.

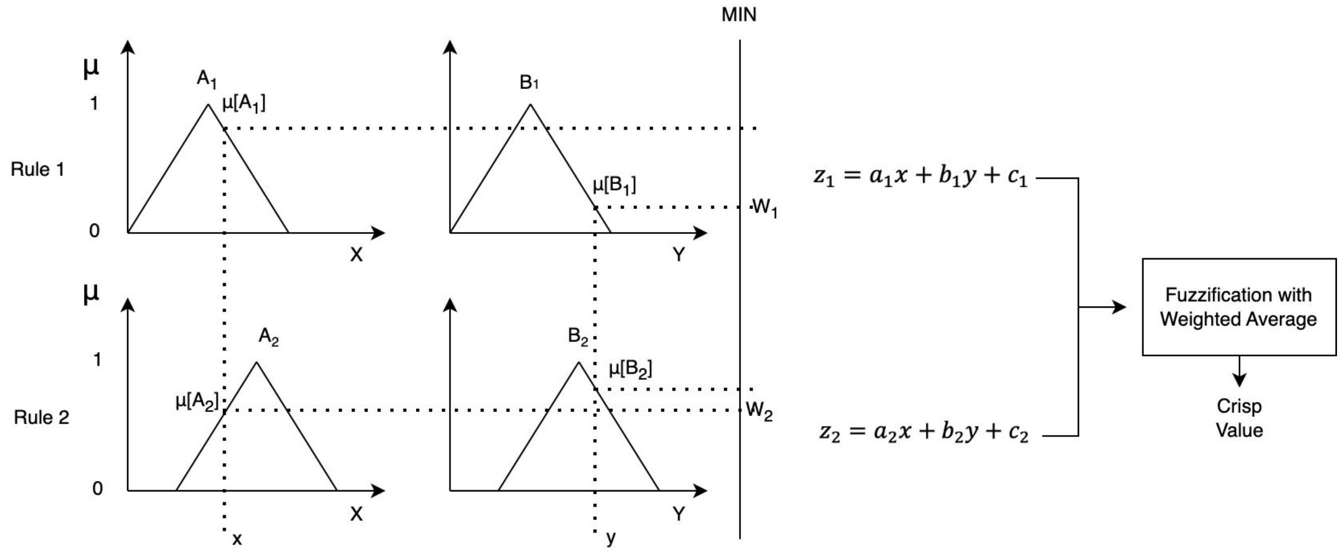

Fig. 4. Machine Inference in FIS-S [67], [78], [79], [80]

D. FIS Evaluation Matrix

The FIS evaluation matrix is an important tool in assessing the performance of FIS in solving various problems across different domains. By using the evaluation matrix, users and developers can gain a better understanding of how well the FIS functions in generating accurate predictions or decisions. In this regard, one of the commonly used evaluation matrices is accuracy [65], [83], [84], [85], [86], [87]. Accuracy measures how close the predictions generated by the FIS are to the actual values. Accuracy provides an overview of the FIS's success rate in predicting data or making decisions. Not only in FIS, several methods combined with fuzzy logic also frequently use accuracy as an evaluation metric [88], [89].

In addition to accuracy, several other evaluation matrices are also frequently used, including MAPE (Mean Absolute Percentage Error) [38], [90], [91], [92], [93], MSE (Mean Squared Error) [94], [95], [96], [97], RMSE (Root Mean Squared Error) [98], [99], [100], [101], MAE (Mean Absolute Error) [101], [102], [103], [104], and F1 Score [64], [105], [106].

MAPE measures the average of the absolute percentage errors between the predicted values by the FIS and the actual values, thus providing an indication of how accurate the predictions are relative to the scale of the predicted values. Meanwhile, MSE measures the average of the squared errors between the predicted values and the actual values, while RMSE is the square root of MSE, providing an indication of the average prediction error in the same units as the predicted variable. MAE measures the average of the absolute errors between the predicted values by the model (or FIS) and the actual values. Whereas, F1 Score is the harmonic mean of precision and recall of a class, providing an overview of the balance between precision (true positive rate) and recall (sensitivity).

E. Differences between Fuzzy and Conventional Logic

Fuzzy and conventional logic are two different approaches in information processing and decision-making. Conventional logic, also known as Boolean logic or crisp logic, operates with strict and binary rules, where each statement or variable only has two possible values: true or false, 1 or 0 [107]. This approach is suitable for situations where decisions must be made with certainty and clarity, without room for ambiguity. On the other hand, fuzzy logic extends the paradigm of conventional logic by introducing the concept of uncertainty and vagueness. In fuzzy logic, variables and statements can have partially true or partially false values, and they are expressed as fuzzy sets that lie between binary categories (between 0 and 1) [108]. This allows for better handling of uncertain or ambiguous information, making it more suitable for situations where concepts like “a little”, “moderate”, or “a lot” are involved, and where decisions cannot always be made definitively [81], [82], [109], [110], [111].

The main difference between the two lies in the flexibility of representing and processing information. Fuzzy logic allows for greater levels of uncertainty and complexity in modeling systems, while conventional logic prioritizes clarity and decisiveness in decision-making. Based on this difference, conventional logic tends to be more suitable for structured and predictive environments, while fuzzy logic is more suitable for situations where environmental conditions are uncertain or constantly changing. The illustration of the difference between fuzzy and conventional (Boolean) logic is shown in Fig. 5.

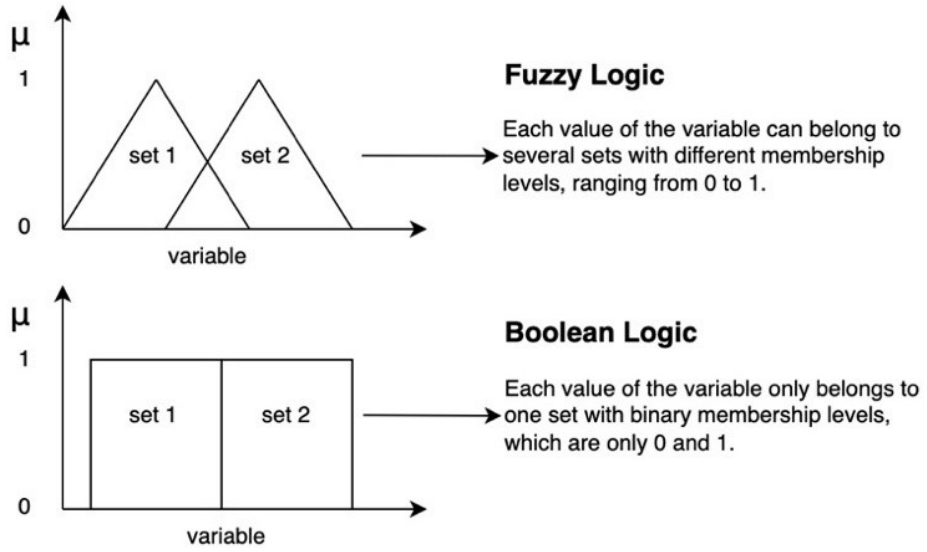

Fig. 5. Illustration of the difference between fuzzy and boolean logic [81], [82].

III. Application of FIS in Handling Uncertainty

FIS is useful in handling uncertainty in various fields. FIS allows models to consider fuzziness and ambiguity in data, which are often difficult to precisely measure using conventional approaches. Generally, FIS applications include decision-making, system control [112], [113], prediction, and data processing. In decision-making, FIS helps evaluate uncertain scenarios by considering various possibilities and assessing the relative levels of certainty among them. This assists decision-makers in choosing the best course of action in complex and ambiguous situations. On the other hand, in system control, FIS works to regulate system behavior adaptively based on sensor inputs and environmental conditions. By calculating uncertainty in real-time in system inputs and outputs, FIS enables more efficient and responsive control.

Additionally, FIS is also used for prediction, where fuzzy models can process uncertain data and generate forecasts or estimates better than deterministic models. This is useful in forecasting future trends, such as market trends, weather conditions, consumer behavior, and more. Apart from forecasting, FIS is also used in data processing to classify or group complex and ambiguous data. This can handle variability and fuzziness in data, enabling more accurate and meaningful analysis.

Moreover, FIS is used in various sectors to address uncertainty, such as healthcare [84], [114], [115], agriculture, finance [116], manufacturing, transportation, and others. Previous research has extensively applied FIS in addressing uncertainty issues [30], [65], [83], [84], [87], [114], [115], [116], [117], [118], [119], [120]. The problems solved vary, such as determining date quality [87], predicting the percentage of the poor population [86], rainfall prediction [30], [31], disease identification [114], [115], stock price prediction [116], determining student satisfaction levels with lecturers [120], and more [65], [83], [85], [121]. Each of these studies has yielded various interesting findings with diverse performance. Details of previous research in the application of FIS to address uncertainty are displayed in Table I.

Table I shows that all three types of FIS (FIS-M, FIS-T, and FIS-S) are utilized in solving various types of cases by employing different membership function curves, such as Gaussian, trapezoidal, triangular, and others. Researchers select the FIS model most suitable for the research objectives and the characteristics of the problems faced. This demonstrates the flexibility and adaptability of FIS techniques across various domains. Furthermore, the achieved accuracy results from each study also provide information about the performance and validity of the applied FIS models. In most cases, accuracy reaches high values, ranging from 81.48% to 99.00%.

Moreover, the variation in the number of rules defined in each FIS model reflects the complexity of the problems encountered by researchers. Some studies involve a larger number of rules, reaching up to 108 rules, while others have fewer rules, ranging from 4 to 22 rules. The number of fuzzy rules is usually influenced by the number of variables and input domains used. The more variables and input domains used, the more rules there tend to be. Conversely, this assumption is not absolute, as researchers are free to use the number of rules according to the needs of the research being conducted.

Table I also provides information that the most successful research in achieving high accuracy levels is often related to the application of FIS in prediction contexts, whether it's predicting the percentage of the poor population, rainfall, stock prices, or disease diagnosis. The accuracy results obtained in prediction cases across the three different FIS types range from 90% to 98.67%. This indicates that FIS has great potential in forecasting or predicting complex and dynamic phenomena.

TABLE I. APPLICATION OF FIS IN HANDLING UNCERTAINTY IN PREVIOUS RESEARCH

Ref.	Year	FIS Type	Membership Function Curve	Num of Rules	Input Variable	Research Objective	Accuracy (%)
N. Alavi [87]	2013	FIS-M	Gaussian curve	15	FL, and FF	Quality determination of Mozafati dates	91.00
R. Rustanuarsi and A. M. Abadi [86]	2018	FIS-M	Triangular and trapezoidal curve	14	UR, and GI	Predict Percentage of Poor Population in Indonesia	94.34
Y. Ardi, *et. al* [30]	2021	FIS-M	Trapezoidal curve	81	WV, VS, DP, and Temp	Performance Analysis on Rainfall Prediction	98.55
Y. Perwira and R. K. Lubis [120]	2021	FIS-M	Triangular, decreasing linear, and increasing linear curve	8	PDC, PRC, PNC, and SCC	Student Satisfaction Level Towards Lecturers	95.00
M. Sridharan [121]	2021	FIS-M	Gaussian	7	BT, BWT, GCIT, and GCOT	Prediction of thermal performance of solar distillation still (SDS)	94.50
V. I. Variani [122]	2021	FIS-M	Shoulder curve	4	MC, and VMC	Calorific value predicting	94.00
D. M. N. Fajri, *et. al* [115]	2017	FIS-T	Trapezoidal curve	22	PL, IG, PN, RG, SG, EBG, BB, and WT	Dental Disease Identification	88.00
P. Lestantyo, *et. al* [117]	2019	FIS-T	Trapezoidal and Shoulder curve	Not specified	EL, AR, SI, AT, Hum, and ST	Suitability of Apple Plantation Land	92.85
E. Nugraha, *et. al* [65]	2019	FIS-T	Trapezoidal curve	108	Significance, Originality, Quality, Clarity, and Relevance	DSS of journal acceptance	95.00
A. D. Permana [84]	2020	FIS-T	Phi bell curve	8	ODP, and PDP	Heart Disease Diagnosis	95.50
Y. Perwira and R. K. Lubis [120]	2021	FIS-T	Triangular, decreasing linear, and increasing linear curve	8	PDC, PRC, PNC, and SCC	Student Satisfaction Level Towards Lecturers	92.00
D. Farhan and F. Sulianta [83]	2023	FIS-T	Decreasing linear and increasing linear curve	4	Demand and Supply	Determine the number of seeds koi fish in the Sukamanah Cianjur farmer`s Group	94.78
U. A.Umoh and A. A. Udosen [116]	2014	FIS-S	Trapezoidal curve	81	CMF, FI, EM, and TI	Stock Price Prediction	90.00
A. Chakraborty, *et. al* [114]	2016	FIS-S	Gaussian	Not specified	Fo (Hz), Fhi (Hz), Flo (Hz), JP, JA, RAP, PPQ, DP, SP, SD, APQ3, APQ5, APQ11, DDA, NHR, HNR	Detection of Parkinson's Disease	97.00
D. Syahputra, *et. al* [119]	2017	FIS-S	Triangular and Shoulder curve	9	Weight, and Height	Determination Natural Patient Status	81.48
R. Bakri, *et. al* [118]	2020	FIS-S	Shoulder curve	4	BPBI, dan JamPJKMU	Determining the number of participants in BPJS Health (Indonesia)	94.17
Y. Ardi, *et. al* [30]	2021	FIS-S	Trapezoidal curve	81	WV, VS, DP, and Temp	Performance Analysis on Rainfall Prediction	98.67
Y. Perwira and R. K. Lubis [120]	2021	FIS-S	Triangular, decreasing linear, and increasing linear curve	8	PDC, PRC, PNC, and SCC	Student Satisfaction Level Towards Lecturers	99.00

BT: Basin temperature, BWT: Basin water temperature, GCIT: Glass cover inside temperature, GCOT: Glass cover outside temperature, AT: Air temperature, MC: Moisture content, VMC: Volatile matter content, UR: Unemployment rate, GI: Gini index, FL: Fruit length, FF: Fruit freshness, DSS: Decision support system, ODP: Monitoring person, PDP: Patients under Supervision, PL: Plaque, IG: Inflamed gums, PN: Pain, RG: Reddened gums, SG: Swollen gums, EBG: Easy bleeding gums, BB: Bad breath, WT: Wobbly teeth, EL: Elevation, AR: Annual rainfall, SI: Sunshine intensity, ST: Soil type, CMF: Chaikin money flow, FI: Force index, EM: Ease of movement, TI: Trend index, BPBI: Non-recipient of premium assistance, JamPJKMU: Jamkesda & PJKMU Askes, WV: Wind velocity, VS: Visibility, DP: Dew point, Temp: Temperature, PDC: Pedagogic competence, PRC: Professional competence, PNC: Personality competence, SCC: Social competence, Fo (Hz): Average vocal fundamental frequency, Fhi (Hz): Maximum vocal fundamental frequency, Flo (Hz): Minimum vocal fundamental frequency, JP: Jitter percentage, JA: Jitter absolute, RAP: Relative average perturbation (%), PPQ: Period perturbation quotient (%), DP: Difference of differences of Periods, SP: Shimmer percentage, SD: Shimmer in decibels, APQ3: Three point Amplitude perturbation quotient (%), APQ5: Five point Amplitude perturbation quotient (%), APQ11: Eleven point Amplitude perturbation quotient (%), DDA: Difference of difference in amplitude, NHR: Noise to harmonic ratio (NHR), HNR: Harmonic to noise ratio (HNR).

IV. Performance Comparison between FIS Types

In providing insights into the performance comparison between the three types of FIS, there is a need for a comparison that offers a more detailed overview of their performance differences, and one of the evaluation metrics that can be used is accuracy. When comparing these three types of FIS, the number of referenced studies for each FIS is 6 studies. The referenced studies have achieved relatively high accuracy, ranging from 81.48% to 99%. A more detailed comparison of accuracy between previous studies is illustrated in Fig. 6. This comparison is marked by three different colors. FIS-M is represented by the green-colored graph, FIS-T by the yellow-colored one, and FIS-S by the red-colored one.

Studies utilizing FIS-M have shown a relatively consistent accuracy range among the referenced studies, ranging from 91% to 98.55%. For instance, N. Alavi (2013) applied FIS-M to assess the quality of Mozafati dates with an accuracy rate of 91.00%, while a study by Y. Ardi, et al. (2021) analyzing rainfall prediction performance using FIS-Mamdani achieved a higher accuracy rate of 98.55%.

Meanwhile, studies employing FIS-T also demonstrated significant accuracy, ranging from 88% to 95.5%. For example, A. D. Permana (2020) implemented FIS-Tsukamoto in diagnosing heart diseases with an accuracy rate of 95.50% [84], whereas D. M. N. Fajri, et al. (2017) for identifying dental diseases achieved an accuracy rate of 88.00% [115]. Compared to FIS-M, FIS-T generally exhibits lower accuracy.

On the other hand, research utilizing FIS-S recorded accuracy ranges from 81.48% to 99%. A study by Y. Perwira and R. K. Lubis (2021) applied FIS-S to evaluate student satisfaction levels with lecturers, achieving an accuracy rate of 99.00% [120], while D. Syahputra, et al. (2017) used FIS-Sugeno to determine patient status naturally with an accuracy rate of 81.48% [119]. These results indicate that FIS-S has a lower level of consistency, as some studies have very high accuracy while others have relatively low accuracy. However, compared to FIS-M and FIS-T, FIS-S is considered superior in certain conditions. This is supported by Y. Perwira and R. K. Lubis [120], who conducted a comparative study of all three types of FIS in the same case, obtaining an accuracy rate of 99% for FIS-S, 95% for FIS-M, and the lowest accuracy for FIS-T at 92%. The superiority of FIS-S is also supported by other studies [39], [123], [124], [125], [126]. One such study is conducted by W. E. Sari et al., which compared the three types of FIS in diagnosing tuberculosis in children. Their research showed that FIS-S had a higher accuracy rate of 93% compared to the accuracy rates of FIS-M and FIS-T at 89% and 92%, respectively [39]. The comparison of maximum, average, and minimum accuracy for each type of FIS is illustrated in Fig. 7.

Fig. 7 shows that FIS-M has the highest average level, at 94.56%. This is because not only are the accuracy values of each study high, but also FIS-M has a narrower accuracy range, ranging only from 91% to 98.55% (7.55%). Meanwhile, FIS-S has a wider accuracy range, from 81.48% to 99% (17.52%). However, if one study with the lowest value is removed from the comparison graph, then FIS-S will have a higher average accuracy rate compared to FIS-M and FIS-T, at 95.77%. The comparison of maximum, average, and minimum accuracy of each type of FIS after removing one study with the lowest value is shown in Fig. 8.

Although this paper review indicates that the FIS-M method is more stable than FIS-T, in some other studies for various cases, there are also cases where FIS-T is better than FIS-M [58], [59]. This suggests that there is no absolute superiority, as each case (data), variable, domain, membership function (curve), fuzzy rules, and defuzzification method can affect the performance of FIS. Therefore, researchers need to carefully consider and assign appropriate values to the relevant factors to obtain the most optimal results.

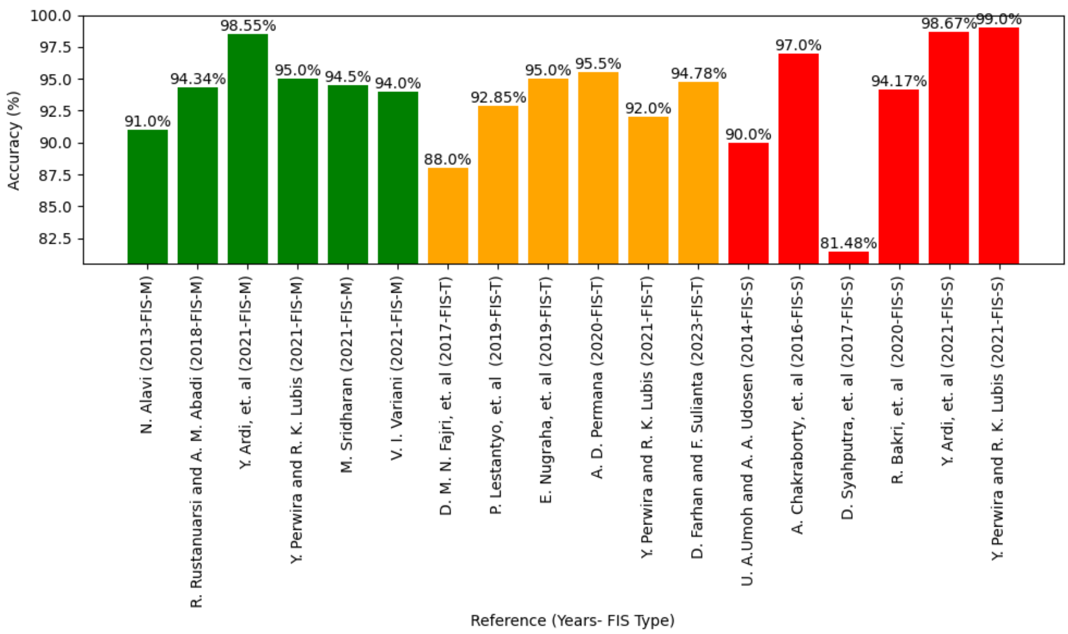

Fig. 6. Comparison of accuracy in previous studies using FIS-M (green), FIS-T (yellow), and FIS-S (red)

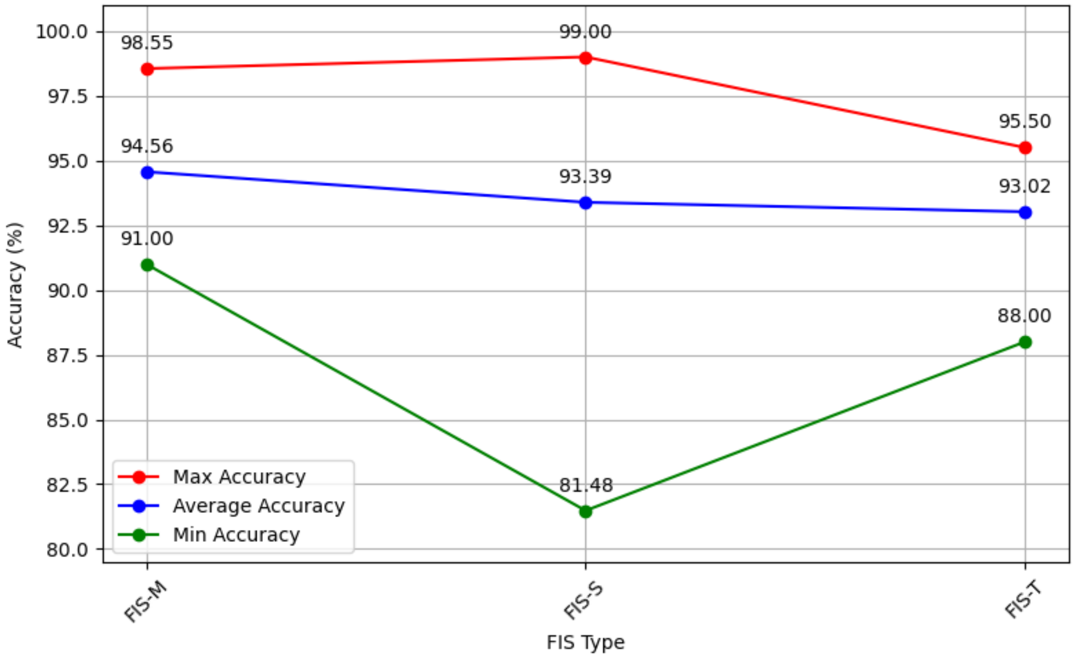

Fig. 7. Comparison of maximum, average, and minimum accuracy of the three types of FIS

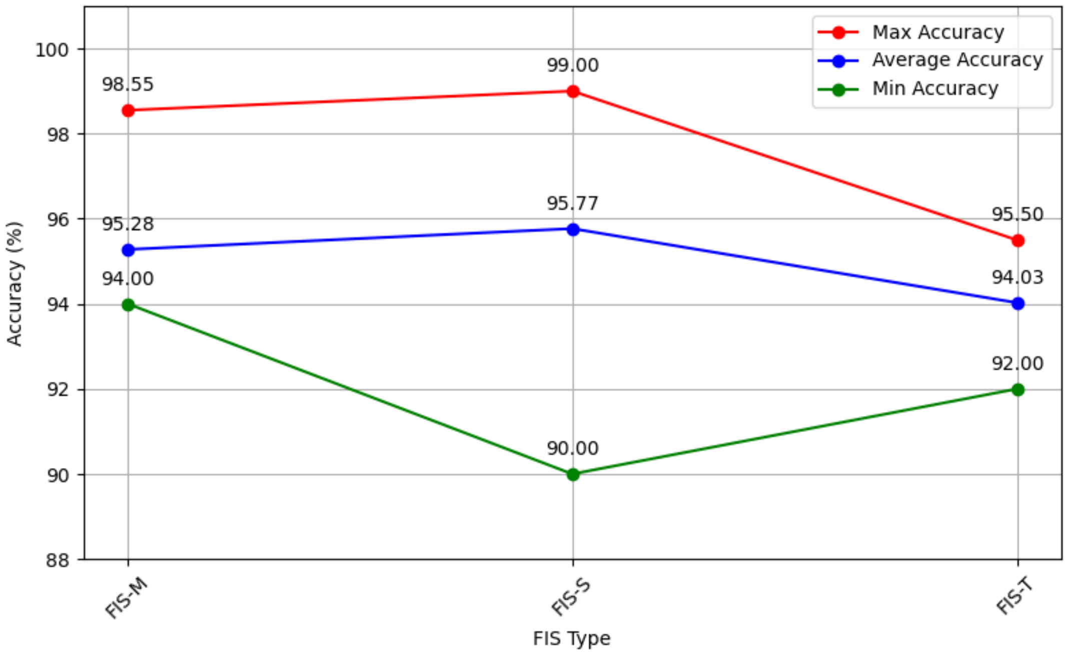

Fig. 8. Comparison of maximum, average, and minimum accuracy of the three types of FIS after removing the study with the lowest value

V. Recent Developments and Challenges

Recent developments in the field of FIS have seen significant progress, especially in their application across various domains and the integration of FIS with other emerging technologies. One notable advancement is the use of deep learning (DL) techniques, such as neural networks [127], [128], [129], [130], in conjunction with FIS to enhance modeling and prediction capabilities. Combining FIS with DL allows for more complex and accurate decision-making systems, capable of handling large-scale datasets and capturing intricate patterns in data. Additionally, there is increasing interest in the development of adaptive [131], [132], [133], [134], [135], [136] and self-learning FIS [137], which can continuously evolve and optimize rules and membership functions based on real-time feedback and changing environmental conditions.

Furthermore, recent developments have focused on improving the interpretability and transparency of FIS models, addressing long-standing challenges in this field. Researchers have proposed various techniques to explain the decision-making process of FIS models, such as rule extraction methods and visualization techniques, enabling users to understand and trust the decisions made by the FIS system. Moreover, advancements in optimization algorithms have facilitated automatic tuning and optimization of FIS parameters, leading to improved performance and efficiency of FIS models.

Despite these advancements, several challenges remain in the development and implementation of FIS. One major challenge is determining the best parameters for each component involved in the FIS process, such as appropriate data, variables used, domains within variables taken, types of membership function curves in each domain within variables, fuzzy rules in machine inference, and suitable defuzzification methods. As explained, these components have a close impact on the accuracy level that will be obtained. Especially for FIS-S, which will have a significant impact if the formed rules do not meet the needs, such as being inaccurate in determining the appropriate constants. Additionally, challenges also exist in integrating FIS with big data analytics and real-time processing frameworks, to enable handling and analysis of large-scale data and data streams. However, if these challenges are successfully addressed, FIS will undoubtedly become more optimal in resolving uncertainty in human life.

VI. Conclusion

In evaluating the role of FIS in managing uncertainty, particularly through accuracy analysis, previous research has consistently shown success in various contexts. Data from several studies indicate that FIS can generate predictions or solutions with high accuracy rates of up to 99%. FIS-S provides more optimal results compared to FIS-M and FIS-T. However, determining the correct constants has a significant influence. If incorrect, the performance of FIS-S may decline. On the other hand, FIS-M demonstrates more consistent results across several previous studies compared to FIS-S and FIS-T. Various applications of FIS, such as in prediction, decision-making, system control, and data processing, demonstrate the great potential of this system in handling complexity and uncertainty. Nevertheless, further development in FIS research is needed to identify areas where improvements can be made.

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