Fuzzy Logic-Driven Reliability Improvement in Power Systems under Environmental Conditions

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Abstract- The Energy Not Supplied (ENS) index is an important indicator for determining the economic performance of power systems. This index analyzes the losses sustained as a result of network faults that prevent the delivery of electrical energy, as well as the economic impact on consumers during power outages. As a direct indication of system reliability, ENS sheds light on the resilience of distribution networks. However, a significant issue in dependability assessments is a lack of adequate statistical data. To address these concerns, fuzzy logic has evolved as a reliable method for modeling uncertainty in engineering parameters. Distribution networks, which operate in a wide range of environmental and geographic conditions—from urban to rural—are frequently vulnerable to natural disasters such as storms, heavy rainfall, and snow, as well as contaminants such as salt, dust, and humidity. Using fuzzy logic, this study analyzes how these ambient and natural elements affect the ENS index. The ENS index is calculated using MATLAB simulations on the RBTS-bus2 network. Results show that by addressing environmental and operational uncertainties, up to 31% improvement in both ENS and SAIFI indices can be achieved, with an overall enhancement of 41.88% in system reliability. These findings demonstrate the value of fuzzy logic in enhancing reliability evaluations even when statistical data is limited.

Keywords: Energy not supplied (ENS), fuzzy logic, repair time, failure rate, distribution network.

1. Introduction

With the rapid growth of technology and the upgrading of societal infrastructure, ensuring consumers have an uninterrupted power supply has become increasingly important. Modern communities, spurred by changing consumption habits and increased reliance on electricity, now expect power networks to offer consistent and reliable energy without disruptions. Absolute continuity, however, is virtually unattainable due to the inherent randomness in the operation of generation units, transmission lines, and distribution network components. Failure or unavailability of any network component can cause service disruptions for consumers, resulting in severe financial and operational losses. While increased infrastructure investments can reduce the frequency of power outages, removing all interruptions is neither practical nor cost-effective.

Reliability studies in power systems are crucial instruments for assessing the continuity of electricity supply and estimating its economic impact. Key indicators for assessing power supply reliability include the frequency and duration of outages, as well as the perceived value of electricity to consumers during periods of unavailability. Factors that influence these measurements include equipment reliability, circuit length and loading, network configuration, and load profile. The statistical data required to compute each component's average failure rate and repair time are typically derived from years of gathered and aggregated data. This process is based on an efficient error logging system that can document critical details such as the time and location of failures, potential causes, the component's lifespan, and the impact of external factors such as weather conditions or third-party activities involving people, animals, or birds.

However, the lack of detailed statistical data presents a substantial barrier in assessing the trustworthiness of distribution networks. As a result, predicting dependability input parameters based on sparse or incomplete data frequently produces errors. These flaws spread throughout the calculations, producing indeterminate and implausible reliability indices. To deal with such uncertainties, fuzzy logic has shown to be a dependable way for modeling and incorporating variability in engineering parameters. Among the different dependability indices, the Energy Not Supplied (ENS) index is particularly important in economic evaluations, acting as a fundamental tool for appraising investments and making power system decisions. The Energy Not Supplied (ENS) index largely reflects the financial and operational losses suffered as a result of network faults that prevent the sale of energy, as well as the inconveniences experienced by consumers during power outages. This index provides a tangible measure of reliability in distribution systems.

Failed components in radial distribution feeders frequently cause power supply interruptions at load sites. The ENS index can be estimated properly by assessing interrupted demand and outage duration [1]. Typically, two ways are used to generate reliability indices: analytical methods and simulation-based procedures. The analytical technique entails creating mathematical models for system components and calculating the desired indices. Common analytical tools include network reduction methods, Markov chains, and the frequency and duration method [2]. The second approach uses Monte Carlo simulations to derive reliability indices by modeling the stochastic behavior of system components [3-5]. This strategy is particularly useful for reflecting the unpredictable and uncertain nature of component failures. Distribution networks operate in a variety of environmental situations, including hilly regions, plains, urban centers, and rural areas, and are subject to a wide range of external obstacles. These include natural disasters like storms, high winds, rainfall, and snow, as well as pollutants like salt, dust, and moisture [6]. Using fuzzy logic, this study analyzes how various environmental and natural elements affect the Energy Not Supplied (ENS) index. The research is carried out on the RBTS-bus2 network using specialist software to generate system indicators. A comparison of the results reveals that these parameters have a considerable influence on the ENS index, providing useful insights into their significance in dependability judgments [7].

In the analysis of environmental uncertainties in distribution systems, fuzzy logic has been identified as an effective method for enhancing reliability assessments. For example, in [8], fuzzy logic was used to include environmental concerns into supply chain management, demonstrating how it can predict uncertainties in complex systems. Similarly, [9] investigated the use of fuzzy logic to evaluate distribution system reliability while accounting for transformer and line uncertainty, confirming its superiority over standard methods. Furthermore, [10] underlined the relevance of developing technology, such as unmanned aerial aircraft, in the face of environmental uncertainty, providing insights that might be used to power systems. The incorporation of fuzzy logic into decision-making, as outlined in [11], provides a framework for dealing with uncertainty in both business strategies and distribution systems. In addition, [12] investigated how fuzzy approaches might balance environmental and cost considerations in sustainable supply chain management, suggesting parallels with managing uncertainty in distribution networks.

Ref. [13] examines the evolution of fuzzy control systems in power quality enhancement, highlighting advancements from Type-1 to Type-2 and hybrid controllers. It categorizes applications based on control strategies, devices, and implementation methodologies, providing insights into their efficacy and efficiency.

Ref. [14] presents a Mamdani-type fuzzy inference system combined with the Bellman-Zadeh decision-making method for evaluating the reliability of power distribution networks. It considers factors like unplanned outages, Energy Not Supplied (ENS), and the age of power lines, demonstrating the model's applicability in practical planning scenarios.

Ref. [15] introduces a hybrid approach combining Type-2 Fuzzy Logic Controllers, Digital Twin technology, and Neural Networks to manage hydropower systems. The integration aims to enhance load management, fault detection, and operational efficiency, achieving significant improvements in predictive accuracy and system reliability.

Ref. [16] proposes a Three-Phase Dynamic Voltage Restorer (DVR) integrated with a Fuzzy Logic Controller to mitigate voltage sags and improve power quality. Simulation results demonstrate the system's effectiveness in enhancing voltage profiles under various disturbance conditions.

Ref. [17] develops a Type-2 fuzzy controller optimized using a hybrid algorithm for frequency regulation in a multi-area power system with renewable integration. The controller effectively manages frequency deviations, enhancing system stability under varying load conditions.

Ref. [18] presents an intelligent controller combining fuzzy logic and sliding mode control for frequency stability in deregulated power systems. Implemented on the OPAL-RT platform, the controller demonstrates robust performance in maintaining frequency stability amidst system disturbances.

This research uses fuzzy logic to investigate the impact of environmental and natural uncertainties on the Energy Not Supplied (ENS) index in distribution networks. Unlike traditional methodologies, which rely heavily on extensive statistical data for reliability assessments, fuzzy logic offers an excellent method for modeling uncertainties in a variety of engineering factors, including failure rates, repair durations, and environmental variables. This technique is especially useful when accurate and complete statistical data is scarce. Furthermore, the paper specifically examines the challenges faced by distribution networks operating in diverse geographic and climatic settings, including mountainous, urban, and rural environments. It positions fuzzy logic as a powerful tool for improving the evaluation and prediction of failures and uncertainties in these complex systems.

Unlike the work in [6], [7], [9] that mostly aim at evaluating the effect of environmental factor or uncertainty in transformers, lines, on the system, the proposed approach in this paper has the novelty of combining the fuzzy theory for capturing uncertainty behavior of many environments and operational parameters. In particular, the novelty of our study lies in: (1) analyzing the direct effects of environmental situations (storms, humidity and pollutants only) on the ENS index; (2) taking into account different geographic areas (urban, rural and mountainous areas) with distribution networks; and (3) in utilizing fuzzy logic to reduce the lack of statistical data at a detailed level, which is a usual restriction of conventional approaches. Reliability evaluations in this way become more accurate and more realistic, even for a lack of complete online data.

As the need for dependable energy supply is growing, to rank the dependability of distribution networks is of utmost importance. Traditional reliability assessment methods, which concentrate in the use of statistical data, can be problematic in the lack of available data and the system uncertainty in its operation. In this context, the Energy Not Supplied (ENS) index as an important reliability index is very sensitive to the network failures and environmental behaviors; however, estimation of this index is frequently impeded by lack of complete data.

Traditional methods like the Monte Carlo simulation focus on system uncertainties but are unable to address complex, uncertain environmental conditions (e.g., storm, humidity, pollutants; etc.) and their impact on the network performance. EfdThese ambiguities, if not properly accounted for, result in pessimistic-erroneous predictions for reliability, which may influence power system managing decisions.

In this paper, this gap is covered by taking environmental uncertainties and their influence on the ENS index into account in fuzzy logic fashion. Fuzzy logic provides a well suited approach for dealing with the imprecision in parameters like failure rates, repair times and environmental factors, particularly in the absence of thorough statistical information. Our work extends the state of the art by including fuzzy logic for more accurate and realistic estimation of ENS in distribution grids affected by varying environment conditions.

2. Modeling the Distribution System using Fuzzy Logic

Fuzzy logic developed by Dr. Lotfi Zadeh in 1965 in his landmark paper "Fuzzy Sets" [19] is a system of logic that demonstrates reasoning with uncertainties. This theory provides a mathematical framework for the representation of vague concepts, variables, and systems, which constitutes a platform for inference, control, and decision making in the presence of uncertainty [20-21]. Since then, fuzzy logic and fuzzy set theory have transformed themselves to tackle ambiguity and uncertainty in different directions. For our purpose here, fuzzy logic supplies a gamut of values, which languishes our human judgment and reasoning down to computation work. Fuzzy logic is well adapted for modeling of complex systems that are insurmountable or extremely difficult with conventional mathematical or classical methods, providing more flexibility and simplicity in these cases.

In this research, fuzzy-based approach is proposed for modelling the effects of both the environmental and operational uncertainties on the EN index of PDS. The employed FIS in this paper is based on the popular Mamdani approach, which has been widely applied due to its interpretability and its capability of modeling uncertain systems effectively.

Modeling consists of the following steps:

- Fuzzification of Inputs: Environmental influences, such as storm strength, humidity, and air pollution, are expressed as fuzzy variables. Each of these parameters is accompanied by a set of membership functions. For example, the linguistic variable 'storm intensity' has a fuzzy set Low, Medium, and High, which is described by the certain triangular or trapezoidal shapes to represent the unavoidably vagueness of such factors. Analogous to the above, membership functions are constructed for other inputs, 'humidity' and 'pollution'.
- Fuzzy Rule Base: The fuzzy rule base is formed by 9 rules and it represents how the environmental parameters influence the ENS index. These rules are expressed in an 'if-then' manner, for example:
    - If storm intensity is High and humidity is High then ENS is High.
    - If storm magnitude is Low and pollution magnitude is Medium then ENS effect is Low. Rules are based on expert knowledge and previous experience of the effects of weather on power system reliability.
- Process of Inference: The fuzzy inputs are inferred using the Mamdani inference. Fuzzy outputs of these rules are calculated by the inferrence mechanism and are aggregated to derive a fuzzy output which expresses the total ENS impact.
- Defuzzification: The defuzzification phase is performed using the centroid procedure. This process then computes the center of gravity of the combined fuzzy output and results in a single operational value for the ENS index. This then enables us to measure the influence of environmental conditions on a power system reliability in a meaningful manner.
- Parameter adjustment: The objective of this paper is to adjust the language templates and diagonal elements as parametric dependent on several simulations in the RBTS-bus2 case. The model was examined under various environmental conditions in order to verify the model results against the actual behavior of real power systems.

This section focuses on the modeling of factors influencing load point indicators through fuzzy membership functions, along with the formulation of if-then rules in the rule base. The factors considered fuzzy in this study, and for which variable membership functions are defined, include distribution network lines and distribution transformers.

2.1. Distribution Network Lines

Transmission and distribution lines are vital components of power systems, primarily responsible for transmitting and distributing electrical energy across various sections of the network. These lines traverse diverse terrains, including plains, mountains, industrial zones, and residential areas, each subject to different natural and artificial influences. Therefore, it is essential to analyze the impact of these external factors on the average lifespan of the system's components and ensure appropriate conditions during their design, construction, and operation.

To successfully simulate changes in failure rates and maintenance times for these lines, the factors impacting these parameters must be defined as input membership functions. This study considers three critical variables—lifespan, risk exposure, and weather conditions.

2.1.1. Lifespan

The impact of aging on equipment performance is critical to the overall efficiency of power systems. As equipment ages, its failure rate increases over the course of its operational life, which in turn affects the system's reliability and imposes costs on the operator. Two major costs influenced by aging-related damage are the costs associated with *energy not supplied* (ENS) and the expenses of replacing or installing new equipment.

At this moment, decisions must be made that balance economic reasons with system reliability. It is vital to weigh equipment-related variables, such as safety, environmental conditions, and maintenance costs, against system-level factors, including load continuity, power quality, and the impact of forced outages due to repair.

Furthermore, identifying the most appropriate time for replacement or refurbishment is critical. Premature replacements cause capital losses, whereas delays jeopardize system reliability. The lifetime variable is described as three fuzzy sets with linear membership functions: "young" (0-8 years), "working period" (4-22 years), and "old" (18-30 years).

2.1.2. Exposure to Risk

This variable includes characteristics such as the quantity of trees along the route, the existence of mountainous terrain, bird migratory routes, and other regional geographic conditions that endanger the distribution lines. Tree branches in the way of power distribution networks cause substantial transient outages, which are typical during storms or high winds when the branches strike the lines.

Furthermore, heavy snowfall can weigh down branches, causing them to fall onto the network, resulting in phase-to-phase or phase-to-ground faults. Excess weight can cause branches to break, resulting in wire damage.

In this study, the presence of trees along the route is considered a key risk factor. The risk level of the lines is defined using three fuzzy sets: "low" risk (0–0.4), "medium" risk (0–2.8), and "high" risk (0.1–6), with linear membership functions. A high-risk level indicates that the distribution network lines are located in areas where 60–100% of the line path is heavily populated by trees.

2.1.3. Climate

All power system networks are influenced by variations in weather conditions. While such changes do not always cause problems, the failure rate of many components is highly dependent on the specific weather conditions in which they operate. In certain weather situations, the failure rate of a component can be several times higher than under more favorable conditions. These weather conditions that lead to increased failure rates are typically rare and short-lived, but during these brief periods, failure rates can escalate quickly. Therefore, ignoring weather conditions when evaluating reliability results would yield overly optimistic and misleading conclusions [22].

Weather conditions that have minimal or negligible impact on failure rates are classified as "natural" weather conditions, while those that significantly affect component performance are categorized as "adverse" weather conditions. Wind speed is used as a key indicator to represent weather conditions. For the weather variable, two fuzzy sets are defined with linear membership functions: "normal" (0–80 km/h) and "unfavorable" (30–100 km/h).

2.1.4. Output Variable: Coefficient of Variation in Distribution Network Line Failure Rate

The output variable, which represents the coefficient of variation in the failure rate of distribution network lines, is defined using five fuzzy sets based on degree of variation. The sets are:

- "Very Low" (range: [0.8–1.2])
- "Low" (range: [1.1–1.5])
- "Moderate" (range: [1.2–4])
- "High" (range: [1.2–9.5])
- "Very High" (range: [2.3–4])

Each set is defined with linear membership functions.

2.1.5. Output Variable: Repair Time

The output variable for repair time is defined using four fuzzy sets with matching repair duration ranges:

- "Good" (range: [4–6] hours)
- "Moderate" (range: [5–9] hours)
- "Bad" (range: [7–15] hours)
- "Very Bad" (range: [12–20] hours)

These sets are also represented by linear membership functions.

2.2. Distribution Transformers

Distribution transformers are one of the most important components of distribution networks. Given their critical importance in guaranteeing system dependability and high cost, they play an important role in power systems [23].

To represent changes in transformer failure rates, the factors that influence them must be defined as input membership functions. The three primary variables evaluated for this purpose are:

- Lifetime
- Vulnerability
- Exploitation

These variables are introduced as input membership functions for the transformer model.

2.2.1. *Life Span*

As equipment ages, the risk of damage and failure grows. Additionally, inappropriate use or neglect during operation increases the likelihood of malfunctions. The transformer life span variable is divided into three fuzzy sets:

- "Young" (range: [0–10] years): Transformers in this range typically operate with high efficiency and low failure rates. This classification aligns with industry standards, where failure rates remain below 1% in the first decade.
- "Working Period" (range: [5–25] years): Components in this range begin to exhibit signs of wear, with increased chances of insulation degradation or thermal stress.
- "Old" (range: [20–35] years): Aging infrastructure experiences significantly higher failure risks, corroborated by IEEE transformer life expectancy studies and utility maintenance reports.

These sets are represented by linear membership functions.

2.2.2. *Exposure to Risk*

Several factors contribute to the increased failure rate and damage of distribution transformers. These include accidents such as car collisions (due to transformers being installed in open spaces), natural events like earthquakes and floods, and geographical conditions such as high humidity and rainfall. The presence of water particles in transformer oil significantly reduces its electrical resistance, which can lead to arcing within the oil. Other contributing factors include overloads, ruptures, severe connections in weak-pressure networks, and pollution in the transformer's oil, all of which heighten the risk of failure.

In this article, the humidity factor is introduced as an indicator that allows the user to assess the transformer's risk status. For the transformer risk variable, three fuzzy sets are defined:

- "Low" risk (range: [0–0.4])
- "Medium" risk (range: [0–2.8])
- "High" risk (range: [0.1–6])

These sets are defined with linear membership functions. The "medium" level of risk indicates that the transformer is in an environment with humidity levels ranging from 20% to 80%. The operator can select the appropriate risk factor based on the system's history and the region's environmental conditions.

2.2.3. *Operation*

Several factors contribute to improper transformer operation, which in turn affects the failure rate. These include neglecting timely maintenance, improper handling such as opening the oil drain valve, failing to follow installation and transport guidelines, not installing adequate protective equipment, using unsuitable oils, and overloading the transformer beyond permissible limits for extended periods. Additionally, the absence of regular inspections and necessary tests further exacerbates the risk of failure.

The number of periodic visits and required testing is introduced as an indication to assess the operational status of the transformer. Two fuzzy sets are developed for this variable.

- "Improper" operation (range: [0–7] visits per year)
- "Proper" operation (range: [3–10] visits per year)

These sets are represented using linear membership functions.

2.2.4. *Output Variable: Coefficient of Change in Transformer Failure Rate*

The output variable denotes the coefficient of change in transformer failure rate. It consists of five fuzzy sets that describe the degree of change:

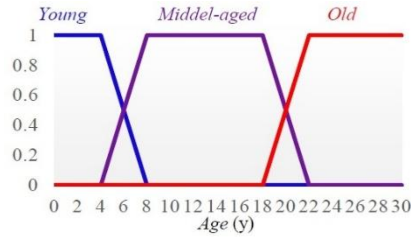
- "Very low" in the range [0.1–8.2]
- "Low" in the range [1.1–1.4]
- "Average" in the range [1.1–3.7]
- "High" in the range [1.2–6.2]
- "Very high" in the range [1.5–2.2]

These fuzzy sets represent different levels of variation in the transformer's failure rate. Figure 1 illustrates the membership functions for the distribution network's input and output variables.

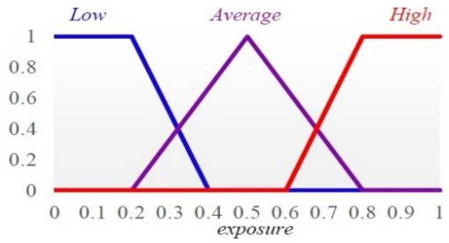
3. Rule Base

Once the membership functions are defined, the appropriate rules must be selected. In the fuzzy inference process, the Mamdani Max-Min Inference System has been applied. The AND and OR operations are represented using the min and max functions, respectively, while the non-fuzzy centroid method is employed for defuzzification.

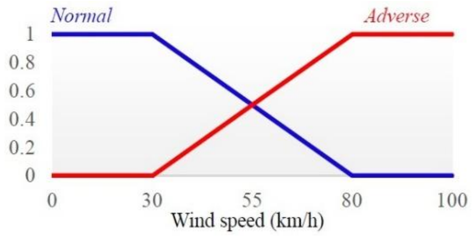
The formulation of the rules is often guided by human reasoning. For instance, it is commonly known that repair times tend to be longer under adverse weather conditions. An example of the rule selection for distribution lines is shown in Table (1).



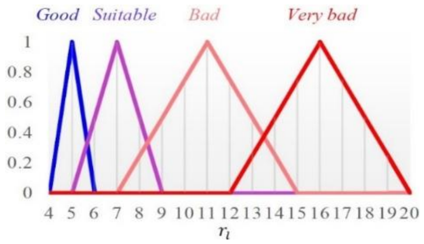
(a) Line's age



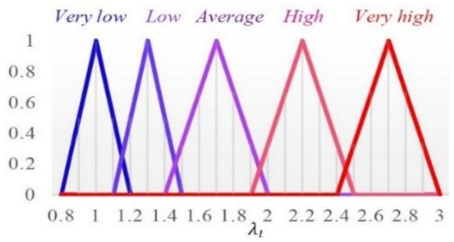
(b) Line's exposure



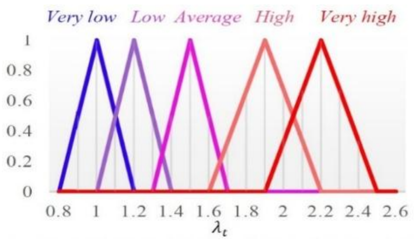
(c) Weather condition



(d) Average outage time of a distribution line



(e) Failure rate of a distribution line



(f) Transformer's failure rate

Fig. 1. Input and output membership functions for distribution network components.

Table 1. Some rules in the rules database related to lines

Rule	If			Then	
	Life Span	Danger Level	Climate Condition	Change Output	Repair Status
1	Work period	Low	Normal	Very low	Good
2	Work period	Medium	Normal	Very low	Good
3	Work period	High	Normal	Medium	Good
4	Old	Low	Normal	Low	Good
5	Old	Medium	Normal	Low	Good
6	Old	High	Normal	Medium	Good
7	Old	High	Inconvenient	Very bad	Very bad

4. Test Results on the RBTS Network

The RBTS-bus2 test system was chosen for analysis in this paper [20]. Because of its realistic structure and ability to simulate distribution network behavior under various conditions, this system is frequently used in reliability assessment research. It is the perfect option for assessing the effects of operational and environmental uncertainties using fuzzy logic because of its standardized configuration and modular design, which enable consistent comparison across studies. Using MATLAB programming, the system's Average Interruption Frequency Index (SAIFI) and Energy Not Supplied (ENS) indicators were calculated. Table 2 presents the input values of the fuzzy sets for various scenarios, which were used to evaluate these indicators.

Table 2. Different inputs of membership functions

Case	Line Inputs	Trans Inputs	Improvement
1	(22, 0.85, 55)	(25, 0.5, 2)	Benchmark
2	(22, 0.85, 25)	(25, 0.5, 2)	Weather Condition
3	(22, 0.85, 25)	(25, 0.5, 2)	Trans Operation
4	(22, 0.85, 25)	(15, 0.5, 5)	Trans Life Span
5	(22, 0.65, 55)	(25, 0.5, 2)	Risk of Lines
6	(10, 0.85, 25)	(25, 0.5, 2)	Lines Life Span
7	(22, 0.25, 22)	(25, 0.5, 6)	Cases 4, 6
8	(10, 0.85, 25)	(15, 0.5, 2)	Lines and Trans Life Span
9	(10, 0.15, 25)	(15, 0.5, 8)	Cases 8, 9

Table 2 shows the input variables for the distribution lines (life, exposure to risk, climate) and transformers (life, exposure to risk, exploitation). The results of the system's performance indicators for various input scenarios are illustrated in Figures 2 through 4.

The system's failure rate is reduced by shortening the lifespan of the lines and transformers, as well as lowering the risk factor for both. This reduction improves system accessibility, decreasing both the SAIFI and ENS indications.

Figure 2 depicts the system's accessibility for several scenarios; it is clear that case 4 has the lowest level of inaccessibility among instances 2 through 6. This is owing to the fact that unavailability is determined by repair time, with transformer repair time set at 200 hours, which is substantially longer than the 5-hour repair time for lines, resulting in reduced availability.

Figure 3 depicts the SAIFI index for the system. Case 1 shows the highest SAIFI value. In this case, unfavorable weather conditions are assumed, and the IEEE standard for a two-case weather model states that the failure rate in such conditions can be several times higher than in favorable conditions. The rules in the database indicate that under adverse weather, failure rates and repair durations are in a highly unfavorable state, severely impacting the indicators related to these rates.

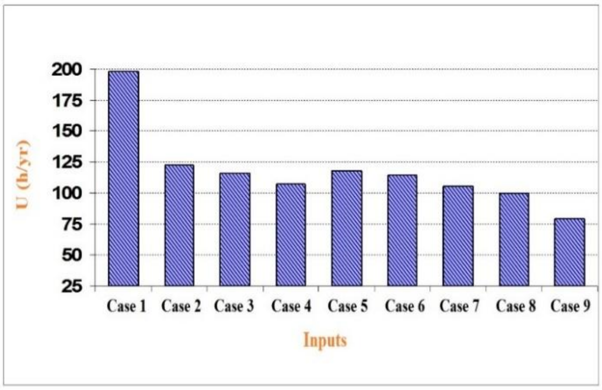


Fig. 2. System inaccessibility levels across different scenarios based on fuzzy modeling of distribution network reliability.

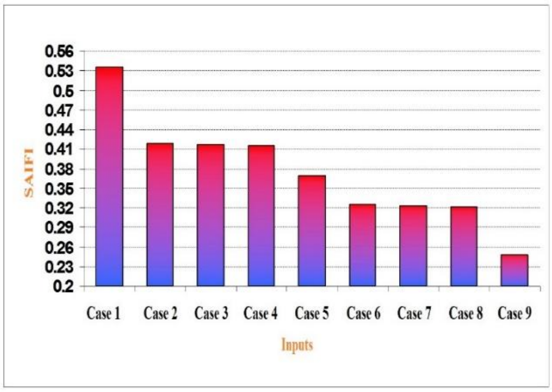


Fig. 3. SAIFI (System Average Interruption Frequency Index) values for various cases.

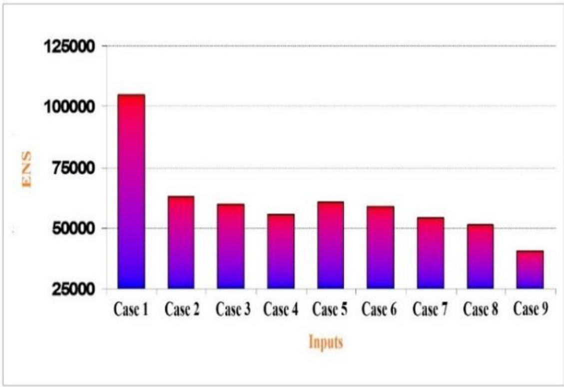


Fig. 4. Energy Not Supplied (ENS) index for different scenarios.

Figure 4 shows the system's energy not supplied (ENS) index under various situations. The ENS index is a function of the average load and unavailability, therefore any change in the inputs impacts this index. As with accessibility, the energy not supplied in example 4 is smaller than in cases 2–6.

Figures 5 and 6 show the percentage improvement in the SAIFI and ENS indices for various situations compared to Case 1. Comparing these outcomes provides useful insights that can be used to make decisions about network equipment optimization, which improves the distribution network's efficiency and productivity, contributing to higher welfare and increased public satisfaction.

As demonstrated in Figures 5 and 6, enhancing the hazardous condition of the lines—achieved by deleting extra branches along the routes—results in a 31% improvement in both the SAIFI and ENS indices, for a total enhancement of 41.88%. This improvement is achieved while maintaining consistent production and increasing customer satisfaction through good management.

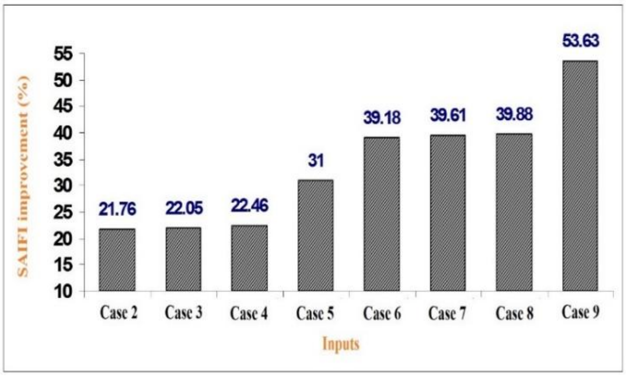


Fig. 5. Percentage improvement in SAIFI compared to baseline Case 1.

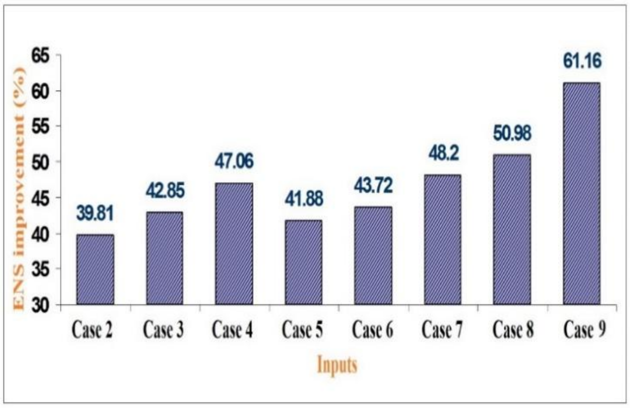


Fig. 6. Percentage improvement in Energy Not Supplied (ENS) compared to baseline Case 1.

The results obtained from the fuzzy modeling provide valuable insights for power system operators. By incorporating environmental uncertainties such as equipment aging, geographical exposure, and weather conditions, the model enables a more realistic estimation of component failure rates and repair durations. As shown in the simulations (Table 2 and Figures 2–6), even moderate improvements in environmental risk factors—such as tree clearance along line paths—can lead to over 30% reductions in SAIFI and ENS indicators. These outcomes underline the importance of proactive maintenance strategies and resource prioritization.

Moreover, the model supports decision-making under uncertainty, allowing operators to assess different scenarios before implementing costly maintenance or replacement actions. This facilitates an optimized balance between operational reliability and investment cost. Such foresight is particularly critical in networks spanning diverse geographic areas with varying climatic and environmental conditions, contributing to increased system resilience and customer satisfaction.

5. Conclusion

In order to assess their influence on reliability metrics like SAIFI and ENS, this study used fuzzy logic to examine important operational and environmental elements influencing distribution network performance. The results show that extending the life of lines and transformers, reducing distribution line risk, and improving transformer operating procedures all have a major impact on system performance and customer satisfaction. Regular maintenance, recurring inspections, vegetation control, and the use of protective equipment are examples of preventive measures that can significantly reduce failure rates and outage times. The most important factors influencing network reliability were found by comparing different input scenarios. Despite the encouraging outcomes, it is important to recognize certain limitations. The fuzzy logic model's generalizability across various grid configurations or geographical conditions may be limited due to its reliance on expert-defined membership functions and rules. Furthermore, accurate and consistent data—which might not always be accessible in real-world situations—are necessary for practical implementation. There are additional difficulties in integrating this model into current grid management systems, especially with regard to operator training and computational resources.

In addition to expanding the model to incorporate real-time environmental and operational data through IoT-enabled devices, future research should concentrate on improving the model's adaptability by incorporating machine learning techniques for automatic rule generation and parameter tuning. Additionally, investigating hybrid approaches that combine fuzzy logic with probabilistic or optimization-based methods could result in more reliable and scalable solutions for real-time power system management.

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