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Distributed Generation System Reliability Evaluation Using Fuzzy Logic with Renewable Energy Sources

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Abstract— The essential challenges in the Distribution System (DS) are reliability and continuity. The electric load architecture of the distribution network altered as a result of social and political changes. The DS becomes less reliable as a result of a lack of maintenance and the aging of the distributing firm's assets. It was difficult for technicians to recognize and categorize assets concerning operational and maintenance requirements. As diverse resources and innovations are being used, distribution generation (DG) is predicted to perform a major role in the successful progression of power systems. DG is most commonly connected with two forms of energy: traditional and renewable. It is extremely difficult to predict when renewable energy will be more unreliable. Fuzzy logic could be employed to estimate DS reliability indices. In this paper, fuzzy logic is used to analyse the DS's reliability indices. The fuzzy toolbox is used to create the IF-THEN rule, which employs inferences depending on past knowledge. Analytical and Monte Carlo Simulation (MCS) methods are used to compare the results of the fuzzy logic method.

Keywords— Electric Vehicle, Motor, Speed, Optimization, Error, Time response.

I. Introduction

The concepts are of reliability and applicable to practically all application areas. Through its widest sense, reliability is a measure of system performance. This metric could be utilized to enable systems to fulfil performance requirements, quantify differences among alternative approaches, and generate economic judgments. The main purpose of reliability assessment is to deal with queries like "Is the network adequately reliable?", "What plan is most prone to failure?" and "where will another money be invested to better the network?" [1]. The objective of a power grid will provide energy to its clients cost-effectively and reliably. It is important to formulate and manage a reliable network since interruptions and electrical problems could have a major impact on the economy and the clients. Presently, deregulated power utilities would be reformed and run as distinct generating, transmitting, and distributing corporations, with accountability for the reliability and quality of the power system.

DG are small-scale (10 MW or fewer) power sources located at the consumer terminal that can produce electricity independently for a few consumers while also connecting to public distribution [2]. DGs include wind turbines, fuel cells, PV cells, internal combustion motors, and renewable sources. DG offers different benefits for power DS support, including decreased energy consumption, investment preservation, utilization of new energy, and enhanced dependability and flexibility. It is utilized frequently in the distribution network. As technology progresses, the use of DG in power distribution networks becomes more prevalent. Concerns of interconnection, protection coordination, and voltage regulation must be addressed when integrating DG into the energy system. However, the main benefits of integrating DG into a power supply are greater reliability and cost reductions.

DG technologies have a significant effect on high-reliability claims, such as providing a capacity source during an emergency or delaying the construction of a local network. During power disruptions, DG can be utilized to provide a more reliable supply. On the client-side, DG's role in reliability is the most direct. When DGs provide local load during disturbances, reliability is enhanced. When a backup DG is installed, the duration of outages is shortened. The addition of DG to the DS improves system resilience since it provides power to loads during islanding [3] operations. The reliability of the DS is evaluated using several indices, including Average Interruption time, duration time and Failure Rate, Average Service Availability Index (ASAI), System Average Interruption Duration Index (SAIDI), Average Service Unavailability Index (ASUI), Customer Average Interruption Duration Index (CAIDI), System Average Interruption Frequency Index (SAIFI), and Expected Unserved Energy (EUE) [4,5]. There are numerous methods for analysing the dependability of electricity systems. Typically, these strategies fall into one of two categories: analytical approaches, MCS techniques, or a combination of the two.

The paper is organized in the following manner: Portion 1 is composed of a detailed description of DG and radiality, Portion 2 survey the previous work, Portion 3 discuss the methodology of the research, Portion 4 details the operation of distributed renewable energy systems, Portion 5 deals with fuzzy inference, Portion 6 evaluates the performance indices for reliability, Portion 7 discussed the result obtained by deploying fuzzy logic, Portion 8 concludes the research work with its importance.

II. LITERATURE SURVEY

Distribution power system (DPS) reliability is assessed using an ANN model that employs a backpropagation learning algorithm to forecast (RPS) using historical data [6]. Simultaneously, real-world DS indices like SAIFI and SAIDI are calculated, and the network technique's findings are compared. The accuracy indices provided by the suggested approach are satisfactory, and the variance of calculated values by the suggested technique is lower than 1%, with a running duration of fewer than 2 seconds in an ASUN network environment. The ANN technique outperforms the network model. The study [7] intends to offer a neural network (NN) approach that may solve the shortcomings of the current reliability evaluation method, such as low accuracy and advanced models, as well as the lengthy implementation time. This paper describes a strategy for creating a learning model that integrates a radial basis function neural network (RBFNN). Use this model to assess numerous reliability indices used in generation planning. The Markov process and a simple probabilistic technique are used to create input-output training patterns for neural networks. RBFNN is demonstrated using a normalized version of this data set. To show the validity of the proposed method, the RBTS, and IEEE-Reliability Test systems are used. In paper [8], the reliability indices of lines and transformers are evaluated using fuzzy logic with six input variables. The IF-THEN rule for fuzzy inferences based on knowledge was created using the MATLAB Fuzzy program. A thorough investigation of the fuzzy system surfaces reveals dynamic and correct linkages between the components under consideration. The defined criteria based on engineering experience accurately describe the Reliability Indices.

Calculating the appropriate load shedding approach for each of the proliferating states is a tough challenge. It has been identified as a stumbling point in the reliability assessment approach. A deep learning-based technique for assessing system resilience in the face of generation and load changes has been provided. The suggested power flow model employs stacked denoising auto-encoders as a multi-layer neural network [9]. Because of its structure, it can extract high-order characteristics from non-linear equations. Contingency state characteristics are critical for achieving the least amount of load decrease while avoiding the time-consuming optimal power flow (OPF). To simulate various states, the RTS-79 system employs the MCS. The numerical results reveal that the SDAE-based method outperforms the others in terms of computation time and accuracy. As an alternative to typical OPF algorithms, the impact-increment approach and other state selection methods can be utilized in conjunction with it. The dependability evaluation and modeling methodologies are first created in research [10] using machine learning. State Space Classification (SSC) is then proposed as the primary method for evaluating reliability by introducing the perceptron classifier. New methods for assessing reliability that lessen the burden of topological observation, such as SSC and Sequential MCS, are employed. To verify the model's accuracy and methodologies proposed, in-depth case studies are conducted on the Roy Billinton Test System (RBTS) bus 2 and a real DS. Reliability evaluation is done more quickly using the proposed methodology, while maintaining accuracy, according to the results of this study. Researchers [11] used a hybrid analytical-simulation method to analyze a microgrid with prioritized loads and distributed RES. Due to its inherent stochasticity, RES impedes any attempt to assess its reliability. The Monte Carlo state sampling simulation is performed to compensate for RES variation. According to the findings, the microgrid structure helps to improve accuracy. For the most maximum stress, reliability indices have risen the most. An upstream network fault-caused microgrid islanding failure is also subjected to sensitivity analysis to determine its effects. Article [12] contains an assessment of the reliability of the RBTS bus-2 system in grid-connected mode, with and without DG factoring. Each microgrid is considered to be connected to the grid in a grid-connected mode, feeder by feeder. The dimensions and position of the DG are also considered in the reliability assessment. The Analytical technique was used to calculate the load point and total system dependability indices. The results from DG and without DG have been compared.

III. METHODOLOGY

The flow chart in Figure 1 summarises the fuzzy theory-based reliability evaluation approach. The steps involved in determining a system's reliability are as follows:

1. Using the MCS technique, random samples are first generated for the failure rate and repair times.

2. Using analytical and random sampling data, the probability distribution modeling program in MATLAB may be employed to calculate the probability density function (PDF) of all process variables.

3. PDF depicts the frequency with which an x occurs in the sample space, given that the function $f(x)$ can be defined. Consequently, the probability that x will happen is indicated by the region under the $f(x)$ the curve between x minimum and x maximum: Construct a fuzzy membership function (MF) from the PDF.

$$\mu(x) = \begin{cases} f_1(x) = 2\int f(x)dx, \quad x \in [x_{min}, x_{m1}] \\ f_2(x) = 2(1 - \int f(x)dx), \quad x \in [x_{m2}, x_{max}] \\ 1, \ x \in [x_{m1}, x_{m2}] \\ 0, \ Otherwise \end{cases} \quad [1]$$

4. Based on the a-cut principle, fuzzy computing has been used to estimate the reliability indexes of fuzzy load points

5. Reliability index evaluation is done using fuzzy load point reliability indexes for each of the fuzzy systems

6. The incentre technique is employed to defuzzify reliability measures for improved graphical interface and analysis reasons.

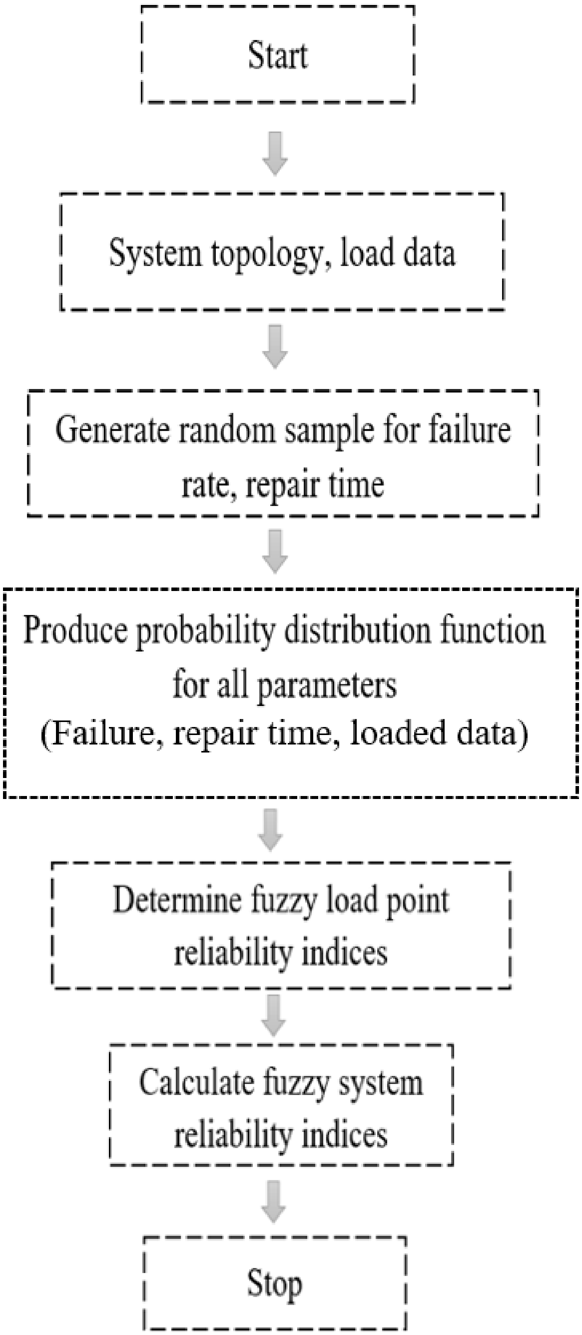

Fig. 1. Flow chart of fuzzy reliability evaluation.

IV. OPERATION OF DISTRIBUTED RENEWABLE ENERGY SYSTEMS

Small-scale customers in a distributed system often do not actively participate in the electrical market to obtain the electricity they require. A load collector, on the other hand, is equipment that provides to the power market by absorbing and transferring energy for the advantage of its users. The load collector's purpose is to provide uninterrupted solutions to customers while decreasing costs. By linking renewable energy sources such as wind and solar power systems, load collectors may better control energy demand and supply. Figure 2 depicts a simulation architecture that includes renewable sources of energy plus power converters.

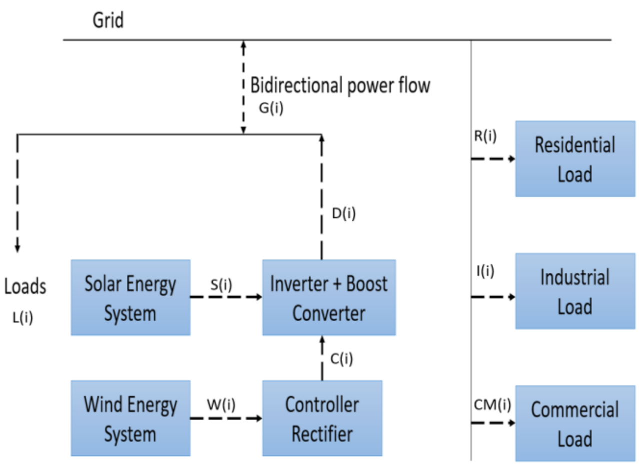

Fig. 2. DS integrated with renewable energy sources.

Just for clarity, the domestic, business, and manufacturing clients, renewable energy sources, and power converters of the DS are represented as a single block. In contrast, more comprehensive modelling, such as scattered modelling through the feeders, can be implemented. In particular, $G(j)$ represents the acquired power of the electricity sector and the grid's supply per j seconds. Solar and wind energy systems supply the distribution network with power $S(i)$ and $W(i)$. D represents the overall energy produced by the renewable system (i). At any given time, household, manufacturing, corporate, and particular local loads, renewable energy supply production, and acquired power equally influence the balance of power. $G(j)$ could become minus if net metering is implemented, which results in the transfer of power from the distributed network to the grid. This is possible if the DS is tied to renewable sources that produce excess electricity. The computation is simplified by the premise of controlled power levels as well as the lack of power loss. This type of information is advantageous to reliability analysis. If any portion of the proposed model fails, the distributed system using renewable energy would function as a hybrid power system with the grid and also in failure mode. The constraints are given below

The constraint of wind energy:

$$0 \leq W(i) \leq W_{max}(i) \qquad [2]$$

The constraint of solar energy:

$$0 \leq S(i) \leq S_{max}(i) \qquad [3]$$

The constraint of power balancing:

$$G(i) + D(i) = R(i) + I(i) + CM(i) + L(i) \qquad [4]$$

V. FUZZY INFERENCE

The Mamdani fuzzy inference technique was introduced by Mamdani and Assilian in 1975 [13]. A suitable fuzzy set is used to create MF, which then become fuzzy input values. That rule's outcome will be determined by its fuzzy set, and then defuzzification will be necessary when all the reshaped sets have been aggregated. Following these steps will get the Mamdani fuzzy inference results: Implication, Aggregation, and Defuzzification are all steps in the defuzzification process that include fuzzifying inputs and selecting the right rules.

Fuzzing the input variable for mapping the inputs to the suitable set of input MF to acquire results from this example. It's then applied to the if-then rules using fuzzy operators (and, or). After then, the input values are subjected to the rule weight (antecedent). To determine which rule is most effective, the weighted input is used. Then, the implication approach is used to conclude. In the implication, the input is a single integer, and the output (consequent) is a fuzzy set of numbers. To reduce the size of the fuzzy set, the "and" approach is used. All subsequent fuzzy sets are aggregated into a single set at the end of each of the if-then-then rules. The aggregated fuzzy collection will finally produce a crisp value when it has been defuzzified. There are a variety of defuzzification techniques to choose from. The centroid approach, commonly known as the centre of mass, will be employed for defuzzification in this study. When it comes to defuzzification, this method is the most commonly used. Using this strategy, you can get a single, precise result from a complex distribution function.

The DS's end customers must receive electrical energy that is consistent and safe. Components of the DS must function properly to safely provide electricity to the end-user. However, there are several reasons why a DS's reliability could be at risk. One of the reasons for this is the large number of components that can be affected by failures induced by external events. Because of their location, overhead power lines are vulnerable to natural disasters and other external factors that could disrupt the flow of electricity. Weather conditions, tree branches falling on cables, bird damage, road accidents, and other such occurrences fall under this category. Those occurrences are impossible to foresee. Another reason for unexpected outages is the overuse of lines, which can cause line deterioration. The time it takes to locate a problem on an underground line is longer than on an overhead line, even though they are more resistant to external influences. End consumers in a deregulated market where they can actively engage in selling generated electricity will be negatively impacted if a component fails. Furthermore, the end consumer would lose money if the energy supply was disrupted. As a result, utilities must do more than just provide electricity; they must also ensure the consistency of that energy. The failure rate and outage duration indices of power system components are commonly used to calculate the reliability of the power system [14].

VI. MONTE CORLO SIMULATION

MCS's major components are sampling, analysis, and evaluation [15]. The essential steps of the evaluation are depicted in Figure 3.

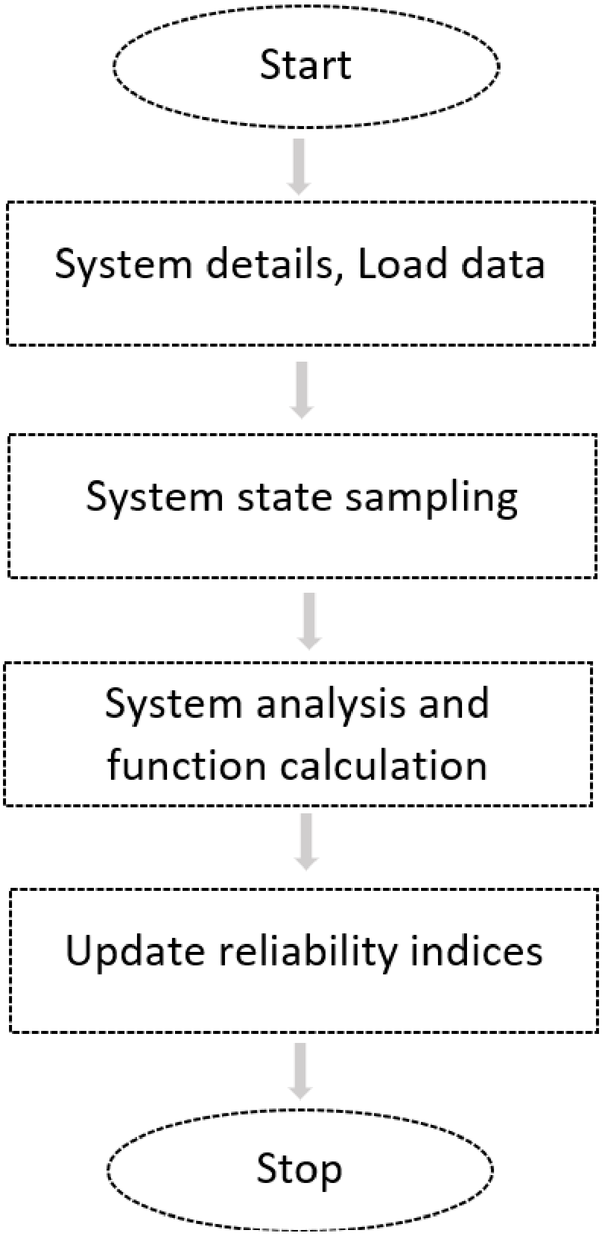

Fig. 3. Flow chart of MCS reliability evaluation.

As seen in the preceding graphic, the MCS necessitates random state sampling of the system, with no respect for the longevity or transfer coefficient of the state. A sampling procedure that is changed across the sampling method decreases contrast and enhances computational efficiency for a more accurate assessment. Whenever the sampling is finished, the system states should be evaluated and the state's testing function value calculated. The reliability indices are calculated using this approach.

VII. RELIABILITY INDICES

There are feeders, sectioning devices, transformers, overhead power lines or connections, and loads in the DS [16]. If the circumferential distribution network fails to deliver elements from the feeder to the loading point, all or a portion of the feeder's consumers would be unable to acquire their supplies. Two criteria can be used to evaluate the reliability of a feeder: failure rate (λ_i) and average outage duration (r_i) for every sequence element (i) from supplier to load level. In a load point, the average failure rate (λ) and average outage duration (U) were calculated as shown in.

$$\lambda = \sum_{i=1}^{N} \lambda \qquad [5]$$

$$U = \sum_{i=1}^{N} \lambda_i r_i \qquad [6]$$

The reliability indices are calculated as follows.

SAIFI is the average sum of long-term failures experienced by each customer. The interruption ratio is defined as the ratio of total disruptions to the total customer.

$$SAIFI = \frac{\sum_{i=1}^{N} \lambda_i N_i}{\sum_{i=1}^{N} N_i} \qquad [7]$$

SAIDI is an average outage duration experienced by a certain number of customers. How many customers are affected by an outage every year is determined by how long it takes for service to be restored.

$$SAIDI = \frac{\sum_{i=1}^{N} U_i N_i}{\sum_{i=1}^{N} N_i} \qquad [8]$$

For each predetermined period, ENS calculates the average amount of energy a customer has not yet received.

$$ENS = \sum_{i=1}^{N} ENS_i \qquad [9]$$

$$ENS_i = Lp_i f_i U_i \qquad [10]$$

This is where N_i is the total number of customers at each load point, ENS_i is the quantity of energy not delivered at that specific load point i, Lp_i is the maximum load at that specific position, and f_i is the load coefficient at that specific place. As previously indicated, the failure rate fluctuates over time and in various operational and environmental conditions. In traditional reliability assessment approaches, these indices are frequently estimated with a fixed failure rate. The archived database can be used to examine and improve the reliability of a DS, which is a reactive strategy that relies on historical performance [17].

Instead of applying measures to improve system reliability right once, system management should wait until problems develop before taking corrective action. Each DS component's failure and repair time is estimated using archival databases. Many archive database components are either inaccessible or incorrect in practice. Using fuzzy sets theory to cope with this type of uncertainty is an excellent way to go. Fuzzy logic generates mathematical models for each load point component that produce the previously defined reliability indices.

VIII. RESULT AND DISCUSSION

The load factor is generated using data from a real-world Indian DS on system loading. Data is collected, and the amount of renewable energy produced is calculated. To assess reliability, we assume that there is no alternative supply, that transformers are not repaired, and that these assumptions will remain consistent during the analysis period. The substation and its protective equipment are considered to be perfect, and any flaws in either are simply eliminated in the computations. The DS requires manual labour to operate.

The suggested fuzzy method is utilized to access the fundamental load point reliability indices (failure rate). For validation, Figure 4 compares the reliability indices of fuzzy techniques to analytical and MCS technique values. When compared to MCS approaches, the proposed one appears to yield nearly equal outcomes with the analytical. The indices produced by the MCS techniques are unaffected by uncertainty in the input. As demonstrated in the image, it is possible to incorporate uncertainty into the load point reliability indices in the fuzzy evaluation approach

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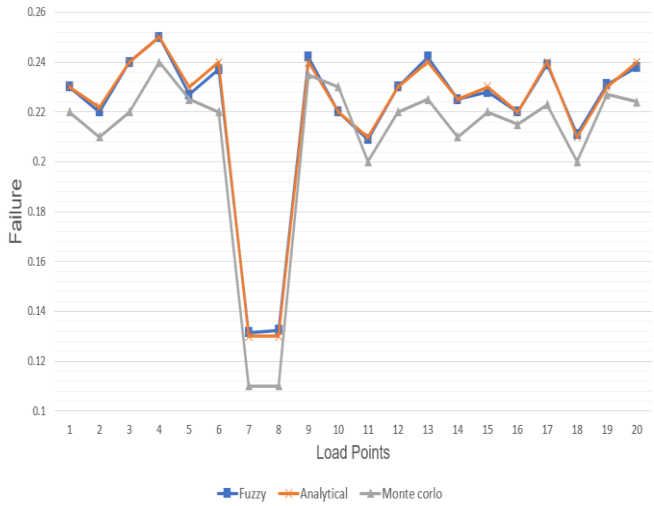

Fig. 4. Reliability indices comparison

To validate the fuzzy process, analytical and MCS methodologies are conducted to evaluate the defuzzified reliability scores. Table 1 shows the reliability metrics for different evaluation approaches. The findings are as follows: Each of the three ways produces nearly the same SAIFI score. The SAIDI and SAIFI scores of the analytical technique are roughly identical to those of the fuzzy method, whereas the SAIDI and SAIFI values of the MCS technique are considerably more useful. Whereas the fuzzy technique has a smaller ENS score than the other methods. In terms of reliability, Table 1 reveals that the proposed fuzzy reliability assessment approach is extremely similar to the analytical and MCS approaches.

Table 1: Reliability indices comparison

Indices	Fuzzy	Analytical	MCS
SAIFI	0.1954	0.1978	0.1703
ENS	32.25	35.58	33.480
SAIDI	2.5345	2. 567	2.8461

IX. CONCLUSION

The power industry is undergoing a transition from the electric grid to a more reliable, secure, efficient, and intelligent grid. Renewable energy sources like solar and wind power sources would be used, maybe on a large size, to meet these aims. This study focuses on improving power system reliability by incorporating renewable energy into the grid by utilizing enhanced intelligence algorithms. In this study, a reliability evaluation approach used fuzzy logic. A standard procedure for converting data into fuzzy MF is provided. The random samples are obtained by averaging the rate of failure, and repairing duration, in the DS. The MATLAB probability distribution tool is used to create a pdf from input samples. Using the typical transformation strategy, these pdfs are converted into fuzzy MF. The fuzzy indices are the results of defuzzified values. These defuzzified findings are validated by comparing them to analytical and MCS reliability indices. The suggested fuzzy method yields the same results as analytical techniques.

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