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## RESEARCH ARTICLE

# Reliability Assessment and Improvement of Electrical Distribution Systems by Using Multinomial Monte Carlo Simulations and a Component Risk Priority Index

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**ABSTRACT** In this paper, a method of assessing and improving the reliability of power distribution systems based on Monte Carlo simulation and a novel risk priority index is proposed. The initialization of the assessment process is carried out by using Multinomial Monte Carlo simulation with a nonsequential technique to assess system reliability in the form of SAIFI and SAIDI indices. Then, the novel per-time-based component reliability indices representing the insights obtained from root-cause analysis for each component in the system are evaluated to make suitable decisions on improvement measures. The proposed indices are derived as a component risk priority index based on the principle of the failure mode and an effect analysis to prioritize and select the implementation points by the Pareto principle. By applying the proposed method, a reliability improvement should be achieved at the correct point with minimal operations. In addition, the proposed method can be used to study the effect of uncertainty regarding some device operations on the system reliability. To verify the performance of the proposed method and demonstrate its application, three case studies were performed on the IEEE RBTS Bus-2 test system. From the first case study, the results of the proposed assessment process were validated by comparison with a standard benchmark. The second case study showed the performance of applying the entire process to improve system reliability, and the results showed that system reliability can be improved significantly. The third case study was performed to determine the effect of uncertainty in protective device operations. The results of the third case showed that there was a significant decrease in overall reliability in terms of a higher level of power outages, while the performance of the protective components was slightly reduced.

**INDEX TERMS** Reliability assessment, nonsequential Monte Carlo simulation, multinomial distribution, multinomial Monte Carlo simulation, component risk priority index, per-time-based component reliability index.

## I. INTRODUCTION

To operate an electric power system with an acceptable level of interruption for all types of users according to economic activities, reactive planning and proactive planning are needed to provide a guaranteed agreement for the provision of effective services. However, excessive concern about reactive

planning leads to a steady increase in editing work, while proactive planning is an unavoidable task that requires in-depth information to be obtained by reliability evaluation, which consists of assessment, prediction, and forecasting. Therefore, proactive planning should be a more efficient way of improving reliability [1], [2], [3], [4].

The reliability of an electrical distribution system is one of the power quality problem topics defined by the IEEE Std. 1159<sup>TM</sup>-2019 standard. Reference [5] Reliability in an

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electrical system addresses interruption statistics, which are compiled based on IEEE Standard 1366–2012. Reference [6] Generally, there are 4 main indices, i.e., the system average interruption duration index (SAIDI), system average interruption frequency index (SAIFI), customer average interruption duration index (CAIDI), and average service availability index (ASAI), which represent interruption indices based on the average number of customers. However, in practice, most utilities, including the distribution system of Thailand, consider the SAIFI and SAIDI indices to be the main indices for evaluating customer service performance in each area because other indices (CAIFI, CAIDI, ASAI and ASUI) cannot provide customers with easy-to-understand insights, and if the SAIFI and SAIDI indices are known, other indices can be derived accordingly. Additionally, ENS and AENS are indices used to assess the loss of opportunity caused by power outages (outage costs) that do not consider the loss of customer opportunities and will cause disparities between retail and large customers. Therefore, they are not commonly used in practice.

These indices are commonly used for describing system reliability; generally, reliability analysis and assessment require historical data to provide a time-to-failure (TTF) data set for obtaining the reliability function and failure rate function based on the Weibull probability distribution model [7] or other models, e.g., Kaplan–Meier estimation based on nonparametric models. Reference [8] In addition, a time-to-restoration (TTR) data set is required as an additional key data set for providing more in-depth information, e.g., failure rate ( $\lambda$ ), mean time to failure (MTTF), mean time to repair (MTTR), mean time to switching (MTTS) and the bathtub curve of the failure rate function. Such information is useful for obtaining reliability predictions for managing all devices in the systems by predicting what will happen at each stage over their lifetimes. Reference [9] Some relevant data sets are commonly characterized as secular trends and cyclical variations, while the rest are seasonal variations and irregular variations. By combining them, a complete time series forecasting model can be derived and used to investigate time-varying related factors causing further changes in system reliability. References [10], [11], and [12] Moreover, time-to-failure analysis and time-series analysis can provide certain indices regarding reliability with corresponding times, such as loading, aging, and risk factors.

In a distribution system, the effect of changes in network structure, operating conditions, and uncertain operation in the system at any time can be analyzed by 2 different approaches, i.e., analytical methods and Monte Carlo simulation (MCS). References [13], [14], [15], and [16] Essentially, the analytical method is suitable for radial distribution systems. The analytical results are defined as expected or average values that are commonly used in practical applications, whereas MCS can be applied to more complex distribution systems or systems with uncertain conditions by considering outcomes in the form of an artificial reliability data set according to the purpose of use. If interruption data sets in the form of

time series are needed, a method based on sequential Monte Carlo simulation (SMCS) techniques should be applied. Reference [17] If determining the interrupting state data sets of specific components is the problem of interest, a method based on nonsequential Monte Carlo simulation (NSMCS) should be selected. Reference [18] At the starting stage, artificial random reliability data sets in a time sequence are generated based on the distribution function of a uniformly distributed random variable, while the failure rate parameter ( $\lambda$ ) is used as a constant value at any fixed time. In general, the exponential distribution is the most popular model for time-to-event random functions, while a nonsequential data set is often modeled by using the Poisson distribution; the modeling process is often referred to as random Monte Carlo simulation (RMCS) [16], [19].

In practice, predictive reliability assessment has become an effective approach for active planning in reliability improvement. There are various typical scenarios for reliability improvement, such as installing load transfers between feeders, substations and feeder expansions; installing line reclosers; installing sectionalizing switches; enabling new feeder tie points; utilizing feeder automation; replacing aerial lines with underground cables; and replacing aging equipment [20], [21].

When a distribution system has a large number of devices and a large maintenance area, the reliability assessment process will be more complicated. From the assessment, reliability indices representing both specific load points and the entire system should be obtained, and the operator and customer should be able to understand them easily. To determine a suitable solution for the reliability problem, the results of the assessment should be consistent and sufficient for identifying the root cause of failure with a minimum workload. The reliability problem can be prioritized by using an additional index, called the risk priority index, as proposed in previous works.

To rank the problems proposed in [22], different techniques based on machine learning models are used to predict the risks of failure for different component groups and feeders. However, it is quite difficult to prioritize problems and compare the results for the components between groups. The weighted average system reliability index (WASRI) [23] has been proposed to compare spatial assessments, although there is a problem of choosing biased weight values between small and large customers. The risk level index of each device (RA) proposed in [24] can assess the outage costs for a utility but may lead to bias when focusing on large customers. However, the risk index category (RT) [25] has been proposed, which can be applied to events with long power outages. Likewise, the index of customer minutes of interruption to dollars (CMI reduction/\$) proposed in [26] has led to inequality between small and large customers. Such indices represent a group of risk priority indices, leading to difficulty in identifying the root cause at the device level. On the other hand, parsing each group of devices may not be an effective way to analyze the overall effect of the problem. Therefore, the

reliability index for each component, which can provide quantitative measurements of the impact on reliability, is an interesting issue, and the risk priority index of the distribution system components is analyzed to find the appropriate model, which is then tested for application in this paper.

An effective method is proposed in this paper for analyzing the reliability of a distribution system with NSMCS and novel component reliability indices, which are averaged across the interruption time. The proposed method uses a principle with a multinomial distribution function considering the uncertainty of the protective components, called Multinomial Monte Carlo simulation (MMCS). [33] The results of MMCS are used for assessing the reliability indices based on the customer numbers in each area, i.e., SAIFI and SAIDI, and the indices based on the total number of power outages in each component, defined as per-time-based component reliability indices. All indices from the assessment can be used to analyze the root cause of the reliability problem and to determine appropriate measures to improve the reliability of a specific area and component. With the per-time-based component reliability index, the component risk priority index (CRPI) will be derived in accordance with the failure mode effect analysis principle (FMEA), which is applied in conjunction with the Pareto principle (20/80) to achieve the best results through the minimum number of actions.

The concept of using MMCS for reliability assessment is described in section II, while the proposed analysis methods and evaluation of the relevant indices are described in section III. To determine the effectiveness of the proposed method, all processes are tested with the IEEE RBTS Bus-2 system using three case studies to validate the results of the assessment process, demonstrate the process of reliability improvement, and study the consequences of uncertainty in protective operation, and a discussion is given in section IV. Finally, the paper is concluded with a supplementary development plan.

## II. MULTINOMIAL DISTRIBUTION MONTE CARLO SIMULATION AND RISK PRIORITY NUMBER

The Multinomial distribution (MD) is an ideal probability distribution function for MCS because it can simplify the MCS process and accord with actual power failures. The result after the process is a data set of artificial power failures that are comparable to actual reports of failure logs in the power distribution system. For example, the most notable random trial scenario for MD is throwing dice, in which up to 6 possible outcomes are produced. In general cases, the considered variables lead to a probability distribution function consisting of the total number of randomized trials ( $n^{th}$ ), the number of possible outcome patterns from one randomized trial ( $k > 2$ ), the outcome of a single randomized trial ( $X$ ), the probability of each possible outcome pattern from one randomized trial ( $p$ ), and the cumulative number of each possible outcome pattern among all randomized trials ( $x$ ). The definition of the probability mass function ( $pmf$ ) model is described in (1), and the quantitative characteristics of all

variables are listed in (2)-(4) below:

$$\begin{aligned} f(x_1, \dots, x_k | p_1, \dots, p_k) &= \Pr ob(X_1 = x_1 \wedge \dots \wedge X_k = x_k) \\ &= \begin{cases} \frac{n^{th}!}{x_1! \dots x_k!} p_1^{x_1} \dots p_k^{x_k} & \text{when } \sum_{i=1}^k x_i = n^{th} \\ 0 & \text{otherwise} \end{cases} \end{aligned} \quad (1)$$

The expected value and variance of each possible outcome pattern can be derived by (2).

$$E(X_i) = n^{th} p_i \text{ and } \text{var}(X_i) = n^{th} p_i (1 - p_i) \quad (2)$$

The preliminary quantitative relationship is described by:

$$\sum_{i=1}^k x_i = n^{th} \text{ and } \sum_{i=1}^k p_i = 1 \quad (3)$$

When the  $p_i$  values are arranged together, the upper boundary value ( $P_i$ ) that is used for converting a pseudouniform random number ( $U$ ) into an outcome ( $X_i$ ), where  $U$  is between 0 and 1 ( $U \in [0, 1)$ ), can be obtained from the following equation:

$$P_i = \sum_{l=1}^i p_l \quad (4)$$

where  $i = 1, 2, 3, \dots, k$

There are distributions classified in the same group as MD or derived from MD that have been effectively applied in various applications, e.g., Dirichlet, Dirichlet multinomial, negative multinomial, and posterior probability. These distribution models have been developed and are widely used in machine learning [26], [27], [28].

For reliability assessment in a distribution system, common indices described in the IEEE Standard 1366–2012 are widely used and recommended, i.e., SAIDI, SAIFI, CAIDI and ASAI. These indices can be calculated from failure log data. Reference [2] In addition to the direct calculation of indices from power failure log data, using appropriate statistical processes in reliability assessment can provide additional useful parameters representing the states of specific components in a system, areas of interest, or an entire system, e.g., the failure rate ( $\lambda$ ), outage time ( $r$ ), annual unavailability ( $U$ ), load disconnected ( $L$ ) and energy not supplied ( $E$ ). With a different point of view or technique for assessment, the equation form for calculating the index may be slightly different but can retain the same meaning.

For reliability assessment, common indices according to the specific load point and the entire system can provide a quantitative description from the customer's point of view and the utility's point of view. From the utility's point of view, however, some additional indices are still needed to specify the key weaknesses of the system, such as ranking problems [22], WASRI [23], RA [24], RT [25], and CMI reduction/\$ [26]. Most have similar components or partial information, such as the risk priority number (RPN) in FMEA, which has the following equation: [29]

$$RPN = \text{Severity} \times \text{Occurrence} \times \text{Detection} \quad (5)$$

where *Severity* is the size of the impact of system failure, *Occurrence* is the frequency or probability of the event, which is the primary cause of failure, and *Detection* is the opportunity to detect the main cause before any failure event occurs.

In this paper, the proposed index, called CRPI, is derived based on the concept of the risk priority index. It is intended to be a service performance indicator and can represent the characteristics of an individual component in the system. The concept of CRPI is quite similar to that of the risk level index of each device (RA) [24], but it is derived as a component index in the form of a proportion of the total values expressed as percentages (%), meaning that it can be simply utilized for the decision-making process. Therefore, CRPI can be calculated from the customer number of the component ( $C_c$ ), interruption duration of the component ( $D_c$ ) and interruption frequency or probability ( $F_c$  or  $P_c$ ). CRPI can be calculated from equation (6):

$$CRPI_c = C_c \times D_c \times F_c \quad (6)$$

where  $c$  is the series number of components.

### III. PROPOSED METHOD

The proposed reliability analysis method is intended to be an efficient approach for evaluating the reliability of a distribution system based on NSMCS with a novel priority index named CRPI. The proposed analysis method consists of 5 processes, i.e., determining the failure state condition, simulating failure events, preassessing system reliability, determining a solution for reliability improvement, and performing post-assessment of system reliability. Figure 1 is a flowchart in an algorithmic format showing continuous processing for practical implementation.

For the process of simulating failure events and performing a preassessment of reliability, events in the system are simulated based on a Monte Carlo simulation with a multinomial distribution, called a Multinomial Monte Carlo simulation (MMCS). In the process of determining a solution for reliability improvement, the results obtained from the reliability assessment will be considered to prioritize the severity of the reliability problem, after which the proposed CRPI will be used for ranking the problem based on the concept of failure mode and effects analysis (FMEA) as well as the Pareto principle. Decision-making for system improvement will be based on the ranking results. Improvement activities and measures will be applied only to selected components. Finally, the reliability of the improved system will be assessed again to verify that it can be improved. Each process in the proposed method is described below.

#### A. STEP 1: DETERMINING FAULT AND FAILURE SCENARIOS, SYSTEM STATES OF FAILURE COMPONENTS, AND LOAD POINT RESTORATION

From the connective network diagram of the components, fault scenarios for random trials can be determined based on statistical data. Essentially, the distribution system accepts

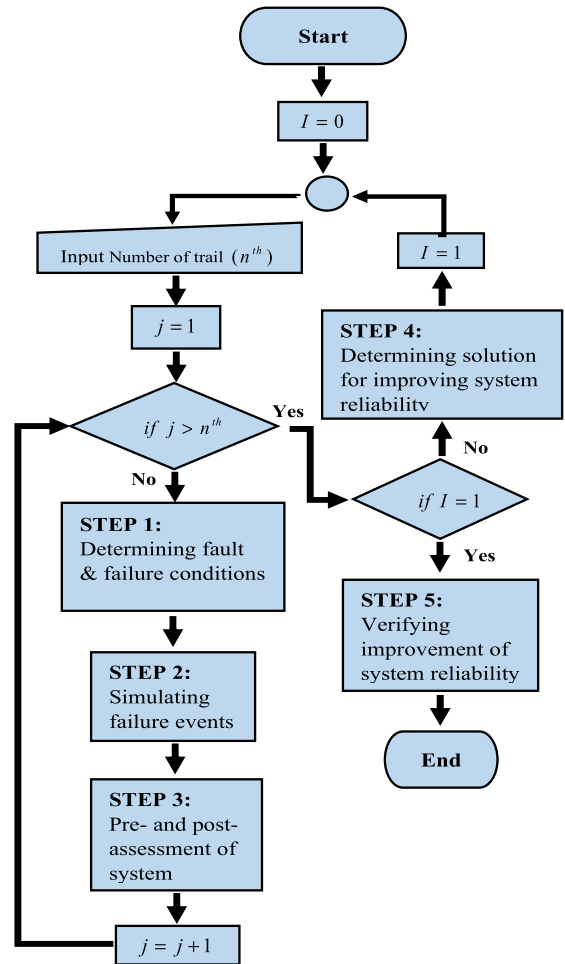


FIGURE 1. Flow chart of the overall process of the proposed method.

the level of  $N-1$  contingency. Therefore, each simulation is defined as a single-failure event, including the success or failure of each piece of protective equipment, which are independent of one another.

To prepare the system states for the failure component and load point restoration, reactive operations are considered based on a four-state component model, whereas reliability assessments normally use the active and passive state component model [31] combined with topology operations. [30] Outcomes can be specified so that the customer number and duration of the load point are restored by switching, replacement or repair.

The situation regarding the equipment failure leading to an interruption and the effects related to the load point location (LPL) will be considered in chronological order. When an interruption occurs at any failure component location (FCL), if there is only one successful protective device—a dropout fuse cutout (D/F), recloser (R) or circuit breaker (CB)—this equipment will be defined as the successful operation protective component (SOPC). Components that are isolated by the operation of such protective devices are in the designed



detection and interrupt zone of the SOPC ( $DIZ_{SOPC}$ ). The load points in this zone are affected differently according to the three failure component recovery options (RO): switching (SW), replacement (RC), and repair (RR). The interrupted customer number ( $N$ ) and interruption duration of the load point ( $D$ ) can be obtained from the load point restoration function (LPRF) as follows:

$$LPRF = f(LPL, FCL, DIZ_{SOPC}, SS_{FCL}) = N_{LPL}, D_{LPL} \quad (7)$$

where:

if  $\{LPL \notin DIZ_{SOPC}\}$  then  $\{N_{LPL}, D_{LPL} = 0, 0\}$   
 if  $\{(LPL \notin DIZ_{SOPC}) \wedge (LPL \in SS_{FCL})\}$   
     then  $\{N_{LPL}, D_{LPL} = N_{SW}, D_{SW}\}$   
 if  $\{(LPL \notin DIZ_{SOPC}) \wedge (LPL \notin SS_{FCL}) \wedge (RO_{FCL} = RC)\}$   
     then  $\{N_{LPL}, D_{LPL} = N_{RC}, D_{RC}\}$   
 if  $\{(LPL \notin DIZ_{SOPC}) \wedge (LPL \notin SS_{FCL}) \wedge (RO_{FCL} = RR)\}$   
     then  $\{N_{LPL}, D_{LPL} = N_{RR}, D_{RR}\}$

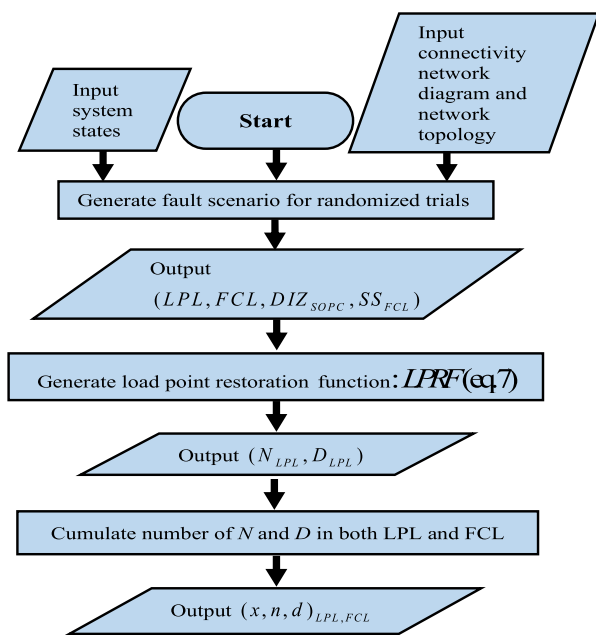


FIGURE 2. Flow chart of step 1: determining fault and failure scenarios, system states of the failure component, and load point restoration.

FCL and SOPC are random variables ( $X_{FCL}$ ) and ( $X_{CB}, X_R, X_{D/F}$ ), respectively, and the failure system states are determined by a set of these variables. The load point restoration function (LPRF) is the transform function that yields the actual results at each load point in the event of a power outage. When a random simulation arrives at the  $n^{th}$  time, the cumulative number of  $N$  and  $D$  in both LPL and FCL, which depend on the cumulative interruption frequency ( $x$ ), cumulative interrupted customers ( $n$ ), and cumulative interruption duration ( $d$ ), will be used to calculate the reliability index. A flow chart of step 1 is shown in Figure 2.

### B. STEP 2: SIMULATING FAILURE EVENTS USING A MULTINOMIAL DISTRIBUTION MONTE CARLO SIMULATION

The outcomes in the randomized trial for the distribution system are divided into two groups, consisting of failure component outcomes ( $X_{FCL}$ ) that create random variables with Multinomial distributions and protective component operation outcomes ( $X_{CB}, X_R, X_{D/F}$ ) that generate random variables with Binomial distributions. From the pattern, the only possible outcomes are success and failure. The failure system states are defined as a set of all variables, i.e.,  $\{X_{FCL}, X_{CB}, X_R, X_{D/F}\}$ , that have a Multinomial distribution. The number of outcomes is equal to the number of permutations ( $k_S = k_{FCL} \times k_{CB} \times k_R \times k_{D/F}$ ), and the system states are created by using a tree diagram method.

The  $p_i$  values that are arranged together to determine the  $P_i$  values, as in equation(4), which is used to convert pseudouniform random numbers ( $U_{FCL}, U_{CB}, U_R, U_{D/F}$ ) into outcomes ( $X_{FCL}, X_{CB}, X_R, X_{D/F}$ ), are determined by equations (8) and (9) as follows:

Probability of failure component outcomes:

$$p_{FCL_i} = \frac{\lambda_{FCL_i}}{\sum_{i=1}^k \lambda_{FCL_i}} = \frac{\lambda_{FCL_i}}{\lambda_{FCL_T}} \quad (8)$$

Probability of protective component operation outcomes:

$$p_{PC_i} = \begin{cases} \text{Pr obability of success} \\ 1 - \text{Pr obability of success} \end{cases} \quad (9)$$

The flow chart of step 2 is shown in Figure 3.

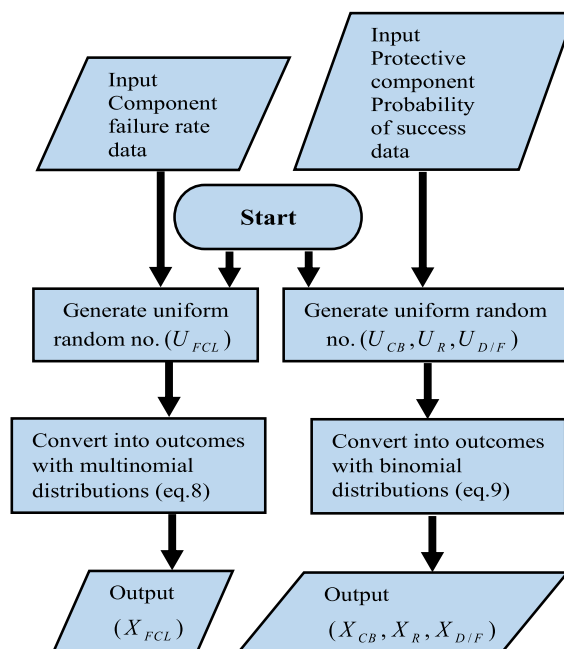


FIGURE 3. Flow chart of step 2: simulation of failure events using a multinomial distribution Monte Carlo simulation.

**C. STEP 3: PRE- AND POSTASSESSMENT OF SYSTEM RELIABILITY**

After the completion of the randomized trial iterations, the variables representing the accumulation of  $N$  and  $D$ , i.e.,  $x$ ,  $n$  and  $d$ , in LPL and FCL are obtained. These variables in LPL are used to calculate the number of customer-based reliability indices in each area (system, feeder, load point) with the following equations:

$$SAIFI_{area} = \frac{\lambda_{FCL\_T} \times \sum_{area} n_{LPL}}{N_T} \quad (10)$$

$$SAIDI_{area} = \frac{\lambda_{FCL\_T} \times \sum_{area} d_{LPL} \times n_{LPL}}{N_T} \quad (11)$$

where  $N_T$  is the total customer number of the areas.

The variables ( $x$ ,  $n$ ,  $d$ ) in the FCL are used to calculate the index value based on the total number of outage events or the per-time-based component reliability index for each component, and details are as follows:

Per-time average interruption probability index:

$$PTAIFI = \frac{x_{FCL}}{n^{th}} \quad (12)$$

Per-time average interruption customer index:

$$PTAICI = \frac{n_{FCL}}{n^{th}} \quad (13)$$

Per-time average interruption duration index:

$$PTAIDI = \frac{d_{FCL}}{n^{th}} \quad (14)$$

These three indices can be used to identify the impact of each element and can be compared to each other because they are based on the same total number of power outages. This can indicate how each component affects the reliability of the system. PTAIFI indicates the proportion of the likelihood that a component will fail and cause one power outage. PTAICI indicates the average proportion of customers affected by a failure at a component that causes one power outage, and PTAIDI represents the average period of recovery from a failure at a component that causes one blackout. PTAIDI is equivalent to CAIDI, which is based on customer numbers.

These indices are used to create a component risk priority index based on the FMEA principle. The component risk priority index can be calculated as follows:

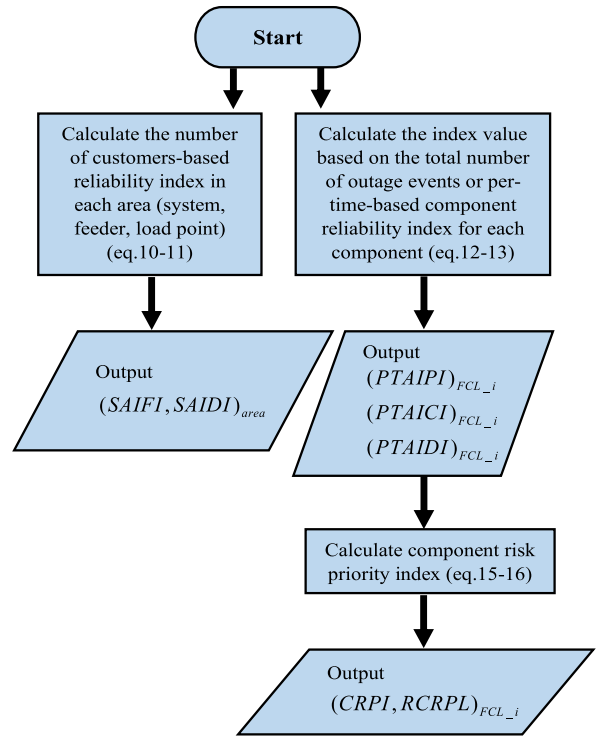
$$CRPI_{FCL\_i} = (PTAIFI \times PTAICI \times PTAIDI)_{FCL\_i} \quad (15)$$

To carry out the ranking process and determine the measures taken for system improvement, an additional index is developed from the CRPI as the rank of the component risk priority index (RCRPI), which can be calculated as follows:

$$RCRPI_{FCL\_i} = \frac{CRPI_{FCL\_i}}{\sum_{i=1}^k CRPI_{FCL\_i}} = \frac{CRPI_{FCL\_i}}{CRPI_{FCL\_T}} \quad (16)$$

RCRPI will be considered in the next step based on the Pareto principle. The flow chart of step 3 is shown in Figure 4.

The per-time-based component reliability index presented in this article, which includes the per-time average interruption probability index (PTAIFI), the per-time average



**FIGURE 4. Flow chart of step 3: pre- and post-assessment of system reliability.**

interruption customer index (PTAICI), the per-time average interruption duration index (PTAIDI), the component risk priority index (CRPI) and the RCRPI, is a new group index. It is observed for each component of the power distribution system and is averaged per number of power outages, thereby providing a way to assess the level of impact on the power distribution system reliability of each component in the area of interest; the traditional index is observed in each area and is averaged per number of customers, thus providing a way to assess the level of the effect of power outages on each area of interest. In this article, traditional indices (SAIFI, SAIDI) are used as performance indicators for the reliability level of power distribution systems, and the new indices (PTAIFI, PTAICI, PTAIDI, CRPI and RCRPI) are used to determine measures to improve the power distribution system through the root-cause analysis process and prioritize components to achieve the highest possible reliability values with minimal operations through the Pareto principle. These indices are created in accordance with the failure mode effect analysis (FMEA) principle, in which the PTAIFI, PTAICI, PTAIDI and CRPI indices are comparable to occurrence, severity, detection and risk priority number (RPN), respectively, while RCRPI depends on a percentile of CRPI.

**D. STEP 4: DETERMINING SOLUTIONS FOR IMPROVING SYSTEM RELIABILITY BASED ON THE PROPOSED PRIORITY INDEX**

With the assessment results in the previous step, the appropriate measures for improving reliability are determined based

on the Pareto principle by using the proposed indices RCRPI, PTAIPI, PTAICI and PTAIDI. First, FCL is prioritized with RCPI, followed by the selection of FCL to implement reliability improvement measures with the Pareto principle from the first FCL list in order of cumulative RCRPI value up to approximately 80%. Finally, the measures for improving reliability in each component are determined according to the indications obtained from the likelihood of failure, the number of customers affected by one power outage and the duration of individual power outage restoration with the PTAIPI, PTAICI and PTAIDI indices, which can be considered a root-cause analysis process. Pareto charts and tables will be considered in completing this process. The flow chart of step 4 is shown in Figure 5.

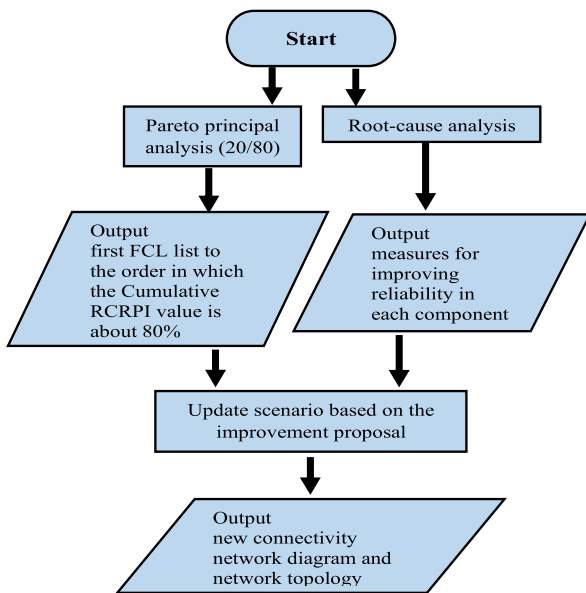


FIGURE 5. Flow chart of step 4: determining the solution for improving system reliability based on the proposed priority index.

**E. STEP 5: COMPARING THE PRE- AND POSTASSESSMENT OF SYSTEM RELIABILITY**

After performing improvement activities, the improved system will be assessed for reliability again, and the outcomes will be compared with those of the original system to determine a measure of reliability improvement. The flow chart of step 5 is shown in Figure 6.

**IV. CASE STUDIES AND RESULTS**

To demonstrate the concepts of the proposed analysis method, the IEEE RBTS Bus-2 system [32] is selected as the test system to perform the case studies. A network diagram of the test system is illustrated in Figure 7. There are three case studies as follows: the base case (case no. 1), the case with system improvement (case no. 2) and the case with uncertainty operations (case no. 3).

The results of the reliability index assessment, i.e., SAIFI and SAIDI from MMCS, with 30,000 iterations of the 3 case studies, are summarized in Tables 1 and 2.

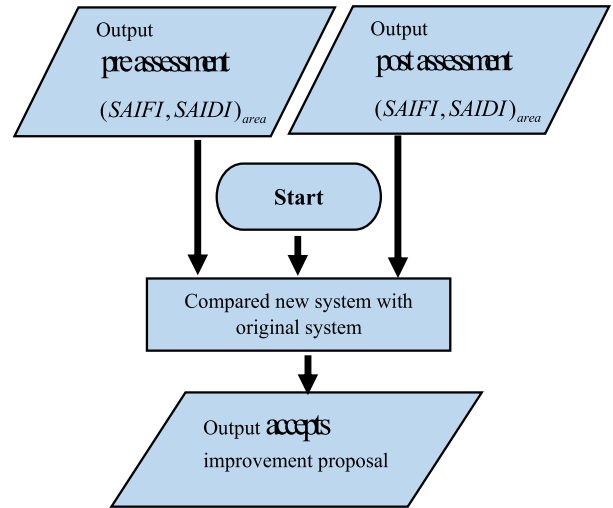


FIGURE 6. Flow chart of Step 5: verifying the improvement results by comparing the pre- and post-assessment of system reliability.

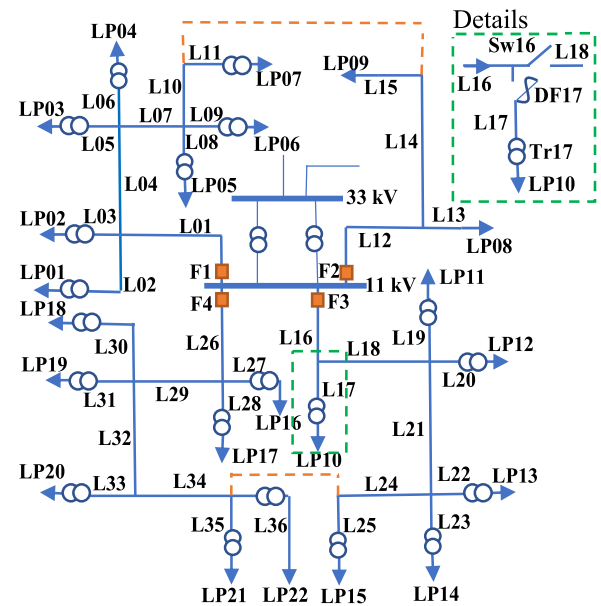


FIGURE 7. Network diagram of the original test system.

**A. CASE NO. 1: BASE CASE WITH THE ORIGINAL SYSTEM**

Case no. 1 represents the base case or the benchmarks for comparison with other cases. In this case, the reliability assessment is performed by using the parameters and system operation conditions based on the original model by RN Allan and R. Billinton 1991, defined as the base case (A) [32]. Considered the benchmark, the SAIFI and SAIDI of the original case are shown in the first rows of Tables 1 and 2. From the results of case no. 1, as shown in Tables 1 and 2, the reliability indices (SAIFI, SAIDI) obtained from the reliability assessment of the proposed method are similar to the original results in reference [32]. In addition, the per-time-based component reliability indices (PTAIPI, PTAICI, PTAIDI) and component risk priority indices (CRPI, RCRPI)

**TABLE 1. SAIFI of the case study (30,000 iterations).**

Case no.	System	F 1	F 2	F 3	F 4
[32]	0.248	0.248	0.140	0.250	0.247
1	0.2476	0.2579	0.1410	0.2500	0.2459
2	0.1410	0.1458	0.1550	0.1368	0.1324
3	0.1829	0.2037	0.1723	0.1747	0.1785

**TABLE 2. SAIDI of the case study (30,000 iterations).**

Case no.	System	F 1	F 2	F 3	F 4
[32]	3.61	3.62	0.52	3.62	3.61
1	3.6083	3.7289	0.5255	3.6794	3.5813
2	1.2570	1.2787	0.5818	1.2686	1.2802
3	1.3064	1.3833	0.6130	1.3076	1.2868

will be evaluated simultaneously, as shown in Table 3. The results will be used in the next case study, no. 2.

### B. CASE NO. 2: ORIGINAL SYSTEM WITH IMPROVEMENTS

Case no. 2 presents improvements in the reliability of the test system following case no. 1 and using improvement options obtained from the original data [32] by selecting the execution point from the RCRPI and Pareto principles. Appropriate improvement measures are determined at each point with root-cause analysis based on PTAIPI, PTAICI and PTAIDI. The results of this case study can verify the performance of the proposed method.

Considering the results of case no. 1, as shown in Table 3, and the Pareto principal chart in Figure 8, RCRPI can provide a minority factor that causes most of the problems according to the Pareto principle (20/80). Root-cause analysis of the PTAIPI, PTAICI, and PTAIDI values can specifically identify the causes at each point, so these results can be used to determine the most effective improvement measures with minimal work.

#### 1) ROOT-CAUSE ANALYSIS

For case no. 2, specific components causing reliability problems are identified, and then the system is modified based on the appropriate improvement proposal. Finally, the reliability of the modified system is compared with that of the original system. From Table 3 and the Pareto chart in Figure 8, it is found that only 19 FCLs (33.93%) among the total FCLs (56 elements) affect reliability at 81.22% (cumulative total of RCRPI) according to the Pareto principle. Considering the relevant indices, the equipment with the highest possibility of causing reliability problems can be identified. Therefore, 19 sets of equipment need measures to improve their reliability, which can be classified as follows:

- 1) There are 12 main power lines that are highly sensitive (PTAIPI is high), and a large number of users were affected according to the per-time average (PTAICI is high).
- 2) There are 2 power lines appearing on the name list that are highly sensitive (PTAIPI is high).

- 3) There are 5 distribution transformers appearing on the name list for which a long time was needed to restore the power supply according to the per-time average (PTAIDI is high).

#### 2) IMPROVEMENT PROPOSAL

The proposed measures for improving the system reliability can be summarized as follows:

- 1) Replacing overhead lines with cable lines to reduce the sensitivity of components according to the PTAIPI value at L01, L04, L07, L10, L16, L18, L20, L21, L24, L26, L29, L31, L32 and L34.
- 2) Replacing switches with a recloser to reduce the number of users affected by 1 power interruption at Sw04, Sw18 and Sw29.
- 3) Sparing at least 5 distribution transformers/year to reduce the restoration time for replacing defective distribution transformers.

The network with the update scenario based on the improvement proposal is shown in Figure 9. The improvement measures result in improved system reliability in terms of both the number and duration of power outages. As shown in Tables 1 and 2, compared to the results of case no. 1, the SAIFI and SAIDI of case no. 2 decrease by 44.91% and 65.16%, respectively.

However, in practice, in improving the reliability of a power distribution system, it is often advised to consider acceptable target indices, cost issues and other practical technical conditions.

### C. CASE NO. 3: IMPROVED SYSTEM WITH UNCERTAIN FACTORS

In case no. 3, the modified system from case no. 2 is used to demonstrate a system with uncertainties in protective device operations. The most prominent feature of reliability assessment with MCS is the ability to analyze the results caused by uncertainties in operation. Therefore, the effects of uncertainties are simply included in the simulation as uncertain factors of the equipment. In this case, uncertain factors are determined for setting the dropout fuse cutout (D/F) and recloser (R) considering that the D/F and R can successfully disconnect a failure section from the main system with 80% probability of successful operation.

From the system shown in Figure 9, a recloser (R) is installed at the center of the feeder's main line, and it is assumed that there is only an 80% probability of the successful operation of the D/F and R to simulate the consequences of a deteriorating electrical protective device problem (D/F and R).

The results of case no. 3 assessed by the proposed method are shown in Tables 1 and 2. Compared to case no. 2, the SAIFI and SAIDI increased by 34.13% and 3.93%, respectively, meaning the reliability level decreased. On the other hand, the number of power outages increased significantly, while the outage period increased slightly.



TABLE 3. Assessment results of component indices for case no. 1 and the improvement proposal for case no. 2.

No.	FCL	PTAIFI	PTAICI	PTAIDI	CRPI	RCRPI	Analysis			Improvement Proposal
							Cumulative RRCPI	Sensitivity PTAIFI	Customer PTAICI	
1	L32	0.02520	15.67440	0.14670	0.057946	0.074103	%7.41	high	high	(1) and (2)
2	L18	0.02537	16.28540	0.12683	0.052396	0.067005	%14.11	high	high	(1)
3	L26	0.02547	15.84027	0.12733	0.051366	0.065689	%20.68	high	high	(1)
4	L07	0.02463	16.06093	0.12317	0.048729	0.062316	%26.91	high	high	(1) and (2)
5	L04	0.02453	15.99573	0.12267	0.048138	0.061560	%33.07	high	high	(1)
6	L16	0.02443	15.68620	0.12217	0.046822	0.059878	%39.06	high	high	(1)
7	L01	0.02387	15.56107	0.11933	0.044319	0.056677	%44.72	high	high	(1)
8	L24	0.02313	14.85160	0.11567	0.039739	0.050820	%49.80	high	high	(1)
9	L29	0.02330	14.49260	0.11650	0.039339	0.050309	%54.84	high	high	(1)
10	L10	0.02027	13.21387	0.10133	0.027137	0.034704	%58.31	high	high	(1)
11	L34	0.01947	12.10827	0.09733	0.022942	0.029339	%61.24	high	high	(1)
12	L21	0.01923	12.34780	0.09617	0.022839	0.029207	%64.16	high	high	(1) and (2)
13	Tr17	0.00793	1.66600	1.58667	0.020971	0.026818	%66.84		high	(3)
14	Tr30	0.00797	1.59333	1.59333	0.020225	0.025864	%69.43		high	(3)
15	Tr03	0.00777	1.63100	1.55333	0.019677	0.025163	%71.95		high	(3)
16	L31	0.02690	5.38000	0.13450	0.019465	0.024893	%74.43	high		(1)
17	L20	0.02627	5.51600	0.13133	0.019028	0.024334	%76.87	high		(1)
18	Tr05	0.00740	1.55400	1.48000	0.017019	0.021765	%79.04		high	(3)
19	Tr20	0.00740	1.55400	1.48000	0.017019	0.021765	%81.22		high	(3)
20	Tr31	0.00747	1.49333	1.49333	0.016651	0.021294	%83.35			
21	L03	0.02507	5.26400	0.12533	0.016538	0.021149	%85.47			
22	Tr19	0.00720	1.51200	1.44000	0.015676	0.020048	%87.47			
23	L05	0.02447	5.13800	0.12233	0.015378	0.019667	%89.44			
24	Tr02	0.00710	1.49100	1.42000	0.015032	0.019224	%91.36			
25	L19	0.02423	5.08900	0.12117	0.014943	0.019109	%93.27			
26	Tr28	0.00690	1.38000	1.38000	0.013140	0.016804	%94.95			
27	L17	0.01980	4.15800	0.09900	0.008151	0.010423	%95.99			
28	L28	0.01973	3.94667	0.09867	0.007684	0.009827	%96.98			
29	L02	0.01903	3.99700	0.09517	0.007240	0.009259	%97.90			
30	L30	0.01913	3.82667	0.09567	0.007004	0.008957	%98.80			
31	L36	0.02713	0.27133	0.13567	0.000999	0.001277	%98.92			
32	Tr09	0.00790	0.07900	1.58000	0.000986	0.001261	%99.05			
33	Tr27	0.00790	0.07900	1.58000	0.000986	0.001261	%99.18			
34	L11	0.02660	0.26600	0.13300	0.000941	0.001203	%99.30			
35	Tr36	0.00773	0.07733	1.54667	0.000925	0.001183	%99.42			
36	Tr25	0.00743	0.07433	1.48667	0.000821	0.001050	%99.52			
37	L27	0.02490	0.24900	0.12450	0.000772	0.000987	%99.62			
38	L09	0.02387	0.23867	0.11933	0.000680	0.000869	%99.71			
39	Tr11	0.00660	0.06600	1.32000	0.000575	0.000735	%99.78			
40	L25	0.01860	0.18600	0.09300	0.000322	0.000411	%99.82			
41	L12	0.02463	0.04927	0.12317	0.000149	0.000191	%99.84			
42	Tr23	0.00830	0.00830	1.66000	0.000114	0.000146	%99.85			
43	L33	0.02707	0.02707	0.13533	0.000099	0.000127	%99.87			
44	Tr35	0.00790	0.00790	1.58000	0.000099	0.000126	%99.88			
45	L08	0.02657	0.02657	0.13283	0.000094	0.000120	%99.89			
46	Tr06	0.00767	0.00767	1.53333	0.000090	0.000115	%99.90			
47	Tr22	0.00767	0.00767	1.53333	0.000090	0.000115	%99.92			
48	L23	0.02613	0.02613	0.13067	0.000089	0.000114	%99.93			
49	L13	0.02583	0.02583	0.12917	0.000086	0.000110	%99.94			
50	L14	0.02030	0.04060	0.10150	0.000084	0.000107	%99.95			
51	L15	0.02537	0.02537	0.12683	0.000082	0.000104	%99.96			
52	L22	0.02463	0.02463	0.12317	0.000075	0.000096	%99.97			
53	Tr07	0.00707	0.00707	1.41333	0.000071	0.000090	%99.98			
54	L35	0.02403	0.02403	0.12017	0.000069	0.000089	%99.99			
55	Tr33	0.00687	0.00687	1.37333	0.000065	0.000083	%99.99			
56	L06	0.02063	0.02063	0.10317	0.000044	0.000056	%100.00			

(1) Replacing the overhead line with a cable line to reduce the sensitivity of the component according to the PTAIFI value

(2) Replacing switches with a recloser to reduce the number of users affected by 1 power interruption

(3) Sparring at least 5 distribution transformers/year to reduce the restoration time for replacing defective distribution transformers

During reliability assessment with MMCS in each case study, the SAIFI and SAIDI values fluctuated at the beginning of the simulation based on the number

of iterations; their trends are illustrated in Figure 10. When the number of iterations increased, the SAIFI and SAIDI values steadily converged to the expected values.

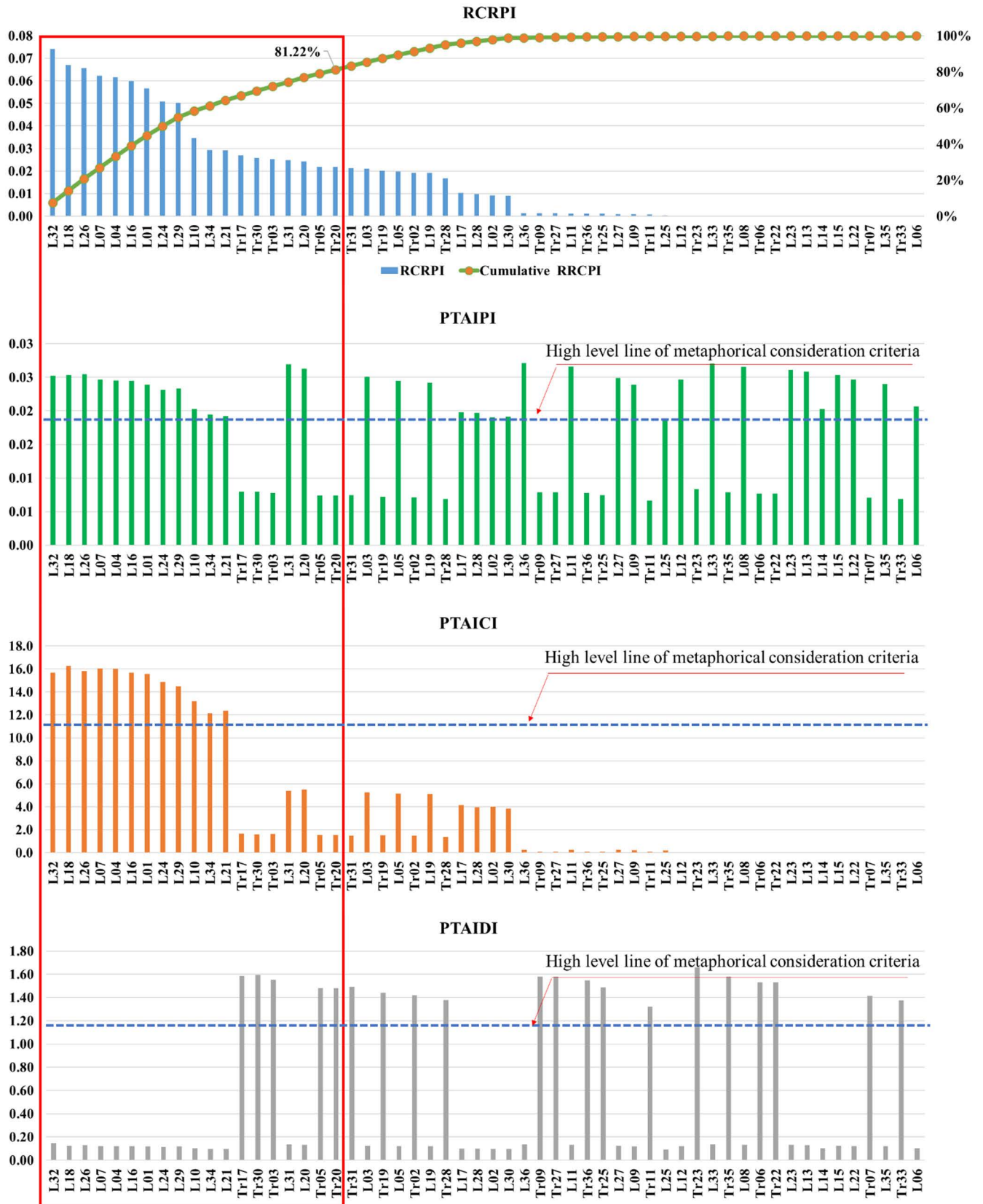


FIGURE 8. Pareto principal chart showing the component risk priority index (CRPI) and component reliability indices (PTAIPI, PTAICI, PTAIDI) for case no. 2.

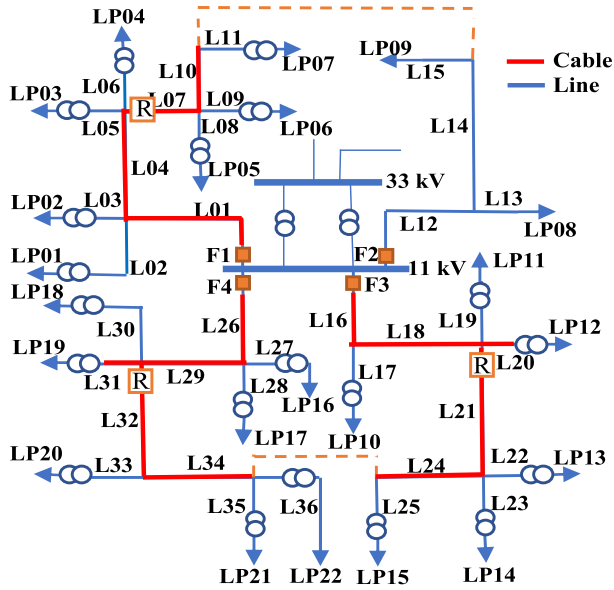


FIGURE 9. Network diagram with improvement scenarios (case nos. 2 and 3).

Therefore, ensuring adequate iterations of MMCS is quite important.

The demonstration of the MMCS reliability assessment process and the use of time-based component indices (PTAIP, PTAIC, PTAID) led to the creation of FMEA-based CRPI and RCRPI to improve the reliability of power distribution systems through IEEE RBTS Bus-2. The efficacy and advantages of the methods presented in this paper were established by three case studies demonstrating the performance of the proposed method. The numerical results showed that reliability assessment and improvement could be achieved successfully on the test system, with and without uncertainty in operation. All of these benefits are key points to be explored in the power distribution system reliability assessment process.

In a power distribution system, reliability management procedures are initiated based on a series of power failure correction report log data. The relevant reliability indices can be evaluated directly from such data. For the predictive assessment in the planning phase, the MCS process can be applied to simulate an artificial blackout event data set. In addition, relevant indices computed from pseudo-outage data can be applied to evaluate real-life outage data for further reliability analysis.

For the practical application of the proposed method, it is necessary to consider the following conditions:

1) If the information regarding the reliability of the system can be provided in the form of actual power outage report data, the reliability indices can be directly evaluated by the definition of the index value without performing the simulation process in steps 1-2.

2) If the information regarding the reliability of the system is in the form of statistical parameters such as the failure

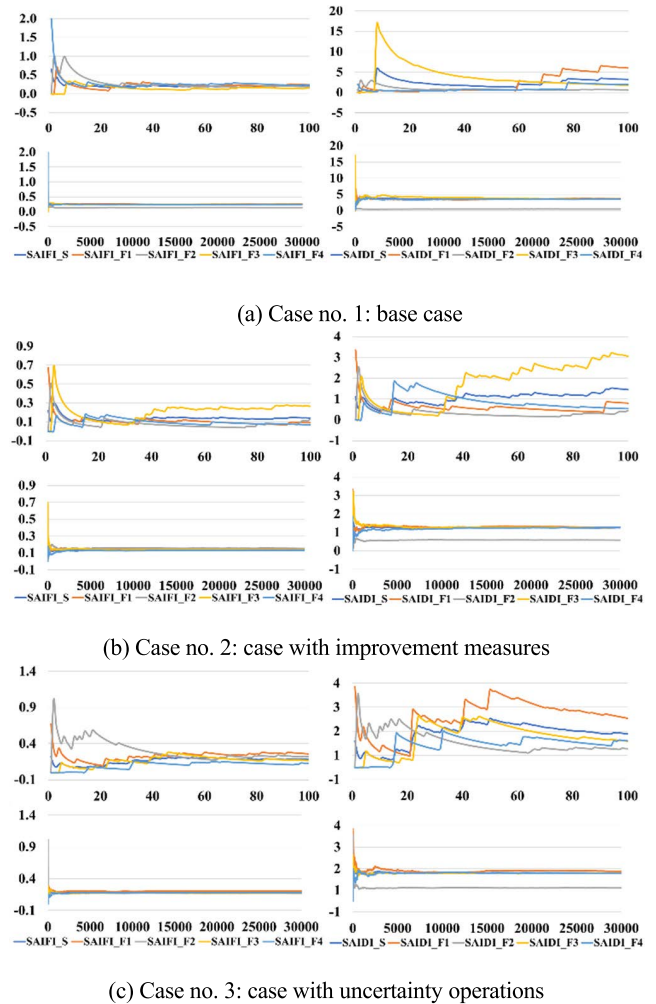


FIGURE 10. SAIFI and SAIDI values during the process of MMCS in all case studies.

rate ( $\lambda$ ), average outage time rate ( $\tau$ ), annual unavailability ( $U$ ) and disconnected load ( $L$ ), the simulation processes in steps 1-2 are required to simulate artificial power outage data for the evaluation of the reliability indices before performing reliability assessment and improvement (step 3-5).

3) To evaluate the potential power outage data with a determined probability level, it is necessary to carry out all 5 steps. For example, from case no. 2, the results showed that the average chance of a transformer being defective is only 5 sets per year, which leads to the correct determination of the number of spare transformers.

4) To evaluate the consequences of uncertainties in device operation affecting the reliability of the power supply system, it is also necessary to carry out all 5 steps. For example, in case no. 3, there is a slight reduction in the chance of success in the operation of the protective equipment, and this significantly increases the number of power outages.

In this article, the IEEE RBT BUS 2 test system consisting of 4 feeders, 34 buses, 36 branches and 56 potentially failed components can represent a moderate practical power distribution system. The models are created in spreadsheet

format and simulated with Microsoft Excel 2019 on personal computers with Intel(R) Core (TM) i5-1035G1 CPUs @ 1.00 GHz and 1.19 GHz and 4.00 GB of RAM. In summary, the processing time for 1 cycle with 30,000 randomized trials was 10.87 seconds for case no. 1, 10.95 seconds for case no. 2 and 10.99 seconds for case no. 3. The processing time depends on the following factors: the number of components in the power distribution system, the amount of protective equipment in the feeder line, the number of uncertain factor variables considered, and the number of randomized trials that can converge with the expected values. These processing times are no different from those of programs that process traditional indices in general practice.

## V. CONCLUSION

In this paper, an effective approach is proposed for analyzing the reliability of a distribution system based on NSMCS and novel priority indices. The proposed analysis method consists of an assessment process and an improvement process. For the assessment process, MMCS is applied to simulate the failure event. For the improvement process, the proposed priority index, called CRPI, is derived based on FMEA and is used for prioritizing the problems of the components based on the Pareto principle. After determining a group of sensitive components, the root-cause analysis can be completed by considering per-time-based indices for each component to propose a solution or activity for improving the component. To verify the performance of the proposed method, numerical case studies were performed on the IEEE RBTS Bus-2 system.

The results of the test system showed that the proposed method can provide valid results for reliability assessment compared with those for the original system. After considering the results of the assessment process, an improvement proposal for the original system can be obtained. The post-assessment showed that the reliability of the system could be improved significantly. The results also showed the capability of reliability improvement by specifying the key weaknesses and the details of specific problems in the system. In addition to better reliability results, a minimum set of activities for improving the system can be obtained. In addition, the proposed method can provide an analysis with uncertainties in protection equipment deterioration. In future work, the proposed method will be developed for use in a practical distribution system with real power outage data, and the improvement proposals will include consideration of economic and other technical conditions for implementation in practice.

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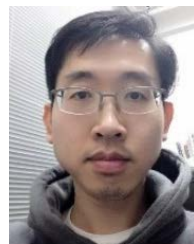
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