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Advances in distribution system reliability assessment

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Advances in distribution system reliability assessment

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दुराशाभूयिष्ठे दुरधिपगृहद्वारघटके

दुरन्ते संसारे दुरितनिलये दुःखजनके ।

मदायासं किं न व्यपनयसि कस्योपकृतये

वदेयं प्रीतिश्चेत्तव शिव कृतार्थाः खलु वयम् ॥

योगक्षेमधुरंधरस्य सकलश्रेयःप्रदोद्योगिनो

दृष्टादृष्टमतोपदेशकृतिनो बाह्यान्तरव्यापिनः ।

सर्वज्ञस्य दयाकरस्य भवतः किं वेदितव्यं मया

शंभो त्वं परमान्तरङ्ग इति मे चित्ते स्मराम्यन्वहम् ॥

Adi Sankara in Sivaanandalahari

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Abstract

Traditionally, reliability of power systems has been an important measure of system performance and a key factor in system planning. Recently, the large-scale changes in the regulations governing the power industry have lead to a growing emphasis on distribution system reliability. Further, the shift towards a more technical and computerized society requires that power supply be increasingly reliable. Advanced models and methods are needed to obtain an improved understanding of the distribution system reliability. Monte Carlo simulation is one such method that can be used to find the statistical distribution of the reliability indices. This dissertation presents a computationally efficient Monte Carlo simulation algorithm for assessing the distribution reliability indices. Several state regulatory agencies have started to prescribe minimum reliability standards to be maintained by the distribution companies. The effect of these regulations has not been fully explored. In this work, a detailed analysis of the impact of various regulatory standards on a practical distribution system is presented. Storms cause a significant fraction of the distribution customer interruptions. While the impact of wind storms on distribution system reliability has been studied earlier, the effect of lightning storms on the reliability indices is not fully understood. Momentary interruptions caused by lightning storms may severely disrupt production at automated manufacturing facilities and other sensitive loads resulting in a loss of millions of dollars per incident. An analysis of lightning storm data is presented in this dissertation along with a method for calculating the impact of lightning storms on distribution system reliability. Finally, several topics for future research are discussed.

1. Introduction

1.1 Deregulation and the growing importance of distribution reliability

Regulations governing the electricity marketplace operation have recently undergone major changes. No longer is a single vertically integrated utility able to generate, transmit, and distribute electricity to captive customers in its designated service territory at a guaranteed rate-of-return. The benefits that come with competition are motivating the breakup of traditional electric utilities into separate entities responsible for generation (GENCOs), transmission (TRANSCOs), distribution companies (DISTCOs) and energy service companies (ESCOs). Competition among these entities is predicted to reduce deadweight monopolistic losses, and to increase overall efficiency.

Customer satisfaction is becoming very important to the electricity suppliers for maintaining a customer base. Although each area undergoing restructuring is following different formats, some areas plan to allow customers to choose their own electric supplier. The reliability of power supplied is a key component of customer satisfaction, and must not be left to chance. Contracts will specify the quality of the electricity to be delivered, and will have provisions for penalizing those not meeting the specifications. Thus, system reliability is a crucial measure of performance on par with the cost and the quality of the power delivered for energy companies as well as for the regulators.

In addition to changing regulations, there are other reasons that distribution system reliability studies have received renewed attention recently [Bill88, Kjøl92]. The shift to a more technical and computerized society has required that power be increasingly reliable. Sustained or momentary interruptions may severely disrupt production at automated manufacturing facilities such as semiconductor fabrication and other sensitive loads and can cost millions of dollars per incident. In the past, power generation and transmission reliability have received more research attention than distribution system reliability [Alla79], de-regulation may give distribution systems their due.

1.2 Quantitative measures of distribution system reliability

A large number of power outages experienced by customers are caused by abnormal conditions occurring on the distribution circuits. Most distribution circuits are operated in a radial topology consisting of many devices such as overhead and underground line segments, circuit breakers, reclosers, protective fuses and sectionalizing switches. The customer load points are widely distributed along the distribution feeders. When an abnormal or unsafe condition, e.g., a short circuit, is detected on the system, a protective device upstream of the fault location interrupts the power supply to all downstream customers. These abnormal system conditions (or fault conditions) may be caused by a number of factors. Animals and trees that come in contact with the distribution equipment, severe weather conditions such as lightning and wind storms, aging and improper maintenance of distribution equipment and traffic accidents are some examples of conditions that may ultimately result in customer interruption [Chow95, Warr92, Parr89, Brow97].

System reliability can be improved by reducing both frequency and duration of faults on the system. Various methods have been suggested for improving the system reliability, such as:

- Performing tree trimming along the right-of-way for overhead lines [Gill92, Kunt99]
- Installing animal guards on distribution circuits [Chow95]
- Installing additional fuses, reclosers and sectionalizing devices [Gill92]
- Improving inspection and preventive maintenance practices for distribution system equipment such as lines, transformers, poles, fuses etc. [Meeu97, Kunt99]

In order to assess the performance of a distribution system, and to compare the effects of these alternate design and maintenance strategies, two sets of reliability indices have been defined, viz. *customer load point indices* and the *system indices* [IEEE98, Bill96a, Bill89]. The load point indices measure the expected annual frequency of outages and their duration for individual customers. The system indices measure the over-all performance of the system. For example, an important system reliability measure is the System Annual Interruption Duration Index (SAIDI) defined as:

$$SAIDI \triangleq \frac{\text{Sum of all customer interruption durations}}{\text{Total number of customers served}} \tag{1.1}$$

The system indices were originally designed for internal use by the distribution companies. Their main purpose was to quantify the system reliability performance and to identify the "weak" feeders. However, in recent times, state regulatory authorities have been specifying the minimum reliability levels to be maintained both at the feeder level and at the system level on an annual basis [SNY91, PPUC99, TAC01]. Consequently, the system planners and the regulators are left with a lot of unanswered questions. Some of the questions include:

- How does a state regulator decide the minimum reliability levels to be maintained by different utilities?
- How does a system planner identify circuits that consistently have poor reliability?
- What is the impact of storms on the system reliability?

It is important to develop new models and methods that help regulators and system operators in predicting the system reliability so that remedial measures may be initiated in order to comply with the regulatory standards and to improve customer satisfaction. Development of such models and methods is the focus of this research.

1.3 Review of previous work

In the first half of the 20th century, distribution system design and expansion planning were performed based on rules of thumb and other heuristics that were extrapolated from previous experience. During the 1960's, Gaver, Montmeat and Patton [Gave64] proposed a quantitative method for evaluating the distribution system reliability based on the reliability characteristics of basic system components. Their method of assessing system reliability is based on certain basic *reliability indices*. They noticed the importance of both the load-point and the system-wide indices. Additional indices were proposed and later incorporated to the standard reliability measures in the IEEE Standard, P1366 for electric power distribution systems [IEEE90, IEEE98].

The reliability assessment method proposed in [Gave64] is based on assuming the distribution circuit is a simple series network. Endrenyi proposed a three-state Markov model to account for post-fault switching actions [Endr71]. Distribution system protection equipment such as fuses, circuit breakers and reclosers sometimes fail to recognize and isolate fault conditions. Koval and Billinton proposed a Markov modeling approach incorporating the characteristics of protection equipment [Kova79]. Kostyal, Vismor and Billinton presented a Failure Modes and Effects Analysis (FMEA) technique for analytical assessment of distribution reliability indices [Kost81]. Chow, Taylor and Chow presented detailed models of restoration times for faults on distribution systems [Chow96]. Models for equipment aging are included in the reliability assessment by Asgarpoor and Mathine [Asga97]. To improve the accuracy of the reliability assessment, historical outage data were directly incorporated into some algorithms [Hsu90, Bill86]. Efforts have been made to associate reliability to customer costs [Wack89, Moor83]. The knowledge of system reliability becomes useful if one can additionally know "where" to spend money so that the performance is improved [Lang00].

The analytical methods for reliability assessment such as the network modeling and Markov modeling techniques provide a fast and accurate prediction of the expected values of the reliability indices. However, the expected spread (or the deviation) of the system indices can be obtained by performing Monte Carlo simulation of the distribution systems. Billinton and Wojczynski presented the probability distributions of the system indices and load point indices for a small sample distribution system using a Monte Carlo simulation [Bill85].

Distribution system reliability indices quantify the system performance and help identify the portions of the system that experience poor reliability. Service reliability can be enhanced by means of changes in the system design and by performing preventive maintenance. The various reliability enhancement schemes must be analyzed thoroughly for maximizing the system reliability while incurring the least cost. Sallam, Desouky and Desouky presented a gradient projection method for obtaining the optimal reliability indices for minimizing the interruption cost [Sall90]. Gilligan presented a simple method for identifying the priority distribution feeders for tree trimming maintenance [Gill92]. Billinton and Jonnavithula proposed a method for placement of switching devices on distribution

feeders that minimizes the cost of installation and maintenance as well as the cost of system outages [Bill96b]. Meeuwsen, Kling and Ploem studied the effects of preventive maintenance of protection equipment of distribution systems and presented a method to calculate optimal inspection frequency for reducing the cost of outages [Meeu97]. Kuntz developed an advanced method for optimal reliability centered maintenance schedules for tree trimming [Kunt99].

The reliability enhancement schemes proposed to date consider only the expected value of the system indices. The statistical distribution of the system indices provides the system planner with a way of measuring the goodness of the different proposed solutions. However, the statistical distribution of system indices for practical distribution systems is not available in published literature.

Also, it must be noted that the system indices were originally designed for internal use by distribution companies. The main purpose of these indices was to quantify the system reliability performance and to identify the "weak" feeders. However, in recent times, regulators have been specifying the minimum reliability levels to be maintained both at the feeder level and at the system level. These regulatory standards are typically specified as reliability indices over a period of time. For example, the Public Utility Commission of Texas specifies (Texas Administrative Code Chapter 25.52(f)(1)):

(A) **SAIFI.** Each utility shall maintain and operate its electric distribution system so that the SAIFI value for the 2000 reporting year does not exceed the interim system-wide SAIFI standard by more than 10%. For the 2001 reporting year and thereafter, the SAIFI value shall not exceed the system-wide SAIFI standard by more than 5.0%.

(B) **SAIDI.** Each utility shall maintain and operate its electric distribution system so that the SAIDI value for the 2000 reporting year does not exceed the interim system-wide SAIDI standard by more than 10%. For the 2001 reporting year and thereafter, the SAIDI value shall not exceed the system-wide SAIDI standard by more than 5.0%.

It is well known that the reliability levels eventually realized in practice are closely related to the extent of maintenance performed on the system. In order to appropriately allocate maintenance budget, the system planners need to know answers to questions such as: "What is the likelihood that the system indices in any year are within 10% (say) of the average value calculated over the last few years (short-term average)?" While the analytical reliability assessment tools evaluate the long-term average value of the system indices, they

do not provide answers to the new questions that challenge distribution engineers. Monte Carlo simulation method is a basic tool that can help answer such questions. For large practical distribution systems Monte Carlo simulations are expected to involve huge computational time [Endr78, Kjøl92]. An efficient Monte Carlo simulation method is likely to facilitate the planners in performing interactive analysis. Computational aspects of Monte Carlo simulations for large distribution systems have not been presented in literature. Similarly, parameters that influence the statistical distribution of the annual reliability indices have not been studied before (sensitivity analysis).

1.4 Distribution system reliability during storm conditions

A large number of distribution system faults (between 25% to 40%) occur during adverse weather conditions [Bill89]. However, there is no consensus yet on the definition of storms, nor is there a standard method for including storm-caused outages in distribution system reliability indices [Warr99]. During an adverse weather period, a large number of outages occur during a small time interval, placing a limit on the number of faults the repair crews can attend at a time. The impact of storms on distribution system reliability depends on the intensity of the storm weather and the number of crews available for restoring the power supply to the customers. Due to these reasons, the traditional models of the failure and repair processes discussed in the previous section tend to be insufficient for analyzing the system reliability during storm conditions [Brow96]. Monte Carlo simulations can easily handle complex system conditions and are commonly used to evaluate the contribution of storm events to the system reliability indices. Fong presented a Monte Carlo simulation approach to distribution system reliability that includes simple models of both normal weather and storm weather conditions [Fong85]. Brown, Gupta, Christie, Venkata and Fletcher presented advanced models for evaluating the effect of wind storms on distribution system reliability [Brow96].

A significant number of momentary outages of the distribution system loads are caused by lightning storms. Anderson and Eriksson documented the parameters of lightning flashes to be used for engineering applications [Ande80]. Based on these parameters, the IEEE Working Group on Lightning Performance of Distribution Lines presented a method of

calculating the failure rate of overhead distribution feeders due to lightning-caused line flashover [IEEE90, IEEE97]. This method can be used to calculate the average values of the distribution system reliability indices caused by lightning storms. However there is a large variability in the number and intensity of lightning storms from one year to the next. In order to maintain a high level of customer satisfaction it is increasingly becoming important for the distribution utilities to possess a deeper understanding of the momentary outages caused by lightning storms, which is also addressed in this dissertation.

1.5 Research objective

The objective of this research is to develop models and methods that aid system operators and planners in improving the reliability of power distribution systems. These predictive assessment tools allow the system engineers to test the effects of various switching and protection strategies on distribution system reliability. This research focuses on the following:

1. Monte Carlo simulation of system reliability for improved computational performance
2. The impact of various regulatory standards on a practical distribution system
3. Models for calculating the impact of lightning storms on distribution system reliability

1.6 Organization of the document

This document is organized as follows: Monte Carlo simulation for distribution system reliability is presented in Chapter 2. The consequences of various regulatory standards on a practical distribution system are explored in Chapter 3. In Chapter 4, the effect of lightning storms on system reliability is presented. Finally, Chapter 5 presents the summary and conclusions of the research performed. Potential ideas for future research are also identified.

The main contributions of this work are:

- Development of an algorithm for Monte Carlo simulation during normal weather conditions for improved computational performance
- Analysis of the impact of various regulatory standards on a practical distribution system
- Application of parametric and non-parametric methods for modeling the intensity and duration of lightning storms
- A Monte Carlo simulation approach for distribution system reliability assessment during lightning storm conditions

2. System Reliability Assessment: Practical Considerations for Monte Carlo Methods

The assessment of service reliability is an important part of distribution system operation and expansion planning. The reliability of distribution systems is usually measured using a set of standard reliability indices [IEEE98, Bill94]. Every year distribution companies determine these reliability indices based on the historical outage data. Traditionally, these reliability indices were used to identify "weak" feeders so that design changes and maintenance activities could be performed in a targeted fashion. The distribution system reliability can be improved by incorporating additional protection and sectionalizing devices, or by adopting advanced maintenance strategies [Gill92, Kunt99]. The additional protection and sectionalizing devices improve the system reliability by reducing the number of customers that experience an outage due to a fault. The system reliability could also be improved by automating the restoration processes. Maintenance activities improve the system reliability by reducing the failure rate of distribution line segments.

In order to evaluate effectiveness of various proposed service improvement schemes, predictive reliability assessment techniques are needed. Many algorithms have been proposed for predictive evaluation of system reliability. These algorithms broadly fall into two categories: the analytical and the simulation methods [Bill94]. In either method, firstly the mathematical models are obtained for faults on the distribution components (such as feeder segments, fuses and other protection equipment) along with the system response. The analytical methods then use the topological connectivity information of these components to evaluate the numerical values of the system reliability indices through a direct (non-iterative) calculation [Bill94]. In the Monte Carlo simulation method, the stochastic nature of outages of the system components and their repairs is simulated for a large number of years. System reliability indices are calculated for each year of simulation and the average of these annual indices is used as the predicted value of the reliability indices [Bill85].

Models of the failure and the repair processes form the core of both the analytical as well as the Monte Carlo simulation methods. The failures on the system are usually assumed

to follow a homogeneous Poisson Process [Bill96a]. A variety of models were proposed for the repair process [Asga97, Bill85, Chow96]. The validity of the model assumptions determines the accuracy of the predicted reliability. Therefore, prior to performing predictive reliability assessment, the historical outage data of the system being studied must be analyzed to obtain appropriate stochastic models of the failure and repair processes.

A significant constraint in using the Monte Carlo simulation method is that it requires long simulation time in order to obtain accurate results, and consequently tends to be computationally intensive for most practical systems. In this chapter, an efficient Monte Carlo simulation technique for improved computational performance is presented along with application to a large practical distribution system. The following topics are discussed in this chapter:

- System reliability indices
- Simulation as a tool for analysis
- Line segment failure and repair processes - Data analysis and modeling
- The Monte Carlo simulation technique
- Probability distribution of reliability indices
- Sensitivity of the SAIFI and SAIDI indices to models of failure and repair processes
- Analysis of SAIFI of individual feeders
- Conclusions

2.1 System reliability indices

Distribution system engineers devised two sets of annual indices that provide a measure of customer power supply reliability, viz. *customer load point indices* and the *system indices* [Bill96a, IEEE98]. The load point indices are a measure of the reliability experienced by individual customers in terms of the frequency and duration of service interruptions. For radial distribution systems, three basic load-point reliability indices have been defined, namely, the average failure rate, λ (failures per year), the average outage duration, r (hours per outage), and the average annual outage duration, U (hours per year) [Bill96a]. On the other hand, the system indices such as SAIDI and SAIFI measure the over-

all performance of the system. The standard definitions of these indices can be found in [IEEE98, Warr99]. The Failure Modes and Effects Analysis (FMEA) method is the most popular analytical method used to calculate the reliability indices. An example of the FMEA method is presented in the Appendix. The work presented in this dissertation is mainly concerned with the system-wide reliability indices.

2.2 Simulation as a tool for analysis

Simulation is a technique that reproduces actual events and processes under test conditions. A computer simulation uses the mathematical description, or the model, of a real system in the form of a computer program. This model is composed of equations in the form of mathematical, logical, or symbolic expressions that duplicate the functional relationships within the real system. Developing a simulation is often a complex mathematical process. Initially a set of rules, relationships, and operating procedures are specified, along with other variables. The interaction of these phenomena creates new situations, even new rules, which further evolve as the simulation proceeds. The computer simulation provides a numerical solution representative of the behavior of the real system [Bank96].

Simulations are especially useful in enabling observers to measure and predict how the functioning of an entire system may be affected by altering individual components within that system. The main advantages of computer simulations are as follows [Bank96]:

- Simulations permit researchers to perform "dry lab" experiments without using rare materials or inaccessible and expensive equipment
- System simulations can be used as a tool for predicting the expected behavior of the system under diverse operating conditions
- Simulations can be used as a design tool to predict the performance of new systems under design based on the properties of the constituent components
- Events that can take anywhere from few hours to a few years in real time can be simulated in a few minutes on a computer. Thus, time compression is a cost-saving feature of simulation technology

Simulation models are classified in different categories [Bank96]. A steady-state simulation model, also called a Monte Carlo model, represents a system at a particular point

in time. A stochastic simulation model has one or more random variables as input. A discrete simulation model has the state variables change at discrete points in time. The simulation models employed in this research are discrete, stochastic Monte Carlo models.

Monte Carlo (MC) methods are preferable to analytical techniques when complex operating conditions are involved. In general, the main advantages of MC methods over analytical techniques include:

- Ability to include system effects or system processes that may have to be approximated in analytical techniques
- Incorporation of probability distributions associated with component failure and restoration activities
- Provision for calculating the distributions of indices, not just the expected values (means) of the indices (random variables)

On the other hand, the MC methods have the following disadvantages.

- Requirement of large computational time
- Possibility of erroneous interpretation if the simulation is not performed for sufficient time
- Need for good random number generators [Park88, Pres88]

2.3 Line segment failure and repair processes - Data analysis and modeling

Short-circuit and open-circuit conditions along distribution line segments may lead to operating conditions that are unsafe for both system equipment and for personnel. Distribution systems incorporate protection features that remove the unsafe or faulted region out of service. This is done by devices such as fuses, circuit breakers, reclosers and automated sectionalizers. Faults are further classified as temporary and permanent. A temporary fault is one that can be corrected by the system itself, without any help of from the repair crews. For example, a fault caused by lightning flashover on an overhead distribution line can be corrected just by the operation of a recloser. On the other hand, a permanent fault is one that can be corrected only by repairing the system component.

Most analytical methods assume that distribution system outages occur at random and that outages (and repairs) are independent of the prevailing weather conditions [Bill96a, Kova79, Broa94]. Failures are assumed to occur at a constant rate that is proportional the length of each line segment. Faults in the distribution system are usually modeled are modeled as a homogeneous Poisson Process (HPP) [IEEE98, Patt79]. An HPP is a Poisson process with a constant recurrence rate. The following assumptions are involved in such a model:

1. The repair action makes the system as good as new.
2. The time-between-faults follows the exponential distribution.
3. As the number of hours in operation of the system increase, there is no deterioration (or improvement) in the system reliability.

Though these models have been in use for a long time, there is no published account that actual utility outages follow the HPP. Usually it is difficult to justify all of the assumptions made in such a model. For example, ageing, and wear and tear lead to the deterioration of the system reliability, while regular maintenance and design enhancements have the effect of improving the system reliability. Good maintenance practices are expected to improve system reliability while poor maintenance practices are likely to cause a deterioration of customer reliability [Gill92, Kunt99].

In the past the average values of indices were of great interest in predictive reliability assessment [IEEE98, Gave64, Kova79]. The simple HPP model for the failure process leads to fast and easy-to-calculate analytical methods for reliability assessment. This may be acceptable for the analytical assessment method because of the difficulty in using models of greater complexity than the HPP models. Additionally, the long-term *average* values of the system indices calculated by the analytical methods depend only on the average failure rate and the average repair rate. The statistical models of the failure and the repair processes do not affect the average system indices [Elsa96].

However, the statistical distributions of the indices are likely to depend on the models of the failure process and the repair process. Monte Carlo simulations can incorporate these models of the failure and repair processes to calculate the most realistic information on the probability density of the reliability indices. In order to make an accurate predictive

assessment of system reliability it is necessary to employ appropriate models of the fault and repair processes in the Monte Carlo simulation.

In most practical distribution systems, the set of components with similar functions are likely to be composed of different design models or materials, and are likely to be subject to widely different stress conditions and maintenance schedules. Further, a large number of the faults are due to extraneous reasons such as trees and animals. For most distribution systems, sufficient fault history of individual components is usually not available.

On the other hand, the individual power distribution systems are likely to be significantly different from one another due to the differences in the reliability levels of individual components, the weather conditions and the repair and replacement policies. Therefore, models of the failure and repair processes for individual distribution systems must be obtained by analyzing the utility's outage data.

Systematic approaches for the analysis of overall system reliability of repairable systems are available in literature [Asch98, Meek98]. Using these methods, the ageing of thermal generators was explored in [Schi88] while an analysis of the reliability data of certain Australian distribution feeders is presented in [Stil00]. The first step in the analysis of outage data is to verify whether the system reliability shows a time-dependent trend. In Figure 2.1 the cumulative number of faults is plotted against the operating time. The plot is nearly linear indicating that the recurrence rate is nearly constant.

The Laplace test is an efficient mathematical method for testing for trend. If T_1, T_2, ... T_m are a set of chronologically arranged outage times, the Laplace test statistic is calculated as:

$$U_L = \frac{\left[\frac{1}{k}\sum_{i=1}^{k} T_i\right] - \frac{1}{2}T^*}{T^*\sqrt{\frac{1}{12k}}} \tag{2.4}$$

where $k = m-1$ and $T^* = T_m$.

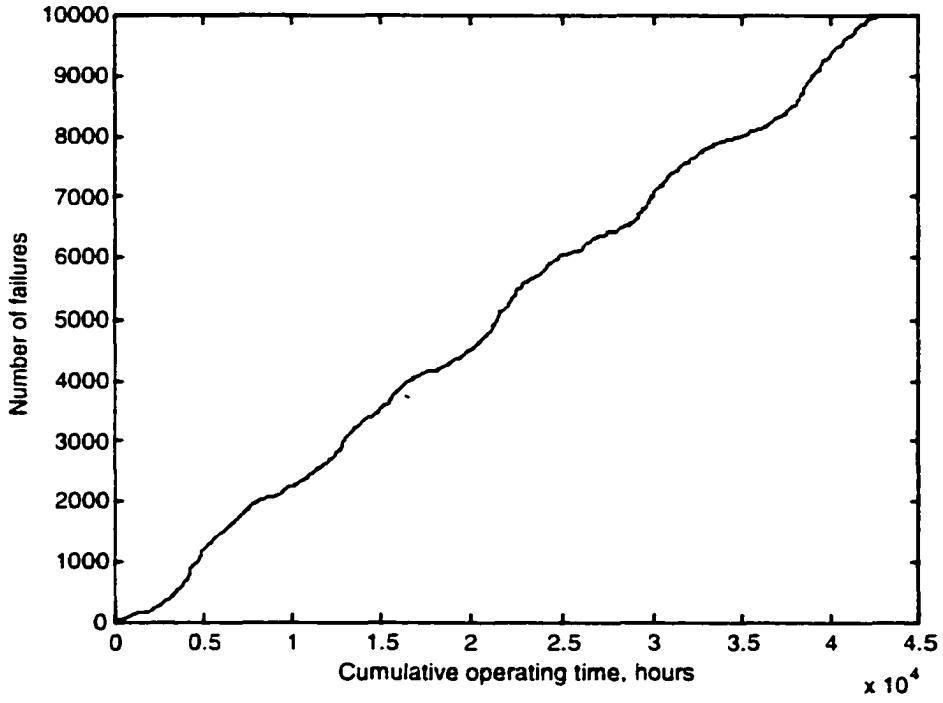


Figure 2.1 Cumulative fault count vs. Operating time

Evidence of a deteriorating trend in the system reliability is detected at a statistical significance level of α if $U_L > z_{\alpha/2}$. Similarly, if $U_L < -z_{\alpha/2}$ then there is evidence of improvement in reliability. For example, at the 95% confidence level, if $U_L > 1.96$ then the system reliability is deteriorating with time, while there is an improvement in the system reliability if $U_L < -1.96$.

The data used in this analysis consisted of five years of outage information from a distribution company in the U. S. The data included about 10,000 faults after excluding those occurring during adverse weather events. For this utility outage data, it was found that U_L = 0.8492, indicating that at the 95% confidence level, there is no evidence of a time-dependent trend.

The second step in the data analysis is to test if the times-between-faults (*tbf*) are independent. This can be evaluated using the serial correlation coefficient of the *tbf* data. The *tbf* data is independent if the correlation coefficient is equal to 0. The data has perfect positive correlation if the correlation coefficient is equal to 1.0, while it is equal to -1.0 for perfectly negative correlated data. The serial correlation coefficient for the outage data is

evaluated and was found to have a value of 0.166, indicating that the times-between-faults are largely independent.

The third step in the analysis is to test if the *tbf* data follows the exponential distribution. The total time on test (TTT) plot is a good indicator to test if the inter-arrival times in the data follow the exponential distribution.

The normalized cumulative TTT statistic is a valid test statistic for testing the null-hypothesis of exponential fit. The normalized cumulative TTT statistic for interarrival times $X_1, X_2, \ldots, X_m$ is calculated as:

$$W = \frac{\left[\sum_{i=1}^{k} S_i\right] - \frac{k-1}{2}}{\sqrt{\frac{k-1}{12}}} \tag{2.5}$$

where X_j, denotes observation j, when the observations are re-ordered by magnitude, and

$$R_i \equiv \sum_{j=1}^{i} (m-j+1)\left[X_{(j)} - X_{(j-1)}\right] \tag{2.6}$$

$$S_i \equiv \frac{R_i}{R_m} \tag{2.7}$$

At the 95% confidence level, the system reliability has a deteriorating trend if $W >$ 1.96, while a value of $W <$ -1.96 indicates a improving trend. For the utility outage data the value of W was -72.38, indicating that at the 95% confidence level, the time between outages does not follow the exponential distribution.

The *tbf* data was tested against lognormal distribution and the Weibull distribution. The Weibull distribution showed a better fit for the data. On the other hand, the outage duration data was tested against the exponential, Weibull and the lognormal distributions, none of which showed a good fit.

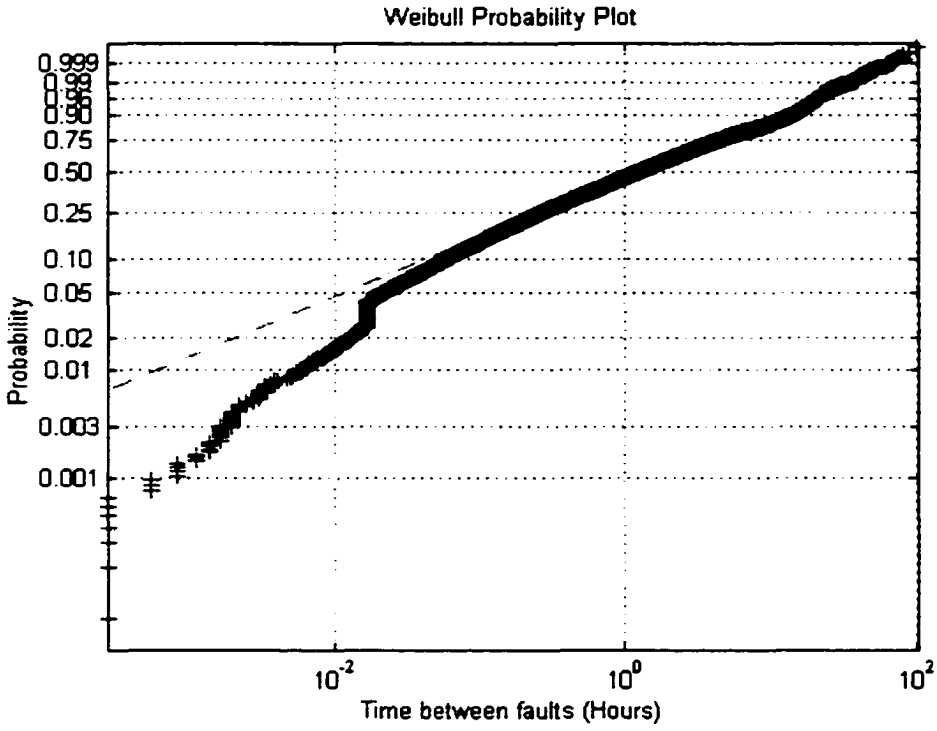


Figure 2.2 Time between failures

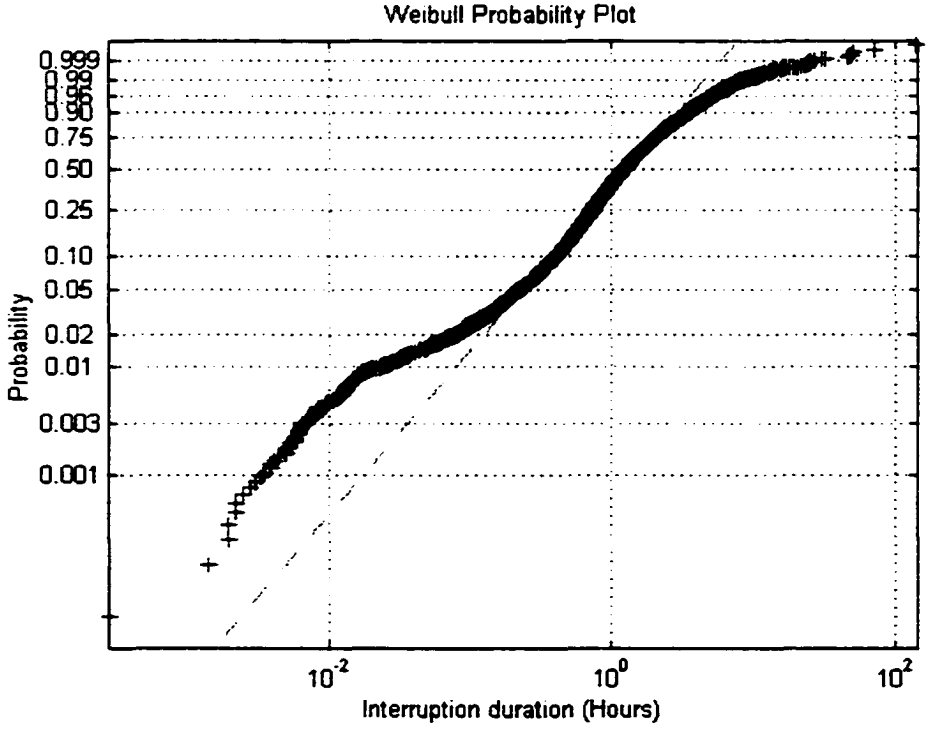


Figure 2.3 Interruption duration

The results of the Laplace test and the serial correlation of the outage data indicate that the failures follow the renewal process model, justifying the assumption that the system becomes as good as new after each repair activity. Though the utility *tbf* data follows a renewal process, the repair duration does not appear to follow any known probability distribution. In order to explore the impact of failure and repair modeling on the annual reliability indices, sensitivity studies are performed using Monte Carlo simulations as described in the Section 2.7.

2.4 Monte Carlo simulation for distribution system reliability

The distribution system is organized as follows: In a service area, power is supplied from several substations. Each substation houses a number of station transformers that supply power to customers through distribution feeders. The set of segments supplied by a transformer is referred to as a feeder. The distribution feeders are usually connected in a network (or a loop) topology but are operated in a radial configuration.

In the Monte Carlo simulation method an artificial history of faults on the line segments is generated for a number of years. The outage history thus obtained is used to calculate the reliability indices for each year of simulation. The number of components in a distribution system is typically very large, even for small systems. Therefore, the Monte Carlo simulation of distribution systems for reliability assessment is a computationally intensive method that involves simulation of a large number of components for a long duration of time. Hence, efforts to improve the computational performance of the Monte Carlo simulation are in order.

Pointers and linked lists of the C language provide an efficient way to store and access such large amounts of topological and outage data [Broa91]. The Monte Carlo simulation algorithm presented in this Chapter makes use of pointers and linked lists for representing the distribution system topology and in the evaluation of annual reliability indices. The computational efficiency of the MC simulation can be improved by taking advantage of the characteristics of the problem. The principle characteristics of the distribution reliability problem are:

- Faults occur infrequently (Low component failure rate)

- Outage time (or repair time) is much smaller as compared to the time between failures, and,
- Faults on one feeder are, to a large extent independent of the faults on other feeders.

Using these features, a time sequential simulation based on the state duration method, similar to [Bill99], is used to generate the artificial history of system faults and their repair duration. The faults on the distribution system are assumed to occur at a rate proportional the length of each line segment.

The generation and processing of the artificial of system faults and their repair duration history can be efficiently performed using the "state duration method" [Bill94, Bill99]. In this method, the operating state and the repair state duration distribution functions are used to identify the faults on the system. In the Monte Carlo simulation, the time between failure of the distribution equipment as well as the repair duration can be modeled as exponential or lognormal random variables [Patt79, Asga98].

For example, if the time between component outages is assumed to follow the exponential distribution, then the artificial fault history is generated as follows:

Let the failure rate of jth component be λ_j and its repair rate be μ_j. The duration for which it stays in the operating state can be sampled as [Bill94a]:

$$T_j = \frac{1}{\lambda_j} \ln U_j \tag{2.8}$$

where U_j is a uniformly distributed random number between 0 and 1. The repair duration is calculated in a similar fashion, by generating a new random number U_j, after replacing the failure rate, λ_j with the repair rate μ_j. Once the operating and repair duration of all the system components have been generated using (2.8), a chronological analysis of the outages can be performed to evaluate the system reliability.

At the outset, the distribution system topological data is pre-processed to identify the "zones". Segments that share the same upstream primary protection or isolation device are grouped into zones. The first segment of each zone has a switch or protection device on it. A typical system after this preprocessing step is shown in Figure 2.4. Once the system zones are

determined in the data pre-processing step, the reliability simulation proceeds as shown in Figure 2.5.

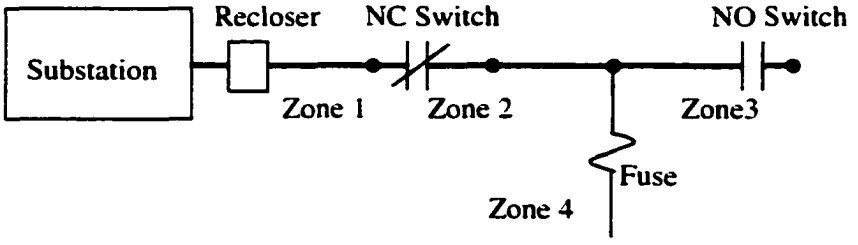


Figure 2.4 System after preprocessing procedure.

2.4.1 Convergence criteria (Confidence testing and time limit for simulation)

The number of years to be simulated in order to obtain satisfactory results of system reliability indices is not known *a priori*. To obtain results with sufficiently high degree of accuracy, the distribution system simulation incorporates two stoppage criteria. The simulation will continue until at least one of the following conditions is satisfied [Bank96]:

- The average system indices are calculated to be within a specified confidence level (confidence testing is based on the central limit theorem)
- The specified maximum number of years to be simulated has been reached.

2.4.2 The simulation algorithm

The artificial outage history generated by the Monte Carlo simulation represents an imaginary log-book of system outages. The operator's log-book contains all outages of the system posted in a chronological order. Feeder-based distinction is not made in reporting the outages. However, faults occurring on one feeder are usually independent of the faults on other feeders. This feature is made use of in developing an iterative simulation algorithm. Thus, the MC simulation is carried out for one feeder at a time, so that the amount of topological and outage data handled at any given time is minimized.

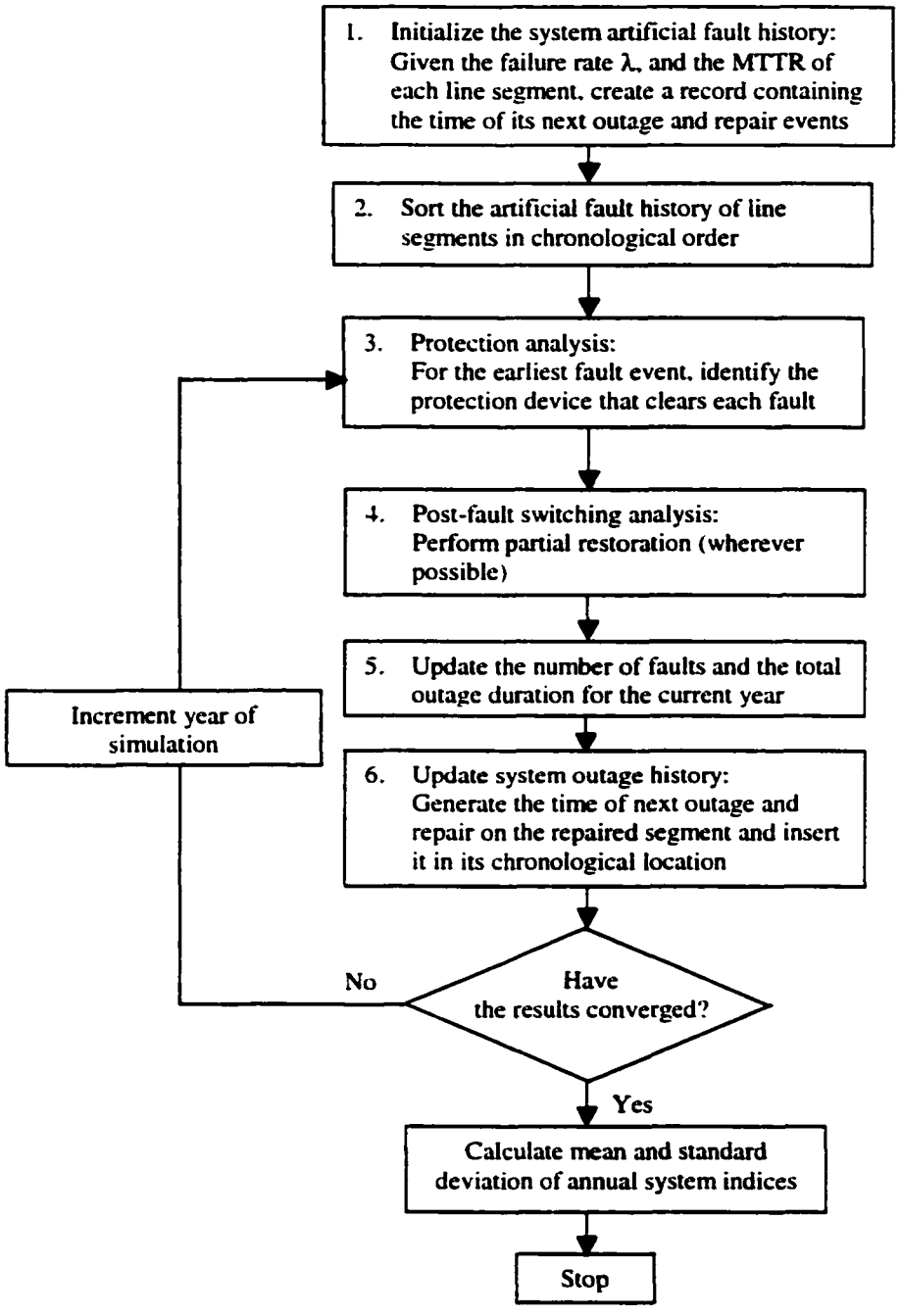


Figure 2.5 Monte Carlo simulation for reliability assessment

The Monte Carlo simulation uses an iterative algorithm. In each iteration, all the feeders are simulated separately for a period of 100 years. At the end of each iteration, the contribution of outages on various feeders is cumulated to calculate the annual system indices. and the confidence level of the output data is calculated. The confidence level of the

output data is then calculated to determine if the simulation has converged to the specified level of precision. The simulation involves the following steps:

1. Generate the time of failure and repair duration of all segments of a feeder
2. Process the faults in a chronological order. Evaluate the contribution of each outage to the annual system indices. Update the time of next fault and the corresponding repair duration on the feeder segment
3. If the time has reached the iteration period of 100 years then load the next feeder. Before loading the new feeder, save the fault and repair times of all the segments so that the next iteration of the simulation can continue from where it was left off.
4. After all the feeders have been simulated, perform confidence test on the annual reliability indices
5. If stoppage criteria are not satisfied, generate the outage history for another 100 years by going back to step 2.

The flow-chart of the simulation algorithm is shown in Figure 2.5. Simulations conducted on a large practical distribution system, show that significant improvement in computation time can be obtained by using the appropriate algorithm.

2.4.3 Computational performance of Monte Carlo simulation

The computational time of the Monte Carlo simulation for a practical distribution system consisting of 100 feeders is plotted in Figure 2.6 and compared with the computation time for the analytical method. Systems of different sizes but similar reliability characteristics were created by randomly selecting subsets of feeders from the 100 feeder system. The simulation is performed until the SAIDI is obtained within 5% error with 98% confidence on a PC with a 300 MHz Pentium II processor. The Monte Carlo simulation took between 9 and 2 times longer than analytical calculation. The ratio of run times dropped as system size increased, and the simulation run time in seconds is fast enough to support interactive analysis.

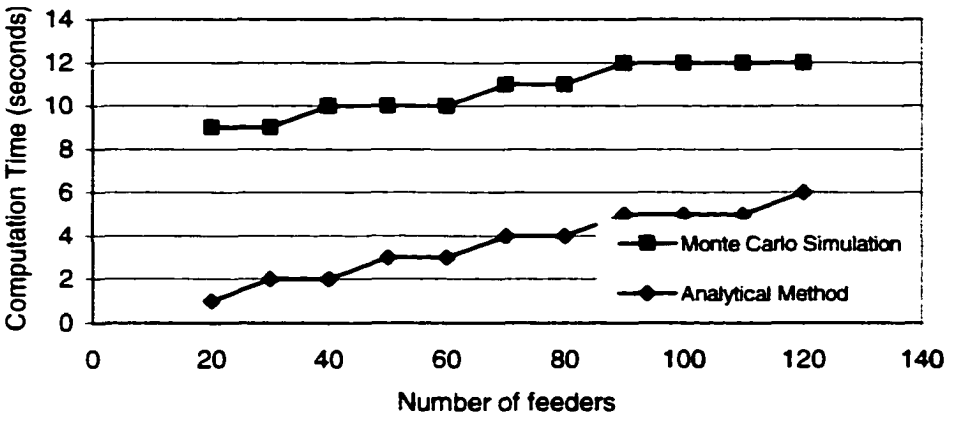


Figure 2.6 Computational performance of the Monte Carlo algorithm

In order to compare the performance of the proposed algorithm, a comparative assessment of the computation times of the Monte Carlo simulations available in literature is presented in Table 1.1. The performance improvement in the proposed algorithm is due to utilizing the following system characteristics:

- The state-duration method employed in the algorithm generates a list of failure times for individual feeder segments, so that the time of all outages in a given year are known *a priori*. The segments are then ordered according to the chronological order of their failure times. Processing of faults based on such chronologically ordering results in fast computationally efficient calculation of annual feeder indices.
- Since failures on one feeder are independent of other feeders, individual feeders can be simulated independently. Due to this at any given time, only the segments of one feeder are processed, instead of all the line segments of the system, thereby reducing the memory requirements, enhancing the computational performance.

Table 1.1 Comparative assessment of computational performance

Source	System Details	Computation time (Seconds)	
		Analytical Method	Monte Carlo Simulation (Years of Computation)
L. Goel and R. Billinton [Goel94]	8 segments (1 feeder)	0.2	12.42 (10,000)
S. Asgarpoor and M. J. Mathine [Asga97]	36 segments (4 feeders)	0.05	5.16 (300)
Proposed method	25,000 segments (100 feeders)	5.27	11.42 (100)

The number of years for which the system was simulated to obtain convergence is plotted as a function of the system size in Figure 2.7. It can be observed from Figure 2.7 that as the system size increases the number of years for which the simulation must be performed to obtain the indices with 98% confidence decreases.

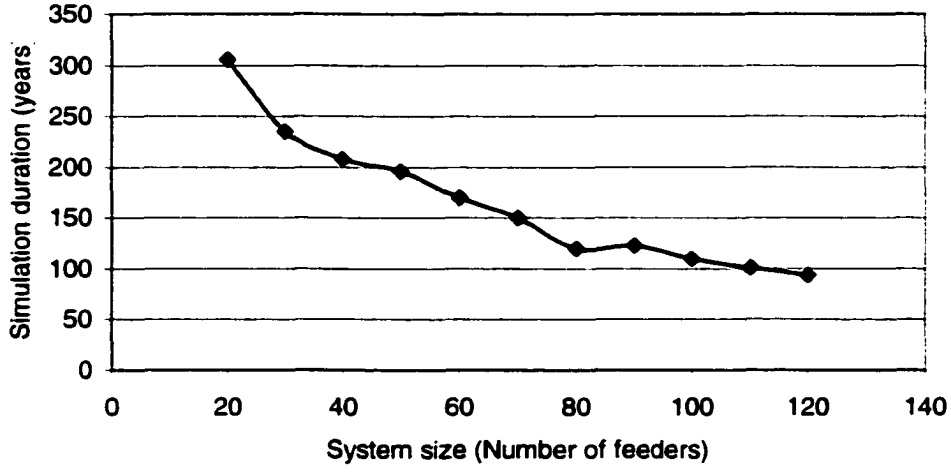


Figure 2.7 Convergence properties of the simulation

The number of faults analyzed to obtain convergence is plotted as a function of the system size in Figure 2.8. From this figure, it is noted approximately the same the number of faults are generated for obtaining a specified accuracy level for systems of different sizes. This indicates that the number of faults that must be simulated for a given accuracy level is independent of the system size.

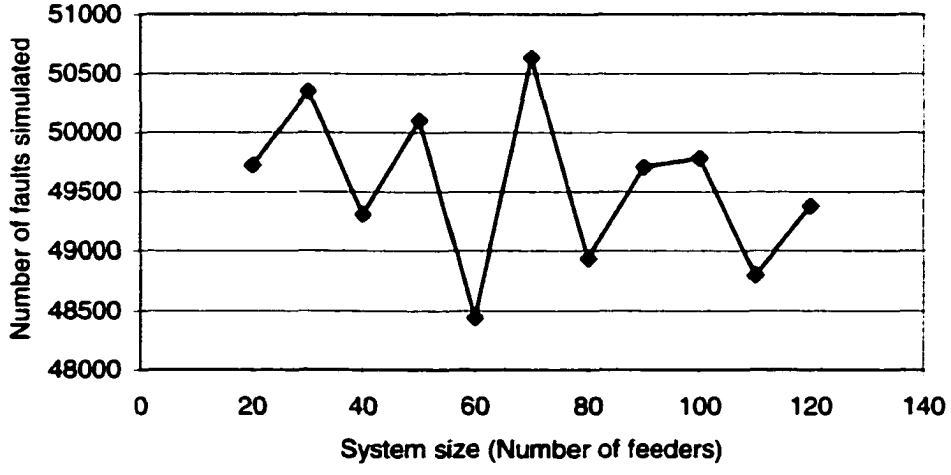


Figure 2.8 Number of faults simulated for convergence

2.5 Probability histograms of the system indices

This Section presents the probability histograms of the various standard reliability indices for a practical distribution system. The histograms are obtained for the 100-feeder test system. To provide an illustrative comparison, the histograms for an individual feeder (feeder F78B) are plotted alongside. Feeder F78B was selected for this purpose since its average SAIDI and SAIFI are close to the system average. The histograms of the interruption *frequency* indices, namely, SAIFI, MAIFI, $MAIFI_E$, CAIFI and ASIFI are presented in the Sections 2.5.1 through 2.5.5. The histograms of the interruption *duration* indices, namely, SAIDI, CAIDI, CTAIDI, ASIDI are presented in Sections 2.5.6 through 2.5.9. The histograms of the service availability index, ASAI, are presented in Section 2.5.10. These probability histograms can be used to obtain the likelihood of the system indices in any year being greater than (say) 10% of the average value. The distribution engineers can use such information in system maintenance and expansion planning. An important application of such information is presented in Chapter 3.

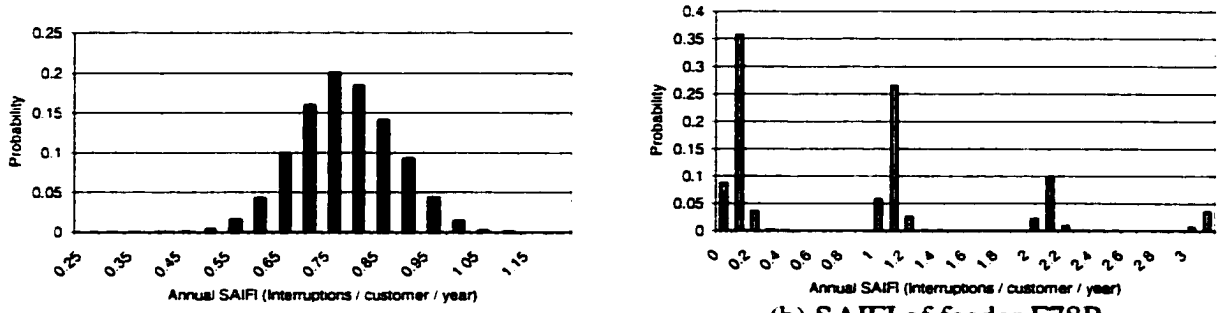
2.5.1 System Average Interruption Frequency Index (*SAIFI*)

The SAIFI indicates the average frequency of sustained interruptions per customer over a predefined area.

$$SAIFI = \frac{Total\ Number\ of\ Customer\ Interruptions}{Total\ Number\ of\ Customers\ Served} \tag{2.9}$$

The SAIFI probability histograms for the 100-feeder test system, and for an individual feeder in the test case are shown in Figure 2.9. The average SAIFI for the 100-feeder test system and for feeder F78B are 0.75 and 0.77 interruptions per customer per year respectively. The system SAIFI has a peak near its average value while the feeder SAIFI exhibits multi-modal characteristics. There is zero probability that the feeder SAIFI in any year will be equal to its average value. Similar multi-modal behavior is observed in the SAIFI of other feeders in the 100-feeder system and in [14]. Such multi-modal characteristics are observed in all the interruption frequency indices of individual feeders. A detailed discussion on the multi-modality of the feeder SAIFI is presented in Section 2.7.

An examination of Figure 2.9 indicates that SAIFI of the *individual* feeder is statistically very different from the indices of a *group* of feeders. The indices tend to show a continuous normal distribution behavior as the system size increases. Therefore, care must be taken when using normal distribution theory for establishing the minimal standards for individual feeder indices.



(a) System SAIFI (b) SAIFI of feeder F78B

Figure 2.9 Probability histogram of SAIFI

For example, some state regulatory agencies benchmark the reliability indices to identify the nominal performance of individual feeders. The benchmark values are usually based on the historic average values of the indices. The performance standards are established at a value slightly greater than the average historic value of the indices such as 10% [TAC01]. Distribution companies are required to operate the feeders such that the maximum value of any annual reliability index shall not exceed the performance standards. In case of feeder F78B, the reliability benchmark for SAIFI would be 0.77 interruptions per customer per year, while the minimum standard would be 0.86 outages per customer per year. There is a 49% probability that in any given year, the feeder SAIFI will exceed the reliability standard. Thus, feeder F78B is likely to violate the reliability standard for SAIFI every other year, though it ranks a distant 32nd among the worst performing feeders.

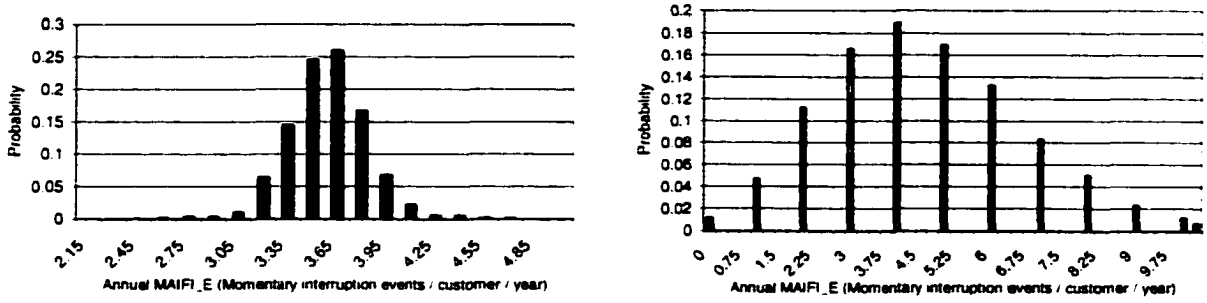
2.5.2 Momentary Average Interruption-Event Frequency Index (*MAIFI$_E$*)

The MAIFI$_E$ indicates the average frequency of momentary interruption events per customer in a year. An interruption of duration less than 5 minutes, but limited to the period required to restore service by a reclosing device is termed as a *momentary interruption event* [IEEE98]. For example, all interruptions caused by breaker/recloser operations related to the

same fault condition, and occurring within 5 minutes of the first interruption can be classified as a single momentary interruption event. The $MAIFI_E$ can be calculated as:

$$MAIFI_E = \frac{Total\ Number\ of\ Customer\ Momentary\ Interruption\ Events}{Total\ Number\ of\ Customers\ Served} \tag{2.10}$$

The $MAIFI_E$ probability histograms for the 100-feeder test system, and for an individual feeder in the test case are shown in Figure 2.10. The average $MAIFI_E$ for the test system and for the feeder F78B are 3.51 and 4.51 momentary interruption events per customer per year respectively. It can be seen that the $MAIFI_E$ of the feeder exhibits a distinct multi-modal behavior similar to the SAIFI.



(a) System $MAIFI_E$ (b) Feeder $MAIFI_E$

Figure 2.10 Probability histogram of system $MAIFI_E$

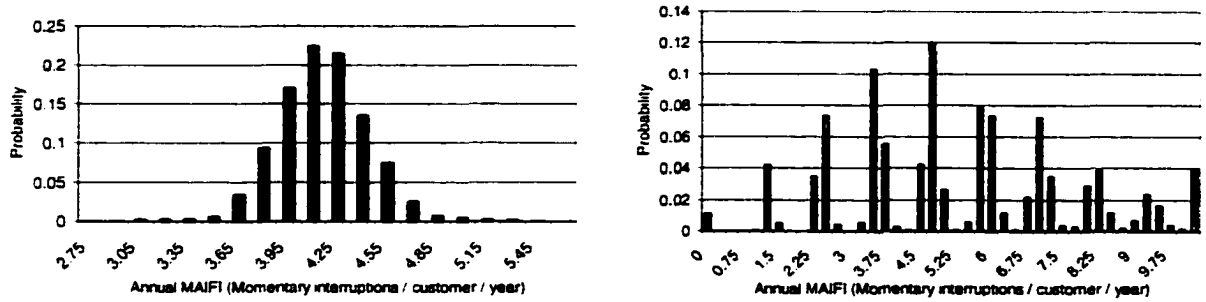
2.5.3 Momentary Average Interruption Frequency Index (*MAIFI*)

The occurrence of each voltage zero condition due to operation of an interrupting device is termed as a *momentary interruption*. For instance, if a temporary fault is cleared after two recloser operations, then all the connected customers would have experienced two momentary interruptions (but only one momentary interruption event). On the other hand, if after two attempts, the recloser locks shut for a permanent fault, the customers again would have experienced two momentary interruptions (but zero momentary interruption events, since the outage will be counted as a sustained interruption).

The average frequency of momentary interruptions per customer is given by MAIFI.

$$MAIFI = \frac{Total\ Number\ of\ Customer\ Momentary\ Interruptions}{Total\ Number\ of\ Customers\ Served} \tag{2.11}$$

The MAIFI probability histograms for the 100-feeder test system, and for an individual feeder in the test case are shown in Figure 2.11. The average MAIFI for the 100-feeder test system and for feeder F78B are 4.08 and 5.23 momentary interruptions per customer per year respectively. It can be seen that the MAIFI of the feeder also exhibits a multi-modal behavior.



(a) System MAIFI (b) Feeder MAIFI

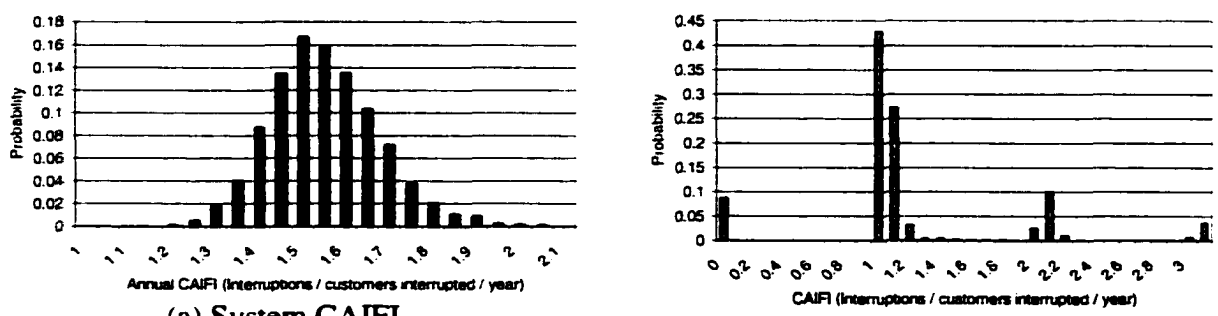
Figure 2.11 Probability histogram of MAIFI

2.5.4 Customer Average Interruption Frequency Index (*CAIFI*)

The CAIFI indicates the average frequency of sustained interruptions for those customers experiencing sustained interruptions.

$$CAIFI = \frac{Total\ Number\ of\ Customer\ Interruptions}{Total\ Number\ of\ Customers\ Interrupted} \tag{2.12}$$

The CAIFI probability histograms for the 100-feeder test system, and for an individual feeder in the test case are shown in Figure 2.12. The average CAIFI for the 100-feeder test system and for feeder F78B are 1.52 and 1.16 interruptions for each interrupted customer per year respectively.



(a) System CAIFI (b) Feeder CAIFI

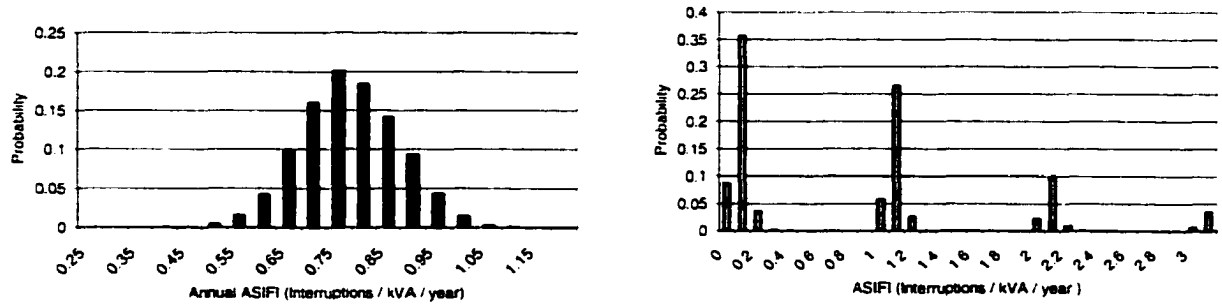
Figure 2.12 Probability histogram of system CAIFI

2.5.5 Average System Interruption Frequency Index (*ASIFI*)

ASIFI is a load-based index different from the customer-count based indices such as SAIFI. ASIFI gives information on the system average interruption frequency per kVA.

$$ASIFI = \frac{(Connected\ kVA\ Interupted)}{Total\ Connected\ kVA\ Served} \tag{2.13}$$

The ASIFI probability histograms for the 100-feeder test system, and for an individual feeder in the test case are shown in Figure 2.13. The average *ASIFI* for the 100-feeder test system and for feeder F78B are 0.75 and 0.78 interruptions per kVA per year respectively.



(a) System ASIFI (b) Feeder ASIFI

Figure 2.13 Probability histogram of system ASIFI

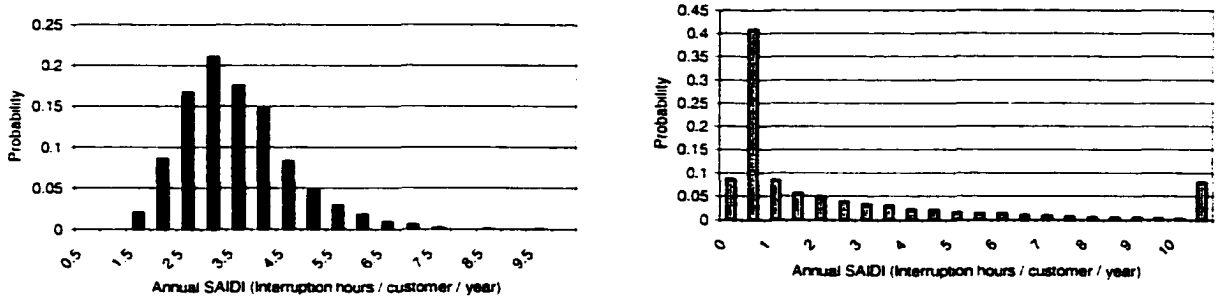
2.5.6 System Average Interruption Duration Index (*SAIDI*)

The SAIDI, also referred to as the 'customer minutes of interruption', or simply, 'customers hours', indicates the average time the customers are interrupted.

$$SAIDI = \frac{\sum Duration\ of\ Customer\ Interruptions}{Total\ Number\ of\ Customers\ Served} \tag{2.14}$$

The SAIDI probability histograms for the 100-feeder test system, and for an individual feeder in the test case are shown in Figure 2.14. The average SAIDI for the 100-feeder test system is 3.18 interruption hours per customer per year respectively. From Figure 2.14(b), long tails can be noticed in the probability distribution of feeder SAIDI. The probability that the annual feeder SAIDI=0.5 hours per customer per year is 41%. However,

the area under the long tail of the plot contributes to the average SAIDI being equal to 3.7 hours per customer per year, with a standard deviation of 9.5 hours per customer per year.



(a) System SAIDI (b) Feeder SAIDI

Figure 2.14 SAIDI Probability histogram

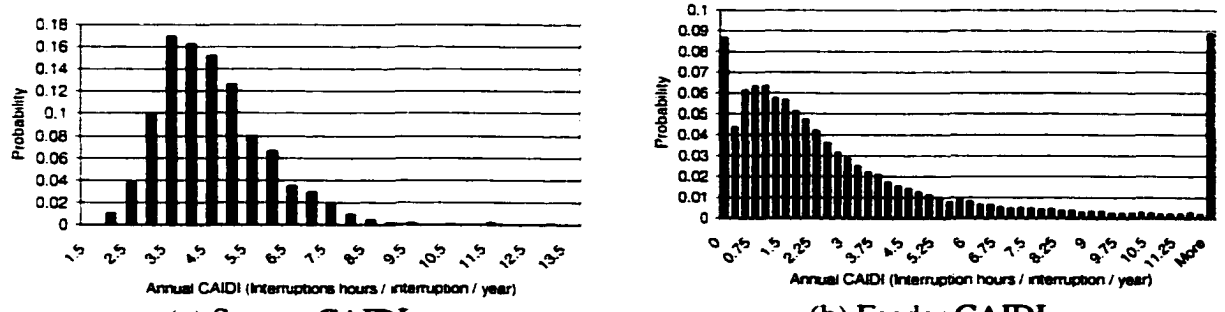
The SAIDI probability histogram of feeder F78B shows a continuous behavior as compared to the frequency indices such as SAIFI. This because the outage duration is a real number while the interruption count can assume only integer values.

2.5.7 Customer Average Interruption Duration Index (*CAIDI*)

CAIDI represents the average time required to restore service to the average customer per sustained interruption.

$$CAIDI = \frac{\sum Duration\ of\ Customer\ Interruptions}{Total\ Number\ of\ Customer\ Interruptions} \tag{2.15}$$

The CAIDI probability histograms for the 100-feeder test system, and for an individual feeder in the test case are shown in Figure 2.15. The average CAIDI for the 100-feeder test system and for feeder F78B are 4.25 and 4.47 hours per interruption per year respectively.



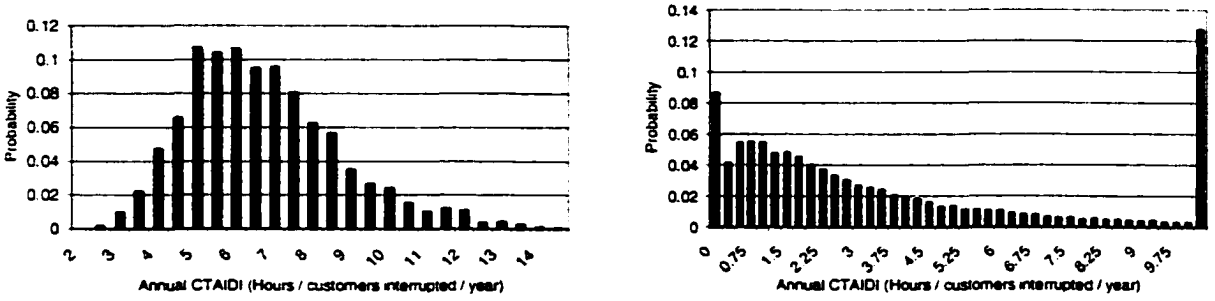
(a) System CAIDI (b) Feeder CAIDI

Figure 2.15 Probability histogram of system CAIDI

2.5.8 Customer Total Average Interruption Duration Index (*CTAIDI*)

The total average time required to restore service to the average customer per sustained interruption is represented by CTAIDI. Calculating CTAIDI is very similar to evaluating CAIDI, except that the customers with multiple interruptions are counted only once.

$$CTAIDI = \frac{\sum Customer\ Interruption\ Durations}{Total\ Number\ of\ Customers\ Interrupted} \tag{2.16}$$



(a) System CTAIDI (b) Feeder CTAIDI

Figure 2.16 Probability histogram of system CTAIDI

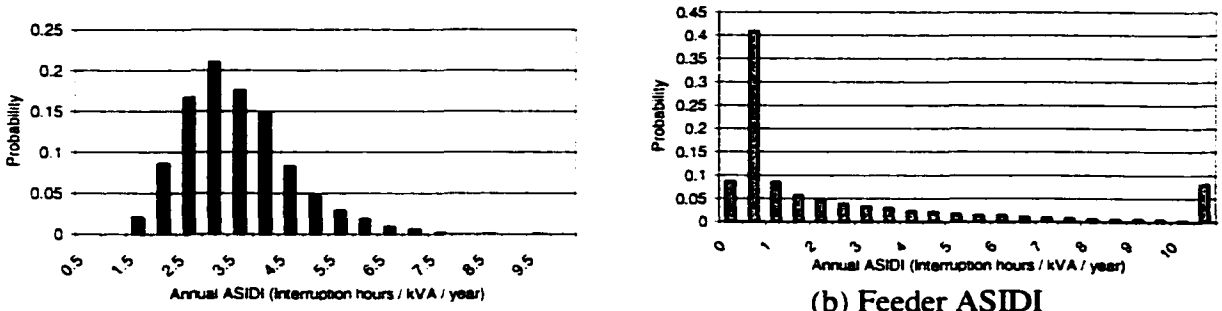
The CTAIDI probability histograms for the 100-feeder test system, and for an individual feeder in the test case are shown in Figure 2.16. The average *CTAIDI* for the 100-feeder test system and for feeder F78B are 6.49 and 5.63 interruption hours per interrupted customer per year respectively.

2.5.9 Average System Interruption Duration Index (*ASIDI*)

ASIDI is a load-based index similar to ASIFI. ASIDI gives information on the system average interruption duration per kVA.

$$ASIDI = \frac{Connected\ kVA\ Interuption\ Duration}{Total\ Connected\ kVA\ Served} \tag{2.17}$$

The ASIDI probability histograms for the 100-feeder test system, and for an individual feeder in the test case are shown in Figure 2.17. The average ASIDI for the 100-feeder test system and for feeder F78B are 3.18 and 3.70 interruption hours per kVA per year respectively.



(a) System ASIDI (b) Feeder ASIDI

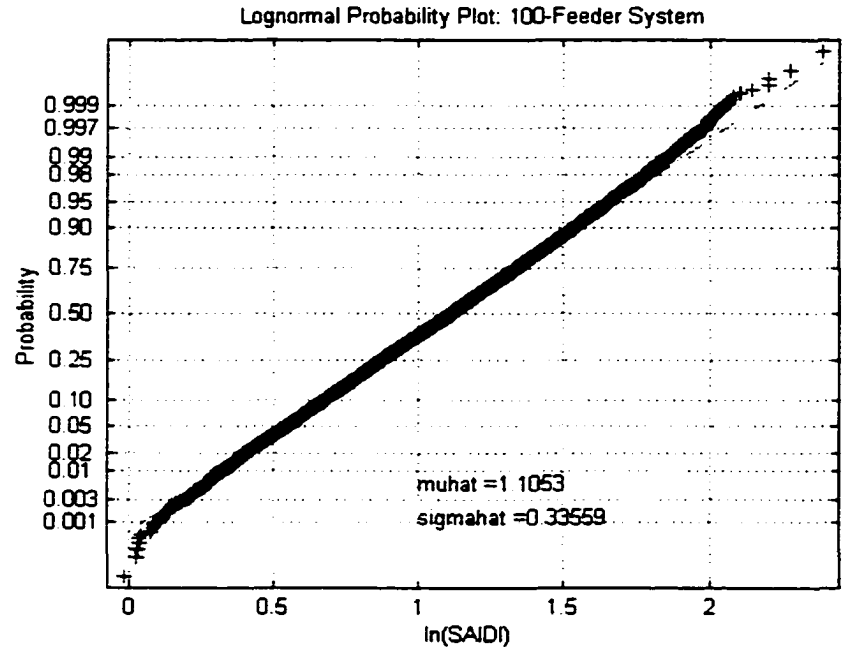
Figure 2.17 Probability histogram of system ASIDI

2.6 Probability plots of SAIDI and SAIFI indices

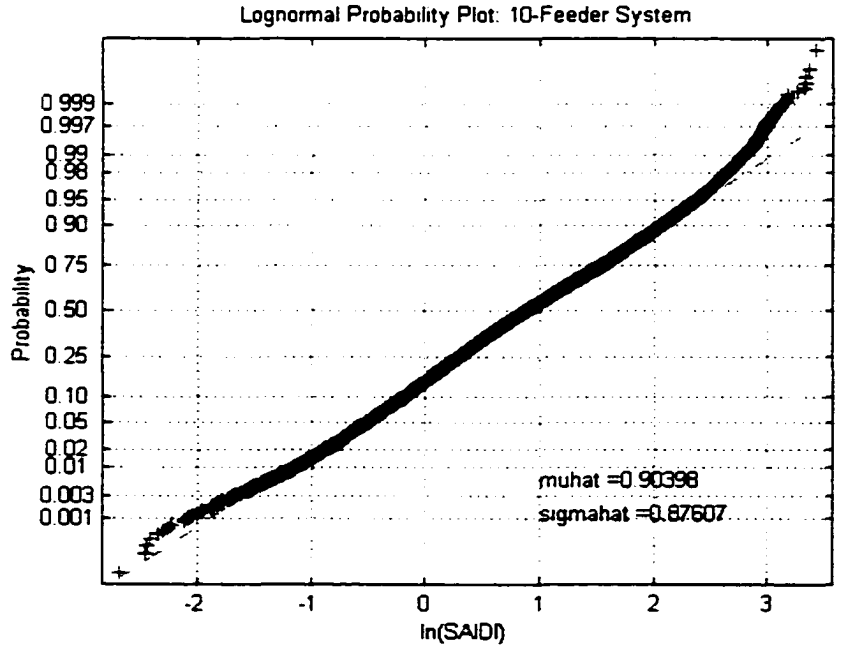
The probability histograms provide visual information on the likelihood of the annual reliability indices being equal to (or greater than) a specified value. This section explores if the system SAIDI and SAIFI follow a known mathematical distribution. There are attempts being made to use the probability distribution of the daily SAIDI to identify the storm-caused outages [Chri01]. The . It must be noted that the probability plots presented in this section are obtained assuming that the component fault rate is independent of the prevailing weather conditions.

2.6.1 System SAIDI probability plots

The probability plots of the SAIDI of the 100-feeder test system and a subsystem containing 10 feeders are plotted in Figure 2.19 (a) and (b) respectively. Similar plots were plotted for other subsystems. It is observed from these plots that the system SAIDI closely follows the lognormal distribution. However, there is some deviation from the lognormality at the tails of the distribution.



(a) 100-feeder system: Lognormal probability plot

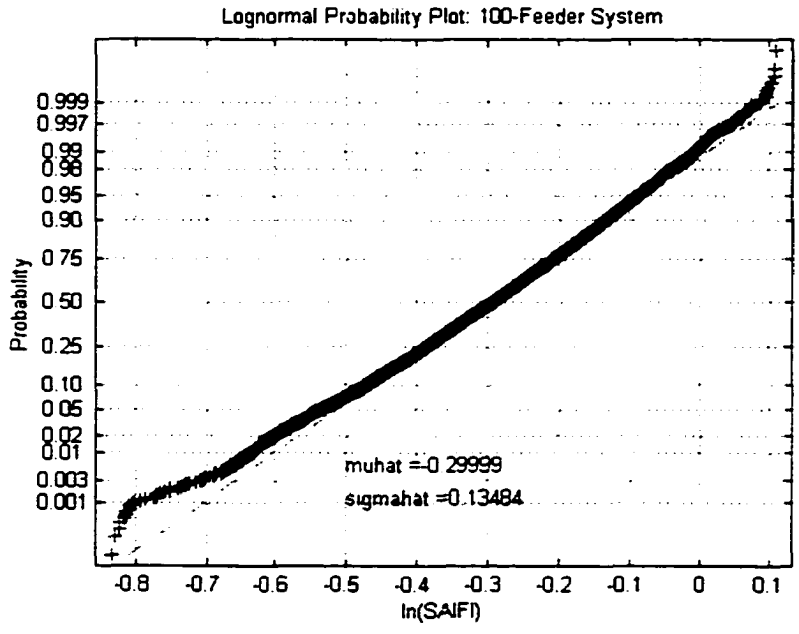


(b) 10-feeder system: Lognormal probability plot

Figure 2.19 Probability plots of system SAIDI

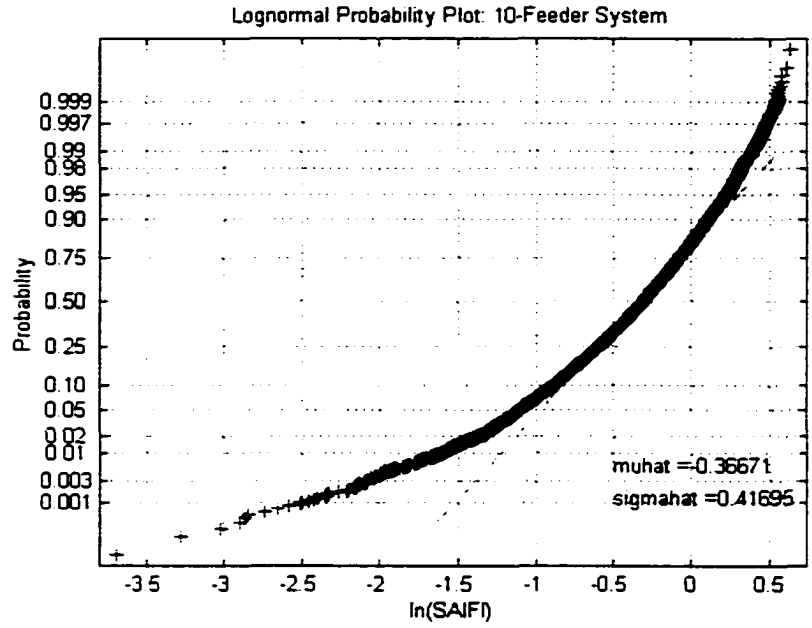
2.6.2 System SAIFI probability plots

The probability plots of the SAIFI of the 100-feeder test system and a subsystem containing 10 feeders are plotted in Figure 2.20 (a), (b) and (c). Figure 2.20 (a) indicates that the SAIFI of the 100-feeder system follows the lognormal distribution fairly well. However, Figures 2.20 (b) and (c), indicate that the Weibull distribution is a closer fit for the SAIFI of the 10-feeder system.

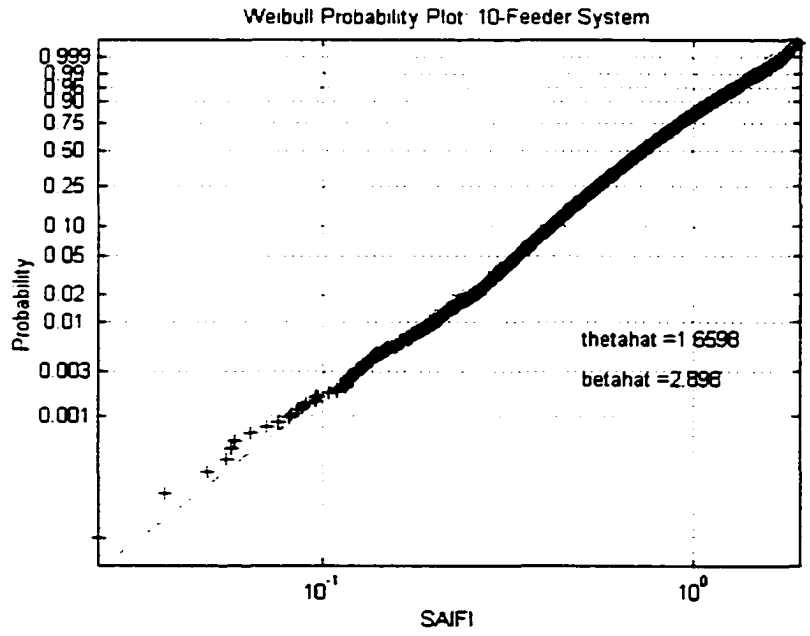


(a) 100-feeder system: Lognormal probability plot

Figure 2.20 Probability plots of system SAIFI



(b) 10-feeder system: Lognormal probability plot



(c) 10-feeder system: Weibull probability plot

Figure 2.20 (Cont.) Probability plots of system SAIFI

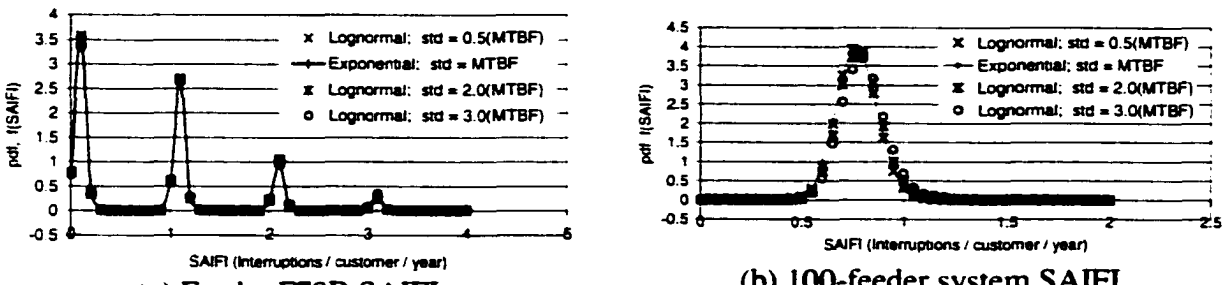
2.7 Sensitivity of SAIDI and SAIFI indices to failure and repair models

Monte Carlo simulations can be used to study the sensitivity of the system indices to failure and repair models. The SAIFI is a measure of the number of failures occurring on the system. Since the repair duration is usually smaller than the times between component failures, the SAIFI is dependent on only the failure process models. On the other hand, the SAIDI depends on the number of outages as well as the repair duration.

2.7.1 Sensitivity of reliability indices to failure models

The probability density plots of the SAIFI for a feeder (feeder F78B) as well as that for the 100-feeder system obtained using a variety of failure models are presented in Figures 2.21. In this analysis, the Mean time Between Failures (MTBF) of the system components is kept constant, while the standard deviation of the time-between-failures is varied. From Figure 2.21, the annual feeder SAIFI is found to be largely independent of the model for the component outage process. This implies that the a reasonable estimate of the statistical distribution of customer interruption frequency indices can be evaluated using just:

- the topological data and the customer count, and
- a constant outage rate model for the failure processes.



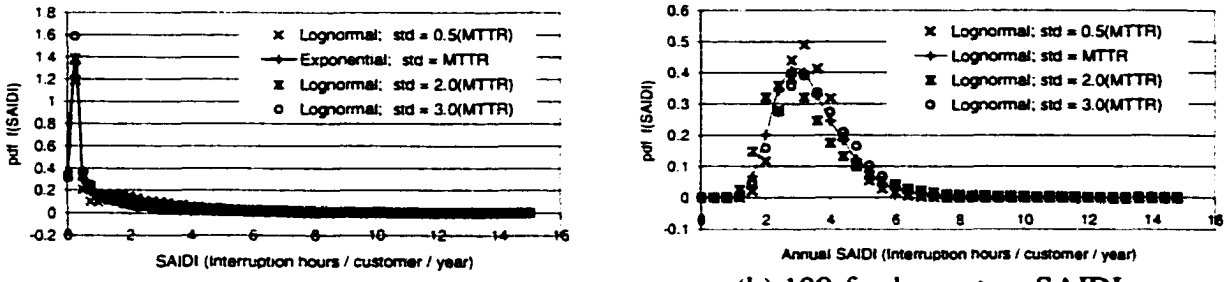
(a) Feeder F78B SAIFI (b) 100-feeder system SAIFI

Figure 2.21 Probability density function plots of SAIFI

2.7.2 Sensitivity of reliability indices to repair models

The probability density of the SAIDI of feeder F78B is presented in Figure 2.22 for a variety of repair models. In this analysis, the Mean Time To Repairs (MTTR) a faulted

component is kept constant, while the standard deviation of the time-to-repair is varied. From Figure 2.22, it is observed that the annual SAIDI distribution is to a great extent dependent on the model for repair duration. Therefore, using the constant repair duration models provides only a rough approximation of the statistical distribution of the customer interruption duration indices. This information is likely to be of value in effecting improvements to be made in distribution outage data collection methods.



(a) Feeder F78B SAIDI (b) 100-feeder system SAIDI

Figure 2.22 Probability density function plots of SAIFI

2.8 Analysis of SAIFI of individual feeders

Plots presented in Sections 2.5.1 through 2.5.6 indicate a distinct multi-modal behavior of the feeder interruption frequency indices. A discussion on the interruption frequency indices is provided in this section. Consider feeder F84A the general topology of the main feeder of which is provided in Figure 2.23.

The substation breaker (marked as 'Sub') is equipped with a recloser. There is a recloser along the feeder on segment S111. Normally closed (NC) switches are located on segments S15 and S115. There are a total of 2,241 customers on the system. Of these, the number of customers downstream to segments S12, S15, S115 and S116 are 348, 460, 231 and 823 respectively. Additionally, lateral segments that supply groups of customers branch out from the main feeder. Each of the lateral branches is equipped with a fuse. If there is a fault along the lateral segment, the fuse operates, isolating the faulted segment from the rest of the system. Such a design feature ensures that faults on the laterals do not lead to an outage on the entire feeder. Feeder F84A has 1056 customers connected along the laterals.

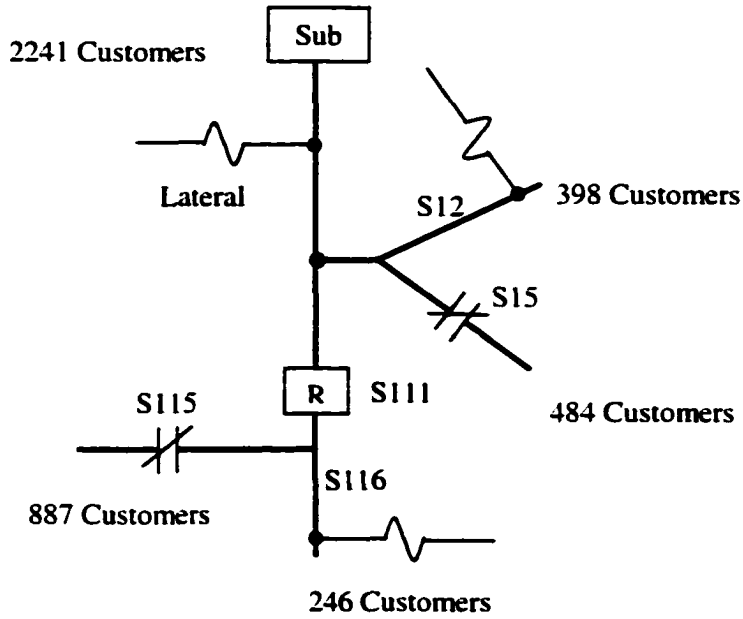


Figure 2.23 Topology of Feeder F84A

Feeder F84A has 1056 customers connected along 66 lateral branches. The number of customers connected on each of these laterals ranges from 2 to 75. Some laterals have no customers connected. The fault rate on the laterals is 1.520 faults/year, while it is 2.568 faults/year along the main feeder.

The SAIFI probability histograms of feeder F84A is plotted in Figure 2.24. The customer interruptions on this system are caused by:

- Faults on the main feeder
- Faults on the laterals

A fault on the main feeder would lead to a loss of power supply to all the customers downstream to the protection device that isolates the fault. In case of feeder F84A, a permanent fault along the main feeder leads to two possible protection actions:

- If the fault location is downstream to segment S111, then the recloser on S111 would lock out open to isolate the fault. This would result in an interruption to all the customers downstream to segments 115 and 116 (887+246 = 1133 customers). If there is one such fault in a year, the SAIFI would be equal to 1133/2241 = 0.5056 interruptions/customer.

- If the fault location is anywhere else on the main feeder, the recloser at the substation would isolate the power supply to the entire feeder. This results in an interruption to all the customers connected to feeder F84A (2241 customers). Each of such faults would contribute to the feeder SAIFI, a value of 1.0 interruption/customer (=2241/2241).

A fault on a lateral segment would usually cause interruption only to the connected local load. The load downstream to the fuses on the laterals is small as compared to the load downstream to the feeder reclosers. Therefore, the contribution of each lateral fault to the system SAIFI is a small fraction as compared to the contribution due to feeder faults.

During some years, the only the lateral segments experience faults - there are no faults on the main feeder. The area of the histogram labeled 'A' in Figure 2.24 corresponds to this case. Consider the case when there is one feeder fault downstream to segment S111 and a few faults on the laterals in a year. The fault on the feeder contributes a SAIFI value of 0.5056 interruptions/customer. The probability histogram for such a case would be similar to area A, offset by 0.5056. The area labeled 'B' corresponds to this case.

Similarly, if there is one feeder fault on a segment that is not downstream to S111, then the substation recloser would isolate the entire system, contributing a SAIFI value of 1.0. The SAIFI histogram for this case would take the same shape as area A, offset by 1.0, as shown in the area labeled 'C'.

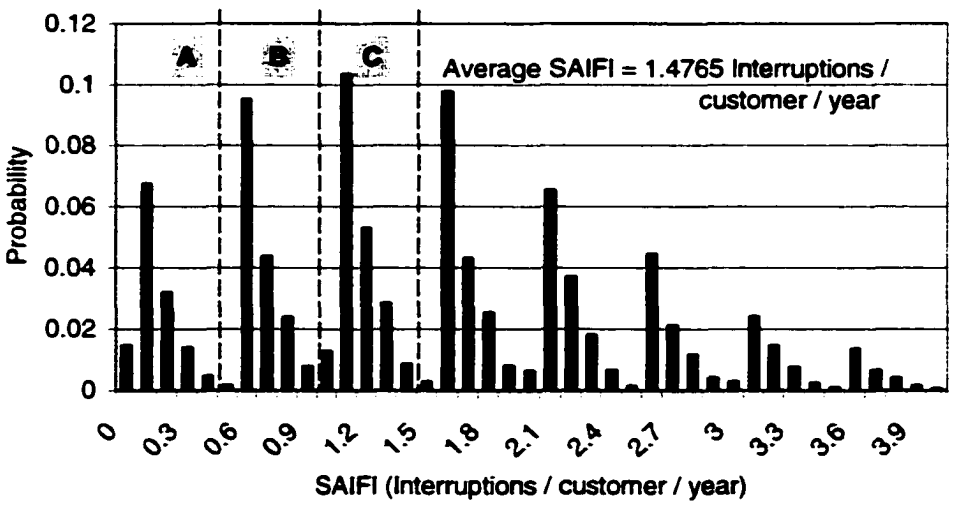


Figure 2.24 SAIFI probability histogram for feeder F84A

Thus, it can be seen that the multi-modal nature of the feeder SAIFI observed in this plot is due to the quantization of the annual number of customer interruptions caused by the location of the protective devices. The protection devices that have the greatest impact on the feeder SAIFI are reclosers and sectionalizers. For example, consider the scenario where the NC switch on segment S115 is converted into a sectionalizer. Further, assume that a sectionalizer is placed on S116. The sectionalizers on S115 and S116 are coordinated with the recloser on S111. The SAIFI probability histogram for such a redesigned feeder is shown in Figure 2.25.

Faults downstream of segments S115 and S116 are now isolated by the sectionalizers. In the original topology shown in Figure 2.23, any feeder segment fault downstream of S111 would result in an interruption to all the 1133 customers (887+246). With the installation of the sectionalizers, a fault downstream of S115 would result in interruption to only 887 customers. Similarly, a fault downstream of S116 would result in interruption to 246 customers.

In the original topology, the area 'B' of Figure 2.24, has a SAIFI offset of 0.5056. Due to the installation of the sectionalizers, this offset is split into two components: one of 0.396 (=887/2241) due to sectionalizer S115 and 0.1098 (=246/2241) due to sectionalizer S116. The impact of such design changes can be seen Figure 2.25.

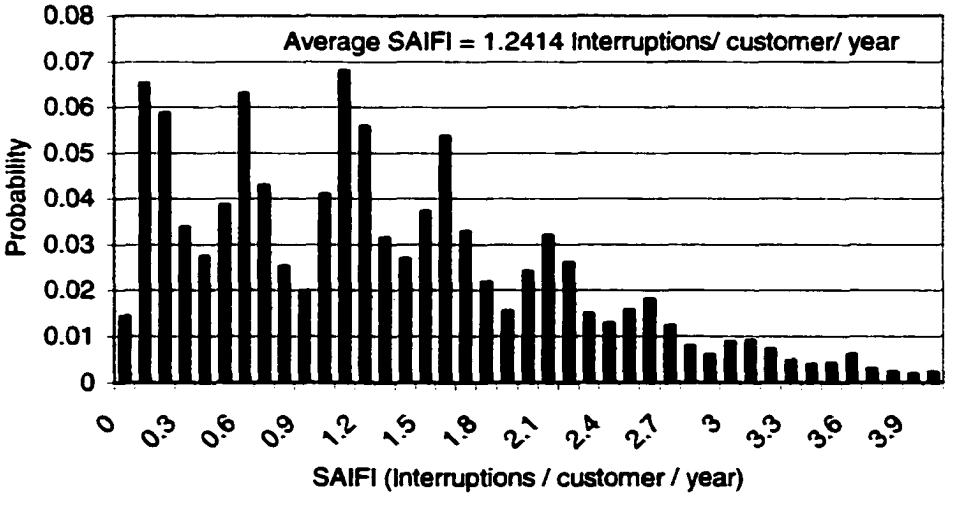


Figure 2.25 SAIFI probability histogram for the redesigned feeder F84A

2.9 Conclusions

Predictive assessment of service reliability is an important part of distribution system operation and expansion planning. The conventional analytical assessment techniques such as the Failure Modes Effects Analysis (FMEA) method can provide only the long-term average value of the system indices. Monte Carlo simulations provide the statistical distribution of the reliability indices along with their average values. In this section, algorithms for improved computational performance of the Monte Carlo simulation for distribution system reliability assessment are presented. The probability histogram plots of a practical distribution system indicate that the feeder indices are much different in their statistical nature from the system-wide indices.

From an analysis of utility outage data from a distribution company, it is noted that the failures might be modeled as a renewal process. Sensitivity studies presented in this Chapter indicate that the probability plots of the SAIFI indices are mostly independent of the statistical model of the failure process. Therefore, knowledge of the topological data in terms of feeder design and load density along with the average failure rate and repair duration can be used to obtain the statistical characteristics of the SAIFI. However, the repair processes are not likely to follow the exponential or lognormal distribution. Hence detailed models of the outage duration are required to obtain the probability plots of the interruption duration indices such as the SAIDI.

The SAIFI histogram of individual feeders of the test system showed multi-modal behavior due to the quantization of the number of customer interruptions caused by the location of the protective devices. The impact of incorporating sectionalizing devices on the feeder SAIFI are also explored in this Chapter.

3. Sensitivity Analysis of Distribution System Reliability Indices

The assessment of service reliability is an important part of distribution system operation and planning. Distribution companies determine the reliability indices based on the historical outage data to identify "weak" feeders and to study the impact of design changes and maintenance activities on system performance. The reliability indices vary from year to year because of the statistical variation in the number of customer outages and the duration of such outages. It is well known that the reliability of a system is closely related to the quality of the system maintenance programs and design improvements. Maintenance activities help to reduce the fault rate of the feeders while design changes such as installation of additional protection and isolation devices reduce the number of customers who experience outages due to a fault [Chow95, Gill92, Kunt99, Meeu97]. In a market structure where companies regularly experience financial difficulties and are subject to acquisitions and mergers, leading to increased pressure on cost control, reliability of power supply could be severely undermined. In order to ensure that the changing utility environment does not adversely affect the reliability of power supplied to customers, several state regulatory agencies have started to prescribe minimum reliability standards to be maintained by the distribution companies. These regulatory standards typically specify the maximum allowable values of either the load point indices or the system-wide indices. Again, the regulatory limits are specified either on the values of the indices every year, or on the values of the indices recorded during the two previous years.

For example, the Public Utility Commission of Texas specifies (Texas Administrative Code Chapter 25.52(f)(1)) limits on annual values of the system indices [TAC01]:

(A) **SAIFI.** Each utility shall maintain and operate its electric distribution system so that the SAIFI value for the 2000 reporting year does not exceed the interim system-wide SAIFI standard by more than 10%. For the 2001 reporting year and thereafter, the SAIFI value shall not exceed the system-wide SAIFI standard by more than 5.0%.

(B) **SAIDI.** Each utility shall maintain and operate its electric distribution system so that the SAIDI value for

> the 2000 reporting year does not exceed the interim system-wide SAIDI standard by more than 10%. For the 2001 reporting year and thereafter, the SAIDI value shall not exceed the system-wide SAIDI standard by more than 5.0%.

The same regulatory board specifies the limits on the feeder indices for the two previous years (Texas Administrative Code Chapter 25.52(f)(2)):

> (A) Each utility shall maintain and operate its distribution system so that no distribution feeder with more than ten customers sustains a SAIDI or SAIFI value for a reporting year that is among the highest (worst) 10% of that utility's feeders for any two consecutive reporting years.
> (B) Each utility shall maintain and operate its distribution system so that no distribution feeder with more than ten customers sustains a SAIDI or SAIFI value for a reporting year that is more than 300% greater than the system average of all feeders during any two consecutive reporting years.

The New York Public Service Commission and the Pennsylvania Public Utilities Commission among other states, however, specify that the annual SAIDI, SAIFI and CAIDI indices shall not exceed the established performance standards [SNY91, PPUC99]. On the other hand, the Illinois Commerce Commission (ICC) and the California Public Utilities Commission specify limits on the customer load point indices. For example, the ICC specifies [Ill00]:

> Customers whose immediate primary source of service operates at 15,000 volts or below should not have experienced:
> i) More than six controllable interruptions in each of the last three consecutive years.
> ii) More than eighteen hours of total interruption duration due to controllable interruptions in each of the last three consecutive years.

It can be noticed that a wide variety of metrics are being used by the regulatory authorities for specifying the minimal standards of customer power supply reliability. Some of the reliability standards have been established based on average value and the spread of the indices calculated from historical data [SNY91, PPUC99]. For example, the Pennsylvania Public Utilities Commission has established the annual feeder reliability standards to be two standard deviations over the historical average value [PPUC99]. Others seem to be based on the subjective judgement of the regulatory authorities.

Presently, the regulatory authorities are monitoring the reliability performance of the distribution systems by means of these reliability standards. Based on the reliability standards, the distribution companies are required to report the circuits that experience poor reliability levels along with the measures taken to improve their performance. The standards are meant to help the utilities identify the weak spots where customers experience persistent reliability problems, rather than as a means for penalizing the distribution companies. The reliability profile of different power distribution systems tends to be dissimilar due to differences in the customer density, length of overhead and underground conductors, and the principal outage causes [Warr99]. It is likely that the same set of measures might not be appropriate for all the distribution systems. The analytical FMEA method cannot easily calculate the impact of such regulatory standards on the different feeders and on different systems. To be effective, the reliability standards adopted must identify feeders that consistently perform poorly, while being insensitive to those that occasionally have poor reliability. The regulators have a delicate task of identifying measures that would lead to a reasonable amount of maintenance expenditure for the utilities so that the customers find a reasonable level of supply reliability. In order to satisfy the regulatory standards and to make appropriate allocation of maintenance funds the system planners need to consider criteria that address these new reliability standards. The system planners are thus faced with a host of questions that were not thoroughly investigated in the past. This chapter explores the impact of the various reliability standards on a large practical distribution system.

Most regulatory authorities distinguish between distribution system outages during normal weather and in adverse weather. In this research, the system indices calculated are based on outages occurring during normal weather. The fault process and the repair process are thus unaffected by the prevailing weather conditions.

The Chapter is organized as follows: An analysis of the measures based on the annual feeder reliability indices, and on the indices for two consecutive years is presented in Section 3.1. Sections 3.2 presents analysis of the measures based on the annual and two consecutive year measurements of the system-wide reliability indices respectively. A discussion of the results is presented in Section 3.3 and the conclusions are presented in Section 3.4.

3.1 Analysis of annual feeder indices

The reliability standards specified by the regulatory authorities on the annual reliability indices are usually based on the mean value and the standard deviation of historical reliability indices calculated for the past few years. As a first step, the average and the standard deviation of the reliability indices of the feeders of a test system are studied. A practical distribution system consisting of 100 feeders is used in this study. A time sequential Monte Carlo simulation based on the state duration method is used to generate the artificial history of system faults and their repair duration [Bill85, Bill99, Bank96]. In the simulation, the time between failure of the distribution equipment as well as the repair duration are assumed to follow the exponential distribution. The failure rate and the repair rate were obtained from the utility outage data. The simulation is performed for a period of 10.000 years.

The probability density function (pdf) plots of SAIDI and SAIFI for feeder F78B are presented in Figures 3.1 and 3.2. Figure 3.1 is essentially the same as Figure 2.22 (a) with the exponentially distributed repair duration. Similarly, Figure 3.2 is the same as Figure 2.21 (a) with exponentially distributed time between failures. The average SAIDI is 3.54 interruption hours/customer/year, with a standard deviation of 9.7 while the average SAIFI is 0.78 interruptions/customer/year, and the SAIFI standard deviation is 0.82. The SAIFI of the feeder displays multi-modal characteristics.

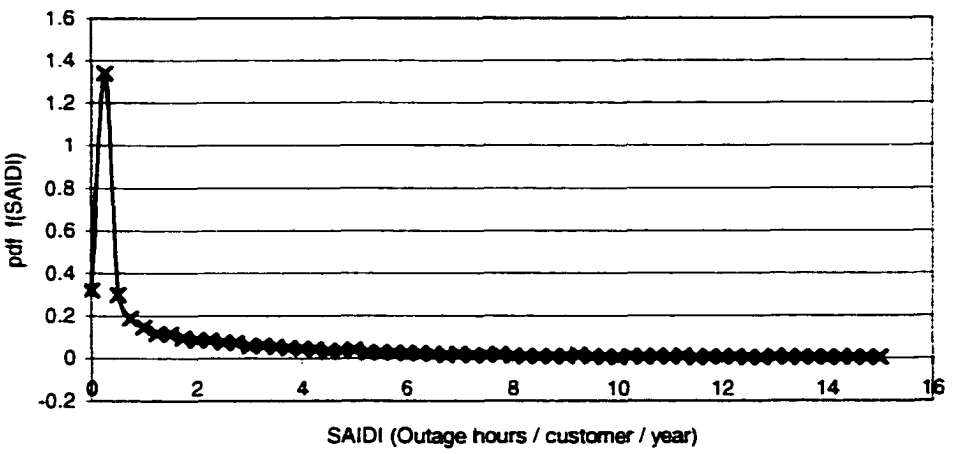


Figure 3.1 Probability plot of SAIDI for feeder F78B

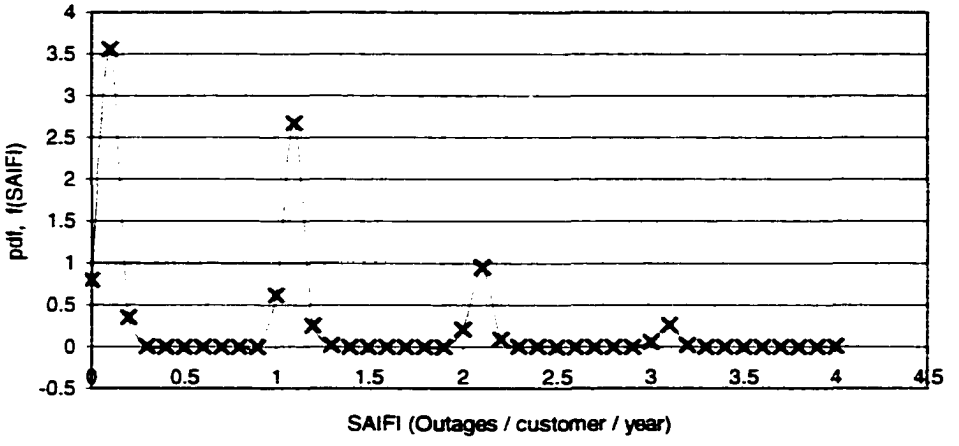


Figure 3.2 Probability plot of SAIFI for feeder F78B

Figures 3.1 and 3.2 indicate that SAIDI and SAIFI indices of individual feeders are statistically very different from the normal distribution. Therefore, care must be taken if normal distribution assumptions are made in establishing the minimal standards for individual feeder indices.

3.1.1 Analysis of annual feeder indices

In establishing the reliability standards, the average values of the SAIDI and SAIFI indices of individual feeders are used as the *performance benchmarks*. The benchmarks are usually based on historic average values of the reliability indices. In order to ensure high levels of supply reliability, limits are imposed on the annual reliability indices of individual feeders. The standard on annual feeder reliability indices considered in this paper is:

F0 Standard: No feeder shall have a SAIDI (SAIFI) of greater than ***x*** *standard deviations over the benchmark value.*

For instance, the Pennsylvania Public Utilities Commission specifies a value of **x** = 2 standard deviations as its minimal reliability standard [PPUC99]. The probability of a feeder violating the F0 standard is termed as the F0-measure. The F0 measures for the SAIDI and SAIFI of individual feeders for a 10-feeder sub-system are presented in Table 3.1 for **x** = 2 standard deviations.

Table 3.1 F0 measure for feeder SAIDI and SAIFI

Feeder	SAIDI	F0 Measure (%)	SAIFI	F0 Measure (%)
F78C	6.21	4.81	0.906	5.76
F57C	5.33	4.54	0.825	4.42
F84A	3.95	3.20	1.463	4.31
F78B	3.78	3.72	0.768	3.87
F77D	3.16	3.30	0.701	2.84
F84B	2.53	2.15	0.915	5.10
F57B	2.40	2.81	0.712	3.43
F57A	2.32	3.08	0.416	6.90
F57D	1.18	1.71	0.393	5.34
F78A	0.61	4.06	0.240	5.79

A feeder that frequently has poor performance is expected to have a high value of the F0-measure while a feeder with good reliability is expected to have a low value of the F0 measure. However, Table 3.1 indicates that for the test system, the probability of the annual indices exceeding the two-standard deviation limit is quite low (less than ~5%). It can also be noticed that the F0 measure is largely independent of the value of SAIDI or SAIFI of the feeders. For example, feeders F78C and F78A have widely different SAIDI values of 6.21 and 0.61 interruption hours/customer/year respectively while their F0 measures (4.81% and 4.06% respectively) do not reflect this difference in performance.

From Table 3.1, it can be noticed that feeders with higher values of SAIDI and SAIFI exceed the F0 standard only marginally more often than those with lower values of the reliability indices. Similar results were observed for the other feeders of the 100-feeder system. Thus, for the test system, the F0-measure would not be very effective in identifying weak feeders.

3.1.2 Analysis of feeder indices over two consecutive years

The reliability standards must be able to distinguish poor performing circuits from the statistical deviants. Feeders with poor reliability are expected to consistently have high

values of the annual reliability indices. Therefore it is expected that such feeders can be easily identified from a study of their reliability indices of two (or more) consecutive years. Two such standards are analyzed in this paper:

F1 Standard: No feeder shall have annual SAIDI (SAIFI) that is y% greater than the system average for two consecutive years.

F2 Standard: No feeder shall be in the worst z% bracket of SAIDI (SAIFI) for two consecutive years.

The Maryland Public Service Commission specifies a value of **z** = 2% [MPSC00], while the Texas Administrative Code employs values of **y** = 300% and **z** = 10% in specifying the minimal reliability standards in the state of Texas [TAC01]. The probability of the F1 and the F2 standards being violated are termed as F1-measure and F2-measure respectively. The annual feeder indices obtained from the Monte Carlo simulation are analyzed to obtain the F1 and F2 measures for all the 100-feeder in the system. The 10 worst performing feeders of the system are shown in Tables 3.2 and 3.3 for **y** = 300% and **z** = 10% respectively.

From Table 3.2 and Table 3.3, it can be observed that the ranking of the feeders by average SAIDI and SAIFI closely tallies with the ranks provided by F1 and F2 measures, confirming the validity of average SAIDI and SAIFI as reasonable quantifiers of system reliability. It can also be noted that the 10 worst performing feeders with respect to SAIDI are different from those with respect to SAIFI. Only four feeders, viz. F28B, F43A, F43B and F47D are common to both lists.

When SAIDI and SAIFI values yield two different sets of "weak" feeders, it is necessary to assess the relative weakness of these feeders in order to identify those feeders that require greater attention. The F1 and F2 measures help make such a decision. While SAIDI and SAIFI are incommensurable quantities, the F1 and the F2 measures, being probabilities can be used to identify feeders that run the greater risk of violating reliability standards.

For example, if the F1 standard is specified for the feeders, then the three most likely events of violation of reliability standards are SAIDI of F71B, SAIFI of F28B, and F43A (probabilities of 11.89%, 9.91% and 7.73% respectively). This information could be useful to system planners in determining the nature of design changes needed for improving the feeder

reliability. Further, the frequency of the feeder violations can be calculated as the inverse of the F1 and F2 measures. That is, feeder F28B is expected to violate the F2 standard for SAIFI once in every $0.3226^{-1} \approx 3$ years. On the other hand, the same feeder is likely to violate the F1 standard for SAIDI only once in almost $0.0491^{-1} \approx 20$ years.

Table 3.2. The 10 worst performing feeders based on SAIDI

Feeder	SAIDI	F1Measure (%)	F1 Rank	F2 Measure (%)	F2 Rank
F71B	13.38	11.89	1	17.22	1
F72A	8.95	5.75	2	10.95	3
F28B	7.22	4.91	3	13.19	2
F43A	6.78	3.60	4	8.51	4
F78C	6.22	2.78	5	5.24	9
F57C	5.33	2.04	7	3.75	14
F14A	5.32	1.98	8	3.71	15
F43B	5.17	2.29	6	8.31	5
F47B	5.11	1.62	12	4.35	12
F47D	4.92	1.83	9	6.00	8

Table 3.3. The 10 worst performing feeders based on SAIFI

Feeder	SAIFI	F1 Measure (%)	F1 Rank	F2 Measure (%)	F2 Rank
F28B	2.10	9.91	1	32.26	1
F43B	1.87	7.73	2	24.26	2
F17A	1.70	4.32	4	20.17	3
F77B	1.69	4.39	3	18.75	4
F17B	1.59	2.40	6	15.50	5
F43A	1.54	3.25	5	13.98	6
F47D	1.47	1.98	7	12.69	7
F84A	1.46	1.06	10	10.06	8
F27A	1.41	0.67	15	8.50	9
F47A	1.33	0.49	18	7.39	12

Based on this analysis, F28B appears to the weakest link in the system, though it is only a distant third in terms of the system SAIDI alone. Similarly, feeder F71B which has the worst SAIDI does not even figure in the 10% worst performing feeders list with respect to SAIFI. Thus, a greater understanding of the relative weakness of various weak feeders can be obtained from the F1 and F2 measures that could not be otherwise obtained from just the annual indices or from the F0 measure discussed in Section 3.1.1. Hence, having multiple measures for longer periods of time is highly desirable.

3.2 Analysis of system reliability indices

In evaluating the F1 and F2 measures the feeder reliability level is compared with the reliability of the entire system. For example, the F2 measure evaluates the rank of the various feeders based on their indices. Such a rank-based measure may fail to detect a deteriorating trend in the system-wide reliability levels. In order to ensure that the reliability of the entire system is maintained at least at the existing level, standards are being specified on the overall system indices as well, along with the standards on the reliability of individual feeders. The average values of the SAIDI and SAIFI indices of the entire system are used as the performance benchmarks in setting the standards on the system. One such standard is:

S0 Standard: The system SAIDI (SAIFI) in any year shall not be greater than x% over the benchmark values.

The Texas Administrative Code uses **x** = 5% as the minimal reliability standard [TAC01]. The probability density plots of SAIDI and SAIFI for the 100-feeder system and a smaller subsystem consisting of 10 feeders are presented in Figures 3.3 and 3.4. It must be noted that the pdf plots of the system reliability indices are quite different from those of feeder indices shown in Figures 3.1 and 3.2. The SAIDI and the SAIFI for some of the systems were found to follow the lognormal or the Weibull distribution as shown Section 2.6.

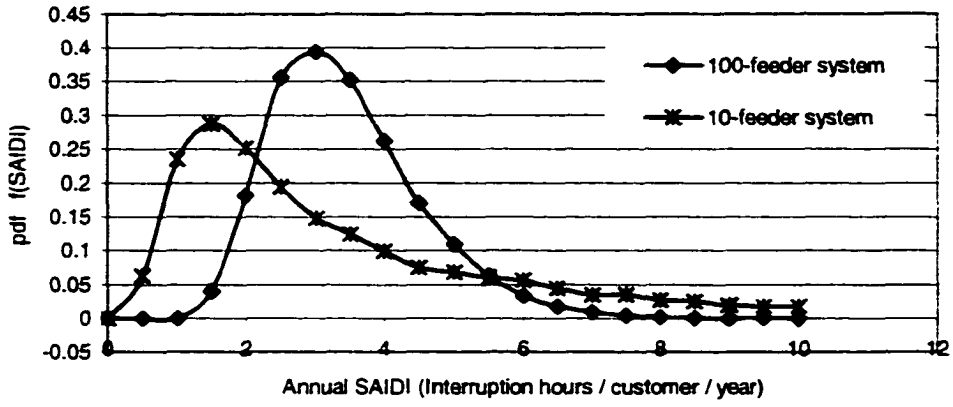


Figure 3.3 Probability plot of system SAIDI

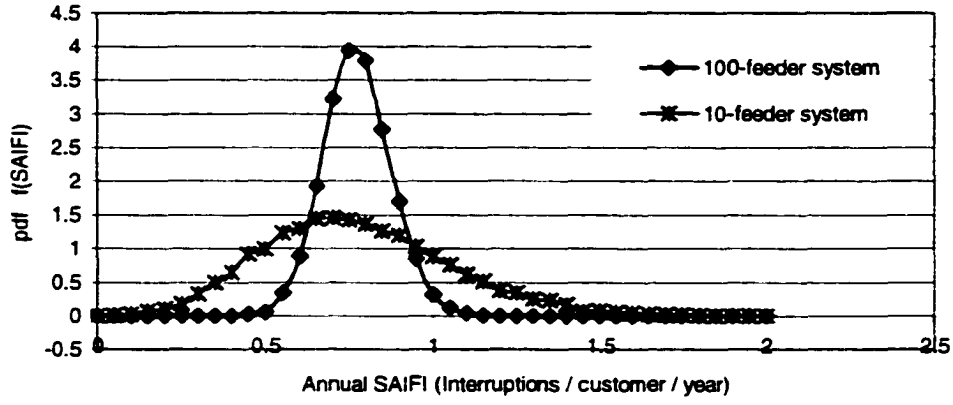


Figure 3.4 Probability plot of system SAIFI

Frequently, the same x% is specified for the various distribution systems within a state. Under such circumstances, there is a concern that the larger systems will have a lower frequency of violating the system standard as compared to the smaller ones [SNY91]. In order to explore the basis for this concern, subsystems of different sizes but similar reliability characteristics (i.e. average SAIDI and SAIFI values) were created from the 100-feeder system. The average SAIDI and SAIFI for the subsystems are presented in Table 3.4. The concept of relative standard deviation can be used to compare the deviation of the reliability indices of different systems. The relative standard deviation is defined as the ratio of the standard deviation of a random variable to its mean value. The relative standard deviation of SAIDI and SAIFI for the systems of different sizes is shown in Figure 3.5.

Table 3.4 SAIDI and SAIFI of different systems

System Size (Feeders)	SAIDI		SAIFI	
	Mean	Standard deviation	Mean	Standard deviation
100	3.19	1.087	0.747	0.0995
90	3.16	1.112	0.745	0.1044
80	3.14	1.226	0.712	0.1090
70	3.27	1.310	0.721	0.1138
60	3.33	1.487	0.702	0.1211
50	3.35	1.618	0.671	0.1291
40	3.48	1.913	0.694	0.1508
30	3.72	2.295	0.722	0.1759
20	3.06	2.237	0.721	0.2048
10	3.57	3.353	0.749	0.2772

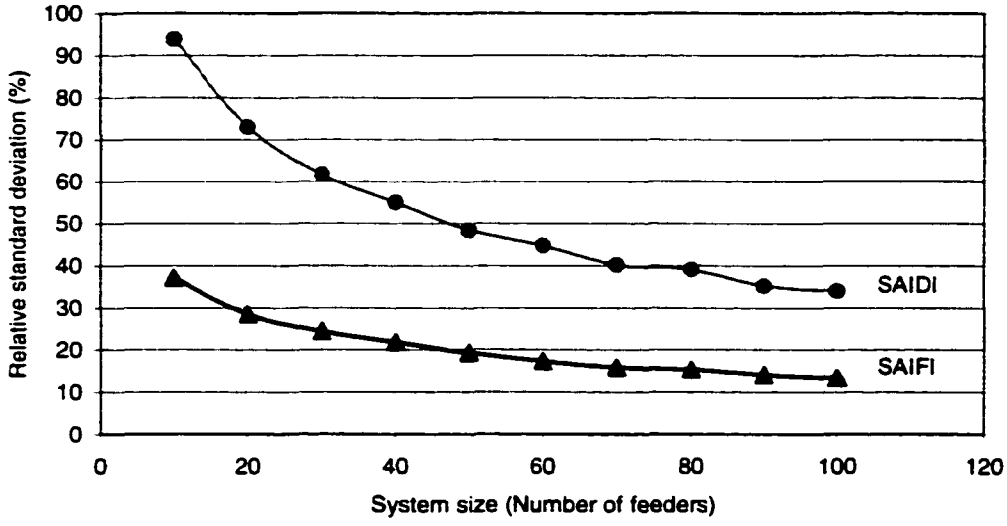


Figure 3.5 Relative standard deviation of SAIFI and SAIDI vs. system size

From Figure 3.5 it is observed that the spread of the annual system indices depends on the size of the system: the smaller the system size, the greater is the deviation in the annual reliability indices. Thus, smaller systems have greater variation in the annual indices as compared to larger systems, even though the average reliability level is the same in both cases. If the same reliability standard of x% is used for different systems, smaller systems could experience a violation of standards more frequently as compared to larger ones. The reliability standards must ensure that smaller systems are not penalized inadvertently. In this

section, the sensitivity of the reliability standards for the test system with respect to the system size is studied.

3.2.1 Analysis of annual system indices

The probability of the S0 standard being violated is termed as the S0-measure. The S0 measure represents the area under the pdf curve (of SAIDI or SAIFI) to the right of a point on the x-axis that represents the regulatory limit. The S0 measure can be calculated numerically from a large number of annual indices generated from Monte Carlo simulation. Alternately, the S0 measure can be calculated analytically if the (lognormal) distribution parameters of the SAIDI and SAIFI indices are known. In this study, the 100-feeder test system is used to numerically calculate the S0 measure for different system sizes as plotted in Figures 3.6 and 3.7. In these plots the probability of the SAIDI and SAIFI in any year being greater than **x**% over the system average are shown, for **x** = 5%, 10%, and 20%.

From Figure 3.6, it can be noticed that irrespective of the system size, there is a high probability (about 35%,) that the system SAIDI in any year will violate the S0 standard for **x** = 5%. This indicates that the system is likely to violate the S0 standard once in every three years, in spite of maintaining the existing component reliability level. From Figure 3.7, it is noticed that the S0 measure for system SAIFI shows a greater dependence on the system size. As the value of the regulatory limit is increased, larger systems are less likely to violate the standard as compared to smaller systems, for the same level of average system reliability (See 20% limit on SAIFI in Figure 3.7). Additionally, for the 100-feeder test system, even if the existing reliability levels are maintained, the S0 for SAIDI measure gives frequent indications of poor reliability (an expected violation in almost every three years).

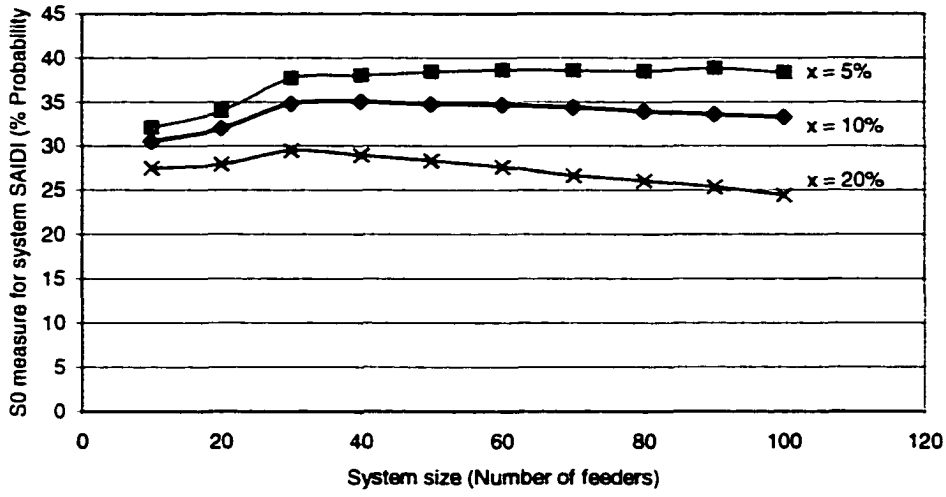


Figure 3.6 S0 measure for SAIDI vs. system size

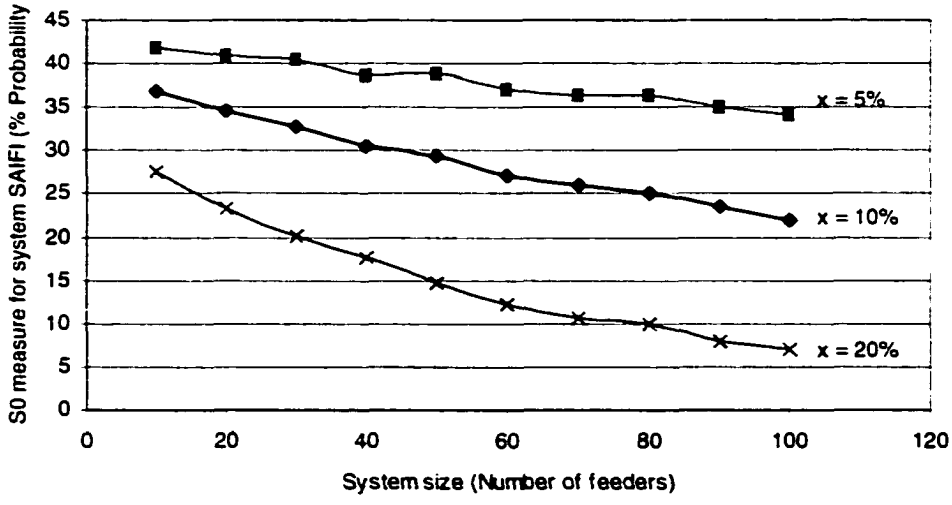


Figure 3.7 S0 measure for SAIFI vs. system size

3.2.2 Analysis of system indices over two consecutive years

Systems with poor system-wide reliability are expected to have consistently high values of the annual reliability indices. A deteriorating trend in the overall system reliability is likely to be detected by monitoring the reliability indices for two or more consecutive years. S1 is such a standard considered in this paper.

<u>S1 Standard</u>: No System shall have annual SAIDI (SAIFI) that is z % (such as 10%) greater than the benchmark value for two consecutive years.

The probability of the S1 standard being violated is termed as the S1-measure. S1 measure can be calculated from the S0 measure using basic probability theory. In this case, the S1 measure is equal to the square of the S0 measure. Alternately, the S1 measure can be calculated numerically from the Monte Carlo data analysis. The S1-measure for SAIDI and SAIFI calculated numerically for various subsystems of the 100-feeder test system are presented in Figures 3.8 and 3.9.

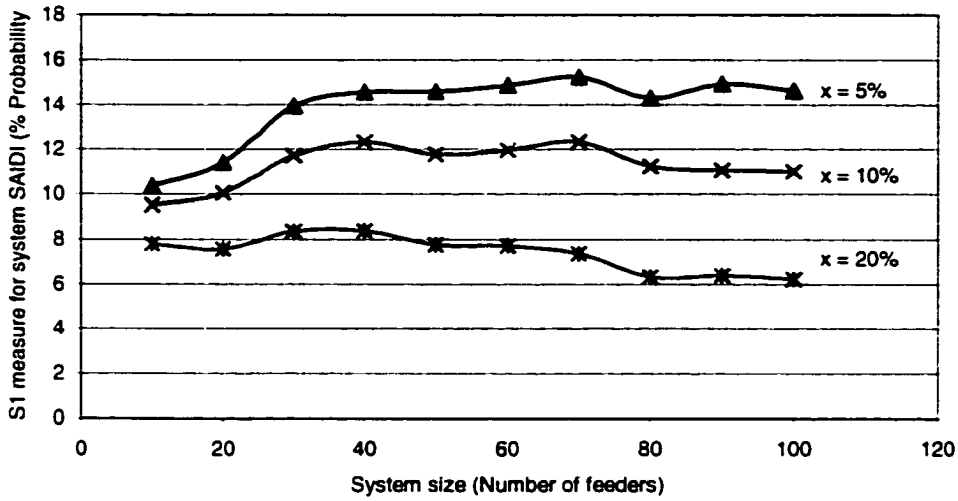


Figure 3.8 S1 measure for SAIDI vs. system size

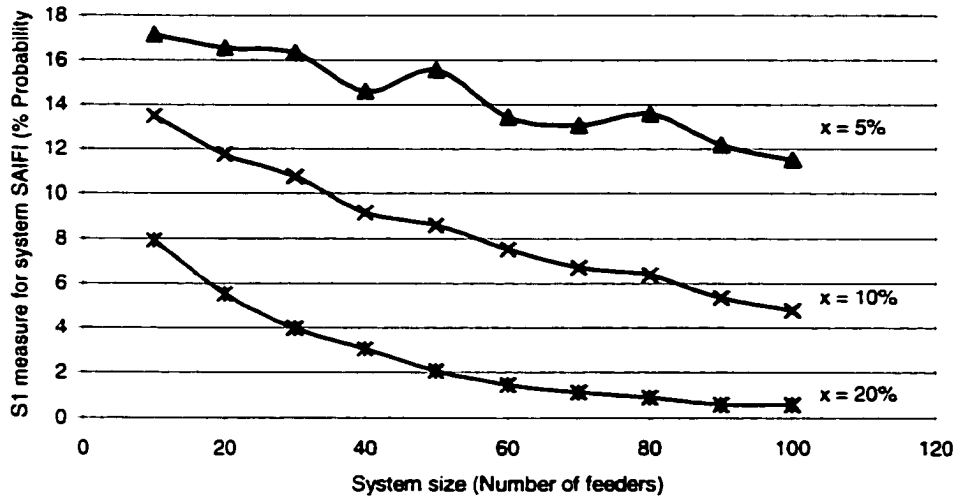


Figure 3.9 S1 measure for SAIFI vs. system size

From Figure 3.8, it can be noted that the S1 measure for system SAIDI is mostly insensitive to the system size. Figure 3.9 indicates that the S1 measure for SAIFI depends on the system size. However, for the 100-feeder test system, the S1 measure gives infrequent indications of poor reliability if the existing reliability levels are maintained (an expected violation in about every ten years). Further, it appears that different numerical values of the regulatory limits (z%) for SAIDI and SAIFI standards would be suitable for monitoring the system-wide reliability.

3.2.3 Sensitivity to prevailing feeder reliability level

The relative deviation of the system indices also depends on the prevailing component reliability level. The relative standard deviation of the system indices is plotted as a function of the component failure rate in Figure 3.10. Figure 3.10 indicates that a high reliability level of individual feeders could lead to an increase in the relative standard deviation of the system indices. This could lead to a scenario where systems with better reliability levels are subject to more restrictive regulatory standards as compared to system with poor component reliability.

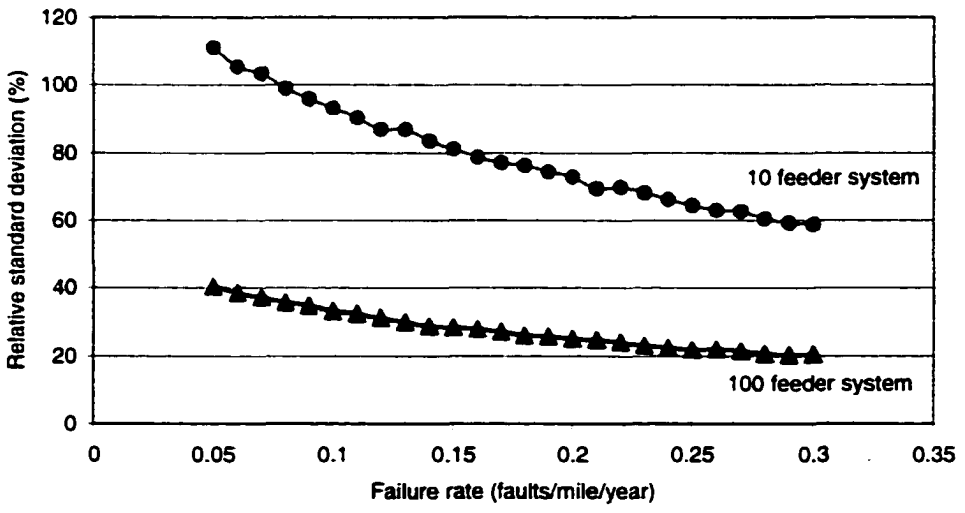


Figure 3.10 Relative standard deviation of SAIDI vs. failure rate

The sensitivity of S0 measure to the component failure rate is plotted for the 10-feeder system in Figures 3.11 and 3.12. From these figures it can be noted that the S0 measure for system SAIDI is largely insensitive to the component reliability level. From

Figure 3.10 and 3.11, it is noticed that though the relative deviation of the system SAIDI is very sensitive to the component failure rate, the value of S0 measure is not so.

Ideally, the S0 measure should show a decreasing trend with decreasing failure rate, so that poor system-wide reliability levels are more easily identified. The failure rate sensitivity plot for system SAIDI shown in Figure 3.11 indicate that improving the overall system reliability might not decrease the likelihood of violating the S0 standard. Further, for the 10-feeder test system, the sensitivity plot for SAIFI shown in Figure 3.12 indicates that improving the component reliability might lead to worse performance in terms of S0 measure.

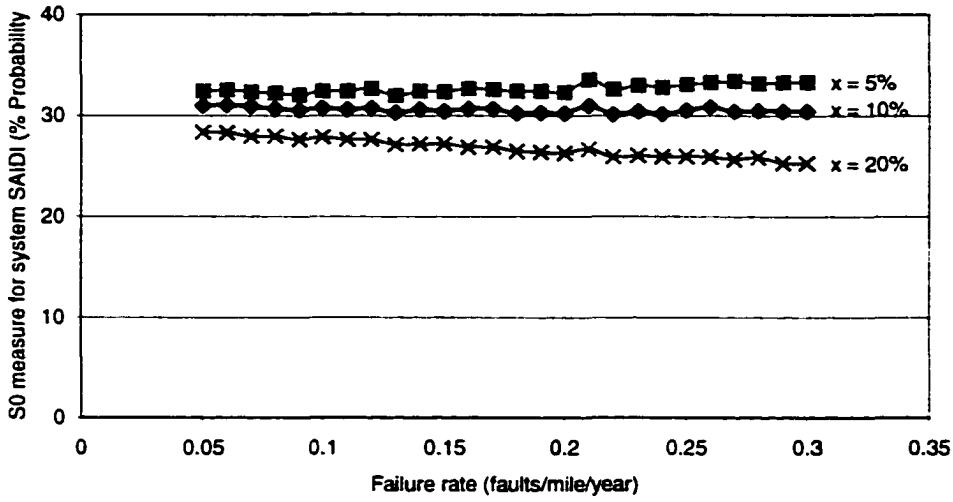


Figure 3.11 S0 measure for SAIDI vs. failure rate

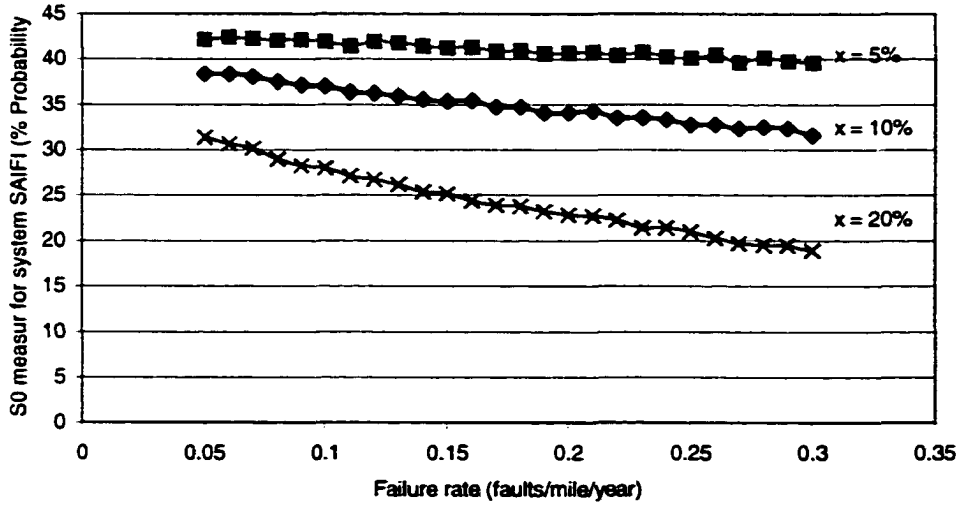


Figure 3.12 S0 measure for SAIFI vs. failure rate

3.3 Discussion

In formulating the distribution reliability standards, the key objective of the regulatory authorities is to ensure that the customers continue to receive satisfactory level of service [CPUC96]. Towards this end, regulatory standards must be designed such that the reliability of individual feeders as well as that of the overall system is maintained at a reasonable level. Practical distribution systems tend to be widely different from one another due to differences in the protection philosophy used at the design stage, and due to differences in load densities, impact of minor storms and the extent to which underground cables are used [MPSC00]. Therefore, each individual system must be analyzed to identify the appropriate reliability standards.

In the study of distribution system reliability, there are a number of issues that are not yet fully resolved, such as storm outages and data collection procedures. Various utilities have their own data collection and reporting procedures. Reliability indices calculated by the utilities are very much dependent on the outage data collection process. Proper data collection and reporting standards are necessary so that different utilities measure and report similar performance metrics. Also, a large number of faults on distribution circuits occur during storm weather conditions. It was reported that between 25% to 40% of all the faults on the distribution systems occur during inclement weather conditions [Bill89].

An analysis of the outages occurring on a practical distribution system over a period of 66 months between January 1993 to June 1998 is presented in Table 3.5. The storm weather was identified for this system by correlating the interruption data with the historical weather data (lightning, wind and rain fall data). About 40% of all the sustained outages occurred during storm weather conditions. During these storms, the fault rate is at least 10 times greater than during normal weather conditions. Further, based on the intensity and duration of the storm weather, it was noticed that storms can be divided as mild, severe and disaster storms. About 80% of the storm events, classified as mild storms, did not lead to delays in restoration due to crew constraints. However, the rest of the storms did not only cause a large fraction of the total system outages but also lead to significant delays in restoration due to crew constraints.

Utilities and the state regulatory authorities are attempting to design robust methods to identify such major events. Different methodologies are being proposed to account for storm-caused outages in the calculation of the system indices [Warr96, MPSC00, Chri01]. There appears to be no consensus even on the definition of adverse weather. A resolution on these matters will help in ensuring that different utilities are held accountable for uniform reliability standards.

The results presented in this paper are based on Monte Carlo simulation of a distribution system. This simulation did not take into account the impact of storm events. Nor is the effect of vegetation maintenance cycles on the component failure rate included in this analysis. However, if appropriate models of storm weather and its effect on distribution systems are available, they can be included in the analysis methodology presented in this Chapter to identify the consequences of regulatory standards on the feeder indices and system-wide indices. In this context, an attempt at developing suitable models of lightning storms is presented in Chapter 4.

Table 3.5 Storm types and their characteristics (66 months of data)

Weather Type → / ↓ Characteristics	1. Normal weather	2. Mild storm weather	3. Severe storm weather	4. Disaster storm weather
1. Number of sustained interruptions during each storm event	——	10 to 50 faults	50 to 350 faults	500 to 1000 faults
2. Duration of the storm event	——	30 minutes to 6 hours	4 hours to 24 hours	2 days to a week
3. Number of storm events	——	107	23	3
4. Fault rate during the storm event	~ 0.4 faults per hour	~ 4 faults per hour	~ 9 faults per hour	~ 10 faults per hour
5. Average outage duration (hours)	**1:47**	**2:34**	**5:01**	**18:53**
6. Crew constraints	No	No	Yes	Yes
7. Number of outages (in 66 months)	9, 626 of 15, 809 (60.88%)	2, 180 of 15, 809 (13.78%)	2, 528 of 15, 809 (15.99%)	1, 475 of 15, 809 (9.33%)

3.4 Conclusions

With a changing market environment, the reliability of distribution systems has come under great scrutiny from regulatory authorities. Several state regulatory authorities have established minimal reliability standards in order to help the distribution companies identify feeders with poor performance, so that remedial action may be initiated to improve customer power supply reliability. Individual distribution systems tend to be very different from one another. The characteristics of individual distribution systems must be taken into account in establishing reliability standards. In this Chapter, the effects of various reliability measures on a practical distribution system are studied. Annual feeder reliability indices might be poor indicators of poor performing feeders. Standards based on reliability indices of two consecutive years are likely to better identify poor performing feeders. The F1, F2 and S1 measures considered in this work focus on the years when the indices are greater than a specified level and can be used to identify the feeders that need attention while ensuring that the overall system reliability is also maintained. Such measures allow the regulators to establish reasonable upper limits for system reliability indices. They also can provide the system planners with information on the relative weakness of the feeders. However, additional work is needed to incorporate maintenance activities and the impact of storms in the analysis of the consequences of reliability standards on other distribution systems. Further, customized analysis of other distribution systems must be performed in order to obtain an improved understanding of the reliability standards.

4. Lightning Storm Reliability Assessment for Distribution Systems

Lightning is a significant cause of faults and outages in many electric power systems and is one of the major causes for poor system reliability [IEEE90, Gold77, Parr89]. In most areas, rainstorms are the primary source of lightning activity [IEEE97]. In this work, "storm" refers to any event of adverse weather that will affect power distribution system performance. During rainstorm periods electric potential differences in clouds are equalized through large current flow from one area to another over ionized air resulting in lightning. During such storm weather conditions, a large number of lightning ground flashes that can cause outages to distribution equipment are incident on the system within a short duration of time.

Distribution reliability indices can be used to identify areas that have poor reliability so that appropriate changes in the system design can be implemented. The assessment of distribution system performance under lightning conditions requires modeling of storm characteristics and the system response. In this chapter, a Monte Carlo simulation for evaluating the distribution system reliability under lightning storm conditions is presented. The results from a practical distribution system show the importance of detailed modeling of storm characteristics and simulation of the system response in assessing the distribution system reliability during lightning storms. The following topics are discussed in this section:

- A brief review of how lightning flashes cause power outages
- An introduction to lightning detection
- Motivation for current research
- Modeling the intensity and duration of storm weather
  - — Parametric models
  - — Non-parametric models
- Calculation of lightning flashover rate from the storm intensity
- Monte Carlo simulation for reliability indices contributed by lightning storms
- Application to a practical distribution system
- Conclusions

4.1 A brief review of how lightning flashes cause power outages

A lightning strike from a cloud to ground is known as a ground flash. A ground flash can cause flashover between phase conductor(s) and the neutral/ground conductor in one of three different ways [Gold77]:

1. Back flashover: Lightning strikes either a distribution pole or the shield wire, changing the potential of the structure sufficiently to cause a flashover to one of the phase conductors.
2. Shielding failure: Lightning strikes any of the phase conductors directly.
3. Induced flashover: The lightning strikes near a distribution line, resulting in an induced voltage that is high enough to cause breakdown of the insulation between the ground and affected phase conductor(s).

The back flashover and the shielding failure modes are jointly known as the direct flashover mode, since these involve a direct lightning strike to some distribution system component. Even though the lightning event may be over quite quickly, its effects may persist much longer. One such effect is known as *power follow*. The arc of a lightning flashover ionizes the air creating a conducting path. This conducting path can lead to 60 Hz power follow current. Power follow conditions are very similar to short circuit conditions.

Lightning flashovers can lead to momentary or sustained outages. If a reclosing protection device opens to clear the lightning flashover and recloses to restore the supply then the system experiences a momentary outage event due to lightning. This is possible because air has the property of rapidly restoring its dielectric strength after an arc has been extinguished. On the other hand, a sustained outage is experienced by the system if the recloser fails to clear the power follow current caused by a lightning strike. Other causes of sustained outages due to lightning strikes include:

- Mechanical failure of conductor or its suspension system
- Failure of automatic reclosers to recognize a temporary fault (protection failure)
- Absence of recloser, or turning off of reclosing function
- Improper protection coordination causing a fuse to blow before the recloser operates

- Blowing of partially melted fuses (tired fuses)
- The recloser registering a permanent fault because of a second lightning flash striking the segment during the time when the dielectric strength of air is being restored following the first flash
- Lightning strikes may cause outages by damaging distribution transformers. These outages may occur through transformer fuse operations and mechanical failure of fuse connectors. The transformer may be damaged by lightning-caused over currents, a rapid increase in lightning current, etc., which might puncture the transformer insulation. The likelihood of damage may increase when multiple flashes occur. Transformer failure can also result from lightning surges on the secondary side of an unprotected distribution transformer.

The number of lightning strikes that cause flashovers on distribution lines varies with the level of shielding. In the vicinity of tall buildings and trees, the number of flashovers is less than the number on similar lines in the open country, under similar lightning storm conditions, since shielding is provided by nearby structures [Parr89]. This implies that a majority of urban power lines, which frequently are in proximity of tall buildings, experience fewer lightning caused flashovers than do rural lines in open country.

4.2 An introduction to lightning detection

The number of lightning flashes occurring in a year varies from place to place. To quantify the intensity of lightning activity, a simple measure known as the ground flash density (GFD) is used. GFD is defined as the average number of cloud-to-ground lightning flashes per unit area per year at a given location. The GFD data can be obtained from the historical lightning data available through lightning location systems and flash-counter networks that have been deployed in North America and various other parts of the world to measure and record lightning information [Ande84, dela89, Cumm98]. Real-time and archived data of individual lightning flashes, including the time, location, amplitude, and polarity of the flash can also be obtained directly from some of the lightning location systems such as the U.S. National Lightning Detection Network (NLDN) [Cumm98].

The NLDN employs a network of ground-based lightning sensors to identify the onset time and location of ground flashes. Two kinds of sensors are used, namely, the Direction Finders (DF's) and the Time of Arrival (ToA) sensors. The DF sensors operate in the low frequency and very low frequency bands (about 1 kHz to 500 kHz). They are designed to identify the characteristic signatures of the electromagnetic fields produced by lightning flashes. The ToA sensors locate the lightning flashes based on the radio frequency signals caused by the lightning flashes, measured at several stations that are synchronized by a Global Positioning System (GPS) clock pulse [Cumm98].

The NLDN sensors are located in such a way that each lightning flash is detected by more than one sensor. Lightning strikes with an estimated peak current of 5 kA are detected by 2-4 sensors while strikes carrying 25kA are detected by 6-8 sensors and strikes of 100 kA are detected by 20 or more sensors. The average value of peak current of a stroke is in the range of 20-35 kA.

A least-squares optimization procedure is employed by the NLDN to minimize the error in the location and the onset time of each lightning strike. The NLDN system is designed to detect 80-90% of strokes that produce a peak current of at least 5 kA. The Detection Efficiency is estimated to be much lower as the peak current falls below 5 kA. However, lightning flashes of less than 5 kA are not a serious threat to power distribution systems. In terms of accuracy of measurements, the NLDN has a median accuracy of 500 m for location measurement, while the onset time is expected to be accurate to about 5 μs.

The average annual GFD is calculated from the individual flashes recorded in the NLDN database. A map of the continental US is converted into a grid of 5-km by 5-km cells. The GFD is calculated by counting the flashes that occurred in each of these cells. Since some of these small cells may record a high number of flashes in a given year, the GFD of each cell is averaged over the nearest eight neighboring cells [Cumm98] making the average more representative of the lightning activity in that region.

4.3 Motivation for current research

Depending on the system protection design and storm severity, lightning-caused flashovers lead to large number of momentary and sustained interruptions on the system

[Ande85, Parr91]. Outages caused by storms are becoming a matter of great concern for distribution companies. A variety of industrial process plants require truly uninterruptible power supply. Momentary interruptions lead to substantial production losses for such plants. Electronic appliances in residential loads such as computers and electric clocks are usually sensitive to momentary outages. Frequent outages to such equipment due to momentary interruptions can lead to reduced customer satisfaction. Depending on the location of the distribution utility, a significant fraction of momentary outages are caused by lightning activity. Also, during storm conditions a large number of faults occur within a short interval of time leading to delays in service restoration [Brow97]. The longer the storm lasts, the greater will be the burden on the repair crews, causing increased delays in the restoration process.

In order to maintain a high level of customer satisfaction and to comply with regulatory requirements, it is important for distribution companies to have an improved understanding of momentary outages [Warr99, Kapp96]. Assessing the distribution system reliability indices associated with lightning storms is the first step toward improving system performance. The intensity of lighting storms affects the rate at which the distribution line segments experience flashover. In contrast, during normal weather conditions, the line segments failure rate is independent of the prevailing weather conditions. An accurate determination and utilization of the line flashover rate during different storm events is fundamental to obtaining valid storm-caused system reliability indices. Accurately assessing system reliability requires modeling of storm intensity, equipment performance, protection schemes, and repair crew response.

The historical storm outage data can be used to predict the system reliability indices for subsequent years. However, there are some significant limitations to such an approach:

- It is very difficult to obtain the storm outage data. Momentary outages during storms are more difficult to monitor since most automatic reclosers are located at locations remote from the substations. They are provided with a counter for counting the number of operations, but the time stamps are usually not recorded along with operations count. Since a significant number of momentary outages occur during storms, this is a serious limitation.

- Predictive models are needed for studying the impact of future changes in the system design. Such studies cannot be performed based only on the historical data.
- The available historical data might be insufficient to accurately predict the range (or spread) of the indices.

Traditionally, the GFD of the utility location was used as the measure of the severity of lightning storms in assessing the lightning performance of the distribution systems. A simple method for predictive assessment of the system reliability due to lightning is as follows:

- Use the annual GFD to evaluate the fault rate on the distribution equipment
- Based on these fault rates, calculate the reliability indices using an analytical Failure Modes and Effects Analysis (FMEA) method.

There are certain important concerns that must be addressed before using such an approach:

- Feeder segments can potentially experience a momentary outage only when they are energized. As a storm progresses in time it causes some sustained outages. Segments that are already experiencing a sustained outage will not affect the momentary outage frequency of the connected customers. Depending on the number of sustained outages occurring during a storm, fewer number of feeder segments may be vulnerable to lightning induced flashover at a time later in the storm. Thus, the flashover rate depends not just on the GFD but also on the number of outages already incident on the system. Further, the analytical FMEA method of reliability assessment does not model the dependence of momentary failure rate on the faults already incident on the system [Bill94].
- The lightning flash count and line flashover count has considerable variability from year to year [Darv80, Ande84, Cini96, Kapp96]. While the GFD is the standard measure of lightning storm intensity, it gives the yearly average count of lightning ground flashes and does not indicate the variability of intensity of lightning storms. This leads to a difficulty in quantifying the mean and the deviation (spread) of the annual lightning performance of the distribution lines.

- During storm conditions a large number of faults occur within a short interval of time leading to delays in the service restoration times [Brow97]. The longer the storm lasts, the greater will be the burden on the repair crews, increasing the delay in restoration process. These delays are not captured in the measured value of the average GFD at a given location.
- Some of the regulatory authorities prescribe performance standards on the number of momentary outages experienced by the customers [PPUC99]. The average value and the standard deviation of the system indices are being used to determine the minimum reliability standards. In order to predict the range of the annual MAIFI, and to evaluate the impact of any reliability improvement schemes, it is necessary to make an accurate assessment of the system MAIFI *and* its variability. The analytical (FMEA) method of [IEEE98] does not provide the variability of the annual reliability indices.

Therefore, in order to model the dependence of the failure process on system conditions, it is necessary to analyze the impact of individual storm events on system reliability.

Under such circumstances, the lightning storm intensity is not accurately modeled by annual GFD alone. Nor does the analytical FMEA method model the effect of storm intensity on the momentary failure rate. Hence, it is necessary to study the impact of individual flashes during lightning storms in order to understand the lightning performance of distribution systems. A Monte Carlo (MC) simulation is the most promising method for making an accurate assessment of the average value and the spread of the system indices. In order to perform the MC simulation, appropriate models for the storm weather are needed.

Since the number of lightning storms and lightning flashes varies greatly from year to year, a large number of years of data are considered necessary in order to assess the variability of the impact of lightning storms [Ande84]. Recent advances in statistical theory indicate that the "bootstrap resampling technique" can provide valid statistical inferences even when only a small data set is available [Diac83]. The bootstrap method has been successfully applied in a wide range of statistical and engineering applications [Diac83, Davi97, Zoub98].

In this research, a non-parametric bootstrap method is presented for assessing the parameters of lightning storms. The parameters of the lightning storms are used in association with the distribution system topological data in performing MC simulations for identifying the impact of lightning storms on system reliability.

The following tasks must be carried out in order to determine the impact of lightning storms on the system reliability indices:

- Modeling of the storm intensity and duration
- Conversion of storm intensity into line segment flashover rate
- Monte Carlo simulation of the distribution system for the duration of the storm in order to take into account the crew constraints.

These topics are discussed in the next few sections.

4.4 Modeling lightning storm intensity and duration

In this work, "lightning storm" refers to any event of adverse weather conditions when a number of lightning ground flashes occur within a short duration of time, potentially leading to interruptions in power supply. The severity of storms can be modeled by identifying the *number* of storms occurring per year, the *intensity* of individual storms measured as the ground flash density during a storm period, and the corresponding storm *duration*. Since these storm parameters are random variables, stochastic models of the duration, intensity and frequency of thunderstorms have been developed in this research. The term "stochastic model" is used to mean the population's Cumulative Distribution Function (CDF). The CDF may be specified either as a mathematical function or as a set of discrete point values. When the CDF is specified in a mathematical form, the statistical model is referred to as a *parametric model*. If the CDF is specified as a set of discrete (independent and identically distributed) values, the statistical model is referred to as a *non-parametric model*. The traditional approach for building stochastic models is the parametric method [Brow97].

This section discusses how to obtain weather models from which the distribution system failure rate models can be deduced. The following topics are discussed in this section:

- The philosophy of parametric modeling
- An example of parametric modeling
- Bootstrap sampling method for lightning storms

4.4.1 The philosophy of parametric modeling

The traditional approach for building statistical models is the parametric method [Silv86, Brow97]. The cumulative distribution function (CDF) of the stochastic variable of interest is obtained as a statistical distribution (such as the log-normal or the Weibull distribution) along with the associated distribution parameters. In the case of storm weather modeling for a particular utility location, consider the population, M, of *all* storm events (past, present, and future), out of which the sample data consists of m observations. The objective of parametric storm weather modeling is to identify a statistical distribution that provides the best fit for the m observations. If the sample size m is large, then by the central limit theorem the sample distribution can be used to approximate the population distribution.

For a given sample data set, the parametric modeling approach can be described as follows [Silv86]:

1. Candidate selection: Assume a parametric distribution (such as log-normal or Weibull or exponential).
2. Parameter estimation: Obtain parameters of the assumed distribution that best fits the data.
3. Model validation: Check for the validity of the assumed parametric distribution by comparing the CDF of the distribution with the sample data. The validity of the parametric distribution for the sample data is usually checked by one of the following two methods: (1) goodness of fit tests (such as the χ^2 test or the Kolmogorov-Smirnoff test), or (2) confidence interval tests.
4. If the assumed distribution is found to be untenable in the validity tests, a different parametric distribution function is assumed and the steps from 1 to 3 are repeated until all known distributions are exhausted.

One of the reasons for the popularity of the parametric modeling method is that a small number of distribution parameters can capture the features of a large population. On the other hand, parametric assumptions are usually difficult to justify.

4.4.2 An example of parametric modeling

From this data, individual lightning storms were identified and analyzed to obtain the parametric statistical models of the intensity, duration, and the frequency of storm events. Various parametric distributions such as the log-normal, the Weibull, the normal, the logistic, and the log-logistic have been considered as candidates for storm intensity and duration models. The storm intensity and duration data plotted on log-normal probability plots, along with 95% confidence intervals, are shown in Figures 4.1 and 4.2.

Parametric estimation works well if the statistical distribution of the population under study is known, either historically or from the physics of the phenomenon being modeled. However, such information is usually not available for storm weather models. If it becomes difficult (or impossible) to identify a parametric distribution that fits the data, one can still analyze the characteristics of the population through non-parametric methods. An efficient tool for identifying the characteristics of the storm weather under such circumstances is the non-parametric methodology. Bootstrap resampling technique is an important non-parametric method for statistical modeling. The bootstrap is a computer-based analysis technique that substitutes considerable amounts of computation in place of the theoretical parametric analysis. It requires very few assumptions in modeling and analysis of data.

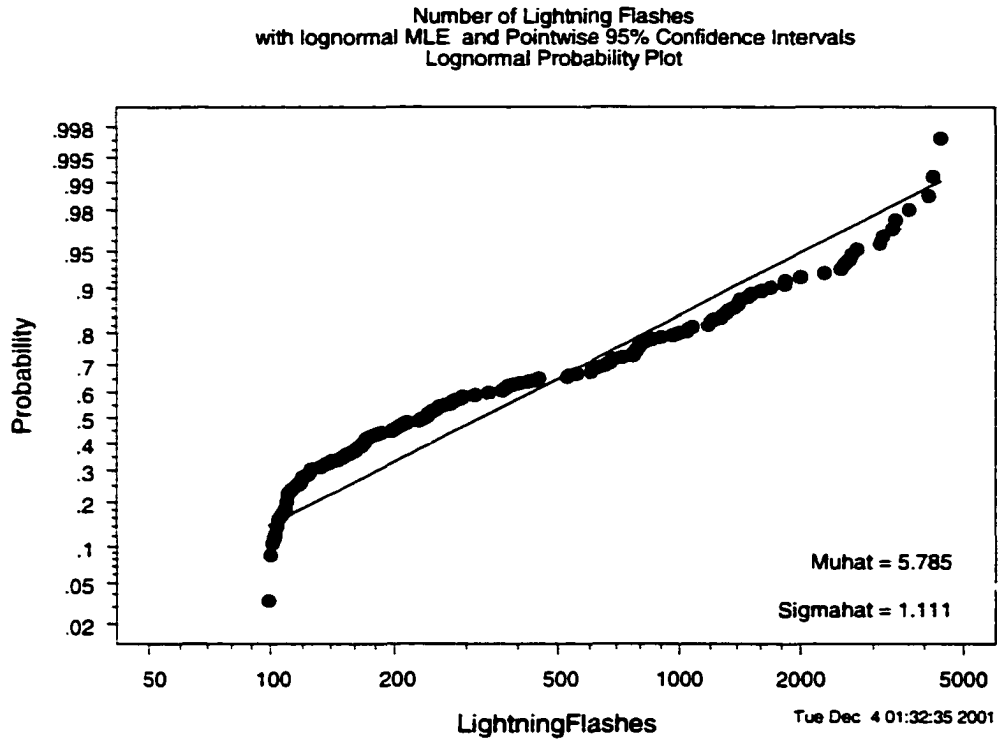


Figure 4.1 Lightning intensity distribution

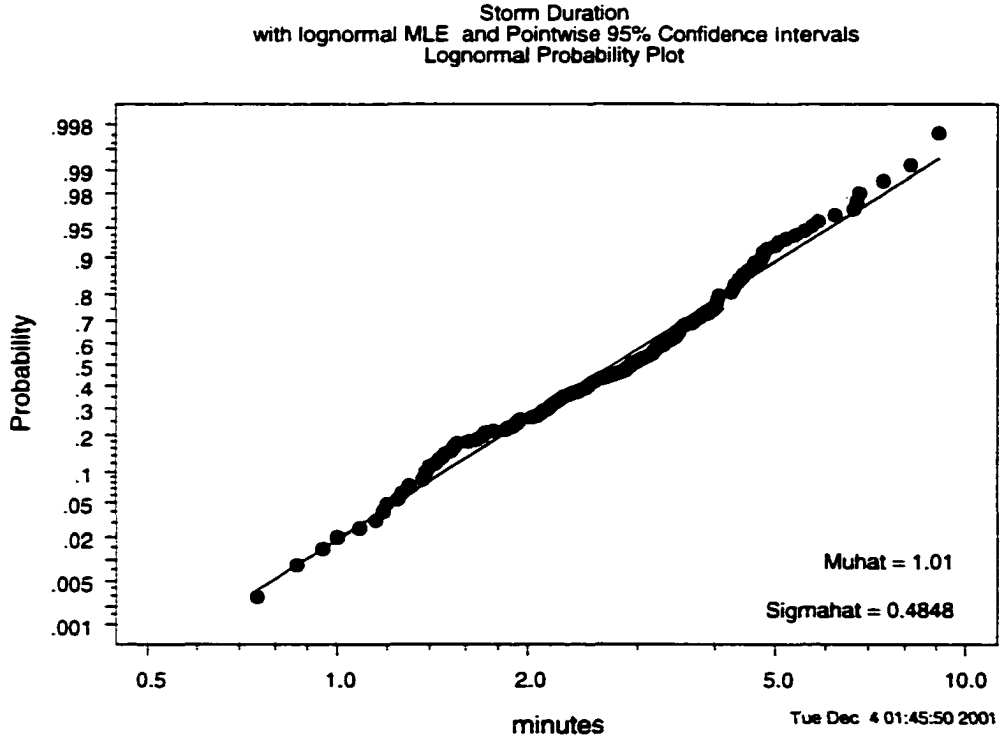


Figure 4.2 Lightning storm duration distribution

4.4.3 Bootstrap sampling for lightning storms

In order to study the statistical properties of the subject of interest, a scientist would perform an experiment a number of times, record the observations of each of the experimental runs, and estimate the statistical measure of interest. Usually, in order to make appropriate conclusions, it is necessary to repeat the experiment a large number of times. The bootstrap is a data-driven method in which computer-based simulations from an available data set are used in place of a large number of experimental runs. In each run of the simulation, the observations from an available data set are randomly reassigned and the estimates are recomputed. The random assignment of data and the computing of the estimates are treated as repeated experiments.

In the non-parametric bootstrap method, the stochastic variable of interest is modeled using an empirical distribution function (EDF). The CDF of the parametric method and the EDF of the non-parametric method both contain the same kind of information. While the parametric method uses just one sample data set to model the random variable of interest as a mathematical function, the non-parametric bootstrap method simulates a large number of artificial data sets to obtain the EDF of the same random variable in a numerical form. One method of obtaining the EDF is as follows:

Let the sample data set be x = $\{X_1, X_2, X_3, \ldots, X_m\}$. Assuming that each observation in the data set occurs with a probability of 1/m, the sample EDF can be constructed as follows:

$$\hat{F}(x) = \frac{1}{m}\sum_{i=1}^{m} I(X_i \le x) \tag{4.1}$$

where $I(X_i \le x)$ is the indicator function. The value of the indicator function is equal to unity if $X_i \le x$ and is equal to zero otherwise.

The bootstrap resampling is performed through a Monte Carlo simulation of the sample storm data [Davi97]. Using a Monte Carlo simulation, construct a large number of artificial data sets by means of statistical resampling from the original data set such that each of the artificial data sets has the same number of elements, m, as the original data set. From this large number of artificial data sets the bootstrap EDF of the random variable of interest is calculated as in (4.1) [Davi97]. Further details on the theoretical and practical aspects of the

bootstrap method can be found in literature [Dia83, Davi97, Zoub98]. In this research, the cumulative distribution function of the storm intensity and duration are obtained through a bootstrap resampling approach.

4.5 Lightning storms and line flashover rate: The IEEE standard method

The reliability of a power distribution system is quantified through a set of reliability indices that can be calculated using either an analytical (FMEA) method, or using a Monte Carlo simulation [Bill94, IEEE98]. The line segment failure rate is the most fundamental characteristic needed to measure the system reliability in either method. The failure rate of overhead lines due to lightning flashes can be calculated from the GFD and the lightning flash parameters, the insulation and shielding levels of distribution lines and the location and spacing of surge arresters [IEEE97, McDe99].

This section discusses the method for translating the lightning storm intensity to the distribution system overhead line segment flashover rate, λ_l,. The lightning flashover rate, λ_l, is composed of two parts. The first is the direct flashover rate, λ_d, due to back flashover and shielding failure modes. The second part is the induced flashover rate, λ_i. The approach presented in this section is recommended by the IEEE Working Group on the Lightning Performance of Distribution Lines [IEEE97].

4.5.1 Direct flashover failure rate

If the GFD at a certain location is N_g lightning flashes per unit area per km^2, then the proportion of these ground flashes that cause lightning flashover of distribution lines can be calculated as [IEEE97]:

$$N = 0.001 N_g (b + 28H^{0.6}) \quad strikes/circuit\ km \tag{4.2}$$

where N_g is the GFD measured as the number of lightning flashes per km^2 per year, N is the number of times a line flashes over, b is the distance in meters between the conductors having the largest horizontal separation, and H is an average of the shield wire heights, if

there is a shield wire, otherwise the average of the top most conductor heights, in meters as measured at the poles.

Most lightning strikes on distribution lines are expected to cause a flashover, and will result in either a momentary or a sustained outage [IEEE97]. The factors that influence the actual number of flashovers resulting from cloud-to-ground lightning strikes include:

- shielding provided by external structures adjacent to the distribution lines and,
- lightning withstand level, in terms of design parameters such as the insulation strength of the distribution poles, cross-arms and other material, the location of surge arresters, the effectiveness of pole grounding, etc.

The insulation strength of distribution lines, poles and other insulating material is measured in terms of the Critical Flashover Voltage (CFO). The CFO is defined as the voltage level at which, statistically, there is a 50% chance of flashover and a 50% chance of withstand.

The flashover count also depends on the lightning protection level in terms of the insulation strength of the distribution poles, cross-arms and other material, the location of surge arresters, the effectiveness of pole grounding etc. The effect of shielding is to reduce the number of direct strikes to the line segments. The "shielding factor" (SF) is used to account for the reduction in the number of direct flashes striking the distribution lines. Detailed electromagnetic modeling analysis of the lightning flashes on the distribution poles and the shielding objects must be performed to calculate the shielding factor [McDe94, McDe00]. Cigré and IEEE working groups documented the electrical parameters of lightning flashes recommended for such calculations appropriate for power system applications [Cigr91, IEEE93]. Using the shielding factor described above along with equation (4.1), the direct flashover rate of an overhead distribution line due to N_g lightning strikes per km^2 per year can be calculated as [IEEE97]:

$$\lambda_d = 0.001 N_g (b + 28H^{0.6})(1 - SF) \quad \textit{flashovers / circuit km} \qquad (4.3)$$

where N_g is the GFD measured as the number of lightning flashes per km^2 per year, b is the distance in meters between the conductors having the largest horizontal separation, H is an average of the heights (measured at the poles) of the shield wire or the top most conductor,

and is given in meters, and SF is the shielding factor. A line that has perfect shielding has SF value equal to 1.0, while SF value equal to 0 indicates that the line has no shielding.

4.5.2 Induced flashover rate

Line failure due to an induced flashover might be caused when lightning strikes a tall object near an energized line. The number of faults caused by induced flashover depends on the number of ground flashes, the distance of shielding objects from the overhead line, and the height of the shielding objects. Figure 4.3 shows the induced flashover rate, N_i of a 10-meter-high overhead line at a location that expects 1.0 lightning ground flashes per km^2 as a function of the distribution line critical flashover voltage (CFO) [Chow89a, Chow89b, IEEE97]. Assuming that the number of induced flashovers is directly proportional to the line height (H) and the lightning strike density during a storm event (N_g lightning strikes per km^2) the lightning-induced overhead line flashover rate, λ_i, can then be obtained as [IEEE97]:

$$\lambda_i = N_i \, N_g \left(\frac{H}{10} \right) \quad strikes / circuit \ \ km \tag{4.4}$$

The total lightning caused overhead line failure rate, λ_l, can now be calculated by the following equation:

$$\lambda_l = \lambda_d + \lambda_i \quad flashovers \ / \ circuit \ km \tag{4.5}$$

where λ_d is the component due to direct flashovers and λ_i is that due to induced flashovers. Note that λ_l includes both temporary and permanent faults. Detailed sample calculations can be found in the IEEE Standard 1410-1997 [IEEE97]. The calculations in [IEEE97] use the term N_g to represent the GFD for the utility area, while the calculations in this work use the term N_g to represent the ground flash density during individual storm events.

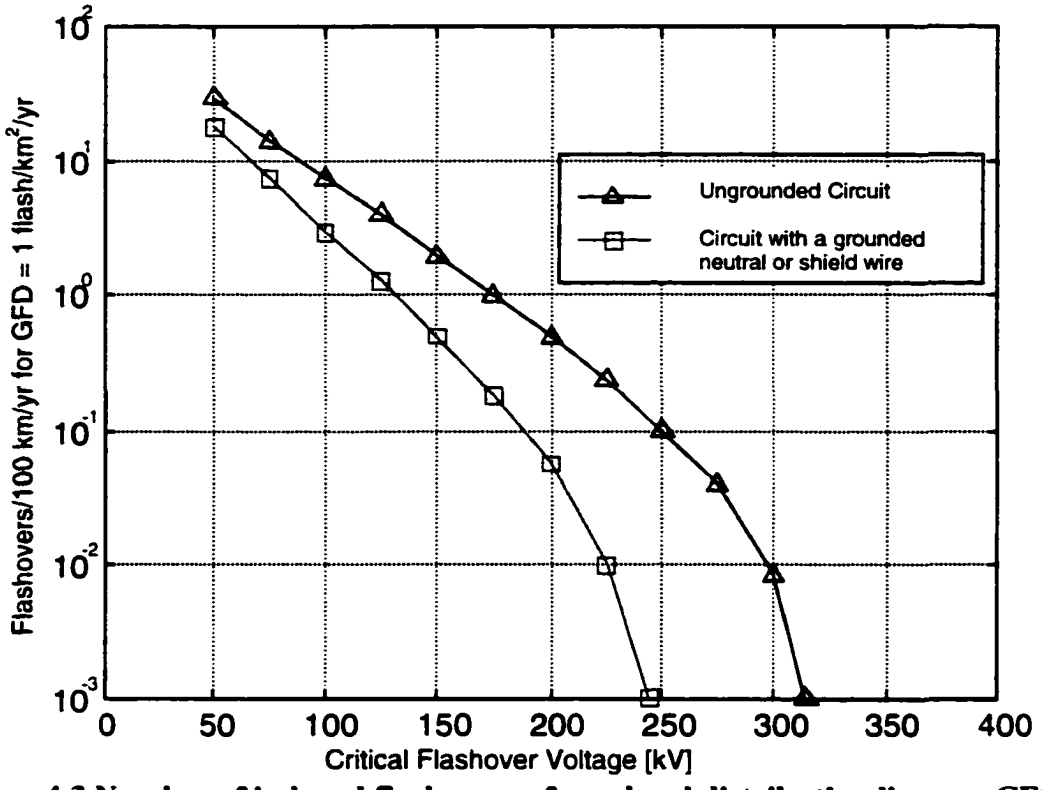


Figure 4.3 Number of induced flashovers of overhead distribution lines *vs.* CFO

4.6 Monte Carlo simulation for lightning storm reliability

The system reliability can be calculated based on the models for the intensity, duration and the number of the lightning storms, and the models for assessing the temporary and permanent lightning fault rate. The reliability assessment is usually performed using either an analytical FMEA method [IEEE98] or using a Monte Carlo simulation [Bill94]. Analytical methods can be used to study simple systems that follow stationary processes. A common assumption made in most analytical reliability assessment techniques is that the mechanisms that lead to permanent and temporary faults are independent of system conditions [IEEE98]. Though this assumption is valid under normal weather conditions, it is difficult to justify under storm conditions.

For example, when part of a distribution feeder is subject to a sustained outage, customers connected to that part of the system do not experience any additional outages until supply is restored. In the context of lightning storms, this implies that the momentary failure

rate depends on the number of segments that remain energized at any given time during the storm. Since the failure rate of line segments (particularly, the temporary fault rate) and the outage duration depend on the severity of the storm, the distribution system under storm weather conditions must be modeled as a complex non-stationary process. Monte Carlo simulation is ideally suited for assessing system reliability under such storm conditions [Brow97].

The overhead line failure rate, λ_t, for all lines is the basic data needed for the reliability assessment. To perform the Monte Carlo simulation, the stochastic models of storm characteristics, namely, the *storm duration* and the *storm intensity* are identified. Once the storm properties are modeled, a time sequential Monte Carlo simulation method is used to evaluate the system reliability for a large number of years (say 10,000 years). The storms simulated each year are determined by the stochastic variable, the *number of storms*. The intensity of each storm is determined by the random variable *flash count*, N_g. In order to account for crew constraints, if any, the length of the storm period is simulated based on the random variable *storm duration* [Brow97]. The overhead line failure rate, λ_l for *each* storm is calculated using the corresponding storm lightning flash density, N_g using (4.3), (4.4) and (4.5) [IEEE97]. Storms tend to travel both in time and in space during the period when they are active. In this work, it is assumed that the storm affects the entire service area for the duration for which the storm is active.

Based on the utility's historical storm outage data, the repair duration is modeled as an exponential distribution with a mean value of 2 hours per repair of a line segment. Using the system topology, the characteristics of protection and switching equipment, the overhead line failure rate, λ_t, and the repair duration models, the impact of lightning is evaluated for each storm simulated [Brow97, Bill94]. At the end of each year of simulation, the load point and system reliability indices are calculated [IEEE98, Bill94]. The simulation is performed for many years until 95% confidence in the calculated results is achieved.

Using the system topology, the characteristics of protection and switching equipment, the overhead line failure rate, λ_l, and the repair duration models, the impact of lighting is evaluated for each storm simulated [Brow97, Bill94]. At the end of each year of simulation, the load point and system reliability indices are calculated [Bill94, IEEE98]. The simulation

is performed until sufficient (95% confidence) confidence in the calculated results is achieved. A flowchart of the steps performed in the Monte Carlo simulation of the distribution system during lightning storms is presented in Figure 4.4.

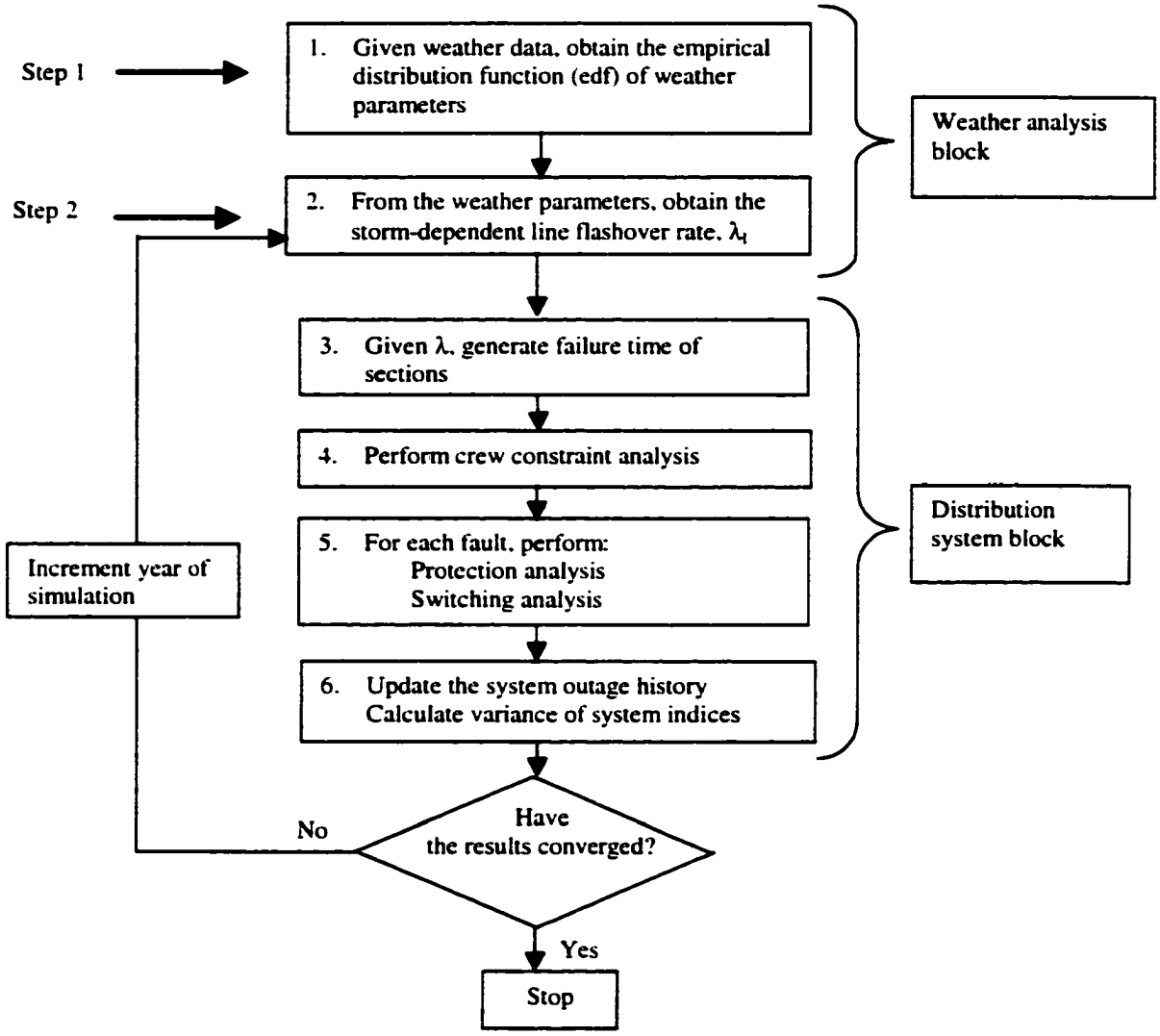


Figure 4.4 Storm reliability assessment module for distribution systems

4.7 Application to a practical system

Lightning storm weather was monitored for a period of 58 months (January 1995 - October 1999) at the location of a distribution company in the Midwest region of the U.S.A.

The distribution system considered in this study consists of 100 feeders, with over 2,000 conductor miles.

4.7.1 Lightning data analysis

Archived data of individual lightning flashes, including the time, location, amplitude, and polarity of the flash, were obtained from the NLDN [Cumm98]. During the period of January 1995 through October 1999, a total of over 110,000 lightning flashes were recorded. The NLDN data was analyzed to assess the lightning flash count during various storm events. From this analysis, individual lightning storms were identified and the statistical models of the intensity, duration, and the frequency of storm events were developed.

In order to identify the intensity and duration of lightning storms, the beginning and the end of each storm event is needed. In performing the storm data analysis, a potential storm event was identified if a minimum of 100 lightning flashes were observed at a minimum of 30 flashes per hour. These criteria are selected based on a close inspection of the lightning data, so that the few occasional lightning flashes that occur during non-storm periods are eliminated. The end of a lightning storm is identified if the time between two successive lightning flashes is greater than 30 minutes. The reason for selecting the minimum time between successive potential storm events as 30 minutes is to account for certain physical phenomena known as meso-scale convective complexes. During these complexes, a series of lightning and wind activity periods (storm events) occur with a gap of between 30 minutes to 2 hours. For example, a meso-scale convective complex could consist of 4 periods of storm activity each lasting for 1 hour separated by periods of calm each lasting for 45 minutes. In order to account for each lightning activity period, the storm periods that could be a part of a meso-scale convective complex are modeled as distinct individual storm events. A total of 177 lightning storm events were identified from the lightning data. It must be noted that the storm identification criteria are likely to be different at other geographical locations.

4.7.2 Momentary and sustained outages

A lightning flashover may lead either to a temporary fault or to a permanent fault. A temporary fault is one that can be cleared by the operation of a reclosing device without requiring any repair action. Each time a reclosing device operates resulting in a temporary loss of voltage, the connected customers experience a momentary interruption. On the other hand, a permanent fault is one that requires attention of the repair crew for service restoration. In order to study the impact of lightning on the system reliability, it is necessary to identify the storm-caused temporary fault rate and permanent fault rate.

Identification of temporary and permanent faults is one of the most difficult tasks in distribution system data collection. In order to overcome this difficulty, it is noted that:

1. A sustained outage occurs either due to a fuse or a circuit breaker clearing a permanent fault, or a temporary fault that is not cleared by a recloser due to its mis-operation but is cleared by a fuse or a circuit breaker.
2. Most lightning flashovers result in temporary faults while only a small fraction of the flashovers result in permanent faults.

If the distribution reclosers are assumed to be highly reliable, then a significant percentage of the temporary faults are cleared by the recloser operation. This leaves only a fraction of temporary faults that actually lead to sustained outages. Hence, the permanent fault rate can be assumed to be approximately equal to the sustained outage rate.

In order to calculate the sustained outage rate, it is necessary to identify the number of lighting flashes during the various storms and the corresponding lightning-caused sustained outages. The number of lightning-caused sustained interruptions during these storm periods was extracted from the outage log of the utility and plotted in Figure 4.5. The expected flashover rate during the storm events calculated based on the IEEE standard calculations presented in Section 4.5 is also plotted in Figure 4.5. From the data analysis, it was found that about 20% of the faults due to lighting flashovers would result in sustained outages. Therefore, the permanent fault rate is assumed to be 20% of the lightning flashover rate and the temporary fault rate is therefore treated as 80% of the flashover rate.

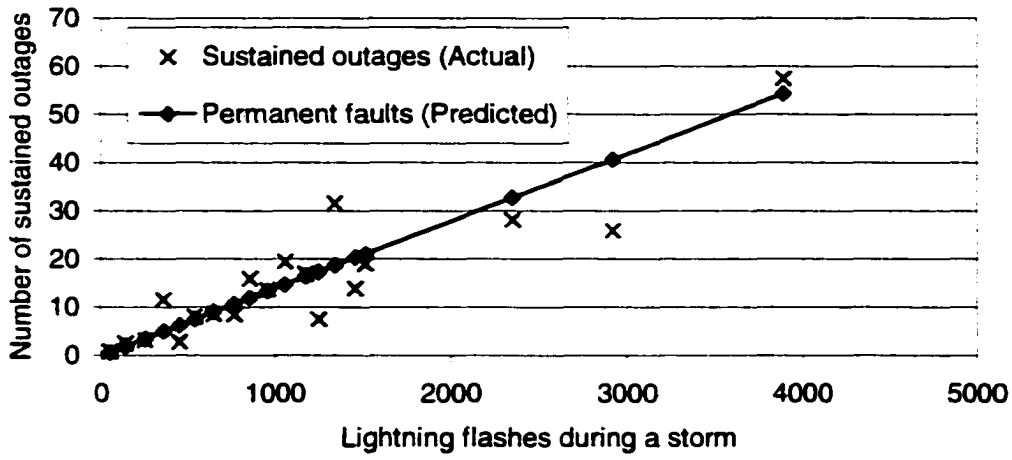


Figure 4.5 Sustained outages and permanent faults vs Number of lightning flashes

4.7.3 Simulation results

The system-wide reliability indices for this test case are evaluated using the Monte Carlo simulation method. Some of the important reliability indices, namely the MAIFI, $MAIFI_E$, SAIFI, and SAIDI obtained using the Monte Carlo simulation are presented in Table 4.1. In order to provide a comparative assessment, the results calculated using an analytical FMEA [Bill94] method are also presented in Table 4.1. In the FMEA method, the GFD is used to calculate the average annual lightning fault rate, while the Monte Carlo simulation method simulates the impact of individual lightning storm events. It must be noted that the indices presented in Table 4.1 represent only a part of the total annual values, since events other than lightning storms also contribute to momentary and sustained outages on the system. However, in some localities in the system studied, lightning *is* the single largest cause of momentary outages and hence the most significant contributor to the system MAIFI and $MAIFI_E$.

From the results in Table 4.1, it can be observed that the values of MAIFI and the $MAIFI_E$ indices obtained are about 12% less than the values calculated using the analytical method. This is due to the fact that at any given time, the system outage rate is proportional to the number of segments that are energized. As a storm progresses, some parts of different feeders would already be out of service, thereby reducing the impact of subsequent lightning flashes on the frequency of customer outages as calculated by MAIFI and $MAIFI_E$. The

analytical FMEA method does not model the dependence of segment temporary fault rate on the status of the overhead line segments (whether the segment is energized or not), thereby overestimating the MAIFI and $MAIFI_E$ indices.

Similar results can be observed for the lighting storm-caused SAIFI and SAIDI. When a part of the system is already isolated, the likelihood of sustained outages on the downstream segments due to lightning-caused equipment damage, or due to protection imperfections, is reduced. The Monte Carlo simulation incorporates such dependence of the outage events on the status of line segments, providing an accurate account of the system reliability indices. The computation time for the system reliability on a 300 MHz Pentium II processor is 7 seconds using the analytical method while it is 10,221 seconds using the Monte Carlo simulation.

The probability plots of the system indices can be used to find the likelihood of the reliability indices in any given year being greater than a specified value. This information helps to distinguish the circuits with consistently poor reliability from those that just have a bad year due to the random nature of weather. The probability histograms of the system MAIFI, $MAIFI_E$, SAIFI, and SAIDI are presented in Figures 4.6 to 4.9. Also, from Table 4.1, it can be seen that the annual lightning storm-caused SAIDI has a large deviation (40%) around the mean value while the corresponding MAIFI, $MAIFI_E$ and SAIFI indices vary to a lesser extent with a standard deviation of 30% around the mean.

Several state regulatory authorities have started specifying minimum reliability standards in terms of the average value and the standard deviation of the historical indices [PPUC99]. The average value and the standard deviation of the system indices are being used to determine the minimum reliability standards. In order to evaluate the impact of system size on the variability of the reliability indices, the feeders of the test system were grouped into smaller subsystems consisting of 10 through 100 feeders. Table 4.2 presents the indices as the size of the system is varied. From Table 4.2 it can be observed that though the variability of the SAIDI and SAIFI indices depends on the system size, the variability of MAIFI and $MAIFI_E$ are independent of system size. Further, the models of storm weather and its impact on distribution reliability can be incorporated in the methodology shown in Chapter 2, to assess the consequences of regulatory standards on distribution systems.

Table 4.1 Reliability indices due to lightning storms (2000 years of simulation).

Model	MAIFI[1]	Standard Deviation of MAIFI	$MAIFI_E$[2]	Standard Deviation of $MAIFI_E$	SAIFI[3]	Standard Deviation of SAIFI	SAIDI[4]	Standard Deviation of SAIDI
Non-parametric model	4.082	1.1160	3.519	1.000	0.334	0.114	0.590	0.243
Analytical method	4.565	NA	3.935	NA	0.392	NA	0.785	NA

[1] momentary interruption events per customer per year
[2] momentary interruptions per customer per year
[3] Interruption hours per customer per year
[4] Interruptions per customer per year

Table 4.2 Mean and standard deviation (std) of reliability indices

System size (feeders)	MAIFI		$MAIFI_E$		SAIFI		SAIDI	
	Mean	std	Mean	Std	Mean	std	Mean	std
10	4.087	1.285	3.523	1.107	0.318	0.196	0.711	0.662
20	4.057	1.217	3.496	1.048	0.328	0.161	0.627	0.438
30	4.080	1.180	3.517	1.016	0.313	0.140	0.572	0.357
40	3.922	1.196	3.380	1.030	0.300	0.128	0.542	0.306
50	3.671	1.089	3.166	0.939	0.295	0.116	0.526	0.275
60	3.808	1.106	3.282	0.953	0.313	0.120	0.560	0.274
70	3.766	1.096	3.247	0.945	0.312	0.113	0.558	0.254
80	3.774	1.090	3.254	0.940	0.312	0.111	0.547	0.239
90	4.070	1.169	3.509	1.008	0.330	0.112	0.582	0.247
100	4.082	1.160	3.519	1.000	0.335	0.114	0.590	0.243

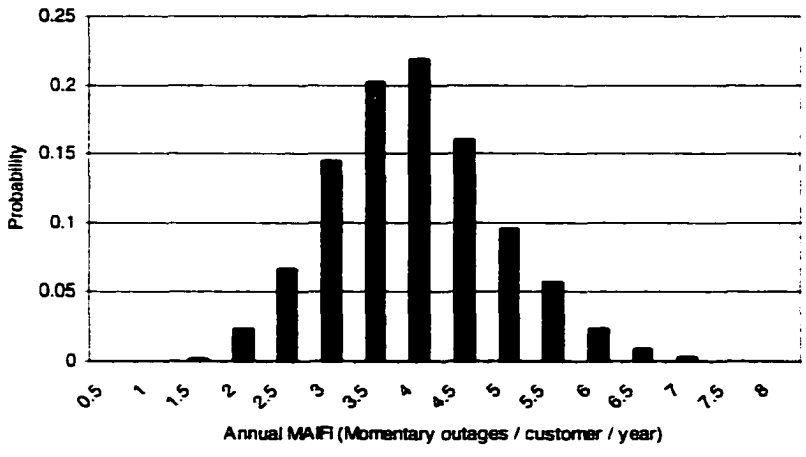


Figure 4.6 MAIFI histogram

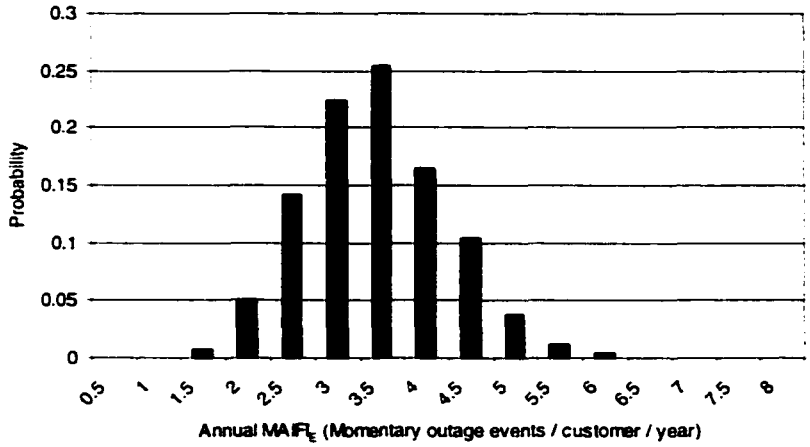


Figure 4.7 MAIFI$_E$ histogram

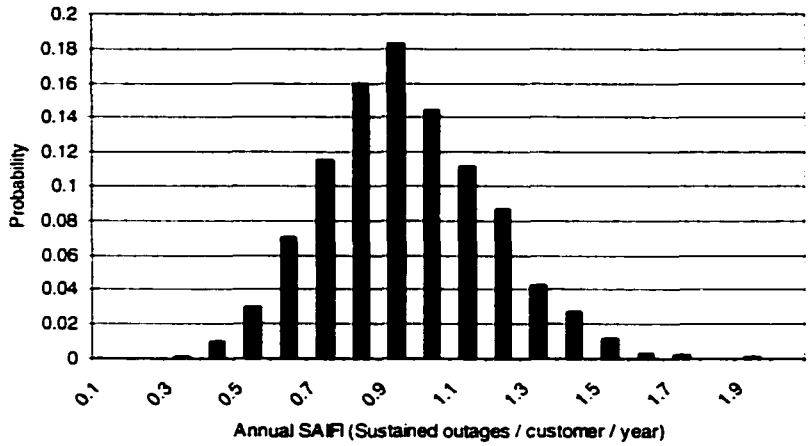


Figure 4.8 SAIFI histogram

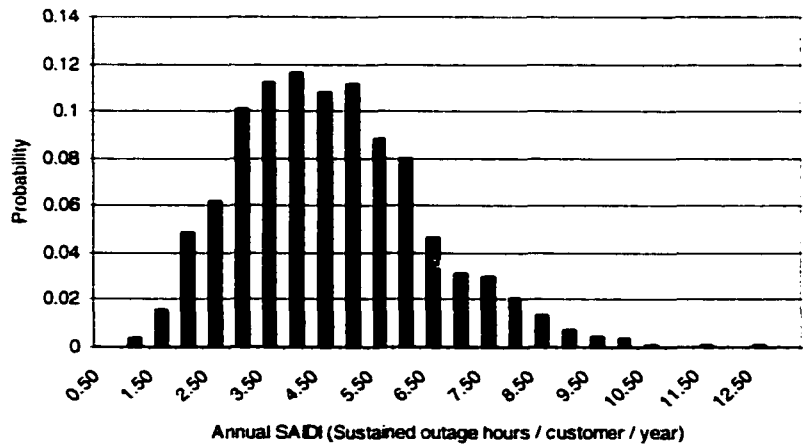


Figure 4.9 SAIDI histogram

4.8 Conclusions

The performance of a distribution system under lightning storm conditions is of great concern for utilities due to a need to maintain high levels of customer satisfaction and to comply with regulatory requirements. Therefore, it is necessary to obtain a realistic quantification of the system reliability. Lightning storms cause a number momentary outages and relatively few sustained outages. The segments with sustained outages, while they await service restoration, prevent new momentary outages to their connected customers, since a momentary outage can occur only if a segment is energized. Thus, the system reliability depends not only on the storm intensity but also on the number of line segments that are energized at any given time. In order to incorporate the dependence of system reliability on the storm intensity and the status of the line segments, it is necessary to evaluate the impact of faults during individual storm events. In this work, the bootstrap method is used to model the lightning storm parameters (Section 4.4.3). A Monte Carlo simulation that uses the storm parameters and the fault rates is presented in Section 4.6 for evaluating the reliability indices under lightning storm conditions. An estimate of the temporary and permanent fault rate is obtained from an analysis of the utility data and the lightning flash data in Section 4.7.2. The results presented in Section 4.7.3 indicate that the Monte Carlo simulation method provides a realistic assessment of the distribution system reliability indices under lightning storm conditions.

5. Summary, Conclusions and Directions for Future Research

5.1 Summary and conclusions

Reliability of power distribution systems is an important criterion for power system planners. The reliability indices can be calculated either from the historical outage data, or using predictive assessment techniques. The computationally fast analytical assessment techniques such as the Failure Modes Effects Analysis (FMEA) method can provide only the long-term average value of the system indices. The Monte Carlo simulation method can provide the statistical distribution of the reliability indices along with the average value. However, the Monte Carlo simulations usually tend to be computationally intensive. The probability histograms of the reliability indices can be used to obtain an improved understanding of the system behavior. This work presets a computationally efficient Monte Carlo simulation algorithm for distribution system reliability assessment. The probability histograms of the standard reliability indices for a practical distribution system are plotted. From these plots it is noted that the feeder indices are much different in their statistical nature from the system-wide indices.

From an analysis of practical outage data from a distribution company, it was noted that the failures might be modeled as a renewal process. Sensitivity studies presented in this work indicate that the probability plots of the SAIFI indices are largely independent of the exact statistical model of the failure process. Therefore, knowledge of the topological data in terms of feeder design and load density along with the average failure rate and repair duration can be used to obtain the statistical characteristics of the reliability indices. However, the repair processes are not likely to follow the exponential or lognormal distribution. Hence detailed models of the outage duration are required to obtain the probability plots of the interruption duration indices such as the SAIDI.

The SAIFI histogram of individual feeders is found to be multi-modal. Analysis of the feeder topology and customer connectivity indicates that the multi-modal behavior of

SAIFI is due to the quantization of the number of customer interruptions caused by the location of the protective devices such as reclosers and sectionalizers. The impact of incorporating sectionalizing devices on the feeder SAIFI are also explored in this work.

In the recent past, the regulatory authorities of various states have started to specify minimum reliability standards to be maintained by the distribution companies. Monte Carlo simulations can help in the assessment of the impact of such standards on distribution systems. Individual distribution systems tend to be very different from one another. The characteristics of individual distribution systems must be taken into account in establishing reliability standards. In this work, the impact of limits on annual reliability as well as limits on reliability indices over 2-consecutive years for a practical distribution system is studied. Such studies allow the regulators to establish reasonable upper limits for system reliability indices. They also can provide the system planners with information on the relative weakness of the feeders. However, analysis of other distribution systems must be performed so that appropriate additional measures can be developed for identifying poor performing feeders.

The performance of a distribution system under lightning storm conditions is of great concern for utilities due to a need to maintain high levels of customer satisfaction and to comply with regulatory requirements. Lightning storms cause a number momentary outages and relatively few sustained outages. The segments with sustained outages, while they await service restoration, prevent new momentary outages to their connected customers, since a momentary outage can occur only if a segment is energized. Thus, the system reliability depends not only on the storm intensity but also on the number of line segments that are energized at any given time. In this work, the bootstrap method is used to model the lightning storm parameters. A Monte Carlo simulation that uses the storm parameters and the fault rates is presented for evaluating the reliability indices under lightning storm conditions. An estimate of the temporary and permanent fault rate is obtained from an analysis of the utility data and the lightning flash data. The results indicate that the Monte Carlo simulation method provides a realistic assessment of the distribution system reliability indices under lightning storm conditions.

5.2 Main contributions

The main contributions of the proposed research work are as follows:

- Developing a fast Monte Carlo simulation algorithm for reliability assessment of large distribution systems using as described in Section 2.4.
- Identifying the probability histograms of the standard reliability indices for a practical distribution system as described in Section 2.5.
- Assessing the impact of reliability standards on individual feeders a practical distribution system as described in Chapter 3.1.
- Assessing the impact of system-wide reliability standards on a practical distribution system as described in Chapter 3.2.
- Assessing distribution system reliability using bootstrap sampling models for the intensity and duration of lightning storms as described in Sections 4.4.3 and 4.7.

5.3 Directions for future research

This research has aimed at obtaining improved understanding of the distribution system reliability indices by means of Monte Carlo simulation methods. However, there are still several topics of interest that are worth some attention. These topics are briefly reviewed in this section.

5.3.1 Impact of reliability standards on load point indices

Some of the state regulatory authorities prescribe minimum performance standards on the load point indices. In order to study the impact of reliability standards on individual feeders, the large number of feeder configurations must be considered. Additionally, the number of connected customers on any system runs into hundreds, if not more. Analyzing the reliability of all the connected customers is a time-consuming process. Interpreting the results obtained is an even greater challenge. Monte Carlo simulations can be used to undertake such a task.

5.3.2 Effect of Dispersed Storage and Generation (DSG) facilities on distribution reliability

There is a growing application of non-conventional power sources such as wind turbines, micro turbines and induction generators. Most of these devices are located on the distribution feeders. The impact of multiple active power sources on the customer reliability needs to be explored.

5.3.3 Reliability of networked distribution systems

Presently, distribution companies operate low voltage networks in major cities that permit multi-directional flow on some links. Under such conditions, some of the customers may be insulated from the effects of feeder outages. New models of the protection and isolation equipment must obtained to evaluate the impact of networked operation of distribution systems.

5.3.4 Modeling of faults caused by wind storms

It is often considered that high winds cause tree branches to deflect more than they usually do, make fleeting contact with overhead distribution feeders, and cause a temporary fault that is cleared by recloser operation, resulting in a momentary outage. Thus, the appropriate method to control this is by trimming trees.

5.3.5 Analytical storm reliability assessment

During storm events, such as wind and snow storms, there is a possibility of several overlapping faults occurring, resulting in more faults than there are crews to attend to the faults. Such crew constraints due to multiple overlapping faults are usually handled with the help of Monte Carlo simulation techniques. However, simulation techniques are computationally slow in comparison to analytical techniques. An analytical technique that is capable of evaluating overlapping fault events would be helpful in interactive analysis for storm reliability.

5.3.6 Including storm-caused outages in vegetation maintenance scheduling

Depending on the location of the distribution system, storms cause a significant percentage of the total customer interruptions. Periodic vegetation maintenance is expected to reduce the number of customer interruptions during storms. The impact of multiple overlapping faults and the consequent crew constraints must be integrated with the storm-caused fault models to arrive at the optimal scheduling of vegetation maintenance. Such a tool would greatly improve the impact of vegetation maintenance on customer reliability.

5.3.7 Integration of statistical distribution of reliability indices in system design

It was observed that the feeder SAIFI could have multi-modal behavior. Such information is not contained in the average values of SAIFI. Incorporating the statistical distribution of in evaluating the alternative design schemes such as switch and protection device placement, and feeder reconfiguration, is likely to provide improved design options.

5.3.8 Statistical modeling of line segment outage rate

A large amount of historical data is required to identify the statistical distribution of the failure rate of individual line segments. For example, the outages on a practical distribution system having 25,000 line segments were recorded over a period of six years. The total of 15,000 fault incidents was observed during the study period. Thus, though the number of observations is large, they are still less than the system size. Under such circumstances, hierarchical modeling methods can be used to determine the distribution of the failure rate of the line segments. Such an analysis is expected to provide insights into the behavior of the line segment failure processes.

Appendix

A brief review of the definitions of distribution system reliability indices along with sample calculations using the FMEA method and the Monte Carlo simulation method are provided in this Appendix.

Terminology and Definitions of Reliability Indices

Definitions of the basic terms used to derive the system indices are as follows [IEEE97]:

1. Sustained interruption: Any interruption longer than 5 minutes is a sustained interruption.
2. Momentary interruption: The occurrence of each voltage zero condition due to operation of an interrupting device is termed as a momentary interruption. For instance, two recloser operations to clear a temporary fault equals two momentary interruptions.
3. Momentary interruption event: An interruption of duration less than 5 minutes, but limited to the period required to restore service by an interrupting device is termed as a momentary interruption event. All breaker/recloser operations related to the same fault condition, occurring within 5 minutes of the first interruption can be classified as a single momentary interruption event. Events immediately preceding a lockout are not included under this definition
4. Interrupting device: "A device capable of being reclosed whose purpose is to interrupt faults and restore service or disconnect loads" is known as an interrupting device. These devices can be manual, automatic or motor-operated. Examples: Circuit breakers, line reclosers etc.
5. Connected Load: The kVA rating of the connected transformer, or the peak load, or the metered demand of the circuit or portion of circuit that is interrupted is the connected load that is not served.

For radial distribution systems, three basic reliability indices have been defined, namely, the average failure rate, λ (failures per year), the average outage duration, r (hours per outage), and the average annual outage duration, U (hours per year). These indices can be

calculated at each load point, and hence are known as load point indices. In the present context, each line segment is considered as a load point.

It is possible that wide differences exist in the number of customers connected and the total connected load incident at different load points. For example, some load points might have a handful of customers connected, while some others might have a few hundred customers connected. Parameters such as the average number of customers affected per year, or the average annual amount of load curtailed, cannot be obtained from the load point indices alone. Since there is a need to measure of the overall performance of the distribution system, additional indices (known as system performance indices) have been defined. The following is the list of annual system wide indices:

1. System Average Interruption Frequency Index (*SAIFI*): The system average interruption frequency index indicates the average frequency of sustained interruptions per customer over a predefined area.

$$SAIFI = \frac{Total\ Number\ of\ Customer\ Interruptions}{Total\ Number\ of\ Customers\ Served} \tag{A1}$$

SAIFI can be calculated as:

$$SAIFI = \frac{\sum N_i}{N_T} = \frac{\sum N_{lp}\lambda_{lp}}{\sum N_{lp}} \tag{A2}$$

where N_T is the total number of customers served for the area being indexed and N_i is the number of customers interrupted by the ith interruption event, N_{lp} and λ_{lp} are the number of customers and the sustained outage rate at load point lp.

2. System Average Interruption Duration Index (*SAIDI*): Also referred to as the 'customer minutes of interruption', or simply, 'customers hours', *SAIDI* indicates the average time the customers are interrupted.

$$SAIDI = \frac{\sum Customer\ Interruption\ Durations}{Total\ Number\ of\ Customers\ Served} \tag{A3}$$

SAIDI can be calculated as:

$$SAIDI = \frac{\sum r_i N_i}{N_T} = \frac{\sum N_{lp} r_{lp}}{\sum N_{lp}} \tag{A4}$$

where N_T is the total number of customers served for the area being indexed, N_i is the number of interrupted customers, r_i is the restoration time due the ith interruption event, N_{lp} and r_{lp} are the number of customers and the average interruption duration at load point lp.

3. Customer Average Interruption Duration Index (*CAIDI*): The average time required to restore service to the average customer per sustained interruption is represented by *CAIDI*.

$$CAIDI = \frac{\sum Customer\ Interruption\ Durations}{Total\ Number\ of\ Customer\ Interruptions} \tag{A5}$$

Alternately, from (A1) and (A3),

$$CAIDI = \frac{SAIDI}{SAIFI}$$

4. Average Service Availability Index (*ASAI*): The fraction of time, in percentage that a customer has power provided per year (or, for the defined reporting time) is represented by *ASAI*.

$$ASAI = \frac{Customer\ Hours\ of\ Available\ Service}{Customers\ Hours\ Demanded} \tag{A6}$$

ASAI can be calculated as:

$$ASAI = \frac{N_T \times 8760 - \sum r_i N_i}{N_T \times 8760} = \frac{N_T \times 8760 - \sum r_{lp} N_{lp}}{N_T \times 8760} \tag{A7}$$

where N_T is the total number of customers served for the area being indexed, N_i is the number of interrupted customers, r_i is the restoration time for the ith interruption event, N_{lp} and r_{lp} are the number of customers and the average outage duration at load point lp.

5. Average System Interruption Frequency Index (*ASIFI*): *ASIFI* is a load-based index, different from the customer-count based indices such as *SAIFI*. *ASIFI* gives information on the system average interruption frequency.

$$ASIFI = \frac{(Connected\ kVA\ Interupted)}{Total\ Connected\ kVA\ Served} \tag{A8}$$

ASIFI can be calculated as:

$$ASIFI = \frac{\sum L_i}{L_T} = \frac{\sum L_{lp}\lambda_{lp}}{\sum L_{lp}} \tag{A9}$$

where L_i is the connected kVA load interrupted by the ith interruption event, L_T is the total connected kVA load being served, N_{lp} and λ_{lp} are the customer kVA capacity and the outage rate at load point *lp*.

6. Average System Interruption Duration Index (*ASIDI*): *ASIDI* gives the system average duration of interruptions.

$$ASIDI = \frac{Connected\ kVA\ Interuption\ Duration}{Total\ Connected\ kVA\ Served} \tag{A10}$$

ASIDI can be evaluated as:

$$ASIFI = \frac{\sum r_i L_i}{L_T} = \frac{\sum L_{lp} r_{lp}}{\sum L_{lp}} \tag{A11}$$

where L_T is the total connected kVA load being served, L_i is the connected kVA load interrupted, r_i is the restoration time by the ith interruption event, N_{lp} and r_{lp} are the number of customers and the average outage duration at load point *lp*.

7. Momentary Average Interruption Frequency Index (*MAIFI*): The average frequency of momentary interruptions per customer is given by *MAIFI*.

$$MAIFI = \frac{Total\ Number\ of\ Customer\ Momentary\ Interruptions}{Total\ Number\ of\ Customers\ Served} \tag{A12}$$

To calculate the index, the following equation can be used:

$$MAIFI = \frac{\sum ID_i N_i}{N_T} \tag{A13}$$

where ID_i is the number of interrupting device operations due to the Ii^{th} temporary fault.

8. Momentary Average Interruption-Event Frequency Index ($MAIFI_E$): The average frequency of momentary interruption events per customer is given by $MAIFI_E$.

$$MAIFI_E = \frac{Total\ Number\ of\ Customer\ Momentary\ Interruption\ Events}{Total\ Number\ of\ Customers\ Served} \tag{A14}$$

To calculate the index, the following equation can be used:

$$MAIFI_E = \frac{\sum ID_E N_i}{N_T} = \frac{\sum N_{lp}\lambda_{lp\,mom}}{\sum N_{lp}} \tag{A15}$$

where ID_E is the number of momentary interruption events due to the ith temporary fault, N_{lp} and $\lambda_{lp\ mom}$ are the number of customers and the momentary outage rate at load point lp.

9. Customer Total Average Interruption Duration Index ($CTAIDI$): The total average time required to restore service to the average customer per sustained interruption is represented by $CTAIDI$. Calculating $CTAIDI$ is very similar to evaluating $CAIDI$, except that the customers with multiple interruptions are counted only once.

$$CTAIDI = \frac{\sum Customer\ Interruption\ Durations}{Total\ Number\ of\ Customers\ Interrupted} \tag{A16}$$

$CTAIDI$ can be calculated as:

$$CTAIDI = \frac{\sum r_i N_i}{CN} = \frac{\sum N_{lp} r_{lp}}{\sum N_{lp}(1-e^{-\lambda_{lp}})} \tag{A17}$$

where CN is the total number of customers who have experienced a sustained interruption.

10. Customer Average Interruption Frequency Index ($CAIFI$): The customer average interruption frequency index indicates the average frequency of sustained interruptions for those customers experiencing sustained interruptions.

$$CAIFI = \frac{Total\ Number\ of\ Customer\ Interruptions}{Total\ Number\ of\ Customers\ Interrupted} \tag{A18}$$

To calculate $CAIFI$, the following equation can be used:

$$CAIFI = \frac{\sum N_i}{CN} = \frac{\sum N_{lp}\lambda_{lp}}{\sum N_{lp}(1-e^{-\lambda_{lp}})} \tag{A19}$$

where CN is the total number of customers interrupted and N_i is the number of customers interrupted by the ith interruption event.

11. Customers Experiencing Multiple Interruptions ($CEMI_n$): $CEMI_n$ indicates the number of customers that experience more than n sustained interruptions.

$$CEMI_n = \frac{Total\ \#\ of\ Customers\ that\ Experienced\ more\ than\ n\ Sustained\ Interruptions}{Total\ Number\ of\ Customers\ Served} \quad \text{(A20)}$$

To calculate the index, the following equation can be used:

$$CEMI_n = \frac{CN_{k>n}}{N_T} \quad \text{(A21)}$$

where $CN_{(k>n)}$ is the total number of customers who have experienced more than n sustained interruptions. $CN_{(k>n)}$ can be calculated as:

$$\mathrm{CN}_{(k>n)} = \sum_{lp} N_{lp}\left(1 - \sum_{k<n} \frac{e^{-\lambda_{lp}} \lambda_{lp}^{\ k}}{k!}\right)$$

12. Customers Experiencing Multiple Sustained Interruptions and Momentary Interruption events ($CEMSMI_n$): This index is a measure of the number of customers that experience more than n interruptions, including both sustained and momentary interruption events.

$$CEMSMI_n = \frac{Total\ \#\ of\ Customers\ that\ Experience\ d\ more\ than\ n\ Interrupti\ ons}{Total\ Number\ of\ Customers\ Served} \quad \text{(A22)}$$

To calculate the index, the following equation can be used:

$$CEMSMI_n = \frac{CNT_{k>n}}{N_T} \quad \text{(A23)}$$

where $CNT_{(k>n)}$ is the total number of customers who have experienced more than n sustained interruptions and momentary interruption events. $CN_{(k>n)}$ can be calculated as:

$$\mathrm{CN}_{(k>n)} = \sum_{lp} N_{lp}\left(1 - \sum_{k<n} \frac{e^{-\lambda'_{lp}} \lambda'_{lp}^{\ k}}{k!}\right)$$

where $\lambda' = \lambda_{lp} + \lambda_{lp\ mom.}$ accounting for both sustained and momentary interruptions.

Example

In this section, a simple example for which hand calculations can be performed to obtain the system reliability indices is presented. Sample calculations of reliability indices using the FMEA method and the Monte Carlo method are included in the example.

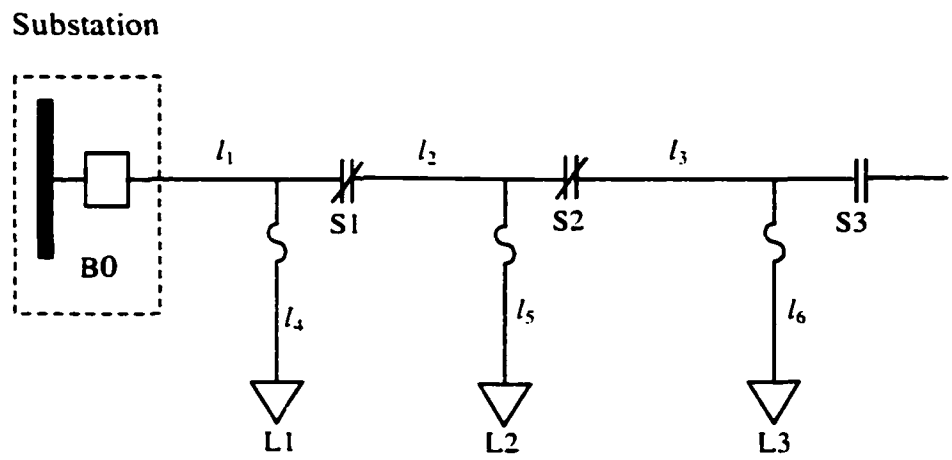


Figure A1. Example system for calculation of reliability indices

Consider the distribution system shown in Figure A1. B0 is the feeder circuit breaker; S1 and S2 are NC sectionalizing switches, while S3 is an NO switch l_1, l_2, l_3, l_4, l_5, and l_6 are line segments that supply loads L1, L2 and L3. The failure rate of line segments l_1, l_2, and l_3 is 0.1, 0.2 and 0.3 faults per year and their average repair duration is 5 hours per fault. The lateral segments l_4, l_5, and l_6 have a failure rate of 0.2, 0.4 and 0.6 faults per year respectively and a repair rate of 3 hours per fault.

Reliability Assessment Using FMEA Method:

In this method, each line segment is considered to be a failure mode. The effect of failure on each segment is calculated to evaluate the load point indices. The procedure is applied to the test system as shown in Table A1. For each mode, the product of the failure rate and the average repair duration ($\lambda * r$) gives the total average annual outage duration (U). The load point average failure rate is calculated as the sum of the failure rates of the

contributing failure modes ($\lambda_{lp} = \Sigma\lambda$) while the average repair duration is calculated as the ratio of the total outage duration to the load point failure rate ($r_{lp} = \Sigma U/\lambda_{lp}$). Similarly, the momentary outage rate is also obtained. The load-point indices are summarized in Table A2.

Table A1. Load point indices calculated using the FMEA method

Failure mode	Load Point A (f/y)			Load Point B (f/y)			Load Point C (f/y)		
	λ (f/y)	r (hr)	$U=\lambda.r$ (hr/y)	λ (f/y)	r (hr)	$U = \lambda.\ r$ (hr/y)	λ (f/y)	r (hr)	$U = \lambda.\ r$ (hr/y)
Section 1	0.1	5	0.5	0.1	5	0.5	0.1	5	0.5
Section 2	0.2	5	1.0	0.2	5	1.0	0.2	5	1.0
Section 3	0.3	5	1.5	0.3	5	1.5	0.3	5	1.5
Lateral 1	0.2	3	0.6						
Lateral 2				0.4	3	1.2			
Lateral 3							0.6	3	1.8
Total	$\Sigma\lambda$	$\Sigma U/\Sigma\lambda$	ΣU	$\Sigma\lambda$	$\Sigma U/\Sigma\lambda$	ΣU	$\Sigma\lambda$	$\Sigma U/\Sigma\lambda$	ΣU
	0.8	4.5	3.6	1.0	4.2	4.2	1.2	4	4.8

Table A2. Customer data and load point reliability data

Load Point	# of customers	Connected Load, kVA	Load point outage rate, λ_{lp}	Load point outage duration, r_{lp}	Momentary outage rate, λ_{lp_mom}
L1	900	1800	0.8	4.5	2.00
L2	550	1100	1.0	4.2	3.25
L3	400	800	1.2	4.0	4.50

Using the load point indices, the system-wide indices are calculated as follows:

1. The average SAIFI can be calculated as:

$$SAIFI = \frac{\Sigma N_{lp}\lambda_{lp}}{\Sigma N_{lp}} = \frac{900*0.8+550*1.0+400*1.2}{900+550+400} = \frac{1750}{1850} = 0.9459 \quad \text{Interruptions/Customer/year}$$

2. The average SAIDI can be calculated as:

$$SAIDI = \frac{\Sigma N_{lp} r_{lp}}{\Sigma N_{lp}} = \frac{900*4.5+550*4.2+400*4.0}{900+550+400} = \frac{7960}{1850} = 4.3027 \quad \text{Hrs/Customer Interruption/year}$$

3. The average CAIDI can be calculated as:

$$CAIDI = \frac{SAIDI}{SAIFI} = \frac{4.3027}{0.9459} = 4.5487 \quad \text{hrs/customer/year}$$

4. The average ASAI can be calculated as:

$$ASAI = \frac{N_T * 8760 - \sum N_{lp} r_{lp}}{\sum N_T * 8760} = \frac{1850 * 8760 - 7960}{1850 * 8760} = 0.999509$$

5. The average ASIFI can be calculated as:

$$ASIFI = \frac{\sum L_{lp} \lambda_{lp}}{\sum L_{lp}} = \frac{1800 * 0.8 + 1100 * 1.0 + 800 * 1.2}{1800 + 110 + 800}$$
$$= \frac{3500}{3700} = 0.9459 \quad \text{Interruptions / kVA/year}$$

6. The average ASIDI can be calculated as:

$$ASIDI = \frac{\sum r_{lp} L_{lp}}{\sum L_{lp}} = \frac{1800 * 4.5 + 110 * 4.2 + 800 * 4.0}{1800 + 110 + 800}$$
$$= \frac{15920}{3700} = 4.3027 \quad \text{Hrs/kVA Interruption/year}$$

7. Assuming that each momentary interruption event involves $mom_{event2int}$ = 3 reclosing operations, the average MAIFI can be calculated as:

$$MAIFI = \frac{\sum N_{lp} \lambda_{lp\,mom} mom_{event2\text{int}}}{\sum N_{lp}} = \frac{(900 * 2.0 + 550 * 3.25 + 400 * 4.5) * 3}{900 + 550 + 400}$$
$$= \frac{5387.5}{1850} = 8.7365 \text{Momentary Interruptions/Customer/year}$$

8. The average $MAIFI_E$ can be calculated as:

$$MAIFI_E = \frac{\sum N_{lp} \lambda_{lp\,mom}}{\sum N_{lp}} = \frac{900 * 2.0 + 550 * 3.25 + 400 * 4.5}{900 + 550 + 400}$$
$$= \frac{5387.5}{1850} = 2.9122 \text{Momentary Interruption Events/Customer/year}$$

9. The average CTAIDI can be calculated as:

$$CTAIDI = \frac{\sum N_{lp} r_{lp}}{\sum N_{lp} (1 - e^{-\lambda_{lp}})}$$
$$= \frac{900 * 4.5 + 550 * 4.2 + 400 * 4.0}{495.60 + 347.66 + 279.52}$$
$$= \frac{7960}{1122.78} = 7.0895 \quad \text{Hrs/Customers Interrupted/year}$$

10. The average CAIFI can be calculated as:

$$CAIFI = \frac{\sum N_{lp}\lambda_{lp}}{\sum N_{lp}(1-e^{-\lambda_{lp}})}$$
$$= \frac{900*0.8+550*1.0+400*1.2}{495.60+347.66+279.52}$$
$$= \frac{1750}{1122.78} = 1.5586 \text{ Interruptions/Customers Interrupted/year}$$

11. The average $CEMI_n$ can be calculated as follows: Initially, calculate the number of customers experiencing multiple outages. For example, the expected number of customers experiencing more than 3 sustained outages in a year can be calculated as:

$$CN_{(k>3)} = \sum_{lp} N_{lp}\left(1-\sum_{k<3}\frac{e^{-\lambda_{lp}}\lambda_{lp}^{\ k}}{k!}\right)$$
$$= 900*0.00907+550*0.01899+400*0.03377 = 32.115 \quad \text{Customers/year}$$

Now, the average $CEMI_n$ can be calculated using:

$$CEMI_n = \frac{CN_{k>n}}{N_T} = \frac{32.115}{1850} = 0.01736$$

12. The average $CEMSMI_n$ can be calculated as follows: Initially, calculate the number of customers experiencing multiple outages. For example, the expected number of customers experiencing more than 3 momentary and sustained outages in a year can be calculated as:

$$CN_{(k>3)} = \sum_{lp} N_{lp}\left(1-\sum_{k<3}\frac{e^{-\lambda'_{lp}}\lambda'_{lp}^{\ k}}{k!}\right)$$
$$= 900*0.3081+550*0.6138+400*0.8200 = 942.88 \quad \text{Customers}$$

Now, the average $CEMSMI_n$ can be calculated using:

$$CEMSMI_3 = \frac{CN_{k>3}}{N_T} = \frac{942.88}{1850} = 0.5097$$

Historical Reliability Assessment Method (Used in Monte Carlo Simulation)

The Monte Carlo method simulates outages on the different feeder segments for a number of years and obtains the average value of the annual reliability indices. In this section, the methodology of calculating the reliability indices for one particular year is presented. The numerical values of the indices presented in this section will be different from

those in the previous section due to the fact that the FMEA method calculates the long-term average value of the indices while the historical indices are calculated for one specific year.

Consider the outage history of the example system for year 1994 shown in Table A3. Individual load point outage data can be extracted from Table A3, as indicated in Table A4. Interruption type S indicates a sustained outage while type M indicates a momentary outage.

Table A3. Outage data for year 1994 for the example system

Date	Time of fault	Time of restoration	Circuit	# Customers	Load kVA	Interruption type
3/17	12:12:20	12:20:30	*l*2	950	1900	S
4/15	18:23:56	18:24:26	*l*5	550	1100	M
5/5	00:23:10	01:34:29	*l*3	400	800	S
6/12	23:17:00	23:47:14	*l*3	400	800	S
7/6	09:30:10	09:31:10	*l*1	1850	3700	M
8/20	15:45:39	20:12:50	*l*6	400	800	S
8/31	08:20:00	10:20:00	*l*4	900	1800	S
9/3	17:10:00	17:20:00	*l*3	950	1900	S
10/27	10:15:00	10:55:00	*l*1	1850	3700	S

Table A4. Extracted load point interruption history

Date	L1		L2		L3	
	Outage duration	Interruption Type	Outage duration	Interruption Type	Outage duration	Interruption Type
3/17	0.5	M	8.17	S	8.17	S
4/15	-	-	0.5	M	0.5	M
5/5	-	-	0.5	M	71.3	S
6/12	-	-	0.5	M	30.3	S
7/6	0.5	M	0.5	M	0.5	M
8/20	-	-	-	-	267.2	S
8/31	120	S	-	-	-	-
9/3	-	-		S	10	S
10/27	40	S	40	S	40	S

Based on Tables A3 and A4, the system reliability indices are calculated as follows:

1. SAIFI can be calculated as:

$$SAIFI = \frac{\sum N_i}{N_{lp}}$$

$$= \frac{950+400+400+400+900+950+1850}{900+550+400} = \frac{5850}{1850} = 3.1622 \quad \text{Interruptions/Customer}$$

2. SAIDI can be calculated as:

$$SAIDI = \frac{\sum N_i r_i}{\sum N_{lp}}$$
$$= \frac{900*8.17+400*71.3+400*30.3+400*267.2+900*120+950*10+1850*40}{900+550+400}$$
$$= \frac{336873}{1850} = 182.09\text{Minutes} = 3.03489\text{Hrs/Customer Interruption}$$

3. CAIDI can be calculated as:

$$CAIDI = \frac{SAIDI}{SAIFI} = \frac{3.0349}{3.1622} = 0.9597 \quad \text{Hrs/Customer}$$

4. ASAI can be calculated as:

$$ASAI = \frac{N_T*8760-\sum N_i r_i}{\sum N_T*8760} = \frac{1850*8760*60-336873}{1850*8760*60} = 0.999653$$

5. ASIFI can be calculated as:

$$ASIFI = \frac{\sum L_i}{\sum L_{lp}} = \frac{1900+800+800+800+1800+1900+3700}{1800+1100+800}$$
$$= \frac{11700}{3700} = 3.1622 \text{ Interruptions/kVA}$$

6. ASIDI can be calculated as:

$$ASIDI = \frac{\sum r_i L_i}{\sum L_i}$$
$$= \frac{1800*8.17+800*71.3+800*30.3+800*267.2+1800*120+1900*10+3700*40}{1800+1100+800}$$
$$= \frac{673746}{3700} = 182.09 \text{ Minutes/kVA Interruption} = 3.0349 \text{ Hrs/kVA Interruption}$$

7. MAIFI includes *all* momentary interruptions. Assuming each momentary event involves 3 operation of reclosers, MAIFI can be calculated from Table 3 as:

$$MAIFI = \frac{\sum ID_E N_i}{\sum N_T}$$
$$= \frac{550+1850}{900+550+400} = \frac{2400}{1850} = 1.2973 \quad \text{Momentary Interruptions/Customer}$$

8. $MAIFI_E$ does not include momentaries immediately preceding a sustained outage. It can be calculated as:

$$MAIFI_E = \frac{\sum ID_E N_i}{\sum N_T}$$
$$= \frac{550+1850}{900+550+400} = \frac{2400}{1850} = 1.2973 \quad \text{MomentaryInterruptionEvents/Customer}$$

9. CTAIDI can be calculated as:

$$CTAIDI = \frac{\sum N_i r_i}{CN}$$
$$= \frac{900*8.17+400*71.3+400*30.3+400*267.2+900*120+950*10+1850*40}{900+550+400}$$
$$= \frac{336873}{1850} = 182.09\text{Minutes} = 3.03489\text{Hrs/Customers Interrupted}$$

10. CAIFI can be calculated as:

$$CAIFI = \frac{\sum N_i}{CN}$$
$$= \frac{950+400+400+400+900+950+1850}{900+550+400}$$
$$= \frac{5850}{1850} = 3.1622 \quad \text{Interruptions/Customers Interrupted}$$

11. $CEMI_n$ can be calculated as follows: Initially, calculate the number of customers experiencing multiple outages. For example, the expected number of customers experiencing more than 3 sustained outages in a year can be obtained from Table A3. as:

$CN_{(k>3)} = 400$ customers, corresponding to load point L3

Now, $CEMI_n$ can be calculated using:

$$CEMI_n = \frac{CN_{k>3}}{N_T} = \frac{400}{1850} = 0.2162$$

12. $CEMSMI_n$ can be calculated as follows: Initially, calculate the number of customers experiencing multiple outages. For example, the expected number of customers experiencing more than 3 sustained and momentary outages in a year can be obtained from Table 3. as:

$CN_{(k>3)} = 1850$ customers, corresponding to load points L1, L2 and L3.

Now, $CEMSMI_n$ can be calculated using:

$$CEMSMI_3 = \frac{CN_{k>3}}{N_T} = \frac{1850}{1850} = 1.0$$

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