Reliability Analysis of Power Systems Considering the Effect of Weather Variability

by

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AUTHOR'S DECLARATION

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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Abstract

The continuity of power supply is affected by numerous factors, one of which is related to the weather conditions to which power system components are exposed. Bad weather conditions have been noticed to be one of the major causes of failure for power system components. Moreover, the severity of weather conditions plays a considerable role in the determination of both commencement and duration of repair activity for failed components. Thus, the effect of weather on both component failure behaviour and repair process imperatively necessitates highlighting that effect on the reliability analysis and the developing of weather-based reliability assessment methodologies in order to help mitigate any associated risks in the short- and long-terms.

As a result, this thesis proposes a new weather-based reliability philosophy that is primarily concerned with studying the effect of weather on power system reliability through the introduction of a new reliability analysis approach called forecasted power system reliability analysis approach (FOPRA). Unlike the conventional reliability indices that are considered statistical quantities, reliability indices developed by the proposed FOPRA approach reflect the actual performance of the system. The FOPRA approach is comprised of two main concepts: 1) weather-based predictive reliability assessment method (PRAM); and 2) weather-based decision-making repair model (DMARM). The application of FOPRA approach on distribution systems is discussed in this thesis.

The PRAM method aims to develop a new weather-based methodology for predicting the performance of a distribution system in a short-term future study period by considering the effects of the weather. The methodology takes many factors into account, most important of which are historical weather-based performance of the system and possible future changes in weather patterns that may occur in a different manner from that of the past. Conventional component reliability indices, failure rate and repair time, are modified to represent the actual variations in component behaviour. A set of analytical equations and Monte Carlo Simulation algorithms are introduced.

The DMARM model, on the other hand, aims to develop a new methodical weather-based decision-making repair model for distribution system components. The proposed model investigates from a financial point of view the reliability improvement due to the reduction of the outage duration resulting from performing repair activities during bad weather for potential weather-related failures and then assigns repair tasks accordingly. The investigation process entails developing an

optimization problem to define the most cost-effective repair decision, where the genetic algorithm (GA) is utilized.

The proposed FOPRA approach is numerically illustrated using a typical distribution system. The results obtained demonstrate the significance of evaluating reliability indices and assigning repair activities according to the methodologies introduced in this thesis on the power system behaviour during bad weather conditions.

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Hani Aldhubaib
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Chapter 1
Introduction

1.1 Motivation

Providing power with a satisfactory level of reliability is an essential operational goal for utilities in today's competitive power market. The rapid increase in demand and globally noticeable change in weather conditions present a strong challenge to achieve this goal. Power system components are exposed to constantly changing weather conditions. Statistics show that some unfavourable weather conditions have considerably affected the overall reliability level of power system. This effect is attributed to the sharp increase of failure rate value during these unfavourable conditions as well as the longer period of outages usually associated with restoring weather-related failures. Most power system components operate outdoors and are exposed to a variety of weather conditions. The occurrence of these weather conditions are outside the control of utilities. Therefore, it is important to pay more attention to this issue and introduce new reliability evaluation techniques to incorporate the effect of weather on reliability assessment in order to mitigate its associated risk.

According to the author's best knowledge, most research on reliability in the literature focuses on measuring the historical performance of system components under different weather conditions. In fact, this practice is vital for the assessment purposes, yet it cannot be relied on to predict the reliability performance as this practice overlooks the possible variations of weather pattern in the future. Climate change plays a considerable role in changing weather patterns which makes predicting future changes in weather conditions difficult. Moreover, to the author's best knowledge, repair processes under unfavourable weather conditions have not received enough attention in the literature. Most research introduced general techniques to evaluate the repair time based upon weather conditions. Solely from a reliability perspective, components should be repaired as soon as they have failed; nevertheless, the case is completely different when the effect of bad weather exists, as the restoration process usually takes longer time because of the severity and risk associated with performing the repair in bad weather conditions. Regardless of the techniques introduced in the literature to evaluate the repair time considering the effect of weather, the essential question that has not been answered is: Should failed component be repaired as soon as it failed even if failure occurred in unfavourable weather or should the repair crew wait until weather improves? The answer of this question should be economically justified. Therefore, there is an imperative need to introduce a new weather-based reliability analysis approach which can respond to the ongoing changes in Earth's climate system and incorporate its effect into reliability assessment as well as develop a repair planning model that can determine the appropriate time to repair weather-related failed components in a cost-effective manner.

1.2 Research Objectives

The main objectives of this thesis are as follows:

- Development of a new weather-based predictive reliability assessment method that can predict the performance of a distribution system over an upcoming short-term study period in the future, taking into account the historical performance of the system in the past and the potential variation of the weather that may occur within a specific time period in the future. The achievement of this objective can offer utilities a good indication on how the system would behave in the future, which in turn, can help utilities make the appropriate necessary operational and planning decisions.

- Development of a new methodical weather-based decision-making repair model to determine the most cost-effective repair decision for distribution system components over an upcoming short-term study period. The developed model should investigate the cost-effectiveness of performing repair activities during bad weather conditions for system components taking into account the forecast of the weather during which the repair is performed as well as the reliability importance of the components to the whole system. In essence, this investigation would help utilities develop a weather-based crew dispatch management scheme that can enable utilities to optimally allocate repair resources in advance and can help define the optimal system reliability level that a utility should target.

1.3 Thesis Outline

This thesis is comprised of seven chapters. Chapter 1 is an introductory chapter presenting the motivation, main objectives, and organization of the thesis. The remaining chapters are organized as follows:

Chapter 2 introduces some background principles for reliability engineering. The evaluation methods used in reliability engineering to evaluate reliability indices for any engineering system are discussed firstly. Then, the applications of these techniques on power systems are presented.

Chapter 3 reviews the prominent research efforts in the literature to study the effect of weather on the reliability of power systems. The author categorized these efforts into two main investigations, the core research works of each are discussed in detail.

Chapter 4 introduces the new proposed weather-based reliability analysis approach which is called forecasted power systems reliability analysis (FOPRA) approach. FOPRA approach comprises two new concepts: 1) weather-based predictive reliability assessment method (PRAM) and; 2) weather-based decision-making repair model (DMARM). The methodologies of PRAM and DMARM are discussed in detail in Chapter 4 and Chapter 5 respectively.

Chapter 6 numerically illustrates the application of the proposed approach using a typical urban distribution system. A base case study is presented followed by a sensitivity analysis for two more case studies.

Chapter 7 concludes the thesis and presents the main contributions. In additions, some future research works are suggested.

1.4 Summary

This chapter is an introductory chapter for the thesis. The motivation for the research and the main objectives are pointed out, and the organization of the rest of thesis is outlined.

Chapter 2
Principles of Reliability

2.1 Introductory Background

Academics and reliability engineers have made great efforts to introduce a comprehensive definition to the term of reliability; however, a commonly accepted definition for reliability can be broadly stated as the probability of a component or system performing a required function for a given period of time (e.g., during a component's physical lifetime) under specific operating conditions (e.g., within a certain degree of temperature or level of voltage). Thus, the term of reliability can be used as a measure index of success for a component or system in fulfilling the intended function without failure [1]–[4].

Conducting reliability assessment for engineering systems is of vital significance to ensure designing, manufacturing, and operating the system in relatively free-from-failure state. The reliability assessment could be performed using two main assessment methods: qualitative and quantitative. The qualitative assessment is dependent on the subjective experience of reliability engineers. In this method of assessment, general engineering judgment is often utilized to determine whether a component is likely to fail or whether the system is reliable. The main drawback of this method is the lack of quantitative representation that numerically describes the failure likelihood of a component or the reliability level of a system under specific operating criteria. Moreover, the qualitative assessment is not appropriate and cannot help when comparing different operational alternatives or performing risk cost analysis, for instance. Therefore, a reliability assessment of engineering systems must be expressed in quantitative terms where reliability parameters are evaluated and measured on a numerical basis [5]–[7]. Quantitative assessment could be used for two main purposes:

- Assessment of past performance; and
- Prediction of future performance.

Assessment of past performance, referred to as historical assessment, measures the actual performance of the system during a specific time period in the past using appropriate sets of reliability indices. Historical assessment requires the collection and analysis of historical data (e.g., frequency of failures, duration of failures, and causes of failures) in order to perceive the past behaviour of the system. Historical assessment is important for the following reasons:

1. To identify the vulnerable and weak areas of the system that need improvement and reinforcement;
2. To serve as a guide to set a system reliability target for an acceptable threshold in future reliability assessment;
3. To compare previous prediction with actual system behaviour; and
4. To assess the response of the system to a reinforcement project.

The future performance of the system, on the other hand, can be measured by conducting a predictive assessment. Predictive assessment combines both historical assessment and mathematical models to predict the behaviour of the system during a time period in the future. Predictive assessment is important to predict the behaviour of the system in the future and to predict the response of the system to different alternative plans [5]–[8]. The vast majority of research work conducted on predictive reliability assessment in the literature involves three main steps, as follows [5]–[8]:

1. Evaluate historical reliability indices of the system.
2. Evaluate reliability indices of different alternative plans for the system. These alternative plans could be called reliability projects and may include, for example:
    - Alternative system configuration including reinforcement and expansion plans; and
    - Alternative system operational conditions and maintenance/repair activities.
3. Quantify the effect of reliability improvement for each project by conducting reliability cost/worth analysis to determine the most cost-effective project.

The quantitative historical and predictive reliability indices of any engineering system can be obtained either analytically using mathematical models or using Monte Carlo Simulation (MCS). In the analytical method, a mathematical model is typically developed to evaluate reliability indices whereas the reliability indices are estimated in the MCS by simulating the actual process and the random behaviour of the system [5], [9]–[13]. The main features of both analytical and MCS methods can be summarized as follows [5], [9], [12], [14]:

1. Numerical results obtained using analytical method are always the same for the same system, the same model, and the same input data; however, results obtained from simulation method are dependent on the random numbers generated as well as the stopping criteria considered.
2. Analytical method may necessitate simplifying large and complicated systems and approximating the results due to the difficulty of studying the whole system together whereas MCS has the

capability of simulating the actual process of the system and its components' random behaviour, which in turn better describes the system's behaviour.

3. Generally speaking, MCS may take a longer computing time to obtain the results compared to analytical methods. However, the ongoing development of computational facilities helps to relatively reduce the extensive computing time.
4. A wide range of output parameters can be obtained using MCS, including for example probability density functions and their respective parameters, whereas analytical method provides only average values.

2.2 Reliability Assessment of Engineering Systems

Engineering systems usually consist of a number of components installed to perform intended functions. Every single component is susceptible to experiencing a failure incident during its physical lifetime. Some components are non-repairable and should be replaced upon failure; most engineering system components are repairable where the process of repairing failed components usually directly follows the occurrence of failure. Therefore, two main states are typically associated with component operational behaviour: operating state "up" and failure state "down". Hence, two primary reliability indices can be introduced to quantitatively describe the transitions between these two states: failure rate and repair time. In this section, the analytical equations of evaluating these primary reliability indices for a single component are introduced followed by a discussion of the evaluation techniques used to evaluate the reliability indices of a complex system containing a group of components.

2.2.1 Reliability Indices of System Components

2.2.1.1 Failure Rate

The failure rate of a component can be defined as the number of failures per unit that the component experienced in a given time period, denoted as λ, and it can be found using the following equation:

$$\lambda = \frac{number\ of\ \ failures\ in\ a\ given\ period\ of\ time}{total\ operating\ time} \tag{2.1}$$

The failure rate is usually expressed by the number of failures per year for most reliability studies; nonetheless, the failure rate could be expressed over any given period of time. A component failure rate value changes over its physical lifetime; this change can be represented using the well-known concept of bathtub curve. The bathtub curve depicts the relationship between component failure rate and lifetime. The bathtub curve consists of three distinct periods: infant mortality period, useful life period, and wear-out period [15]. Fig. 2-1 shows a typical bathtub curve of an electrical power system component.

For the bathtub curve presented in Fig. 2-1, the infant mortality period represents the first and shortest lifetime period of a component. Although the component is still new during this period, the failure rate value during this period is relatively high due to the possibility of failure because of manufacturing defects, shipping damages, or incorrect installation. If the component survives this infant mortality period, it enters the useful life period where failure events may occur randomly and independently of age. The failure rate during this period can be modelled by a constant failure rate which usually follows the exponential probability distribution. The useful life period terminates once the component starts to wear out, at which point the number of failures increases as the component ages. During the wear-out period, the failure rate becomes dependent on age and it exponentially increases. It should be mentioned that most reliability studies, including the proposed approach of this thesis, deal with the useful life period. From now on, the failure rate term in this thesis will be generally referred to as the failure rate during the useful life period.

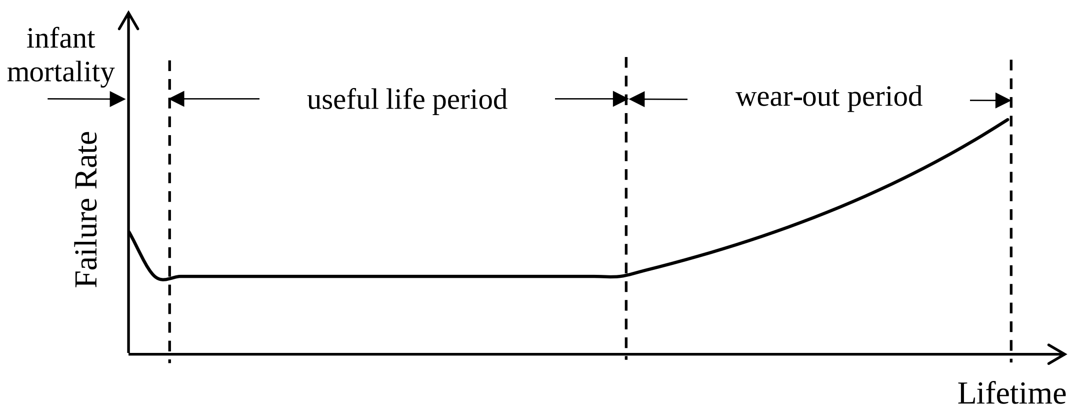


Fig. 2-1: Component Failure Rate vs. Lifetime

The reciprocal value of component failure rate is designated as component mean time to failure (MTTF). The term MTTF represents the average time for a failure to occur, and it is only applied to the useful life period when the failure rate is constant. Thus, the MTTF in hours for a component that has a failure rate λ expressed in failures per year can be found as:

$$MTTF = 8760 \times \frac{1}{\lambda} \tag{2.2}$$

2.2.1.2 Repair Time

The second primary component in the reliability indices is the repair time, denoted as *r* and usually expressed in hours. The repair time of a component is also known in most reliability references as mean time to repair (MTTR), which can be defined as the average time required for restoring the component from the failure state "down" to the operating state "up". The replacement time to install a new component can also be considered a repair time [8]. Therefore, the operational process of a component can be generally modelled using a chronological up-down-up operating cycle as shown in Fig. 2-2. When a component is installed in a system, it is expected to operate for time-to-failure (TTF_1) time units before it fails, is repaired for time-to-repair (TTR_1) time units, and is returned to operate for (TTF_2) time units, and so on. The summation of all TTF values represents component total operating time which can be substituted in equation (2.1).

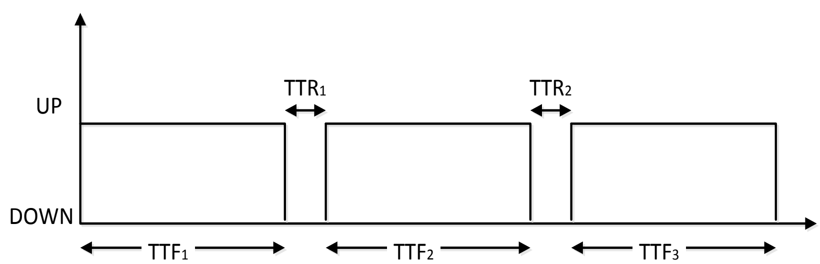


Fig. 2-2: Up-Down-Up Process of a Repairable Component

Thus, component repair time in hours can be evaluated as follows:

$$MTTR = \frac{total\ period\ of\ time\ the\ component\ was\ being\ repaired}{number\ of\ repairs\ in\ a\ given\ period\ of\ time} \tag{2.3}$$

The numerator of equation (2.3), total period of time the component was being repaired, signifies the summation of all TTR values. Similar to failure rate, a repair rate, μ, is the reciprocal of MTTR and is usually expressed in number of repairs per year. Thus, the repair rate in number of repairs per year for a component that has a MTTR expressed in hours is given by:

$$\mu = 8760 \times \frac{1}{MTTR} \tag{2.4}$$

2.2.1.3 Availability and Unavailability

In addition to failure rate and repair time, the percentage of time that the component was not operating (unavailable) can also be evaluated, which is referred to as unavailability and denoted as *U*. Thus, component unavailability is expressed as:

$$U = \frac{MTTR}{MTTF + MTTR} = \frac{\lambda}{\lambda + \mu} \tag{2.5}$$

The complement of component unavailability is availability, and it can also be evaluated as:

$$\overline{U} = \frac{MTTF}{MTTF + MTTR} = \frac{\mu}{\lambda + \mu} = 1 - U \tag{2.6}$$

The unavailability and availability equations of (2.5) and (2.6) represent probability values. The unavailability, *U*, can also be evaluated in terms of hours per year to express the average annual outage time, as follows:

$$U = \lambda \times r \tag{2.7}$$

It should be noted that the units of λ and *r* in equation (2.7) determine the unit of *U*. If λ and *r* have the same units of time, then the value of *U* is a probability value; however, if λ and *r* have different units of time, then the value of *U* is expressed in a unit associated with the units of λ and *r*. For example, if λ is expressed in failures per hour and *r* is expressed in hours, then the value of *U* represents component unavailability, i.e., a probability value; however, if λ and *r* are expressed in failures per year and hours respectively, then the value of *U* represents component annual outage time expressed in hours per year.

The values of component λ, *r*, and *U* are not deterministic values; they are average values of a probability density function (usually exponential distribution for useful life period) representing long-run average values [10].

2.2.2 Reliability Indices of Complex Engineering System

A complex system may be referred to as either a radial or a meshed system containing *NC* number of components. A system is said to be radial if it consists of a set of series components. The components in a set are considered series, from a reliability point of view, if all components are available and in an operating state for system success or if only one component needs to fail for system failure. On the other hand, a meshed system usually consists of a combination of series and parallel components. The components in a set are considered parallel if at least one must work for system success or if all must fail for system failure [7], [10].

The evaluation of reliability indices of complex systems necessitates finding the total equivalent reliability indices for the components that the complex system is made of. Many evaluation techniques can be used to evaluate reliability indices for complex systems, including Markov model and approximate equation techniques [7].

2.2.2.1 Markov Model

The transition between component operational states can be described by the Markov model, which is commonly used to describe the transitional process between states of a wide range of reliability problems [7]. In Markov model, the states in which the system can reside are represented by a so-called state space diagram. State space diagram is a descriptive construction of the possible transitions that occur between all possible states within the system despite system configuration. The state space diagram of a single component is shown in Fig. 2-3 where the component can either be in operating state (UP) or failure state (DOWN).

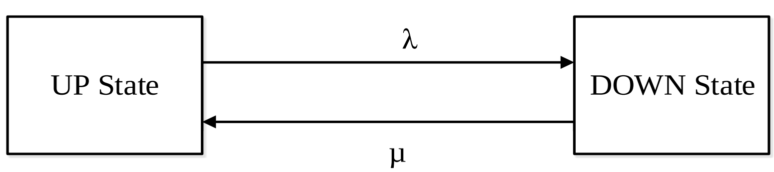


Fig. 2-3: State Space Diagram of Single Repairable Component

Where the failure rate, λ, and repair rate, μ, represent the transition rates between the states. The steady state probabilities of residing in a given state can be found as follows:

$$P_0 = \frac{\mu}{\lambda + \mu} \tag{2.8}$$

$$P_1 = \frac{\lambda}{\lambda + \mu} \tag{2.9}$$

Where P_0 represents the probability that a component is in the operating "up" state (availability) and P_1 represents the probability that a component is in the failed "down" state (unavailability). The MTTF and MTTR of a one-component system can be deduced using equations (2.2) and (2.4), respectively.

Markov model can be extended to any number of states as long as the transition rates between states are known. For instance, the state space diagram of a two-component repairable system can be illustrated as shown in Fig. 2-4.

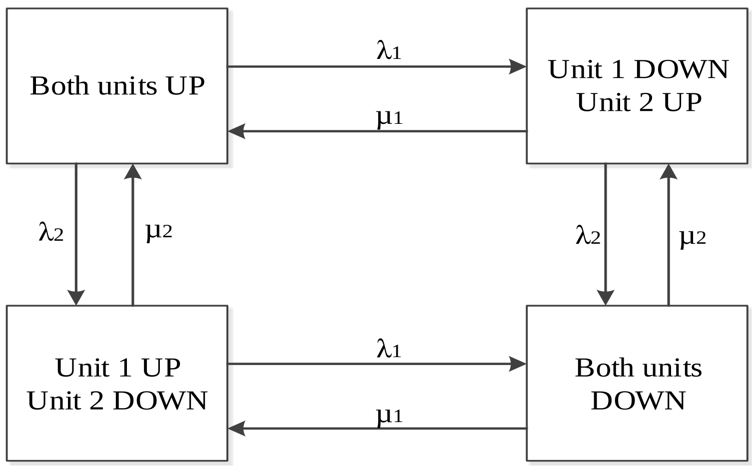


Fig. 2-4: State Space Diagram of Two-Component Repairable System

Where λ_k and μ_k are failure rate and repair rate of component k respectively. Given that the transition rates between the individual states are known, the system stochastic transitional probability matrix (STPM) can be constructed. The STPM is a matrix whose elements represent the transitional probabilities of the stochastic process. The STPM is used to deduce the steady state probabilities, overall system transition rates, and mean state durations of a multi-state system. More details about constructing the stochastic transitional probability matrix and deducing the relevant parameters can be found in [7]. Nevertheless, it should be noted that the process of obtaining the primary reliability indices (e.g. MTTF, MTTR, and U) for a multi-state system is not as straightforward as that of a single component system as it may involve complex mathematical analysis due to the increased number of states. Fig. 2-5 shows the state space diagram of a three-component system in which each component has two states, where U and D represent the "up" and "down" states respectively.

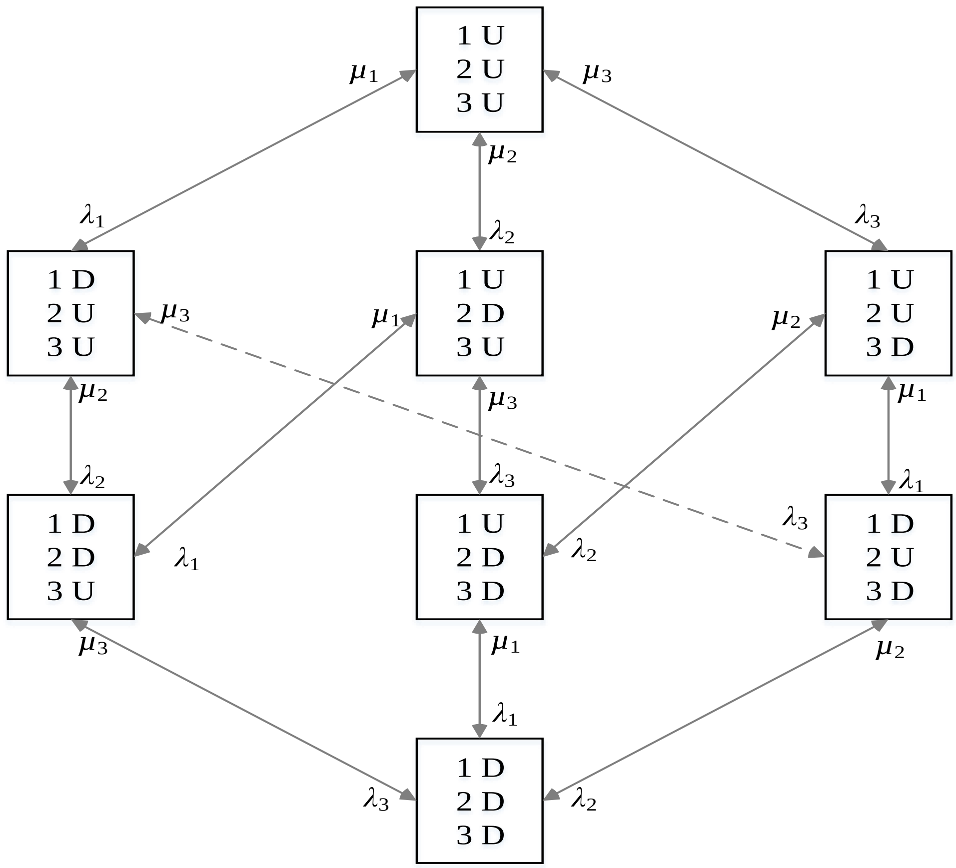
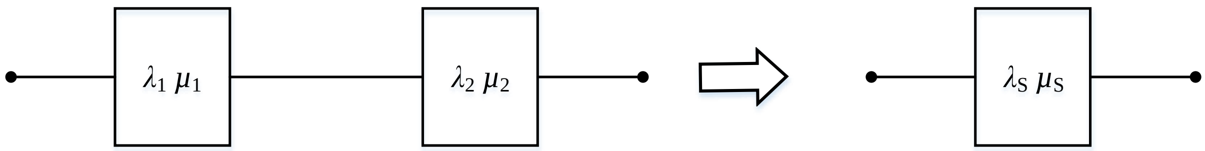


Fig. 2-5: State Space Diagram of a Three-Component Repairable System

It can be clearly shown from Fig. 2-4 and Fig. 2-5 that the more components that the system consists of, the more complicated and cumbersome the model becomes. Thus, the evaluation process of reliability indices for a complex system with a large number of components using Markov model would be unmanageable; therefore, further techniques are used to simplify the evaluation of reliability indices for such complex systems. As a result, approximate equation techniques have been introduced in the literature for this purpose [7]. The principles of these techniques are discussed in the following subsections. The application of these techniques on a distribution system are presented thereafter in Section 2.5.

2.2.2.2 Approximate Series Systems

Consider the system shown in Fig. 2-6 (a) with two components connected in series. These two components can be combined to give the equivalent component shown in Fig. 2-6 (b).



(a) Two Series-Component System (b) Equivalent System

Fig. 2-6: Representation of Two Components Connected in Series

Since the failure of any component would result in a failure of the whole system, the overall failure rate of the series system, λ_s, is equal to the summation of both component failure rates.

$$\lambda_s = \lambda_1 + \lambda_2 \tag{2.10}$$

Thus, a generalized formula for the overall failure rate of a system containing *NC* number of components connected in a series can be deduced as follows:

$$\lambda_s = \sum_{k=1}^{NC} \lambda_k \tag{2.11}$$

The repair time of the series system, r_s, can be approximated to:

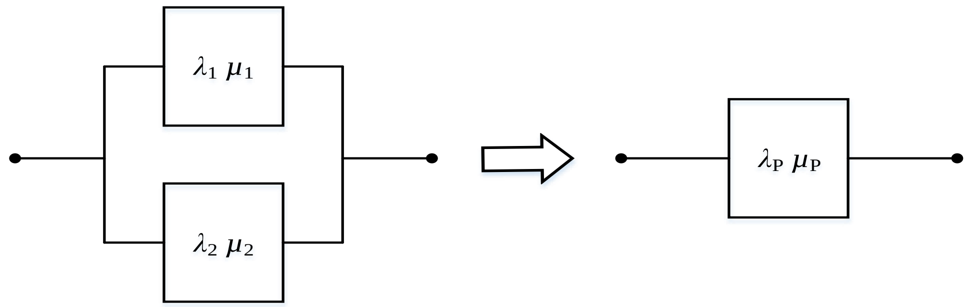
$$r_s = \frac{\sum_{k=1}^{NC} \lambda_k \times r_k}{\lambda_s} \tag{2.12}$$

The unavailability/annual outage time of the series system, U_s, can thus be found as follows:

$$U_s = \lambda_s \times r_s = \sum_{k=1}^{NC} \lambda_k \times r_k \tag{2.13}$$

2.2.2.3 Approximate Parallel Systems

The system shown in Fig. 2-7 (a) represents a two-component system whose components are connected in parallel.



(a) Two Parallel-Component System (b) Equivalent System

Fig. 2-7: Representation of Two Components Connected in Parallel

This system is considered to be in a failure state if both components are simultaneously found to be in a failure state for a certain period of time. The failure event caused by the failure of component 1 and component 2 is referred to as an overlapping failure event.

The equivalent system of the two parallel-component system is shown in Fig. 2-7 (b), where the overlapping failure rate, λ_p, and overlapping repair time, r_p, are given by:

$$\lambda_p = \lambda_1 \times \lambda_2 (r_1 + r_2) \tag{2.14}$$

$$r_p = \frac{r_1 \times r_2}{r_1 + r_2} \tag{2.15}$$

Similar to equation (2.13), the overlapping unavailability, U_p, of a system with two parallel components is:

$$U_p = \lambda_p \times r_p = \lambda_1 \times \lambda_2 \times r_1 \times r_2 \tag{2.16}$$

The overlapping failure rate, λ_p, overlapping repair time, r_p, and overlapping unavailability, U_p, of a system containing three components are given by equations (2.17), (2.18), and (2.19) respectively.

$$\lambda_p = \lambda_1 \times \lambda_2 \times \lambda_3 (r_1 \times r_2 + r_1 \times r_3 + r_2 \times r_3) \tag{2.17}$$

$$r_p = \frac{r_1 \times r_2 \times r_3}{r_1 \times r_2 + r_1 \times r_3 + r_2 \times r_3} \tag{2.18}$$

$$U_p = \lambda_p \times r_p = \lambda_1 \times \lambda_2 \times \lambda_3 \times r_1 \times r_2 \times r_3 \tag{2.19}$$

Unlike the equations of approximate series systems, the equations used to obtain reliability indices of parallel systems cannot be easily extended to a generalized formula with *NC* number of parallel components. Nevertheless, the overlapping reliability indices for a system with a large number of components connected in parallel can be evaluated by combining two components at a time using equations (2.14) to (2.16).

2.2.2.4 Approximate Series-Parallel System

Most systems consist of a combination of series and parallel components. Fig. 2-8 shows an example of a system containing a combination of series and parallel components.

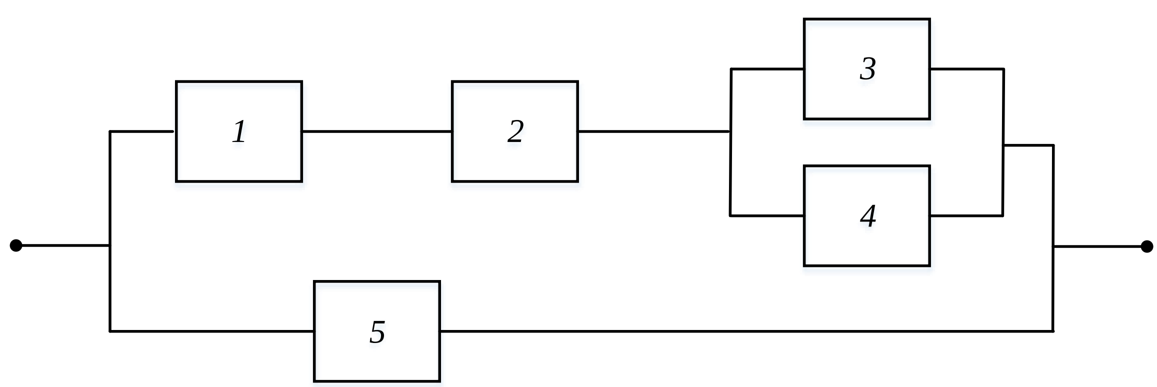
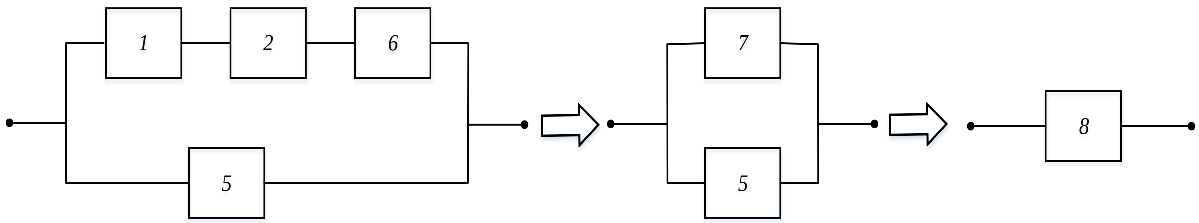


Fig. 2-8: Representation of Series-Parallel System

Several evaluation techniques can be used to obtain system reliability indices for series-parallel systems. The techniques most frequently used in most engineering reliability problems are network reduction technique and minimal cut set technique, both of which are discussed herein.

2.2.2.4.1 Network Reduction Technique

The principle of this technique is to reduce the complexity of the configuration by combining appropriate series and parallel components until an equivalent component is obtained, the reliability indices of which represent the equivalent reliability indices of the original configuration. For example, the reduction steps of Fig. 2-8 are shown in Fig. 2-9, where the process of deducing equivalent reliability indices starts by combining components 3 and 4, connected in parallel, to give equivalent component 6.



(a) First Reduction (b) Second Reduction (c) Third Reduction

Fig. 2-9: Reduction Process of Series-Parallel Systems Using Network Reduction Technique

Reliability indices of components 3 and 4 are substituted in equations (2.14) to (2.16) to obtain the reliability indices of equivalent component 6. Next, components 1 and 2 are combined with equivalent component 6, all of which are connected in series, using equations (2.11) to (2.13) to give equivalent component 7. Finally, equivalent component 7 is combined with component 5 using approximate parallel equations to give the system equivalent component 8. The reliability indices of equivalent component 8 represent system equivalent reliability indices.

2.2.2.4.2 Minimal Cut Set Technique

This technique aims to identify a number of minimal cut sets, each of which contains a set of system components that causes system failures when all of the components in the set fail. That is, a set of components is said to be a minimal cut set if all of its components must fail to cause system failure. The process starts by identifying all possible minimal cut sets in the system. After that, the appropriate series or parallel equations are used to obtain reliability indices for each minimal cut set. Then, the overall system reliability indices can be evaluated using equations (2.11) to (2.13). Referring to Fig. 2-8, three minimal cut sets can be easily identified: (1 and 5), (2 and 5), and (3 and 4 and 5). The first minimal cut set, for instance, signifies that the whole system will experience a failure if components 1 and 5 fail at the same time irrespective of the states of the other components. The equivalent reliability indices of the first cut set can be evaluated using equations (2.14) to (2.16) since components 1 and 5 are connected in parallel. The components of both second and third minimal cut sets are connected in parallel. Likewise, reliability indices of second and third minimal cut sets are evaluated. After that, equations (2.11) to (2.13) are used to evaluate system reliability indices using the reliability indices of each minimal cut set.

2.2.3 Illustrative Example

To numerically illustrate the process of evaluating reliability indices of a complex system, reconsider Fig. 2-8 to evaluate system reliability indices, given that all components have a failure rate value of λ = 0.05 f/yr and repair time of r = 20 h. The data of this example are obtained from [7].

A. Network Reduction Techniques

Following the process explained in Subsection 2.2.2.4.1, reliability indices of equivalent component 6 are:

$\lambda_6 = 0.05 \times 0.05(20+20)/8760 = 0.0000114$ f/yr;

$r_6 = \dfrac{20 \times 20}{20+20} = 10$ h.

The reliability indices of equivalent component 7 are:

$\lambda_7 = 0.05 + 0.05 + 0.0000114 = 0.10$ f/yr;

$r_7 = \dfrac{0.05 \times 20 + 0.05 \times 20 + 0.0000114 \times 10}{0.1} = 20$ h.

The reliability indices of equivalent component 8 which represent system indices are evaluated as follows:

$\lambda_8 = 0.05 \times 0.10(20+20)/8760 = 0.0000228$ f/yr and;

$r_8 = \dfrac{20 \times 20}{20+20} = 10$ h

$U_8 = 0.0000228 \times 10 = 0.000228$ h/yr.

B. Minimal Cut Set Technique

The process of identifying minimal cut sets and evaluating reliability indices for each minimal cut set is discussed in Subsection 2.2.2.4.2. The reliability indices of each minimal cut set and the system are tabulated in Table 2-1.

Table 2-1: System and minimal cut sets reliability indices

Cut set	λ (f/yr)	r (h)	U (h/yr)
1 and 5	0.0000114	10	0.000114
2 and 5	0.0000114	10	0.000114
3 and 4 and 5	1.95×10^{-9}	6.667	1.30×10^{-8}
System	0.0000228	10	0.000228

2.3 Reliability Assessment of Power Systems

The main function of a power system is to supply customers with electrical energy as economically as possible and with an acceptable degree of reliability. The assessment of power system reliability can be divided into two basic aspects of system adequacy and system security, as presented in Fig. 2-10.

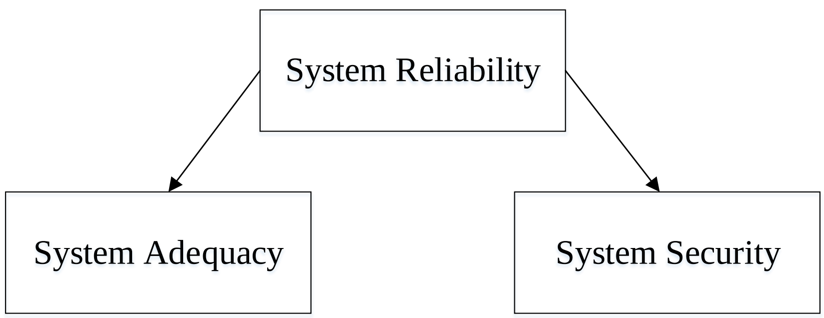


Fig. 2-10: Subdivisions of Power System Reliability

Adequacy relates to the existence of sufficient facilities within the system to satisfy load demand, including generation facilitates to generate sufficient energy as well as associated transmission and distribution facilities to transport the energy to the customers. Therefore, system dynamic and transient disturbances that may arise in the system are not involved under the assessment of adequacy. Security, on the other hand, relates to the ability of the system to respond to dynamic and transient disturbances arising within the system, including conditions associated with both local and widespread disturbances and the loss of major generation and/or transmission facilities that may lead to dynamic, transient, or voltage instability of the system. However, most reliability assessment work focuses on the assessment of system adequacy [9], [12].

2.4 Functional Zones and Hierarchical Levels of Power System

A power system can be divided into three main functional zones: generation, transmission, and distribution. For reliability adequacy assessments, these zones can be illustrated in hierarchical levels (HL) as depicted in Fig. 2-11. The reliability assessment at the first hierarchical level (HL1) is concerned only with generation facilities whereas at the second hierarchical level (HL2) the reliability assessment is concerned with both generation and transmission facilities. In addition to the generation and transmission facilities, the distribution facilities are included in the reliability assessment at the third hierarchical level (HL3). Nevertheless, it is not easy to conduct a reliability assessment for the complete system at HL3; instead, reliability assessment is performed at HL3 for the distribution zone only using the indices of HL2 as input data [10], [12].

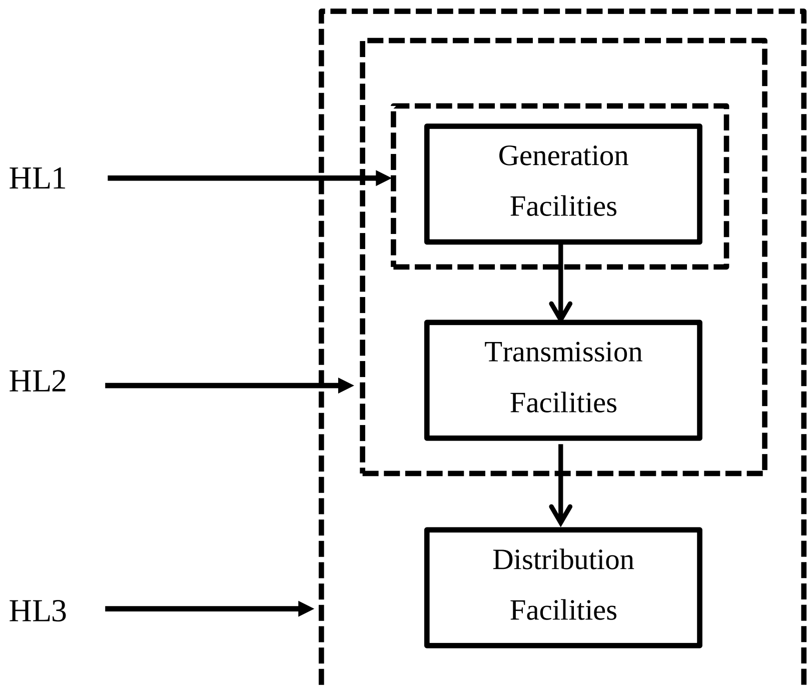


Fig. 2-11: Power System Hierarchical Levels

In the first hierarchical level (HL1), an adequacy assessment is performed to examine generation system adequacy to meet the required load demand which is quite important in power system planning-related studies. This adequacy assessment is referred to as the generation capacity reliability assessment, with the main objective to estimate the necessary generating capacity required to supply the load demand and to examine the system adequacy upon the unavailability of generation facilities due to taking the generating facilities out of service for planned maintenance activities or unplanned forced failures. The reliability assessment of the transmission system is not involved at HL1; hence, the generation-load model illustrated in Fig. 2-12 is typically used as a system model at HL1. The generation system in Fig. 2-12 represents the total available generation capacity while the total load demand is represented by the total system load. From a reliability perspective, the generation system should have a capacity reserve exceeding the required load demand.

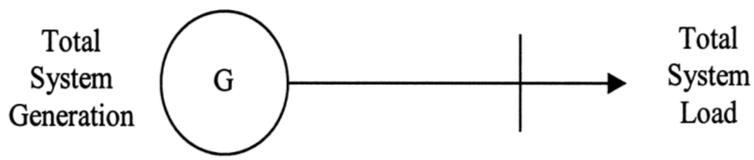


Fig. 2-12: Hierarchical Level HL 1 Model

The adequacy of the generation system to meet the total load requirement can be expressed by using some expectation risk indices such as loss of load expectation (LOLE) and loss of energy expectation (LOEE). The adequacy assessment at HL1 consists of three main parts: generation model, load model, and risk model as shown in Fig. 2-13.

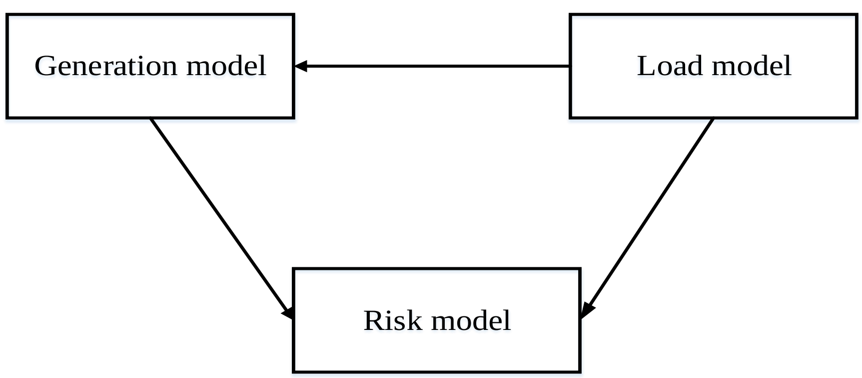


Fig. 2-13: A Conceptual Illustration of the Reliability Assessment Tasks at HL1

The generation model can be formed by creating a capacity outage probability table (COPT). The COPT represents all possible capacity outage states of the generation system and the associated probability of each state. The load model can be represented by different models such as the daily peak load variation curve (DPLVC) or the load duration curve (LDC). The DPLVC contains the peak loads of each day whereas the LDC represents the hourly variation of the load. The generation and load models are combined to form the risk model, which is represented by a set of risk indices calculated using generation and load models. The DPLVC is utilized to calculate the LOLE while the LDC is utilized to calculate the LOEE [9]–[12].

In the second hierarchical level (HL2), the generation-load model shown in Fig. 2-12 is extended to include a transmission system. The main function of the transmission system is to transport generated energy to specific geographical areas at HL3. The adequacy assessment at HL2 is referred to as a composite system assessment, in which the primary aim is to assess the adequacy of an existing or proposed system by examining the effect of several reinforcement alternatives for both generation and transmission systems. A sample composite system is shown in Fig 2-14.

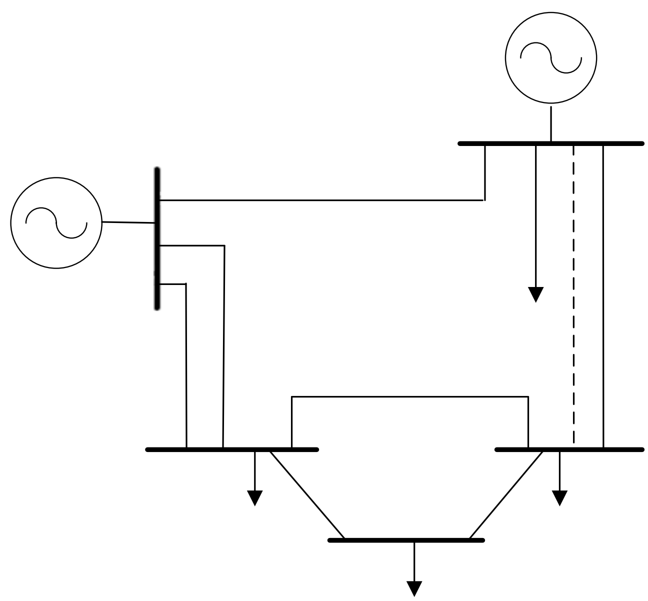


Fig. 2-14: A Sample Composite System

The adequacy assessment at HL2 is assessed by evaluating two sets of complementary indices: load-point indices and overall system indices. The load point indices assess the effect of reinforcement alternatives at each load point in the system and provide input values for system indices [9]–[12].

The third hierarchical level (HL3) involves all power system facilities starting from generation units and ending at individual customers. However, due to the complexity of evaluating the adequacy of all hierarchical levels together, only the adequacy assessment of the distribution system is performed at HL3 using the load-point indices obtained from HL2 as input values. The distribution system mainly distributes the energy to individual consumers within a specific geographical area. There are two basic configurations for conventional distribution systems: radial or meshed [9]–[12]. Based on the configuration of the distribution system, the approximate evaluation techniques introduced in Section 2.2.2 can be used to obtain load-point distribution reliability indices. More details about the reliability assessment of the distribution system are discussed in the following section.

2.5 Reliability Assessment of Distribution Systems

Distribution system is quite important in power grid as it represents the final link between the bulk power system and customers. Unlike generation and transmission systems where the reliability assessment is usually system-oriented, the reliability assessment of a distribution system is customer-oriented. Many studies in the literature have reported that more than 80 per cent of all customer interruptions occurred because of failures in distribution system components due to the radiality of structure associated with most distribution circuits [16].

In terms of system construction, a conventional distribution system could be considered either radial or meshed based on the way that the distribution system components are arranged. A radial distribution system consists of a set of series components between the supply point and a customer. On the other hand, a meshed distribution system usually consists of a combination of series and parallel components [7], [10]. The reliability assessment of a distribution system starts by evaluating the primary reliability indices for each component in the distribution system. Then, component reliability indices are used to evaluate load-point indices which in turn are used as input data to evaluate the overall reliability indices of the distribution system.

2.5.1 Component Primary Reliability Indices

The same equations introduced in Section 2.2.1 for engineering system components are used to evaluate the primary reliability indices of distribution system components. Distribution system components may include lines, cables, disconnects, isolators, transformers, busbars, etc.

2.5.2 Load-Point Reliability Indices

A conventional distribution system usually consists of a distribution substation supplying one or more distribution feeders. Customers (loads) could be supplied directly from a feeder or through laterals that are branched from one of the feeders. Reliability data of customers supplied from the same feeder or lateral are analyzed together as one load point, taking into account the number of customers for each load type at every load point (e.g., percentage of residential customers in comparison to the whole number of customers). Similar to component reliability indices, three basic reliability indices can be evaluated for each load point: load-point failure rate (λ_L), load-point repair time (r_L), and load-point outage time (U_L). Based on the configuration of the distribution system (i.e., radial or meshed), these load-point indices can be evaluated using the evaluation techniques of complex engineering systems discussed in Section 2.2.2. The protection scheme of the system plays an important role in the evaluation of load point indices. The processes of evaluating load-point indices for both radial and meshed distribution systems are discussed in the subsequent subsections using typical distribution systems.

2.5.2.1 Radial Distribution System

As pointed out previously, a radial distribution system usually consists of a set of series components. Load-point indices, consequently, can be evaluated using the approximate series systems technique discussed in Subsection 2.2.2.2. Consider the simple radial distribution system shown in Fig. 2-15. The main feeder of the distribution system has three sections (sections 1, 2, 3) feeding three load points (loads A, B, C). Feeder sections are referred to as distribution system components. Any short circuit on the feeder will cause the main breaker installed at section 1 to immediately open; however, if the faulted point is located at sections 2 or 3, then the relevant Normally Closed (N.C.) disconnect will open, thereby allowing the main breaker to re-close. The average time of switching and isolation is 60 minutes.

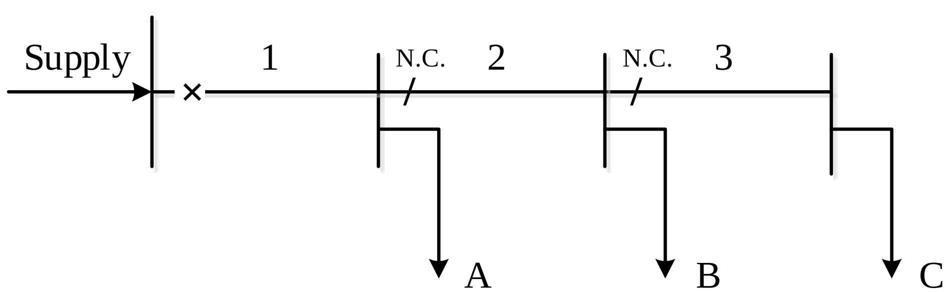


Fig. 2-15: Simple Radial Distribution System

For the sake of illustration, all distribution system components are assumed to have the same failure rate and repair time values of λ = 0.5 f/yr; and r = 4 h respectively. Table 2-2 shows a detailed evaluation of load-point indices using the principles of series systems.

Table 2-2: Reliability load-point indices

Component failure	Load A			Load B			Load C		
	λ (f/yr)	r (h)	U (h/yr)	λ (f/yr)	r (h)	U (h/yr)	λ (f/yr)	r (h)	U (h/yr)
1	0.5	4	2	0.5	4	2	0.5	4	2
2	0.5	1	0.5	0.5	4	2	0.5	4	2
3	0.5	1	0.5	0.5	1	0.5	0.5	4	2
Total	1.5	2	3	1.5	3	4.5	1.5	4	6

2.5.2.2 Meshed Distribution System

The second common configuration of conventional distribution systems is meshed network, which usually consists of a combination of series and parallel components. Fig. 2-16 shows a typical meshed network with two lines (C1 and C2) and two transformers (C3 and C4) feeding one load point. The network of Fig. 2-16 could be a part of a distribution system containing one or more radial and/or meshed networks. The reliability data of Fig. 2-16 components are shown in Table 2-3.

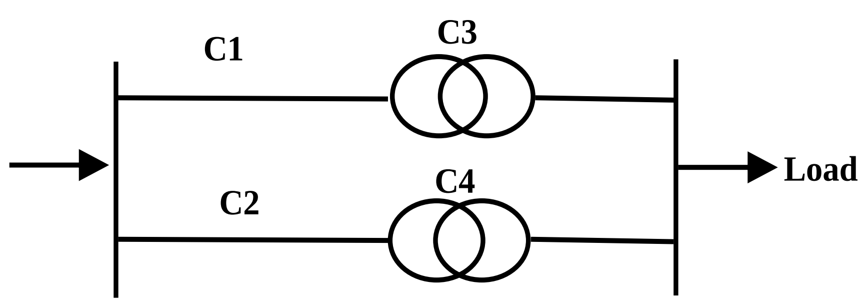


Fig. 2-16: **A Typical Meshed Network**

Table 2-3: Component reliability data

Component	λ (f/yr)	r (h)
C1, C2	0.5	4
C3, C4	0.015	11

The network reduction technique or minimal cut set technique can be used to evaluate load-point indices. Components C1 and C3 are connected in series; and components C2 and C4 are connected in series as well. Thus, using the network reduction technique, components C1 and C3 can be combined to give equivalent component C5; similarly, components C2 and C4 are combined to give equivalent C6. The failure event caused by equivalent components C5 and C6 represents an overlapping failure event. Combining equivalent components C5 and C6 in parallel gives equivalent component C7, the λ, r, and U of which represent the load-point indices. These indices are tabulated in Table 2-4.

Table 2-4: Reliability indices of equivalent components

Component	λ (f/yr)	r (h)	U (h/yr)
C5, C6	0.515	4.2	2.165
C7	0.000255	2.1	0.000535

Similarly, the minimal cut set can be used to evaluate the load-point indices of Fig. 2-16. The process of identifying the minimal cut sets of a network is discussed in Section 2.2.2.4.2. Table 2-5 shows the minimal cut sets of the network and the respective indices.

Table 2-5: System and minimal cut sets reliability indices

Cut set	λ (f/yr)	r (h)	U (h/yr)
C1 and C2	0.000228	2	0.000457
C1 and C4	0.000013	2.93	0.000038
C3 and C2	0.000013	2.93	0.000038
C3 and C4	5.65×10^{-7}	5.5	0.000003
System	0.000255	2.1	0.000535

2.5.3 Distribution System Reliability Indices

Load-point reliability indices are essential to evaluate the reliability of the distribution system at each load point in the distribution system. However, these indices are system-oriented and cannot reflect system behaviour in terms of customer effect. Therefore, additional customer-oriented indices are required to enrich the reliability evaluation of a distribution system by taking into account further considerations including, for instance, the number of customers connected to every load point and their average load demand. The most commonly used distribution reliability indices that can be used are defined and calculated as follows [10]:

- System average interruption frequency index, SAIFI (interruption/customer yr);
- System average interruption duration index, SAIDI (h/customer yr);
- Customer average interruption duration index, CAIDI (h/customer interruption);
- Energy not supplied index, ENS (kWh/yr).

$$SAIFI = \frac{\sum_{j=1}^{NP} \lambda_j \times N_j}{\sum_{j=1}^{NP} N_j} \tag{2.20}$$

$$SAIDI = \frac{\sum_{j=1}^{NP} U_j \times N_j}{\sum_{j=1}^{NP} N_j} \tag{2.21}$$

$$CAIDI = \frac{SAIDI}{SAIFI} = \frac{\sum_{j=1}^{NP} U_j \times N_j}{\sum_{j=1}^{NP} \lambda_j \times N_j} \tag{2.22}$$

$$ENS = \sum_{j=1}^{NP} U_j \times L_j \tag{2.23}$$

Where

λ_j Failure rate for load point *j* (f/yr);

N_j Number of customers connected to load point *j*;

NP Number of load points in the distribution system;

U_j Annual outage time for load point *j* (h/yr); and

L_j Average load connected to load point *j* (kW).

The unavailability of the system can be measured based on the average service unavailability index (ASUI), as follows:

$$ASUI = \frac{\sum_{j=1}^{NP} U_j \times N_j}{\sum_{j=1}^{NP} N_j \times 8760} = \frac{SAIDI}{8760} \tag{2.24}$$

The complement of ASUI, the average service availability index (ASAI), is given by:

$$ASAI = \frac{\sum_{j=1}^{NP} N_j \times 8760 - \sum_{j=1}^{NP} U_j \times N_j}{\sum_{j=1}^{NP} N_j \times 8760} = 1 - ASUI \tag{2.25}$$

To numerically illustrate the evaluation of customer-oriented indices, reconsider the radial distribution system shown in Fig. 2-15 with customer data presented in Table 2-6.

Table 2-6: Customer data

Load point	Number of customers	Average load (kW)
A	500	2000
B	300	1100
C	200	800
Total	1000	3900

The customer-oriented distribution system indices are evaluated using equations (2.20) to (2.25) and shown in Table 2-7.

Table 2-7: Customer-oriented reliability indices

SAIFI (interruption/customer yr)	SAIDI (h/customer yr)	CAIDI (h/customer interruption)
1.5	4.05	2.7
ASUI	ASAI	ENS (kWh/yr)
0.000462329	0.999537671	15750

2.6 Summary

Reliability is introduced in this chapter as an important engineering term used to measure the success of an engineering system to perform the task it has been designed to do. The term engineering reliability is broadly defined. Then, the importance of conducting reliability assessment for engineering systems and the main assessment methods are addressed. The commonly used reliability indices used to assess the reliability of engineering systems are outlined. A general discussion follows about the functional zones of power system and the methodology to conduct reliability assessment at each zone. Since the focus of this thesis is on the distribution system, the reliability assessment in the distribution system is discussed in detail.

Chapter 3

Inclusion of Weather Effect on Power System Reliability: A Literature Review

3.1 Introduction

Providing customers with a satisfactory level of power continuity has been a primary goal for electric utilities in the deregulated and competitive environment of today's power industry. The achievement of this goal necessitates assuring that power system is designed and operated within an adequate and acceptable level of reliability; however, a variety of conditions and challenges hinders achieving this noble goal including bad weather. Although the probability of the occurrence of most bad weather events is generally low compared to that of prevailing normal weather conditions, such weather events have been observed to have a profound impact on the reliability of power grid. Several statistics clearly show that power system as a whole is vulnerable to the effects of unfavourable weather. For example, SaskPower, the electric utility that serves the Canadian province of Saskatchewan, has revealed that 31 per cent of the forced outages that occurred between 2013 and 2017 were caused by bad weather [17]. In the United States, between 2003 and 2012 bad weather was responsible for approximately 80 per cent of all power outages in the country, affecting more than 147 million customers [18]. Furthermore, the ongoing changes in Earth's climate system are projected to worsen in the future [19]–[21], potentially aggravating the effect of weather on many sectors, including the electricity sector. Consequently, researchers have realized the imperative need to highlight the effect of weather on reliability. The effect of weather should be incorporated into reliability assessment in order to mitigate the associated risk through both operational and development planning. Numerous studies published in the literature have devoted significant effort to discussing the effect of weather on power system reliability; these efforts can be categorized into two main weather-based reliability-centred investigations:

1. Investigate the weather-based failure behaviour of power system components upon exposure to different weather conditions and the associated consequences affecting the reliability level of the system; and
2. Investigate the weather-based repair process for failed power system components, specifically the commencement and duration of performing repair activity.

This chapter discusses firstly the modelling of weather states in the context of reliability. Secondly, a general discussion is presented about how the exposure to varying weather conditions may affect component failure rate and repair time. Thirdly, this chapter presents an overview of the most prominent research efforts which have tackled the main weather-based reliability-centred investigations. Finally, this chapter concludes by highlighting the main drawbacks and limitations of the core weather-based reliability studies in the literature.

3.2 Weather State Modelling

The first step to studying the effect of weather on power system reliability is to define and classify the states of weather in terms of their effect on the continuity of power. Consequently, weather conditions can be generally divided into three states: normal, adverse, and major storm disaster [22].

Normal weather includes all weather conditions not designated as adverse or major storm disaster [22].

> Adverse weather is defined as weather condition which causes an abnormally high rate of forced outages for exposed components during the periods that such conditions persist, but do not qualify as major storm disasters. Adverse weather conditions can be defined for a particular system by selecting the proper values and combinations of weather conditions reported: thunderstorms, tornadoes, wind velocities, precipitation, temperature, and so on [22].

Major storm disaster is designated in [22] as weather conditions which produce stresses in the electric component that exceed its design limits and satisfy all of the following:

- Extensive mechanical damage to facilities;
- More than a pre-set specified percentage of customers out of service; and
- Service restoration time longer than a pre-set specified duration.

It should be noted that this classification is general and can be modified according to each utility’s environmental circumstances. Reference [23] shows different types of weather state modelling where weather conditions are modelled in two-, three-, and multi-weather states. Weather classification is dependent on its effect on component failure rate [10].

Chronological variation of a three-state weather model is depicted in Fig. 3-1. However, adverse and major adverse can be merged into one bad weather state, which is commonly considered for most weather-based reliability analyses.

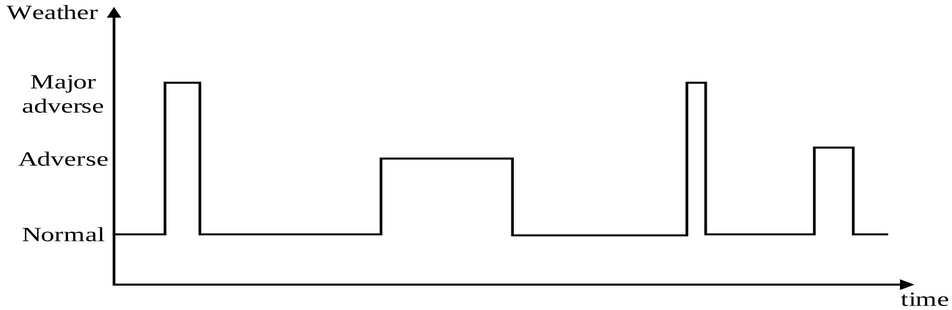


Fig. 3-1: Chronological Variation of Weather States

The transitions between weather states can be represented using Markov model [24], [25]. The principle of Markov model is discussed in Section 2.2.2 to describe the transitions between component operational states. However, Markov model can also be used to describe the transitions between weather states using the same logic. For example, a weather model with three states – normal, adverse, and major adverse – is shown in Fig. 3-2.

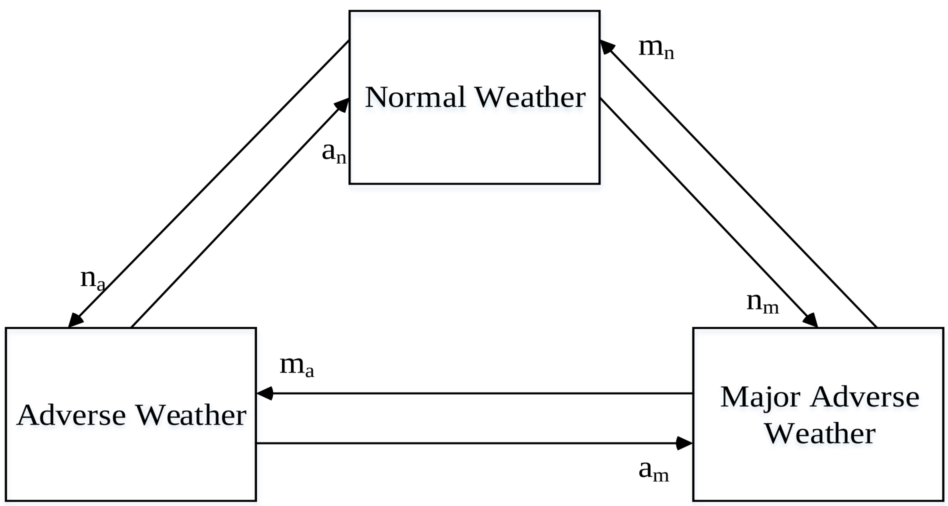


Fig. 3-2: Three-State Weather Model

Where

a_n Transition rate from adverse weather state to normal weather state;
n_a Transition rate from normal weather state to adverse weather state;
m_a Transition rate from major adverse weather state to adverse weather state;
a_m Transition rate from adverse weather state to major adverse weather state;
n_m Transition rate from normal weather state to major adverse weather state; and
m_n Transition rate from major adverse weather state to normal weather state.

The mean durations of individual states are the average durations of normal weather state (T_N), the average durations of adverse weather state (T_A), and the average durations of major adverse weather state (T_{MA}). These average values can be evaluated as follows [24], [25]:

$$T_N = \frac{1}{n_a + n_m} \tag{3.1}$$

$$T_A = \frac{1}{a_n + a_m} \tag{3.2}$$

$$T_{MA} = \frac{1}{m_a + m_n} \tag{3.3}$$

The steady state probabilities of residing at normal, adverse, and major adverse weather states are P_N, P_A, and P_{MA} respectively. In other words, P_N, P_A, and P_{MA} represent the probabilities of having normal, adverse, and major adverse weather states respectively [24], [25].

$$P_N = \frac{m_a\, a_n + m_n\, a_n + m_n\, a_m}{D} \tag{3.4}$$

$$P_A = \frac{m_a\, n_a + m_a\, n_m + m_n\, n_a}{D} \tag{3.5}$$

$$P_{MA} = \frac{n_a\, a_m + n_m\, a_n + n_m\, a_m}{D} \tag{3.6}$$

$$D = m_a\, n_a + m_a\, n_m + m_a\, a_n + n_a\, a_m + n_m\, a_n + n_m\, a_m + m_n\, a_n + m_n\, a_m + m_n\, n_a \tag{3.7}$$

Similarly, the state space diagram of a two-state weather model is shown in Fig. 3-3. The relevant probabilities and average durations are evaluated using equations (3.8) – (3.11).

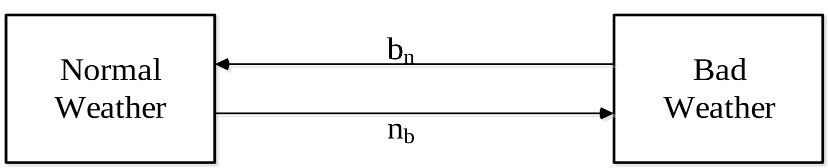


Fig. 3-3: Two-State Weather Model

$$T_N = \frac{1}{n_b} \tag{3.8}$$

$$T_B = \frac{1}{b_n} \tag{3.9}$$

$$P_N = \frac{b_n}{b_n + n_b} = \frac{T_N}{T_N + T_B} \tag{3.10}$$

$$P_B = \frac{n_b}{b_n + n_b} = \frac{T_B}{T_N + T_B} \tag{3.11}$$

Where

n_b Transition rate from normal weather state to bad weather state;
T_B Average duration of bad weather state;
b_n Transition rate from bad weather state to normal weather state; and
P_B Probability of bad weather state.

3.3 The Effect of Weather on Component Failure Rate and Repair Time

The failure behaviour and repair process of power system components are affected by the weather condition to which the component is exposed. Regarding the failure behaviour, outdoor components are usually exposed to a wide range of weather conditions and are more likely to experience a failure event when operating in bad weather conditions compared to components that operate in favourable weather conditions. During some unfavourable weather conditions, the failure rate value of certain components significantly increases and thus the probability of failure accordingly increases [10], [26], [27]. Therefore, the effect of weather should be demonstrated by incorporating weather effect in component failure rate calculations.

To demonstrate the effect of weather, the failure rate should be evaluated as the average number of failures per weather state instead of the commonly used method that expresses the failure rate as the average number of failures per calendar year. In fact, such a demonstration will guarantee manifesting the contribution of weather to the failure rate value. Nevertheless, expressing failure rate in terms of weather state requires identifying the appropriate and sufficient environmental and relevant failure data. That is, utilities should allocate failure events to their own weather state classification as well as identify the starting and finishing times of each weather state even if no failure event has occurred

[10]. Nonetheless, practically speaking, most utilities used the total average number of failures per calendar year in their reliability studies and overlooked recognizing the failure rate in terms of weather state [10]. Indeed, this practice could be due to two main reasons:

1. Bad weather events add only a small contribution to the total average failure rate. Bad weather is generally brief in duration and infrequent in occurrence, which make its probability of occurrence low compared to the probability of occurrence of normal weather. This concept can be elucidated using the principle of expected value, in which the average failure rate considering the relation of weather states can be generally given by:

$$\lambda_{avg} = \sum_{all\,w} \lambda_w \times P_w \tag{3.12}$$

Where

λ_{avg} Component average failure rate per calendar year;
λ_w Component average failure rate per year of weather state *w*; and
P_w Probability of weather state *w*.

It can be seen from equation (3.12) that the total average failure rate is dependent on the value of the failure rate during a particular weather state and the associated probability of having that particular weather sate. Although the failure rate in bad weather is much greater than that in normal weather, the low probability of occurrence of bad weather makes the contribution of bad weather events to the average failure rate value relatively small and hence makes the failure rate value in normal weather very close to the total average failure rate. An illustration of the relationship between average failure rate and failure rate values in normal and bad weather is shown in Fig. 3-4 for a two–state weather model [10].

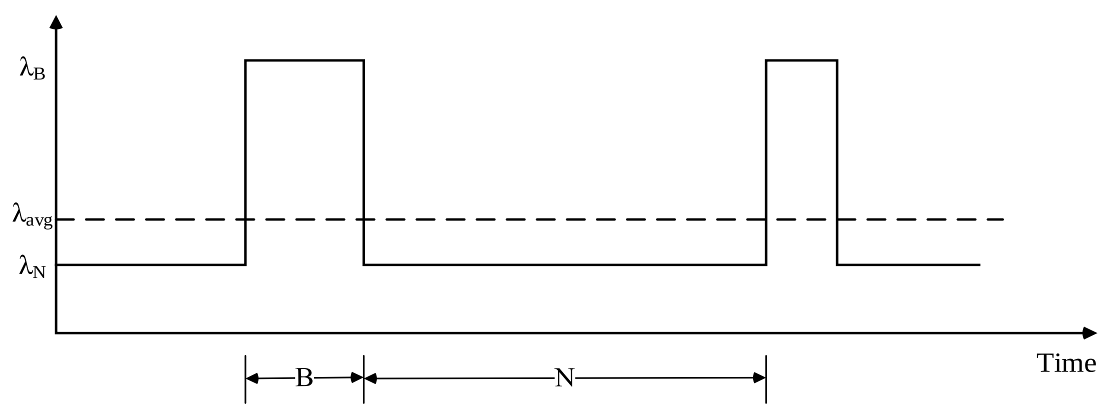


Fig. 3-4: Failure Rate Profile

Where, λ_N and λ_B represent failure rates in normal (N) and bad (B) weather conditions respectively.

It can be noticed from Fig. 3-4 that the value of failure rate in bad weather is much higher than that in normal weather although bad weather duration is shorter and less frequent. This high value of failure rate sharply increases the probability of component failure during this period, especially for overlapping failures of multiple components. Therefore, evaluating the failure rate as the number of failures per weather state instead of merely considering the average failure rate value is vital to manifest the effect of weather on component reliability indices. In addition, average failure rate cannot give an accurate representation of the actual performance of the component during a specific weather condition as it is a statistical quantity that gives the average failure performance of a component irrespective of the weather conditions to which the component was exposed [10].

2. There is difficulty associated with collecting sufficient failure data in bad weather conditions. Normal weather is the prevailing weather condition and the proportion of failures occurring during its duration is usually less than the proportion of failures occurring in bad weather, thus recognizing that the failure rate value in normal weather is simple and straightforward. However, the failure rate value in bad weather is challenging in most cases as several historical operating cycles in bad weather states may be required to recognize the failure rate value in bad weather [10].

With regards to the repair process, the effect of weather is not limited to the failure behaviour of power system components but also includes the repair process. The condition of weather while repair activity is performed plays an important role in determining the actual duration of restoring failed components. In some bad weather conditions, the repair process may take longer than it usually takes in prevailing favourable weather conditions. Therefore, the effect of weather on the repair process should be incorporated in repair time calculations.

3.4 Overview of Weather-based Reliability-centred Investigations in the Literature

3.4.1 Investigation 1: Failure Behaviour

The significance of recognizing the component failure rate in terms of the weather condition instead of the widely used average failure rate is highly emphasized in [10]. The average failure rate is a statistical quantity obtained by using historical failure data regardless of the failure causes; hence, the average failure rate does not represent the real behaviour of the component during specific weather conditions. Therefore, much of the work reported in the literature has been directed at tackling the impact of weather on component failure behaviour through the introduction of methodologies for incorporating its effect into failure rate calculations [10], [23]–[25], [28]–[36]. The approximate equation technique and the Markov model [7] were used in [10], [23]–[25], [31], [32] as a means of evaluating the overall system failure rate while taking into account the phenomenon of failure bunching (overlapping failure) due to the effect of bad weather on parallel redundant components. Researchers have derived a set of approximate equations for assessing the failure rate for a two-state weather model, as presented in [10], and for a three-state weather model, as explained in [24]. In [23]–[25] and [31], the Markov model was employed for illustrating the impact of weather on system components for different weather states; this method was combined with the effect of a common mode failure event in [32]. The primary method reported in [10], [23]–[25], [31], and [32] is the probability of the occurrence of normal and bad weather states as a means for incorporating weather effects into failure rate equations. The concept of a weather-based time-varying failure rate was introduced in [33] and further developed by the authors of [34] and [35]. The weather-related failure rate of overhead lines has been modelled using Poisson regression and Bayesian network models, as described in [36], and has been based on a fuzzy model of weather conditions, as presented in [28]. The effects of weather and the inherent aging of the components have been considered together for the modelling of the failure rate introduced in [29] and [30].

To assess the reliability performance of transmission and distribution systems, other reliability evaluation approaches have been introduced with the goal of incorporating the effects of weather into system reliability indices [37]–[41]. From the perspective of reliability worth, the authors of [37] discussed the impact of failures caused by bad weather with respect to the well-being of a subtransmission system. In the work presented in [38]–[41], the effect of weather was incorporated into customer-orientated distribution reliability indices in order to assess the reliability performance of a variety of distribution system configurations. The researchers of [42] and [43] introduced a method that can include the effects of weather in the evaluation of composite system adequacy when transmission lines traverse several geographical regions and are exposed to different weather conditions.

Several studies have discussed measuring the effects of weather conditions on system reliability performance to find a correlation between the occurrence of particular weather conditions and the level of reliability in regional systems. Examples of this work include examinations of the effects of lightning on transmission lines in Croatia, Bosnia, and Herzegovina [44]; of storms on the Kansas City Power and Light system in Missouri [45]; of temperature and relative humidity on the Bangladesh power system [46]; and of snowfall on central areas of the United States [47]. Some researchers have investigated the effect of a variety of specific weather variables on the reliability of a particular system [48]–[50]. Reference [48] investigated the statistical relationship between some weather variables (lightning, wind, temperature, and rainfall) and system outages for a utility in South-East Queensland in Australia. The correlations between rainfall, relative humidity, wind speed, and protection trips of transmission lines in southern Brazil were studied in [49]. In Florida, a higher degree of correlation was observed between outages and lightning than between outages and either wind speed or precipitation [50]. Another report [51] compared the effects of lightning on system reliability for three different systems: the Detroit Edison system, the Carolina Power and Light system, and the Florida Power system.

3.4.2 Investigation 2: Repair Process

Timely restoration of failed components is a fundamental and essential activity to reduce the outage time associated with a failure event. Reducing the outage time is of paramount importance to improve the overall level of system reliability. Solely from a reliability perspective, a component of a power system should be repaired once it experiences a failure event. Nevertheless, the repair decision is governed by several factors that may defer the commencement of performing repair activity, most importantly of which are the availability of repair resources at the time of failure occurrence as well as the severity of bad weather condition during which repair activity is performed. Both of these factors have been discussed in numerous studies in the literature [10], [25], [33]–[35], [52]–[54].

Having adequate repair resources available at the time of failure plays a key role in reducing the duration of outage. However, most electric utilities have limited resources, which therefore make the need to properly and efficiently allocate these resources crucial. References [52] and [53] introduced a commendable risk-based strategy to optimally allocate maintenance resources for distribution system components. However, the introduced strategy did not consider the effect of weather in the risk analysis nor did it show how the severity of bad weather might influence the allocation of resources.

On the other hand, the time required to restore a failed component during bad weather conditions might be longer than that required during prevailing favourable weather conditions, which makes this factor absolutely vital upon evaluating the repair time. This factor has been tackled in the literature from two main perspectives. The first perspective, as described in [10], [25], and [54], introduced two weather-based repair scenarios: 1) repair can be performed during bad weather; and 2) repair cannot be performed during bad weather. The associated repair time is evaluated based on the repair scenario considered. In the second perspective, the repair time is evaluated as a time-varying value using certain weight factors obtained from past repair experience in order to express the variation of weather, as presented in [33]–[35].

3.5 Core Weather-based Reliability Research Works

This section discusses the key research works that have tackled the inclusion of weather effect on the reliability assessment of a power system, particularly of a distribution system. These research works can be classified into two main weather-based reliability assessment studies:

- Historical weather-based reliability assessment; and
- Predictive weather-based reliability assessment.

The methodologies and the associated introduced equations for both assessment methods on a distribution system are presented in detail in this section.

3.5.1 Historical Weather-Based Reliability Assessment

The inclusion of weather effect on historical reliability assessment of a power system has been investigated by many studies in the literature [10], [23]–[25], [33], [40], where the first step is to incorporate the effect of weather into component reliability indices, i.e. component failure rate and repair time. Historical assessment necessitates the collection of reliability data including frequency and duration of failures as well as weather data including frequency and duration of bad weather conditions. Accordingly, two main approaches have been developed in the literature:

1. Probabilities of Weather Conditions Approach; and
2. Time-Varying Weight Factor Approach.

3.5.1.1 Probabilities of Weather Conditions Approach

This approach mainly focuses on studying the overlapping failures of parallel redundant components caused by bad weather. Since failure rate value sharply increases during some bad weather conditions, the probability of overlapping failures during these periods increases. This phenomenon is referred to as failure bunching due to bad weather. The principle of approximate parallel systems discussed in Subsection 2.2.2.3 is used to evaluate the overall reliability indices.

However, it should be emphasized that the phenomenon of failure bunching due to bad weather for parallel components should be handled as an independent failure event, not as a common cause failure. A common cause failure mode involves simultaneous failure events of multiple components due to a common cause whereas failure bunching is an independent failure event in a common environment where the failure of one component does not influence the failure of the other component(s).

The first step in the Probabilities of Weather Conditions Approach is to find the failure rate values in normal and bad weather conditions for each component in the parallel-component system and then obtain the respective weather probabilities.

Component average failure rate can be expressed in terms of weather-related failures and associated weather probabilities using the concept of expected value, as indicated in equation (3.12). For a two–state weather model, the average failure rate can be written as:

$$\lambda_{avg} = P_N \times \lambda_N + P_B \times \lambda_B \tag{3.13}$$

The probabilities of normal weather, P_N, and bad weather, P_B, of a two-state weather model can be easily evaluated from equations (3.10) and (3.11) respectively, where the average duration of normal weather, T_N, and average duration of bad weather, T_B, can be obtained from the appropriate weather centre. The main concern in equation (3.13) is the difficulty associated with the evaluation of failure rate in bad weather, λ_B. Generally speaking, normal weather is the predominant and prevailing weather in which a component operates; thus, sufficient failure data during normal weather are usually available which makes λ_N typically capable of being evaluated. However, the evaluation of λ_B requires sufficient data of several calendar years of operation in bad weather, which may not be statistically available due to the short duration and infrequency of bad weather. Therefore, the concept of proportion of failures occurring in bad weather (PoF_B) has been introduced in the literature in order to facilitate the evaluation of λ_B. The PoF_B term helps to allocate failure events based on the weather conditions in which failures have occurred and to identify the percentage of failures in every bad weather condition.

Recall and rearrange equation (3.13) to evaluate the failure rate in normal weather [10]:

$$P_N \times \lambda_N = \lambda_{avg} - P_B \times \lambda_B \tag{3.14a}$$

$$\lambda_N = \frac{1}{P_N} \times \lambda_{avg} - \frac{1}{P_N} \times P_B \times \lambda_B \tag{3.14b}$$

$$\lambda_N = \frac{1}{P_N} \times \lambda_{avg} (1 - P_B \times \frac{\lambda_B}{\lambda_{avg}}) \tag{3.14c}$$

Finally, component failure rate in normal weather, expressed in failures per year of normal weather, can be written as [10]:

$$\lambda_N = \frac{1}{P_N} \times \lambda_{avg} (1 - PoF_B) \tag{3.14d}$$

Where,

$$PoF_B = P_B \times \frac{\lambda_B}{\lambda_{avg}} = \frac{T_B}{T_N + T_B} \times \frac{\lambda_B}{\lambda_{avg}} \tag{3.15}$$

Accordingly,

$$1 - PoF_B = P_N \times \frac{\lambda_N}{\lambda_{avg}} = \frac{T_N}{T_N + T_B} \times \frac{\lambda_N}{\lambda_{avg}} \tag{3.16}$$

Similarly, the failure rate in bad weather can be derived from equation (3.13) as follows [10]:

$$P_B \times \lambda_B = \lambda_{avg} - P_N \times \lambda_N \tag{3.17a}$$

$$\lambda_B = \frac{1}{P_B} \times \lambda_{avg} - \frac{1}{P_B} \times P_N \times \lambda_N \tag{3.17b}$$

$$\lambda_B = \frac{1}{P_B} \times \lambda_{avg} (1 - P_N \times \frac{\lambda_N}{\lambda_{avg}}) \tag{3.17c}$$

Substituting (3.16) in (3.17c) gives:

$$\lambda_B = \frac{1}{P_B} \times \lambda_{avg} (1 - (1 - PoF_B)) \tag{3.17d}$$

Thus, component failure rate in bad weather, expressed in failures per year of bad weather, is given by:

$$\lambda_B = \frac{1}{P_B} \times \lambda_{avg} \times PoF_B \tag{3.17e}$$

If PoF_B is unknown or cannot be estimated, then a sensitive analysis for $0 \le PoF_B \le 1$ is carried out to study the effect of different failure proportions in bad weather. If $PoF_B = 0$, this means that no failures occurred in bad weather whereas $PoF_B = 1$ means that all failures occurred in bad weather.

Equations (3.14d) and (3.17e) are used to express failure rate values of a component in normal and bad weather conditions respectively in the studies of failure bunching for a two-state weather model. However, the concept can be extended to a larger number of weather states by deducing the appropriate set of equations using the same basic logic.

The summation of proportions of failures occurring in each bad weather state will give the total proportion of failures occurring in all bad weather states. Thus, equations (3.14d) and (3.17e) can be generalized to evaluate component weather-based failure rates of multi-state weather model with NB number of bad weather states. The failure rate in normal weather in a multi-state weather model can then be expressed as:

$$\lambda_N = \lambda_{avg} \times \frac{1}{P_N} \times (1 - \sum_{i=1}^{NB} PoF_{B_i}) \tag{3.18}$$

Where PoF_{Bi} is the proportion of failures occurring in bad weather B_i.

The average failure rate in bad weather B_i can be evaluated using the probability of having that particular bad weather occur, as follows:

$$\lambda_{B_i} = \lambda_{avg} \times \frac{1}{P_{B_i}} \times PoF_{B_i} \tag{3.19}$$

In the literature, two fundamental evaluation techniques have been used to evaluate the overlapping failure rate of parallel redundant components considering the phenomenon of failure bunching due to bad weather, namely Markov model and the approximate equations technique, the principles of both of which are discussed in detail in Section 2.2.2.

3.5.1.1.1 Markov Model

The outage model of repairable components and transitional model of weather states using state space diagram are discussed in Subsection 2.2.2.1 and Section 3.2 respectively. These two models could be combined into a composite state space model to represent independent failure events with weather states model. Fig. 3-5 and Fig. 3-6 show how the state space diagram of a two-component system can be constructed considering the inclusion of weather. The state space diagrams of two components in two-state weather and in three-state weather are shown in Fig. 3-5 and Fig. 3-6 respectively. As evident in these figures, both composite models assume that no repair is performed except under normal weather conditions; however, the model can be modified to include performing repair activities during bad weather conditions.

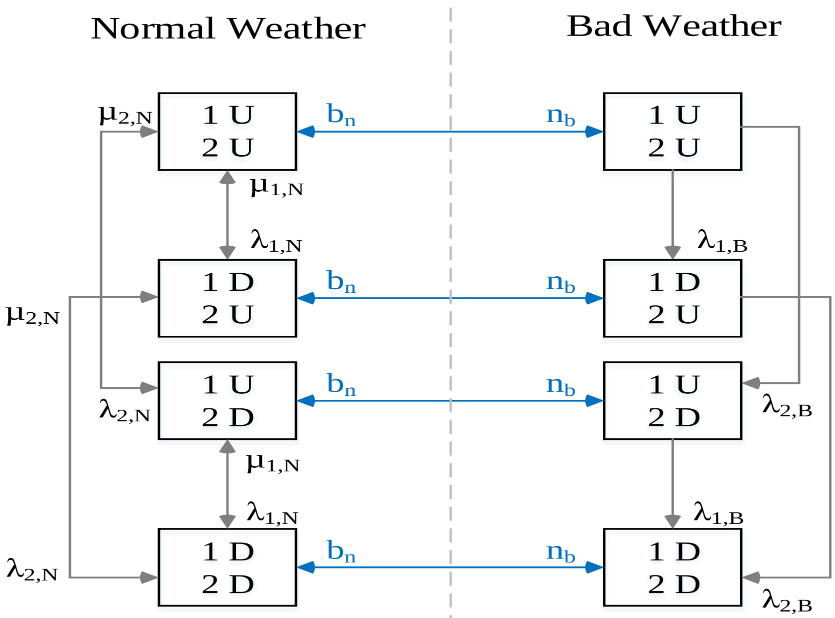


Fig. 3-5: Two-Component Failure Events with Two-State Weather Model

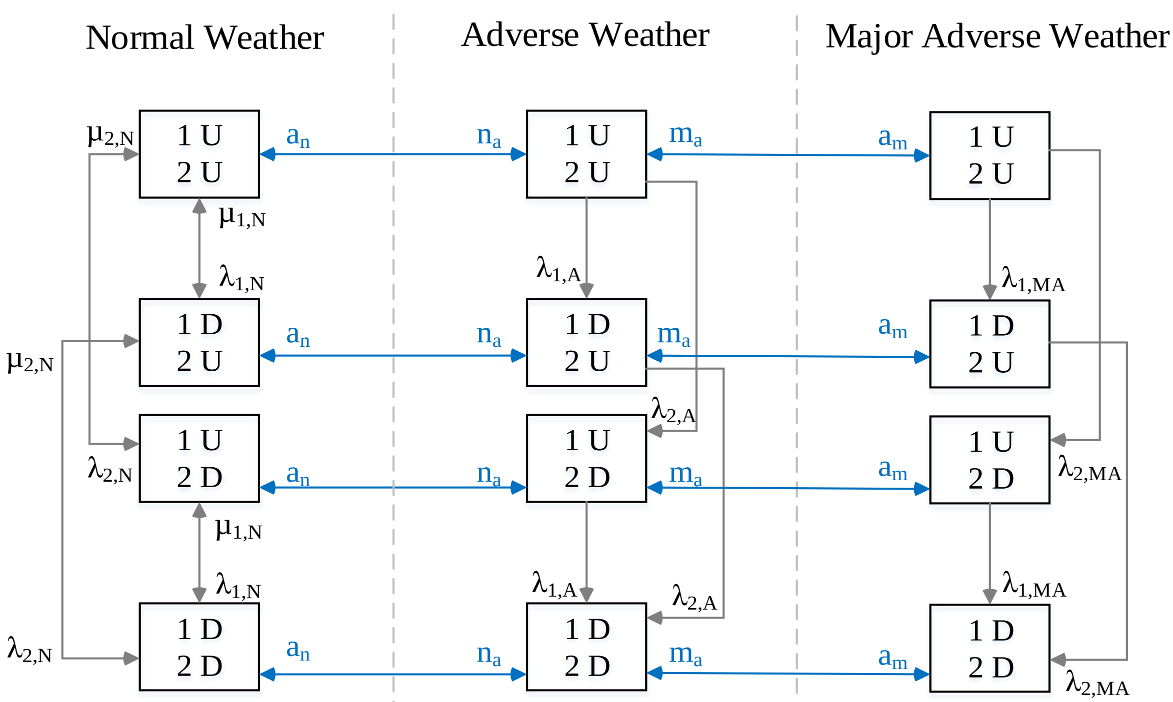


Fig. 3-6: Two-Component Failure Events with Three-State Weather Model

The probabilities of each weather state can be obtained by using equations (3.4) – (3.7) for three-state weather model or by using equations (3.10) – (3.11) for two-state weather model. The proportion of failures in each weather state is identified either from historical record or through establishing sensitivity analysis for different proportion values. As discussed in Subsection 2.2.2.1, the system stochastic transitional probability matrix (STPM) is used to evaluate the failure rates and repair times.

3.5.1.1.2 Approximate Equations Technique

As pointed out in Subsection 2.2.2.1, a large number of states cannot be easily modelled using Markov model due to the complexity associated with constructing the state space diagram and evaluating transitional rates of large models. Although any Markovian model can theoretically be extended to multi-state model, the combination of two separate Markovian models (component outage model and weather state model) together makes the combined model extremely intractable — particularly for a large number of states. Therefore, the approximate equations technique has been used in the literature as an alternative method to the Markov model to evaluate overlapping failure rate considering the phenomenon of failure bunching in bad weather. Based on whether the configuration of the system is series or parallel, a set of approximate equations can be derived [7], [10], [24]. The analysis starts by identifying all possible failure modes in all possible weather states. Then, the equivalent failure rate is evaluated by summing up the failure rate values of all failure modes. For instance, a two-parallel component system with two weather states has four mutually exclusive failure modes:

a) The first component fails in normal weather and the second component fails in normal weather.

b) The first component fails in normal weather and the second component fails in bad weather.

c) The first component fails in bad weather and the second component fails in normal weather.

d) The first component fails in bad weather and the second component fails in bad weather.

The second failure mode, for example, means that the first component fails in normal weather. While it is in an outage state, the weather condition changes to bad and then the second component fails. The consequence of the second failure mode is a failure of two-parallel component systems due to overlapping failures of both components in different weather conditions.

As described above, the second failure occurs during the outage time of the first component. This outage time could be one of two situations: 1) the repair time in which the component is being repaired; or 2) the wait time until bad weather improves as well as the repair time during which the component is being repaired. The first situation leads to a repair scenario that assumes repair can be performed during any weather condition, either normal or bad. The second situation leads to another repair scenario where repair cannot be performed during bad weather. Both repair scenarios are considered to deduce the failure rate equations.

○ *Repair can be performed during bad weather*

The failure rate value of each failure mode can be calculated using equations (3.20) – (3.23), as discussed in [7], [10], [24]:

$$\lambda_a = \frac{T_N}{T_N + T_B}[\lambda_{1,N}\lambda_{2,N}(r_1 + r_2)] \tag{3.20}$$

$$\lambda_b = \frac{T_N}{T_N + T_B}\left[\lambda_{1,N}\left(\frac{r_1}{T_N}\right)\left(\lambda_{2,B}\frac{T_B\ r_1}{T_B + r_1}\right) + \lambda_{2,B}\left(\frac{r_2}{T_N}\right)\left(\lambda_{1,B}\frac{T_B\ r_2}{T_B + r_2}\right)\right] \tag{3.21}$$

$$\lambda_c = \frac{T_B}{T_N + T_B}[\lambda_{1,B}\lambda_{2,N}r_1 + \lambda_{2,B}\lambda_{1,N}r_2] \tag{3.22}$$

$$\lambda_d = \frac{T_B}{T_N + T_B}\left[\lambda_{1,B}\left(\lambda_{2,B}\frac{T_B\ r_1}{T_B + r_1}\right) + \lambda_{2,B}\left(\lambda_{1,B}\frac{T_B\ r_2}{T_B + r_2}\right)\right] \tag{3.23}$$

Where r_1 and r_2 are the average repair durations of component 1 and component 2 respectively. Thus, the overall failure rate is:

$$\lambda_p = \lambda_a + \lambda_b + \lambda_c + \lambda_d \tag{3.24}$$

○ *Repair cannot be performed during bad weather*

The failure rate equations of the failure modes are given by (3.25) – (3.28), as discussed in [7], [10], [24]:

$$\lambda_a = \frac{T_N}{T_N + T_B}[\lambda_{1,N}\lambda_{2,N}(r_1 + r_2)] \tag{3.25}$$

$$\lambda_b = \frac{T_N}{T_N + T_B}\left[\lambda_{1,N}\left(\frac{r_1}{T_N}\right)\lambda_{2,B}T_B + \lambda_{2,N}\left(\frac{r_2}{T_N}\right)\lambda_{1,B}T_B\right] \tag{3.26}$$

$$\lambda_c = \frac{T_N}{T_N + T_B}[\lambda_{1,B}\lambda_{2,N}r_1 + \lambda_{2,B}\lambda_{1,N}r_2] \tag{3.27}$$

$$\lambda_d = \frac{T_B}{T_N + T_B}\left[2\lambda_{1,B}\lambda_{2,B}T_B\right] \tag{3.28}$$

The total average failure rate is:

$$\lambda_p = \lambda_a + \lambda_b + \lambda_c + \lambda_d \tag{3.29}$$

Similarly to the Markov model, the overlapping failure analysis using approximate equations considering the effect of weather can be extended to any number of weather states.

With regards to the incorporation of weather effect into the evaluation of repair time using the Probabilities of Weather Conditions Approach, two main repair scenarios have been considered in the literature. The first repair scenario is *repair can be performed during bad weather* whereas the second repair scenario is *repair cannot be performed during bad weather*. The substantial difference between the two scenarios is the outage time. The outage time is longer when the repair cannot be performed in bad weather because the outage time would involve both actual average repair time as well as the duration of bad weather.

As pointed out previously, the probabilities of Weather Conditions Approach is used to evaluate overlapping failure rate and repair time caused by failure bunching in bad weather for parallel redundant components. These overlapping indices can be used as part of a network reduction process or minimal cut set analysis to evaluate load-point indices and then distribution system indices.

3.5.1.2 Time-Varying Weight Factor Approach

The concept of time-varying weight factors has been introduced in the literature to incorporate the effect of weather conditions into component failure rate and repair time [33]. Since the Probabilities of Weather Conditions Approach focuses on the evaluation of overlapping reliability indices for a parallel redundant system, the Time-Varying Weight Factor Approach has been introduced to evaluate reliability indices for both series and parallel connected components. A number of time-varying weight factors are introduced to represent the time-varying nature of component behaviour during different weather conditions. The failure rate is calculated in this approach as a time-varying value obtained using the average failure rate in normal weather weighted by a weather factor [33]. Thus, component time-varying failure rate (TVFR), λ_t, can be evaluated as follows:

$$\lambda_t = w_t \times \lambda_N \tag{3.30}$$

Where w_t is the time-varying weather weight factor and λ_N is the failure rate in normal weather. The weather factor, w_t, is obtained from past experience during different seasons.

Similarly, the effect of weather on the repair process has been addressed considering the time-varying nature. The restoration time is considered to be varying in terms of time and weather in which repair is being performed. The restoration time is weighted by weather and time weight factors obtained from past repair experience. The weather weight factor is obtained for different weather conditions whereas the time weight factor represents the variations in days and hours. Considering the effect of weather, the time-varying repair time (TVRT), r_t, is obtained by multiplying the average repair time by the appropriate values of weather and time weight factors as follows:

$$r_t = w_t \times w_d \times w_h \times r \tag{3.31}$$

Where the factors w_d and w_h are the daily time-varying weight factor and the hourly time-varying weight factor respectively. Fig. 3-7 depicts an example of an hourly time-varying weather weight factor representation for a typical day.

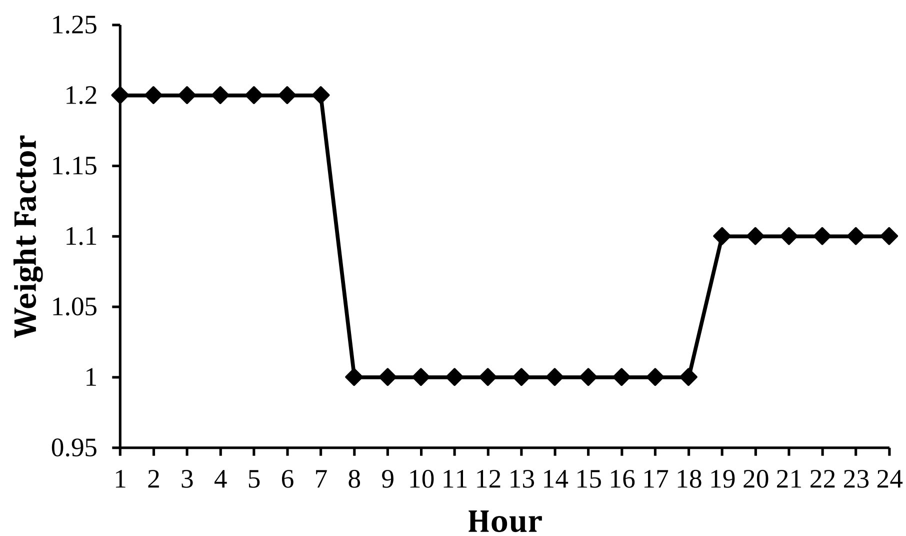


Fig. 3-7: Hourly Time-Varying Weather Weight Factor

The failure rate and repair time for each component are evaluated and then used in subsequent reliability analysis to evaluate load-point and distribution system indices.

3.5.2 Predictive Weather-Based Reliability Assessment

The prediction of system performance entails the assessment of historical reliability behaviour of the system in the past in addition to the assessment of alternative projects, as discussed in the introductory background of Section 2.1. In the context of inclusion of weather effect, the alternative projects are assessed in the literature by the evaluation of reliability indices in alternative weather state models [31], [39]. All core studies that predict reliability indices have used the Probabilities of Weather Conditions Approach to assess historical weather-based reliability performance. Reference [31] evaluated overall failure rate and repair time for a two-redundant-component transmission line incorporating the effect of two weather state models. The first model considered two weather states of normal and adverse weather conditions whereas the second model was extended to incorporate three weather states of normal, adverse, and major adverse weather conditions. System overlapping failure rate and repair time were evaluated for both alternative weather models and for different proportions of failures using Markov model. Reference [39] presented a reliability index segmentation method to evaluate weather-based distribution reliability indices for a distribution system incorporating the effect of a three-weather-states model: normal (*N*), adverse (*A*), and major adverse (*MA*). The method used the concept of expected value to predict system indices. The first step of prediction is to evaluate overall failure rate, repair time, and outage time for every load point in each weather state. For instance, the failure rate, repair time, and outage time values of load point *j* in normal weather state, *N*, is denoted as λ_j^N, r_j^N, and U_j^N respectively. The process of obtaining these load point indices is similar to the process discussed in Section 2.2.2; however, only respective weather-related reliability data are used upon the evaluation of weather-based load point indices in particular weather states.

Then, using the respective weather probability, distribution system indices are evaluated in each weather state. For example, *SAIFI* in normal weather, $SAIFI^N$, can be evaluated using the concept of expected value as follows:

$$SAIFI^N = P_N \frac{\sum_{j=1}^{NP} \lambda_j^N \times N_j}{\sum_{j=1}^{NP} N_j} \tag{3.32}$$

Similarly, *SAIDI* in normal weather is given by:

$$SAIDI^{N} = P_{N} \frac{\sum_{j=1}^{NP} U_{j}^{N} \times N_{j}}{\sum_{j=1}^{NP} N_{j}} \tag{3.33}$$

System indices are similarly evaluated in each weather state. The summation of system indices in each weather state presents the expected indices, which are given by:

$$SAIFI = SAIFI^{N} + SAIFI^{A} + SAIFI^{MA} \tag{3.34}$$

$$SAIDI = SAIDI^{N} + SAIDI^{A} + SAIDI^{MA} \tag{3.35}$$

Using the indices of equations (3.34) and (3.35), the performance of the system is predicted for alternative proportions of failures.

3.6 Main Limitations and Drawbacks in the Literature

Indeed, all of the core weather-based reliability research efforts described in this chapter are commendable in terms of inclusion of weather effects on reliability. Nonetheless, the author has observed some opportunities for further development in these studies to overcome some limitations and drawbacks, which can be summarized and compiled as follows:

1. Weather conditions have been classified in most studies into two or three weather states. In fact, the restriction to only a few weather states may result in placing different weather conditions into one weather state if their effect on reliability is relatively close. However, the effect of weather conditions on reliability should be carefully identified based on which weather conditions should be distinguished and accordingly placed in the appropriate weather states even if two or more weather conditions have close but different effects.
2. The evaluation of failure rate in both historical and predictive weather-based reliability assessment methods introduced in the literature is usually obtained from long-run historical weather and failure data by looking back at the past failure behaviour of the component during specific weather conditions. Historical data may include component average failure rate, proportion of failures occurring during each bad weather condition, and average durations of bad and normal weather conditions. The historical failure behaviour of a component during every

weather condition is represented by a set of failure rate values, each of which is expressed as the number of failures per year of the respective weather condition. That is, the failure behaviour during any given weather condition is modelled over a whole year of that particular weather. This practice of evaluation is mathematically valid for the purpose of developing a historical weather-based statistical failure model for system components and conducting historical reliability assessment for the system; nonetheless, this practice may not help conduct a predictive weather-based reliability assessment for two practical reasons:

- Future weather patterns are subject to continual unpredictable variations due to globally observed climate-related changes [21]. Weather conditions that have occurred in the past cannot be guaranteed to happen again in the future with the same duration, frequency, or probability of occurrence. The sole dependence upon historical weather data while overlooking the fact that weather patterns may change in the future may result in inaccurate evaluation for reliability indices, and consequently may lead to misleading operational and planning decisions. Potential variations in weather patterns should therefore also be included as a feature of weather profiles.
- The predictive weather-based reliability assessment method introduced in the literature used the concept of expected value to predict weather-based distribution reliability indices in different weather state models, where primary reliability indices in a particular weather state are multiplied by the respective weather probabilities. In fact, this practice of evaluation for weather-based predictive assessment could be considerably misleading. Most weather events that have profound effect on failure rate value are generally infrequent and of a short duration compared to prevailing normal weather conditions, which means low probability of occurrence for bad weather. When these low probabilities are multiplied by the very high value of failure rates, the outcome of multiplication is relatively small and does not reflect the effect of the very high value of failure rate. That is, the instantaneous stress that a bad weather condition may pose on the failure rate value during the actual duration of that particular bad weather condition in the future may not be clearly recognized and manifested. Therefore, it is imperative to develop a new predictive method to attentively highlight the instantaneous effect on failure rate value that low-probability-of-occurrence weather events may cause in the future.

3. The weight factors introduced in the Time-Varying Weight Factor Approach are derived using rule-of-thumb principle. Inaccurate estimation to these weights would definitely result in

misleadingness in reliability assessment and consequently in operational and planning decision-making. Therefore, instead of using qualitative judgment to estimate the effect of weather on failure rate and repair time, a quantitative assessment of the severity level of every bad weather condition should be developed.

4. In terms of evaluating the repair time of a failed component, two weather-based repair scenarios have been introduced in the literature: 1) repair can be performed during bad weather; and 2) repair cannot be performed during bad weather. These two repair scenarios need further development to resolve three fundamental flaws.
    - First, the research works that discuss these scenarios have not introduced a methodology to determine which repair scenario should be chosen.
    - Second, no research works in the literature have demonstrated the effect of longer duration of repair performed during some improbable bad weather conditions. The time required to repair a failed component during bad weather might be longer than the time required during prevailing and favourable weather conditions. Since an average repair time index is typically obtained using long-run historical repair data, this longer duration of repair activity during bad weather represents a piece of outlier data compared to the other durations of repair in normal weather due to the infrequency of most bad weather events. As a result, when historical repair durations are averaged over large-sized data, the effect caused by bad weather on repair duration could not be clearly reflected on the average repair time index. The sole reliance on average repair time while overlooking actual repair time during improbable bad weather events may not help to give utilities a clear perception of the actual repair time or resources required to perform repair activities during such bad weather conditions that may occur in the future. This point is significant since most utilities recognize only the average repair time in most repair-related decisions. The necessity to demonstrate the significant effect of such outlier data has not been tackled in the literature.
    - Third, it is assumed that only one repair scenario can be applied to all components in the system. In fact, the limitation to only one repair decision for all components overlooks the reliability importance of a component (the risk) to the whole system since all components do not have the same level of importance in terms of repair decision. Indeed, the consequence of failure for some components in the system may result in higher risk than that caused by some other components which in turn entails giving the higher risk components higher priority for

repair during bad weather. This point becomes even more vital when the limitation of repair resources issue is considered.

5. No studies in the literature have discussed the costs associated with performing the repair during bad weather conditions, nor have they investigated its cost-effectiveness. The commencement of performing repair activity for weather-related failed components once the failure has occurred rather than waiting until weather improves would definitely help reduce the outage time and consequently improve the reliability; nonetheless, the costs of performing the repair during bad weather could be higher than that incurred during normal weather and hence such reduction in outage time should be economically justifiable.

3.7 Summary

This chapter reviews the research efforts that address the effect of weather on reliability studies. First, the weather state models used in the literature are introduced. Second, the effect of varying weather conditions on component failure rate and repair time is discussed. Third, the author of this thesis categorizes the main efforts to address the effect of weather on reliability studies into two main investigations, both of which are outlined. Fourth, the author elucidates the core weather-based reliability research works in the literature. Finally, some opportunities for further development in the research work of these core weather-based reliability studies are pointed out.

Chapter 4
The Proposed Weather-based Predictive Reliability Assessment Method

4.1 Introduction

The continuity of power supply is liable to inevitable power interruptions due to a range of interruption causes, including unfavourable weather conditions. Although most power systems are usually designed to sustain operation in varying weather conditions, the statistics presented in Chapter 3 show that a power system as a whole is vulnerable to the effect of bad weather. Researchers and technical engineers have devoted great efforts in the area of weather-based reliability analysis to studying the effect of weather on reliability and developing several techniques to incorporate this effect into reliability assessment. However, further development efforts are still needed in this research area, particularly in the process of overcoming the limitations and drawbacks outlined in Section 3.6. Consequently, an imperative need exists to respond to these limitations and drawbacks effectively through the introduction of new short-term, medium-term, and long-term weather-based reliability analysis approaches.

Short-term approaches should conduct a predictive reliability assessment for the power system so that it can predict the reliability behaviour of the system on a yearly basis and enable the appropriate necessary operational planning decisions to be made in advance. Medium- and long-term approaches, on the other hand, should facilitate the creation of a sustainable development planning strategy capable of mitigating and adapting to the risk associated with weather implications related to the reliability level of the power grid over a time horizon of 7 to 30 years. It should be emphasized that these approaches must take into consideration all the limitations and drawbacks presented earlier. The work introduced in this thesis is focused primarily on addressing the effects of weather on reliability over a short time horizon, and thus proposes a new weather-based reliability analysis approach called forecasted power system reliability analysis (FOPRA) approach.

4.2 The New FOPRA Approach

The FOPRA approach is a new reliability philosophy which is primarily concerned with studying the impact of weather on power system reliability. The focus in this thesis is on the application of

FOPRA approach on distribution systems. The fundamental objectives of the proposed FOPRA approach are as follows:

1. Develop a new weather-based method to predict the performance of distribution systems in the future; and
2. Develop a new methodical weather-based decision-making repair model for distribution system components.

Thus, FOPRA approach comprises two new concepts:

1. The concept of weather-based predictive reliability assessment method (PRAM); and
2. The concept of weather-based decision-making repair model (DMARM).

The PRAM method aims to predict the reliability level of the distribution system by taking into consideration the effect of future weather forecast and different repair scenarios. The DMARM model aims to allocate repair resources for distribution system components in a cost-effective manner. The implementation process of the proposed FOPRA approach is shown in Fig. 4-1.

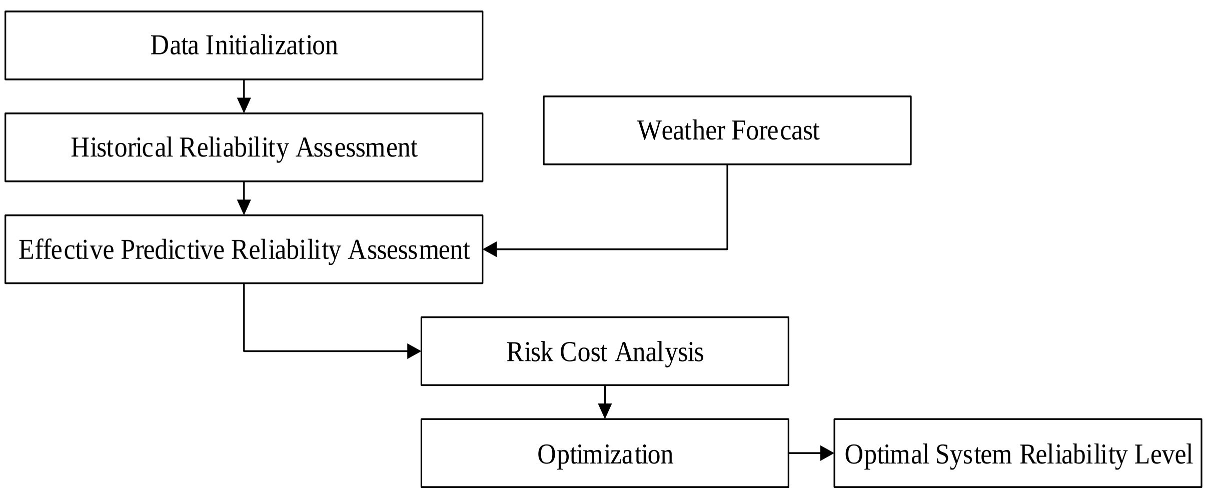


Fig. 4-1: Implementation Process of FOPRA Approach

The methodology of the weather-based predictive reliability assessment method (PRAM) is discussed in this chapter while the methodical weather-based decision-making repair model (DMARM) is introduced in Chapter 5.

4.3 The Concept of Weather-based Predictive Reliability Assessment Method

The objective of this new PRAM method is to develop a new methodology to incorporate the effect of weather into reliability indices. The new methodology is essentially developed to help predict the weather-based reliability behaviour of a distribution system by taking into account the forecast of the weather conditions to which distribution system components will be exposed over a particular future period as well as the historical system reliability behaviour under a variety of past weather conditions. The achievement of this objective can offer utilities an indication of how the system would behave in the future, which in turn could help utilities make appropriate necessary operational and planning decisions. The introduced PRAM method involves four main stages:

1. Data Initialization;
2. Historical Reliability Assessment;
3. Weather Forecast; and
4. Effective Predictive Reliability Assessment.

Two sets of data are initialized in the first stage, which are subsequently used to evaluate some reliability parameters in the second stage. In the second stage, a historical reliability assessment is conducted including decomposition of the component's average failure rate value obtained from historical data into two sets of segmented values in terms of: 1) the number of failures occurring during every weather condition; and 2) the number of failures occurring during every month. A predictive reliability assessment is conducted in the fourth stage over a future time horizon of one year. The first month of that year (the first month to be considered in the calculation) is called the forecasted month and is designated as FM. The determination of this month among the forecasted year's months is a utility decision. The FM could be identified as the first month of the calendar year (i.e., January), the month that has been historically observed to have a higher number of failures, or the month that has the least amount of historical recognized weather-based failure data. The rule of determining the FM may differ from one utility to another. For a typical day (24 hours) from the FM, weather forecast data are imported to be used in evaluating a new proposed set of component reliability indices. The new proposed indices, which measure the predicted performance of the component during that particular day, are subsequently normalized to represent the predicted performance of the component during the FM. The predictive reliability indices of the component during the FM are used in conjunction with the historical reliability indices during the other eleven months to evaluate a new set of proposed component effective reliability indices, which represents the

predicted performance of the component over a future year. The new PRAM method introduced in this thesis satisfies the main steps of predictive reliability assessment outlined in Section 2.1.
More details about the implementation of PRAM stages are discussed in the subsequent sections.

4.3.1 Stage 1: Data Initialization

The first stage of the proposed PRAM method involves identifying a set of historical weather, outage, and customer data. Weather and outage data are used to develop statistical failure and repair models for each component in the system and to develop historical weather models. Customer data are used upon the evaluation of distribution system indices and reliability cost/worth indices. Fig. 4-2 depicts the required data to be initialized.

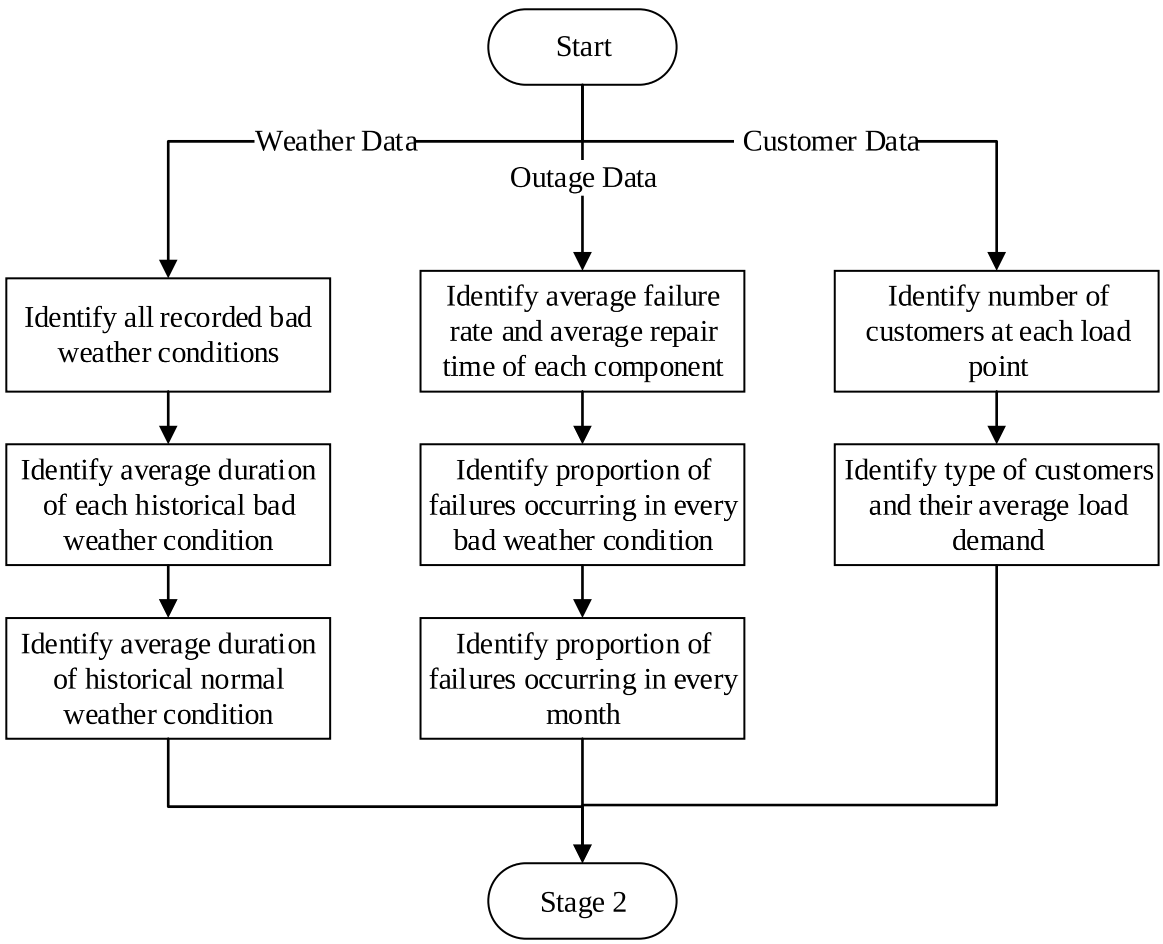


Fig. 4-2: Data Initialization Process

4.3.1.1 Weather Data

In FOPRA approach, weather conditions are broadly classified from a reliability perspective into two main categories: normal (N) and bad (B) weather conditions. Normal weather is defined as the favourable and prevailing weather conditions to which a component is usually exposed or under which it normally operates, and whose contribution to the forced failure of the component is either none or negligible. In contrast, any weather condition proven to cause noticeable forced failure for the component is classified as bad weather condition. Thus, based on this classification, historical data for the weather conditions to which each component in the distribution system was exposed should be collected and processed to yield the following information:

- The number and average durations of all historically recorded bad weather conditions; and
- The average duration of normal weather.

In FOPRA approach, every bad weather condition is modelled as a separate weather state, which gives the reliability assessment more insight into and a deeper understanding of bad weather's effect upon reliability. The collection of weather statistics must consider all historical periods of normal and bad weather conditions regardless of the number of failure events occurring during any given period, as emphasized in [10]. While historical weather data could be obtained from governmental weather centres, utilities are recommended to develop their own weather-related reliability-based records.

4.3.1.2 Outage and Customer Data

The outage data are records of historical reliability data collected for each component in the system and include the following:

1. The average failure rate (λ) per year;
2. The average repair time (r) in hours;
3. The proportion of failures (PoF_{Bi}) occurring in every bad weather B_i; and
4. The proportion of failures (PoF_m) occurring in every month m.

The concept of proportion of failures (PoF_B) occurring in bad weather B was introduced in the literature to facilitate the evaluation of the failure rate in bad weather conditions. The aim is to find the percentage of failures occurring during every bad weather condition, as discussed in detail in Section 3.5. Similarly, the proposed FOPRA approach extends the concept of proportion of failures to involve the allocation of failure events according to the month in which the failures occurred. Thus, the concept of proportion of failures (PoF_m) occurring in month m is introduced in this thesis in order to identify the percentage of failures occurring in every month m. The proportion of failures occurring in every month is identified for each component in the system from historical failure records, regardless of failure causes. Monthly failure data are usually available in most utilities; however, a sensitive analysis for $0 \leq PoF_m \leq 1$ could be carried out if PoF_m cannot be identified or estimated. More details about the identification of PoF_m are discussed in Section 4.3.2.3.

Customer data include number of customers at each load point as well as customer type (e.g., residential, industrial, etc.) and customer average load demand.

4.3.2 Stage 2: Historical Reliability Assessment

The primary goal of this stage is to assess the historical reliability performance of the distribution system components by evaluating a set of historical parameters. For all distribution system components, the available historical data are analyzed to evaluate historical failure rates during normal and bad weather conditions, to assess the seriousness of the recorded bad weather with respect to component failure, and to evaluate historical failure rates during every month. The steps of the historical reliability assessment stage are depicted in Fig. 4-3.

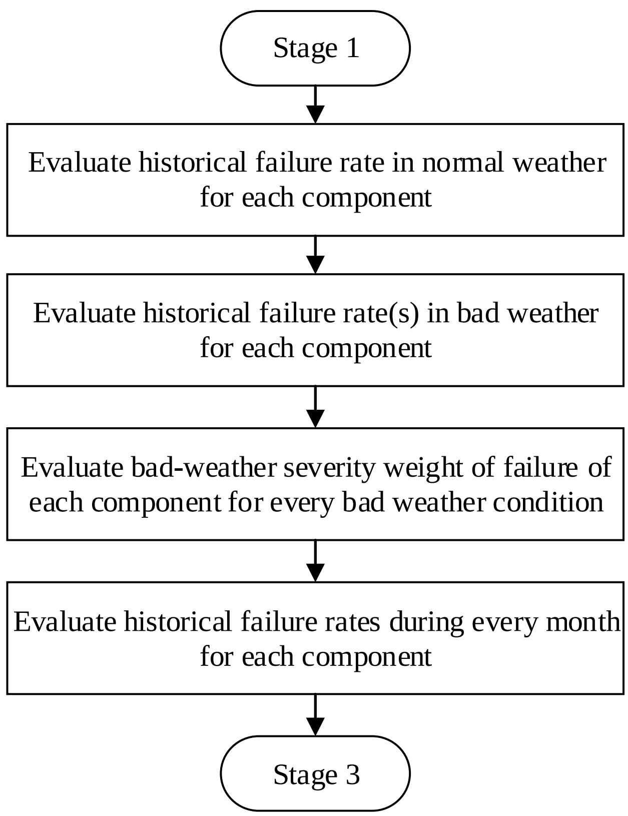


Fig. 4-3: Historical Reliability Assessment Process

4.3.2.1 Evaluate historical failure rates in normal and bad weather conditions

As pointed out at the beginning of Section 4.3, historical component average failure rate is decomposed into two sets of segmented values. The first segment is expressed in terms of the number of failures occurring during every historical weather condition. The evaluation of these historical weather-based failure rate values is discussed in Section 3.5 through equations (3.14d) and (3.17e). The Probabilities of Weather Conditions Approach, discussed in Section 3.5, is used in this thesis to evaluate component failure rates in normal and bad weather conditions. Thus, component failure rates in normal weather N and in bad weather B_i can be evaluated using equations (4.1) and (4.2) respectively.

$$\lambda_N = \lambda \frac{T_N + \sum_{i=1}^{NB} T_{B_i}}{T_N} \left(1 - \sum_{i=1}^{NB} PoF_{B_i}\right) \tag{4.1}$$

$$\lambda_{B_i} = \lambda \frac{T_N + \sum_{i=1}^{NB} T_{B_i}}{T_{B_i}} PoF_{B_i} \tag{4.2}$$

Terms and symbols of equations (4.1) and (4.2) have already been defined in Chapter 3; however, for the sake of coherence, they are redefined in this chapter as follows:

λ_N Component average failure rate during normal weather (f/year of normal weather);

λ Component average failure rate (f/year);

T_N Average duration of normal weather (h);

T_{Bi} Average duration of bad weather B_i (h);

NB Total number of recorded bad weather conditions;

PoF_{Bi} Proportion of failures that occurred during bad weather B_i; and

λ_{Bi} Component average failure rate during bad weather B_i (f/year of bad weather B_i).

4.3.2.2 Evaluate the severity level of bad weather on component failure

The severity level of bad weather with respect to component failure should be evaluated for every recorded bad weather condition in order to perceive the effect that a bad weather condition may cause to the failure rate value. Thus, a new bad-weather severity weight of failure *wf* is introduced in this thesis, and is given by:

$$wf_{B_i} = \frac{\lambda_{B_i}}{\lambda_N} \tag{4.3}$$

Where the weight wf_{Bi} represents the multiplier increase that a bad weather condition B_i contributes to the value of component failure rate in normal weather, and it is valid for $\lambda_N > 0$.

4.3.2.3 Evaluate historical failure rates during every month

FOPRA approach introduces a new representation of the component average failure rate value. In this step, the average failure rate is decomposed into a set of segmented failure rate values, each of which is expressed as the number of failures per month. The representation of failure rate on a short-term basis (monthly basis in this thesis) can help to demonstrate the effect of low-probability-of-occurrence failure causes, especially those related to bad weather events. According to [31], the effect of extremely adverse weather conditions on the long-term system reliability indices is negligible due to the infrequency and the short duration of these weather conditions. Since it is extremely difficult to categorize and set apart historical weather-related failures into a monthly basis, all failures, irrespective of their causes, are allocated on a monthly basis.

Component failure rate in month *m*, expressed in failures per month (λ_m), can be derived using the concept of expected value from the average component failure rate value expressed in the number of failures per year, the number of days of that particular month (ND_m), and the total number of days in the year (*TND*). An average component failure rate expressed in the number of failures per year can be given as:

$$\lambda = 12\sum_{m=1}^{12} \frac{ND_m}{TND} \times \lambda_m \tag{4.4a}$$

Equation (4.4a) can be expanded to the whole year as:

$$\lambda = 12\left[\frac{ND_{Jan.}}{TND} \times \lambda_{Jan.} + \frac{ND_{Feb.}}{TND} \times \lambda_{Feb.} + \ldots + \frac{ND_{Dec.}}{TND} \times \lambda_{Dec.}\right] \tag{4.4b}$$

Thus, component failure rate in the month of January can be expressed by the number of failures per month as follows:

$$12\times\frac{ND_{Jan.}}{TND}\times\lambda_{Jan.}=\lambda-12\left[\frac{ND_{Feb.}}{TND}\times\lambda_{Feb.}+\ldots+\frac{ND_{Dec.}}{TND}\times\lambda_{Dec.}\right] \tag{4.4c}$$

$$\lambda_{Jan.}=\frac{1}{12}\times\frac{TND}{ND_{Jan.}}\left[\lambda-12\left(\frac{ND_{Feb.}}{TND}\times\lambda_{Feb.}+\ldots+\frac{ND_{Dec.}}{TND}\times\lambda_{Dec.}\right)\right] \tag{4.4d}$$

$$\lambda_{Jan.}=\frac{1}{12}\times\frac{TND}{ND_{Jan.}}\times\lambda\left[1-12\left(\frac{ND_{Feb.}}{TND}\times\frac{\lambda_{Feb.}}{\lambda}+\ldots+\frac{ND_{Dec.}}{TND}\times\frac{\lambda_{Dec.}}{\lambda}\right)\right] \tag{4.4e}$$

Finally, component failure rate during the month of January can be written as:

$$\lambda_{Jan.}=\frac{1}{12}\times\frac{TND}{ND_{Jan.}}\times\lambda\times PoF_{Jan.} \tag{4.4f}$$

Where the proportion of failures that occurred during the month of January ($PoF_{Jan.}$) is given by:

$$PoF_{Jan.}=1-12\left(\frac{ND_{Feb.}}{TND}\times\frac{\lambda_{Feb.}}{\lambda}+\ldots+\frac{ND_{Dec.}}{TND}\times\frac{\lambda_{Dec.}}{\lambda}\right) \tag{4.5}$$

Thus, component failure rate at any given month *m*, in terms of number of failures per month, can be expressed in a generalized form as:

$$\lambda_m=\frac{1}{12}\times\frac{TND}{ND_m}\times\lambda\times PoF_m \tag{4.6}$$

Where

$$\sum_{m=1}^{12}PoF_m=1 \tag{4.7}$$

By the end of Stage 2, the following reliability parameters are identified for each component: λ_N, λ_{Bi} for all B_i, wf_{Bi} for all B_i, and λ_m for all *m*.

4.3.3 Stage 3: Weather Forecast

The determination of the FM is followed by the determination of a typical day from the FM, the weather of which is presumed to represent the common and prevailing weather of the whole month of FM. This day is called the forecasted day and is denoted as FD. The determination of the FD could be identified based on historical weather data or based on long-term weather forecasting.The objective of this stage is to forecast the state of the atmosphere during the FD for the geographic areas where distribution system components are located. The purpose of the forecast is to check whether any of the recorded bad weather conditions that caused component failure in the past are expected to occur within a specific window of time in the future. This window of time is referred to as the forecast period which represents the duration of the FD, designated as T_F, and expressed in hours.

Several forecasting methods are employed by meteorologists to forecast weather conditions including, for instance, persistence, trends, climatology, analog, and numerical weather prediction (NWP). The choice of forecasting method is dependent on the application for which the weather forecast is required and the degree of accuracy that is needed [55]. The NWP method is considered the most accurate method, especially for the short-term prediction of major weather conditions [55], [56].

The NWP is a computer-based forecasting model whose fundamental concept is the use of the physical laws that govern the atmosphere to express current atmospheric observations as mathematical models for predicting the future evolution of the atmosphere [56]–[58]. The extreme complexity of this process requires supercomputers that are available only at meteorological centres and some research centres, such as the Canadian Meteorological Centre (CMC). These centres produce weather forecast maps and statistics, and provide local commercial weather forecast companies, such as AccuWeather, with raw data [59].

A weather pattern is typically chaotic and unpredictable, which consequently makes forecasting weather patterns over the long range less accurate [60]. For this reason, the forecast period in this thesis has been chosen to be short in order to obtain weather data with a high degree of spatial resolution. Using short-term weather forecasts also helps to highlight any changes in historical weather patterns and facilitates recognition of improbable weather incidents. According to [60], a short-range forecast period can be defined as extending up to 48 hours. Bad weather events are assumed to be mutually exclusive events. That is, if a bad weather condition is forecasted to occur at a specific hour t, then all other bad weather conditions are precluded at that particular hour. Thus, for the designated locations and over the forecast period, the following real-time weather forecasted data are imported once at the beginning of the forecast period from the appropriate local weather forecast centre:

- The frequency and interval of normal and bad weather conditions; and
- The probability of occurrence of bad weather conditions at every forecasted bad-weather hour.

For safety purposes, if a bad weather condition is forecasted to occur over a particular period of time but the probability of occurrence is not available or cannot be accurately estimated, then the probability of occurrence of that bad weather condition is considered unity during every hour of that particular period of time.

It should be highly emphasized that if the probability of occurrence of a bad weather B_i at any hour t, $PoB_{i,t}$, is greater than zero, then that hour is designated as a bad-weather hour even if B_i is forecasted to last for less than 60 minutes. The forecast period T_F is thus defined as follows:

$$T_F = \alpha + \beta \tag{4.8}$$

Where the weather parameters α and β denote the forecasted durations in hours of normal and all bad weather conditions respectively. The forecasted duration of all bad weather conditions, β, is given by:

$$\beta = \sum_{i=1}^{NB} \beta_{B_i} \tag{4.9}$$

Where β_{Bi} represents the forecasted duration in hours of bad weather condition B_i. Fig. 4-4 shows the main steps of this stage.

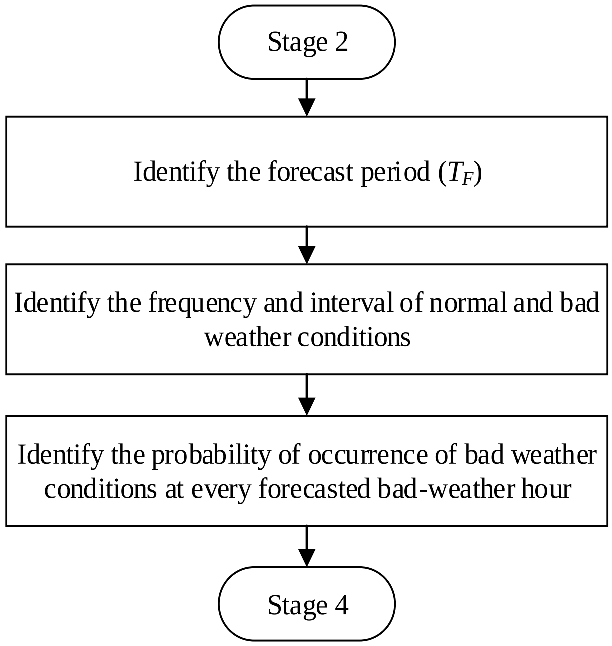


Fig. 4-4: Weather Forecast Process

4.3.4 Stage 4: Effective Predictive Reliability Assessment

The prediction of system reliability performance over a certain time period in the future necessitates combining historical reliability performance and mathematical models to predict the response of the system to alternative plans. The assessment of historical performance has been discussed in Stage 2 while the mathematical models used to measure the response of the system are introduced in this stage through the introduction of new sets of predictive reliability indices. This stage is comprised of the following steps:

1. Evaluation of component forecasted reliability indices;
2. Evaluation of component effective reliability indices;
3. Evaluation of load-point reliability indices; and
4. Evaluation of distribution system reliability indices.

In this stage, two new proposed sets of reliability indices are evaluated for each component in the distribution system. The first set of reliability indices include the new indices of forecasted failure rate (FFR) and forecasted repair rate (FRR), both of which are evaluated on a daily basis based on the weather forecast data of the FD and subsequently normalized on a monthly basis. The FRR is evaluated based on two repair scenarios: 1) repair can be performed during bad weather; and 2) repair cannot be performed during bad weather. Since the FFR and FRR are evaluated for a typical day of a particular FM, their monthly-based normalized values are deemed to represent the forecasted reliability performance of the component during that particular month. The evaluation of FFR and FRR are presented using two evaluation techniques in this thesis: analytical and MCS. After the evaluation of component FFR and FRR during the FM, the historical monthly-based failure rates evaluated at Stage 2 are used to represent the reliability failure behaviour of the component during the respective remaining elven months. Then, the historical eleven monthly-based failure rates are combined with the FFR using a new mathematical model introduced in this thesis. Since data collection schemes of most utilities do not recognize the evaluation of repair time on a monthly basis, component average repair time identified at Stage 1 is combined with the reciprocal of FRR, which is the forecasted repair time (FRT), r^F. The new combined reliability indices represent the second new proposed set of reliability indices, which are referred to as effective failure rate (EFR) and effective repair time (ERT). The EFR and ERT values for all components are thereafter used to evaluate reliability indices for load points and then distribution reliability indices.

The methodologies of evaluating all of these indices are discussed in the following sections.

4.3.4.1 Component Forecasted Reliability Indices (Analytical)

The main goal of this step is to predict the performance of distribution system components upon exposure to the weather conditions that are forecasted to occur over a predetermined forecast period of a particular FD in the future. Based on the historical perception of component weather-based performance, weather forecasted data are interpreted into a reliability language that can describe in terms of reliability indices the predicted reliability behaviour of the component in the future. This prediction is measured using the proposed new set of forecasted reliability indices: FFR and FRT. The objective of introducing this new set of forecasted indices is to clearly identify the effect of weather on the prediction of component behaviour.

The proposed forecasted indices are evaluated on a short-term basis, per every T_F period of time, for two fundamental reasons:

- To ensure a high degree of accuracy with respect to the incorporation of weather forecast data into the indices; and
- To provide clear evidence of the effect of bad weather conditions, particularly those weather events associated with a low probability of occurrence in spite of their profound effects on system reliability. Because most weather events that affect system reliability are generally infrequent and

of a short duration [10], evaluating reliability indices on a long-term basis might not render their effects readily apparent.

The operational states of a repairable distribution system component in the context of weather forecast variation can be represented using the two-state model depicted in Fig. 4-5, where λ^F and μ^F are the forecasted failure rate (FFR) and the forecasted repair rate (FRR), respectively. The proposed FFR and FRR introduced in this thesis are functions of the forecasted weather conditions to which the component is exposed and are assumed to be constant for the designated forecast period T_F. That is, FFR and FRR are evaluated per T_F and are updated for every T_F period. The inevitable uncertainty associated with weather forecast is taken into account in the evaluations of both FFR and FRR. The originality of the new forecasted indices lies in the mathematical combination of the historical failure behaviour and repair process of the system under specific weather conditions together with the forecasted weather conditions to which the system is expected to be exposed over a particular forecast period.

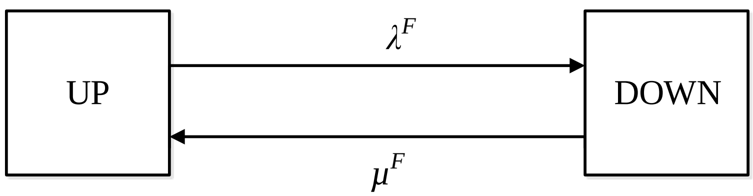


Fig. 4-5: Forecasted Two-State Component Outage Model

The following subsections outline the process of obtaining FFR and FRR for each component in the system using analytical equations. The methodology introduced in this thesis to evaluate the forecasted reliability indices is described to a common weather environment; however, it is applicable to any type of varying weather condition.

4.3.4.1.1 Forecasted Failure Rate (FFR)

The proposed FFR, λ^F, represents the component forecasted failure rate and is expressed as the number of failures per T_F. The FFR varies in accordance with the variations of weather conditions to which the component is expected to be exposed. The FFR describes the forecasted failure behaviour of the component over the forecast period using a set of hourly weather-based discrete states. Each hourly state describes the component failure rate at that hour by considering the forecast of weather and the probability of bad weather occurrence at that particular hour. The FFR, λ^F, of a component can be obtained from the following equation:

$$\lambda^{F} = \frac{1}{8760}\left[\sum_{i=1}^{NB}\left(\sum_{t=1}^{T_F} PoB_{i,t} \times \lambda_{B_i}\right) + \sum_{t=1}^{T_F}\left(1 - \sum_{i=1}^{NB} PoB_{i,t}\right) \times \lambda_N\right] \tag{4.10}$$

This equation is explained in the following sentences. The concept of expected value is used to average the hourly variation of component failure rate over the forecast period T_F. The process starts by evaluating the forecasted failure rate at every hour. If the weather forecasted data indicate that a historically recorded bad weather condition B_i is expected to occur at an hour t with a probability of occurrence $PoB_{i,t}$, then the respective component historical failure rate in that particular bad weather condition is multiplied by the imported probability of occurrence $PoB_{i,t}$. Moreover, for the same hour t that has been expected to have the bad weather B_i with the probability of occurrence $PoB_{i,t}$, if the $PoB_{i,t}$ at that hour is less than 1, then the complement of $PoB_{i,t}$ (i.e., $1 - PoB_{i,t}$) is also multiplied by the historical failure rate in normal weather. Therefore, the forecasted failure rate of the component at any given hour is obtained using the $PoB_{i,t}$ multiplied by the respective λ_{Bi} plus the complement of $PoB_{i,t}$ multiplied by the λ_N. As pointed out earlier, bad weather conditions are assumed to be mutually exclusive events at any given hour t. If the forecasted weather data indicate that no bad weather is forecasted to occur at an hour t, then the historical failure rate in normal weather is used to represent the failure rate of the component during that hour. This process is repeated for every hour over the forecast period where the occurrence of all NB historically recorded bad weather conditions should be checked. The failure rate values at each hour are summed up and the result is divided by the total number of hours in the year, 8760 hours. The same process is applied to all distribution system components.

4.3.4.1.2 Forecasted Repair Rate (FRR)

Any repairable component with a two-state outage model is generally in either an up or a down state. The time period during which the component is in a down state and being repaired is called downtime, and its average value represents component average repair time, r. When the effect of weather is considered in the repair process, two repair scenarios exist: the repair can be performed during bad weather, and the repair cannot be performed during bad weather. The evaluation of the proposed FRR considers both repair scenarios. However, it should be emphasized that when repair activity is assigned to be performed during a bad weather condition, then this assignment should adhere to safety rules and regulations developed and set by the governmental electricity regulatory authority.

- *Repair can be performed during bad weather:*

  The condition of weather at the time when repair activity is performed has a considerable effect on the repair process, mainly on the duration of repair. The time required to repair a failed component during bad weather is usually longer than that required during prevailing and favourable weather conditions. Nonetheless, this increase in repair duration is not clearly demonstrated in the average repair time index, as discussed in Section 3.6. Therefore, the severity of bad weather should be reflected in the evaluation of repair rate. This thesis proposes a new method to evaluate component repair rate where the duration of repair is proportional to the severity of weather. Assuming the repair is permissible during bad weather, the FRR, μ^F, of a component, expressed as number of repairs per T_F (repair/T_F), can be given by:

$$\mu^F = \sum_{i=1}^{NB}\left(\sum_{t=1}^{T_F} PoB_{i,t} \times \frac{1}{r \times wf_{B_i}}\right) + \sum_{t=1}^{T_F}\left(1 - \sum_{i=1}^{NB} PoB_{i,t}\right) \times \frac{1}{r} \tag{4.11}$$

  Equation (4.11) is explained in the following sentences. The process of evaluating FRR is similar to the process of evaluating FFR. Likewise, the repair rate at any hour t is comprised of two parts. The first part represents the repair rate in bad weather multiplied by the appropriate probability of bad weather occurrence whereas the second part represents the repair rate in normal weather multiplied by the complement of probability of bad weather occurrence. To reflect the severity of bad weather on the evaluation of repair rate, if a bad weather condition B_i is forecasted to occur at an hour t with a probability of occurrence $PoB_{i,t}$, then the average repair time in the first part is multiplied by the respective bad-weather severity weight of failure wf_{Bi}.

- *Repair cannot be performed during bad weather:*

  The second repair scenario entails waiting until the bad weather conditions have ended before commencing the repair activity. This waiting time mainly corresponds to the bad weather duration β. However, if β is composed of small periods throughout the forecast period during which the duration of forecasted hours of normal weather that lie between the periods of β is shorter than the repair time r, then repair activity cannot be performed during these forecasted hours of normal weather because the full repair activity cannot be completed before the beginning of the next forecasted bad weather period. Consequently, the duration of such no-repair interval periods of forecasted hours of normal weather should also be involved in the waiting time, which is designated as γ and expressed in hours, where $\gamma \leq \alpha$. That is, the term γ is defined as the summation of all interval periods of normal-weather hours with each period meeting the following conditions: 1) precedes and/or follows a bad-weather period(s); and 2) has a duration that is less than the time required for completing the full repair activity. Since the assessment is conducted on a short-term basis, this waiting time should be reflected in the repair rate calculations. Assuming that no repair is performed during the bad weather, the FRR, μ^F, of a component is given by:

$$\mu^F = T_F \frac{1}{FDT} \tag{4.12}$$

The term FDT denotes the forecasted downtime expressed in hours, which can be determined as follows:

$$FDT = \begin{cases} r + TPoB + \gamma, & r + TPoB + \gamma < T_F \\ T_F, & r + TPoB + \gamma \geq T_F \end{cases} \tag{4.13}$$

Where *TPoB* is the total probabilities of occurrences of bad weather conditions, evaluated as follows:

$$TPoB = \sum_{t=1}^{T_F} \sum_{i=1}^{NB} PoB_{i,t} \tag{4.14}$$

Regardless of the repair scenario considered, the reciprocal of the forecasted repair rate designates the forecasted time required to restore the component, which is the forecasted repair time (FRT), r^F.

4.3.4.2 Component Forecasted Reliability Indices (Monte Carlo Simulation)

The methodology used to obtain component FFR and FRT has been introduced in the previous subsection using a set of analytical equations, the main core of which is the novelty of evaluating these forecasted indices as predictive quantities that consider the historical reliability assessment and the future weather forecast data. This subsection presents the process of obtaining component FFR and FRT using MCS technique, which can be used as an alternative evaluation technique or to validate the results obtained from the analytical method.

The process to evaluate component FFR and FRT using MCS are discussed herein. In the analytical technique, an hour *t* is designated as a bad-weather hour if the probability of occurrence of that bad weather at that hour, $PoB_{i,t}$, is greater than zero. However, in this section the forecasted weather condition for every hour is modelled by MCS using the imported $PoB_{i,t}$. Thus, the process of evaluating component forecasted reliability indices can be summarized as follows:

1. Initialize the duration of bad weather B_i ($\beta_{Bi} = 0$).
2. Check the chance of having bad weather B_i at every hour t throughout the forecast period T_F. If hour t is forecasted to have a bad weather B_i with $PoB_{i,t} > 0$, then generate a uniform random number R in the interval (0,1).
3. If $R \leq PoB_{i,t}$, then this hour is deemed to be bad B_i and the duration of B_i is updated to be $\beta_{Bi} = \beta_{Bi}+1$; otherwise, this hour is deemed to be normal N ($\beta_{Bi} = \beta_{Bi}+0$).
4. Repeat steps 1 – 3 for every hour t to find the total duration of bad weather B_i, β_{Bi}.
5. Repeat steps 1 – 4 for all recorded NB number of bad weather conditions.
6. Calculate the total duration of all bad weather conditions, β, in hours as follows:

$$\beta = \sum_{i=1}^{NB} \beta_{B_i} \tag{4.15}$$

7. Calculate the duration of normal weather, α, in hours as follows:

$$\alpha = T_F - \beta \tag{4.16}$$

8. Evaluate the forecasted failure rate (f/T_F) using the concept of expected value:

$$\lambda^F = \frac{1}{8760}\left(\alpha \times \lambda_N + \sum_{i=1}^{NB} \beta_{B_i} \times \lambda_{B_i}\right) \tag{4.17}$$

   The λ^F of the component over the forecasted period T_F is evaluated by multiplying the forecasted duration of every weather condition by the respective historical failure rate of that particular weather divided by the 8760 duration hours of the year.
9. If repair can be performed during bad weather, go to step 10; otherwise, go to step 12.
10. The severity associated with performing repair activity during bad weather conditions should be reflected in the calculation of the repair rate equation. To make this calculation, the repair time required to repair a component during a bad weather condition should be expressed in terms of the severity weight of that particular bad weather condition. Therefore, the forecasted repair rate, μ^F, (rep/T_F) of a component is evaluated as follows:

$$\mu^F = \alpha \times \frac{1}{r} + \sum_{i=1}^{NB} \beta_{B_i} \times \frac{1}{r \times wf_{B_i}} \tag{4.18}$$

The μ^F is found by summing up the multiplication of forecasted duration of normal weather by the reciprocal of the average repair time and the multiplication of forecasted duration of every bad weather condition by the reciprocal of the average repair time and the reciprocal of the respective bad-weather severity weight of failure wf_{Bi}.

11. Go to step 14.
12. Identify γ (h), which represents the total duration of all interval periods of normal-weather hours that lie between the interval periods of bad-weather hours where the duration of each individual interval period of those normal-weather hours is less than that of the repair time.
13. Evaluate the forecasted repair rate, μ^F, (rep/T_F) as follows:

$$\mu^F = \begin{cases} T_F \times \dfrac{1}{r+\beta+\gamma}, & r+\beta+\gamma < T_F \\ 1, & r+\beta+\gamma \geq T_F \end{cases} \tag{4.19}$$

14. Evaluate the forecasted repair time, r^F, (h):

$$r^F = T_F \times \frac{1}{\mu^F} \tag{4.20}$$

15. Repeat steps 1–14 for a desired number of simulations until acceptable values of λ^F and r^F are reached.
16. Repeat steps 1–15 for each component in the system.

4.3.4.3 Component Effective Reliability Indices

As discussed in the literature review chapter, the major limitation of the conventional method to evaluate component average failure rate and repair time is that the conventional method cannot clearly demonstrate the effect of bad weather on these averaged indices. This incapability of demonstrating this effect is due to the infrequency and short duration of most improbable bad weather events. Therefore, the proposed FOPRA approach introduces the concept of effective failure rate (EFR) and effective repair time (ERT) to overcome the limitations of the conventional averaged values of failure rate and repair time.

When the FM is identified and the associated FFR and FRT are evaluated for each component in the system, then the historical monthly basis reliability indices of the remaining eleven months are combined with the typical FFR and FRT in order to derive the new set of EFR and ERT. The EFR and ERT are evaluated on a yearly basis using equations (4.21) and (4.22), respectively.

$$\lambda^{E} = 12\left[\sum_{m=1}^{11}\frac{ND_m}{TND}\times\lambda_m + \frac{ND_m^F}{TND}\times\lambda^F\times ND_m^F\right] \quad (4.21)$$

$$r^{E} = \frac{1}{12}\left[\sum_{m=1}^{11} r_m + r^F\right] \quad (4.22)$$

Where

λ^E	Component effective failure rate (f/year);
$ND_m{}^F$	Number of days of the FM. The weather forecast data for a typical day of this FM are imported from the weather forecast centre;
r^E	Component effective repair time (h); and
r_m	Component average repair time during month *m* (h).

In equation (4.21), the FFR, evaluated for a given typical FD in a given FM, is annualized to be expressed on a one-year basis. Likewise, the historical monthly basis failure rates are also annualized.

The term r_m is introduced in equation (4.22) to add more resolution to the evaluation of an equivalent repair time. Nevertheless, if r_m is not available, which is the case in most utilities, then the average repair time r is used instead.

Equations (4.21) and (4.22) show the significance of recognizing the evaluation of λ_m, λ^F, r_m and r^F to manifest their effects on λ^E and r^E, which should be used in reliability analysis instead of the conventional λ and r. These effects are clearly demonstrated in the case study presented in Chapter 6.

4.3.4.4 Load-Point Reliability Indices

The EFR and ERT, evaluated for each component, are used to evaluate the basic indices of distribution system load points. These load point indices include effective failure rate, effective repair time, and effective outage time for each load point. The purpose of evaluating these indices is to measure the reliability level at each load point and identify critical customers.

Based on the system configuration, a variety of evaluation techniques are available for evaluating the effective load point indices. Section 2.2.2 discusses in detail the principle of these techniques.

4.3.4.5 Distribution System Reliability Indices

Load point indices can help measure the reliability level for system load points; however, additional distribution reliability indices are required to understand the complete behaviour of the system. These distribution reliability indices are referred to as customer- and energy-based indices. The evaluation of these indices, discussed in Section 2.5.3, is recalled in this chapter for the sake of coherence. The conventional load-point failure rate, repair time, and outage time used to evaluate the customer- and energy-based indices are replaced by their respective effective load-point indices, as follows:

- System average interruption frequency index, SAIFI (interruption/customer yr);
- System average interruption duration index, SAIDI (h/customer yr);
- Customer average interruption duration index, CAIDI (h/customer interruption);
- Energy not supplied index, ENS (kWh/yr);
- Average service unavailability index, ASUI; and
- Average service availability index, ASAI.

$$SAIFI = \frac{\sum_{j=1}^{NP} \lambda_j^E \times N_j}{\sum_{j=1}^{NP} N_j} \tag{4.23}$$

$$SAIDI = \frac{\sum_{j=1}^{NP} U_j^E \times N_j}{\sum_{j=1}^{NP} N_j} \tag{4.24}$$

$$CAIDI = \frac{SAIDI}{SAIFI} = \frac{\sum_{j=1}^{NP} U_j^E \times N_j}{\sum_{j=1}^{NP} \lambda_j^E \times N_j} \tag{4.25}$$

$$ENS = \sum_{j=1}^{NP} U_j^E \times L_j \tag{4.26}$$

$$ASUI = \frac{\sum_{j=1}^{NP} U_j^E \times N_j}{\sum_{j=1}^{NP} N_j \times 8760} = \frac{SAIDI}{8760} \tag{4.27}$$

$$ASAI = \frac{\sum_{j=1}^{NP} N_j \times 8760 - \sum_{j=1}^{NP} U_j^E \times N_j}{\sum_{j=1}^{NP} N_j \times 8760} = 1 - ASUI \tag{4.28}$$

Where

λ_j^E Effective failure rate for load point *j* (f/yr);

N_j Number of customers connected to load point *j*;

NP Number of load points in the distribution system;

U_j^E Effective annual outage time for load point *j* (h/yr); and

L_j Average load connected to load point *j* (kW).

The general process of Stage 4 is conceptually summarized in Fig. 4-6.

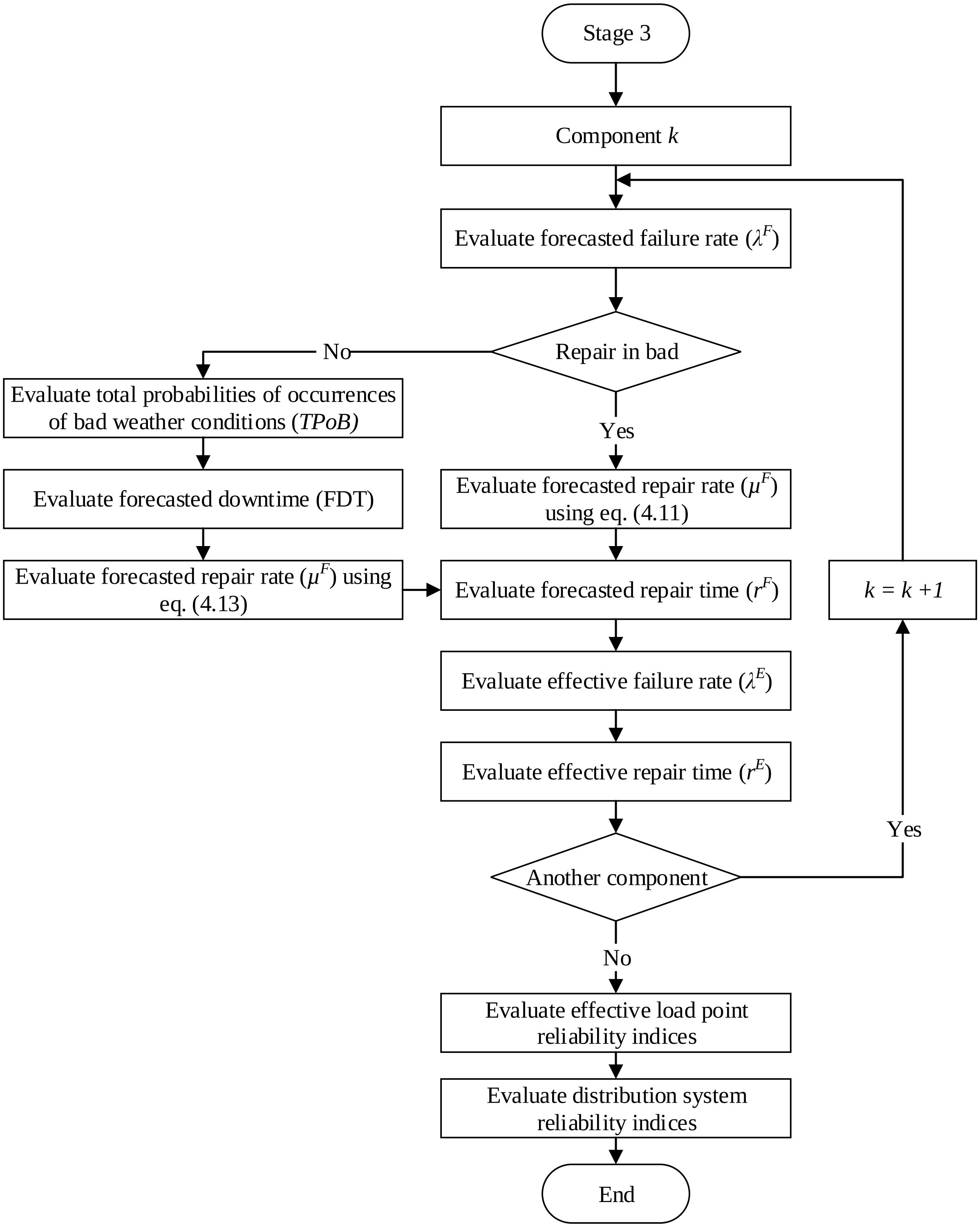


Fig. 4-6: Process of Indices Evaluation

4.4 Summary

This chapter introduces the proposed FOPRA approach and its two main concepts of PRAM method and DMARM model. The PRAM method has four main stages: data initialization, historical reliability assessment, weather forecast, and effective predictive reliability assessment; all of which are explained in detail. In the first stage, a set of historical weather, outage, and customer data is collected. The historical average failure rate value is decomposed into two sets of segmented failure rate values in the second stage. The new bad-weather severity weight of failure is evaluated in the second stage. The required weather forecast parameters are defined in Stage 3. In Stage 4, the new forecasted and effective reliability indices are introduced, and their evaluation methods are explained. The DMARM model is discussed in the next chapter.

Chapter 5
The Proposed Weather-based Decision-making Repair Model

5.1 Introduction

The deregulation and competition of the power market have placed great pressure on utilities to supply customers with a satisfactory level of reliability, which in turn may lead to higher costs in both design and operation stages. Therefore, the need for utilities to strike a balance between fulfilling customer demand for reliably and managing the associated costs effectively has become a vital practice within utilities' asset management strategies.

Restoration of failed components in a timely manner is an essential activity of a utility to reduce the outage time associated with a failure event. Reducing the outage time is of paramount importance to improve the overall level of system reliability. Solely from a reliability perspective, a component of a power system should be repaired once it experiences a failure event; nevertheless, the repair decision is governed by several factors that may defer the commencement of repair activity. Most important among these factors is the availability of repair resources at the time of failure occurrence as well as the severity of bad weather condition during which the repair activity is performed. The proposed FOPRA approach introduced in this thesis comprises two main concepts: the weather-based predictive reliability assessment method (PRAM) and the weather-based decision-making repair model (DMARM). The first concept is discussed in Chapter 4 while the second concept is introduced in this chapter.

5.2 The Concept of Weather-based Decision-making Repair Model

The previous chapter discusses the prediction of distribution system reliability performance over a future study period of one year through the introduced concept of PRAM using the newly proposed effective reliability indices. These effective reliability indices are evaluated by combining both 1) the forecasted reliability indices obtained for the future FM based on the forecast of the weather conditions of the predetermined typical FD; and 2) the historical reliability indices of the remaining eleven months. The forecasted reliability indices are FFR and FRR. The FRR is evaluated for two repair scenarios: 1) repair can be performed during bad weather; and 2) repair cannot be performed during bad weather. Thus, effective reliability indices are evaluated twice for each repair scenario. The axiomatic question arising herein is: Which repair scenario should be chosen for each component to evaluate effective reliability indices that can be used in subsequent reliability analysis? In order to determine which repair scenario should be chosen, an exhaustive investigation should be carried out for all components in the system where the cost-effectiveness of both repair scenarios is examined. Therefore, this thesis proposes a new weather-based decision-making repair model (DMARM), the objective of which is to investigate the cost-effectiveness of performing repair activities for failed components during bad weather conditions and then determine the most cost-effective repair decision for all system components. The most cost-effective repair decision is the decision that achieves minimizing the total cost while the level of reliability is maximized. Thus, an optimization problem is developed to conduct a risk cost analysis, the goal of which is minimizing the total cost (TCOST). While several optimization techniques can be employed, the Genetic Algorithms (GA) is used as an optimization tool due to its powerful feature of avoiding multiple minima. In essence, this proposed repair model would help utilities develop a weather-based crew dispatch management scheme that can enable utilities to optimally allocate repair resources in advance.

The proposed DMARM model involves the four stages of the PRAM method in addition to two additional stages. The additional stages involve: 1) conducting a risk cost analysis to find the optimal TCOST; and 2) defining the optimal system reliability level. The following steps describe the process of these stages.

5.2.1 Risk Cost Analysis

The terms risk and reliability are two sides of the same coin; that is, higher reliability means lower risk and vice versa. The risk cost analysis refers to the process of combining risk and economic factors into a unified scale of monetary value, as defined in [11]. The risk associated with a component failure and the effect of this failure on the system reliability as well as the associated costs are considered in the risk cost analysis conducted in this chapter. Particularly, the risk cost analysis aims to determine the most cost-effective repair decision with the lowest TCOST for distribution system components. The TCOST is a function of a set of reliability parameters, most important of which is the duration of repair which varies according to the repair scenario considered. Assuming that the repair activity during the forecasted bad weather conditions adheres to the safety rules and regulations developed by the governmental electricity regulatory authority, then the two scenarios of repair are considered for each component in this risk cost analysis. Thus, each component would have two possible weather-based repair scenarios: *repair can be performed during bad weather* and *repair cannot be performed during bad weather*. These two repair scenarios are the main variables of the risk cost analysis. As a result, a system containing *NC* number of components would have a total of 2^{NC} repair decisions. These entire 2^{NC} possible repair decisions are examined in terms of cost-effectiveness by evaluating the TCOST for each repair decision until the repair decision that achieves the minimum TCOST is obtained.

More details about the methodology of obtaining the optimal TCOST using the GA are explained in the next sections.

5.2.1.1 Generating Population

The GA has been commonly used as an optimization technique in a wide range of engineering problems that require identifying an optimal solution. The GA mimics the natural process of biological evolution. Biologically speaking, the human body is made up of many different kinds of cells. Each cell is composed of some parts, the control centre of which is called the nucleus. A chromosome, defined as threadlike structures located inside the nucleus, carries the genetic information in the form of genes. Thus, each chromosome contains many genes which contain the biological properties. The genes are responsible for passing on these biological properties from parents to children. Each possible value of the genes is called an allele. Alleles are variant forms of genes and they control some biological properties.

In the risk cost analysis presented in this thesis, repair decisions are formed in terms of chromosomes. Each chromosome (repair decision) consists of a number of genes. The number of genes in every chromosome is equal to the *NC* number of components in the system. Each gene (component) has two biological properties (repair scenarios) represented by binary alleles. The alleles are represented by a value of “1” or “0” for repair can be performed during bad weather or repair cannot be performed during bad weather scenarios, respectively. An example of a possible chromosome (repair decision) for a system with nine genes (components) and binary alleles (repair scenarios) is represented in Fig. 5-1:

Component 1	Component 2	Component 3	Component 4	Component 5	Component 6	Component 7	Component 8	Component 9
1	**1**	**0**	**1**	**0**	**1**	**0**	**0**	**1**

Fig. 5-1: An Example of a Repair Decision Structure

The repair decision shown in Fig. 5-1 indicates that components 1, 2, 4, 6, and 9 can be repaired during bad weather while components 3, 5, 7, and 8 cannot be repaired during bad weather.

Thus, each repair decision represents a string of repair scenarios, which are considered the optimization variables. The GA can be used as a search tool [61]–[63] to randomly generate different repair decisions with a full search space of 2^{NC}. To illustrate the construction of repair decisions using a small system, consider a system containing three components. The components are forecasted to be exposed to bad weather and all are eligible for both repair scenarios. The full search space of possible repair decisions for this three-component system is 2^3=8 as shown in Table 5-1.

Table 5-1: All possible repair decisions for a three-component system

Repair Decision	Repair Scenarios		
	First Component	Second Component	Third Component
1	1	1	1
2	1	1	0
3	1	0	1
4	1	0	0
5	0	1	1
6	0	1	0
7	0	0	1
8	0	0	0

To illustrate, repair decision 3, for instance, indicates that components 1 and 3 can be repaired during bad weather if any of them experienced a failure during a bad weather condition, while component 2 can only be repaired during normal weather. Thus, the reciprocal of equation (4.11) gives the r^F values of components 1 and 3 whereas the r^F of component 2 can be evaluated using the reciprocal of equation (4.12). Repair decision 1 indicates that all three components can be repaired during bad weather whereas repair decision 8 signifies that the repair crew cannot be dispatched to restore failed components during bad weather conditions as the repair can only be performed during normal weather.

5.2.1.2 Problem Formulation

The cost-effectiveness of all possible repair decisions is investigated by examining both repair scenarios for each component in the system. The investigation takes into account the effect that the failure may cause on the system's reliability and the associated costs. All repair-related decision costs that a utility may incur should be evaluated. Thus, a new reliability cost/worth index called total cost (TCOST) is introduced in this thesis. The TCOST is comprised of three reliability cost/worth indices: customer interruption cost (CIC), component repair cost (CRC), and lost revenue cost (LRC).

$$TCOST = CIC + CRC + LRC \tag{5.1}$$

The TCOST is evaluated for each repair decision, and the most effective repair decision has the lowest TCOST (fitness function).

5.2.1.2.1 Customer Interruption Cost (CIC)

The term CIC represents the costs incurred due to power outages. The evaluation of the CIC introduced in the literature has been based on two methods:

1. Gross Domestic Product (GDP) method [64]: The CIC is evaluated by finding the ratio of the Gross Domestic Product (GDP) to the total annual electric energy consumption in dollar per kWh. This ratio could be obtained for a particular province or for the whole country. The CIC obtained using this method represents the average economic damage cost due to energy loss for the whole province or country. The GDP method reflects the average monetary loss for the province or country; nonetheless, this method does not take into consideration customer types and their contributed impact to the economy.
2. Sector Customer Damage Function (SCDF) method [65]: The CIC is evaluated based on the estimated value of SCDF for different customer types. The concept of SCDF has been introduced based on a survey conducted in participation with the Power System Research Group at the University of Saskatchewan and all major Canadian utilities. The survey aimed to estimate the interruption loss per kW in terms of economic cost for different customer sectors. The SCDF represents the average social damage cost caused by power interruption, which varies according to both customer type and interruption duration. The concept of SCDF is used in this thesis to evaluate the CIC since the impact that every customer type may contribute to CIC is taken into consideration in this method.

Table 5-2 shows the SCDF costs of five outage durations for different customer sectors where the outage durations represent the effective repair time values of system load points.

Table 5-2: SCDF for all sector types [65]

Sector	Interruption Duration (min.) and Cost ($/kW)				
	1 min.	20 min.	60 min.	240 min.	480 min.
Large users	1.005	1.508	2.225	3.968	8.240
Industrial	1.625	3.868	9.085	25.16	55.81
Commercial	0.381	2.969	8.552	31.32	83.01
Agricultural	0.060	0.343	0.649	2.064	4.120
Residential	0.001	0.093	0.482	4.914	15.69
Governmental	0.044	0.369	1.492	6.558	26.04
Small users	4.778	9.878	21.06	68.83	119.2

The method of linear interpolation between two known points can be used to estimate the SCDF cost if the interruption duration lies between any two time slots of Table 5-2 for a given sector type. To explain the linear interpolation method, consider the straight line shown in Fig. 5-2 between the two known red points that are given by the coordinates (x_1, y_1) and (x_2, y_2). If the value of x in the blue point that belongs to the interval (x_1, x_2) is known, then the unknown value of y in the blue point can be obtained using the equation of slope, as follows:

$$\frac{y - y_1}{x - x_1} = \frac{y_2 - y_1}{x_2 - x_1} \tag{5.2}$$

Thus, for any point along the straight line, the value of y can be found using the linear interpolation method as long as the value of x is known and within the known interval (x_1, x_2). Likewise, the value of x can be found if the value of y is known and within the known interval (y_1, y_2).

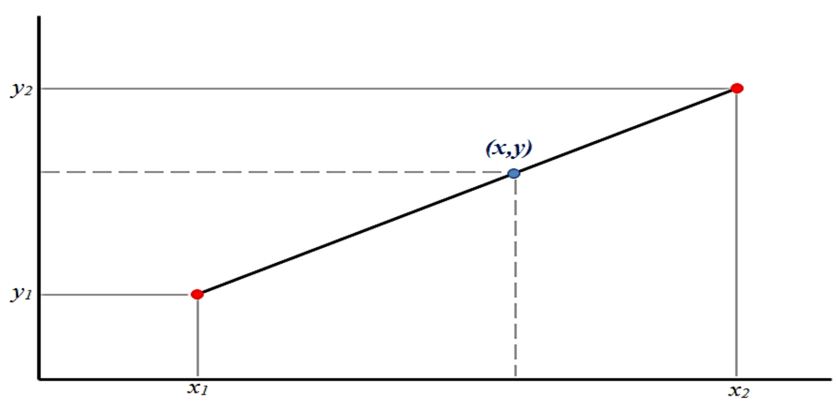


Fig. 5-2: Linear Interpolation Illustration

The Y axis represents the SCDF values whereas the interruption duration is represented by the X axis. Thus, y represents a required SCDF value to be calculated for a given interruption duration x. The interruption duration x lies between interruption durations x_1 and x_2. The SCDF values of interruption durations x_1 and x_2 are y_1 and y_2 respectively. The right side of equation (5.2) represents the slope of the straight line whose starting and ending points are (x_1, y_1) and (x_2, y_2) respectively. If the interruption duration x is greater than 480 minutes, then the same slope of the straight line whose interruption duration values x_1=240 minutes and x_2=480 minutes are used to evaluate the respective SCDF value. The SCDF is evaluated for each load point and then substituted in equation (5.3) to find the CIC of the system. Thus, for a distribution system containing NP number of load points, the CIC of the system can be evaluated as follows:

$$CIC = \sum_{j=1}^{NP} \lambda_j^E \times L_j \times SCDF_j \tag{5.3}$$

Where

CIC	Customer interruption cost ($);
λ_j^E	Effective failure rate for load point j (f/yr); and
$SCDF_j$	Sector customer damage function of load point j.

If a given load consists of several customer sectors, then the group customer damage function (GCDF) is used instead of the SCDF. The percentage of each sector u is identified [65], [66]. The GCDF of load point j is given by:

$$GCDF_j = \sum_{v=1}^{NS} SCDF_{j,v} \times u_{j,v} \tag{5.4}$$

Where

$GCDF_j$	Group customer damage function of load point j;
NS	Number of load sectors at load point j;
$SCDF_{j,v}$	Sector customer damage function of load sector v at load point j; and
$u_{j,v}$	Percentage of load sector v at load point j.

As evident in Table 5-2, the longer the interruption duration lasts, the higher the SCDF (or GCDF) and the CIC become. For failures that may occur during bad weather, performing repair activity for those failures during bad weather would reduce the interruption duration, improve the level of reliability, and consequently keep the CIC minimized. Nonetheless, this reduction in interruption duration should be economically justifiable since performing repair activity during bad weather conditions could be costlier than performing repair activity during normal weather conditions. Therefore, besides the CIC, the cost of repair should also be involved in the risk cost analysis.

5.2.1.2.2 Component Repair Cost (CRC)

The term CRC represents the cost paid to perform the repair activity for failed components. When a component experiences a failure incident, the environmental condition in which repair activity is performed has a certain effect on the cost of repair. Technically and logically speaking, performing repair activity for a failed component during bad weather conditions would be costlier than deferring the repair activity until the weather improves. The additional charge in repair cost caused by performing the repair during bad weather is because of the risk associated with sending out the repair crew in unfavourable weather. This thesis proposes a new method to evaluate component repair cost, which mainly aims to mathematically quantify the relationship between the cost of repair and the severity level of weather during which the repair activity is performed. The method introduced in this thesis to evaluate the CRC takes into consideration the contributed effect that the severity of bad weather may pose on the process of performing repair activity and expresses that effect in terms of monetary value. The CRC of component *k* is proposed to be calculated using (5.5) as follows:

$$CRC_k = (a \times \frac{\sum_{m=1}^{11} r_m + r^F \times wr}{12} + b) \times \lambda^E \tag{5.5}$$

The CRC_k represents component repair cost of component *k*. Factor *a* is a labour cost that varies depending on the duration of the outage whereas factor *b* is a constant amount of cost spent for every repair activity. The numerical values of these cost factors (*a* and *b*) are dependent on the accessibility of the component and its importance to the system. These factors are neglected when a component is in a switching state. The severity level associated with performing repair activity during bad weather is higher than that associated with normal weather; therefore, the severity level associated with the weather condition during which repair is performed should be expressed in terms of cost. Thus, a new bad-weather severity weight of repair *wr* is introduced in this thesis (shown in equation 5.5). The *wr* of a component, which is dependent upon the probability of bad weather occurrence and severity of failure during bad weather conditions, can be found as follows:

$$wr = \begin{cases} 1, & \textit{Repair cannot be performed during bad weather} \\ \dfrac{1}{T_F}[\sum_{i=1}^{NB}\sum_{t=1}^{T_F} PoB_{i,t} \times wf_{B_i} + \sum_{t=1}^{T_F}(1-\sum_{i=1}^{NB} PoB_{i,t})], & \textit{Repair can be performed during bad weather} \end{cases} \tag{5.6}$$

For any given component in the system that may experience a failure during the FD, if a component cannot be repaired during bad weather conditions and the repair can only be performed during normal weather, there is no weather severity associated with performing the repair activity since the repair is performed in favourable weather. As a result, the bad-weather severity weight of repair, *wr*, is substituted in equation (5.5) by a unity value and consequently the CRC does not involve any weather-related extra charge. In contrast, if the component can be repaired during bad weather conditions, then additional charges are expected due to the risk associated with performing the repair activity during unfavourable weather. These additional charges are mathematically expressed by the bad-weather severity weight of repair, *wr*. For a given hour *t*, the probability of occurrence of bad weather B_i at that hour *t*, $PoB_{i,t}$, is multiplied by the respective component bad-weather severity weight of failure of that particular bad weather B_i, wf_{Bi}. If $PoB_{i,t}$ is less than 100 per cent, then the complement of $PoB_{i,t}$ (i.e., 1- $PoB_{i,t}$,) is also added to the multiplication outcome of $PoB_{i,t}$ by wf_{Bi}. This mathematical operation is repeated for every hour and the summation of all hourly *wr* values are averaged over the T_F hours of the FD. The averaged value of *wr* is then substituted at equation (5.5) to evaluate CRC. This process is repeated for every component in the system using its own reliability and cost parameters. Next, the total CRC of all distribution system components is evaluated. The CRC of a distribution system containing *NC* number of components is thus given by:

$$CRC = \sum_{k=1}^{NC} CRC_k \tag{5.7}$$

Equestions (5.5) and (5.6) have introduced weather-based mathematical expressions to estimate the additional charges of performing repair activity during bad weather conditions and to evaluate the associated cost of repair.

5.2.1.2.3 Lost Revenue Cost (LRC)

The LRC refers to the profit that the electric utility missed from selling energy to consumers due to power interruption. As interruption duration increases, the LRC will increase proportionally and vice versa. In other words, the decision to perform repair activity during bad weather would help reduce the interruption duration and consequently keep LRC minimized. However, the benefit of reducing the LRC by performing repair during bad weather should be investigated. The LRC of the system can be evaluated as follows:

$$LRC = ENS \times tariff \tag{5.8}$$

Where the tariff represents the price of energy consumption that the consumers pay, expressed in dollars per kWh. The tariff varies from country to country and may vary from utility to utility within a particular country. Beside energy consumption charge, the tariff could also involve some additional fixed charges including, for instance, delivery and regulatory charges.

Equations (5.3), (5.7), and (5.8) are used to evaluate the TCOST of equation (5.1) for every possible repair decision. Possible repair decisions of a distribution system's components are bound by two repair bounds: all components can be repaired during bad weather; and all components cannot be repaired during bad weather. These are referred to as lower bound of repair and upper bound of repair respectively. A comparison between these two bounds of repair in terms of CIC, CRC, and LRC can be viewed in Table 5-3.

Table 5-3: A comparison between lower and upper bounds of repair

Cost	Repair Decision	
	Lower bound of repair: all components *can* be repaired during bad weather	**Upper bound of repair: all components *cannot* be repaired during bad weather**
Customer Interruption Cost (CIC)	The lowest CIC among all repair decisions since this repair decision guarantees keeping the interruption at the shortest possible duration by sending the repair crew immediately regardless of the condition of weather	The highest CIC among all repair decisions because all components may be left in a failure state until the weather improves and consequently result in a longer interruption duration
Component Repair Cost (CRC)	The highest CRC due to incorporating the risk associated with sending the repair crew in bad weather conditions as a cost factor in the repair cost equation	The lowest CRC due to the absence of any weather-related repair risk; all components are repaired during favourable weather conditions
Lost Revenue Cost (LRC)	The lowest LRC as this repair decision has the shortest interruption duration and consequently keeps the system's ENS minimized	The highest LRC due to long interruption duration

Referring to the example of repair decisions of a three-component system presented in Table 5-1, repair decision 1 represents the lower bound of repair for the system since all components can be repaired during bad weather whereas the upper bound of repair for the system is represented by repair decision 8 since all components cannot be repaired during bad weather.

5.2.1.3 Selection, Crossover, and Mutation

The procedure of finding the most cost-effective repair decision is outlined in the flowchart of Fig. 5-3. The first iteration starts by randomly generating an initial population of repair decisions (individual chromosomes). The TCOST (fitness function) is evaluated for each repair decision. Then, repair decisions are ranked based on their fitness where repair decisions with higher fitness scores have a greater chance to be selected as parents. After that, the uniform crossover technique with a probability of 0.5 is used to generate the offspring chromosomes. A mutation rate of 0.1 is considered to preserve diversity where a random number between 0 and 1 is generated for each repair scenario (variable). The variable that has a random number less than or equal to the mutation rate will be mutated. The mutation process entails changing a 1 to a 0 and vice versa. The stopping criterion of identifying the most cost-effective repair decision with optimal TCOST is the examination of all repair decisions where the maximum number of iterations has been reached.

By identifying the most cost-effective repair decision, the solution of the problem is obtained and the utility is advised on which components can be repaired during bad weather and on which components must have their repair activities postponed until the weather improves. Accordingly, the utility can allocate the required repair resources in advance.

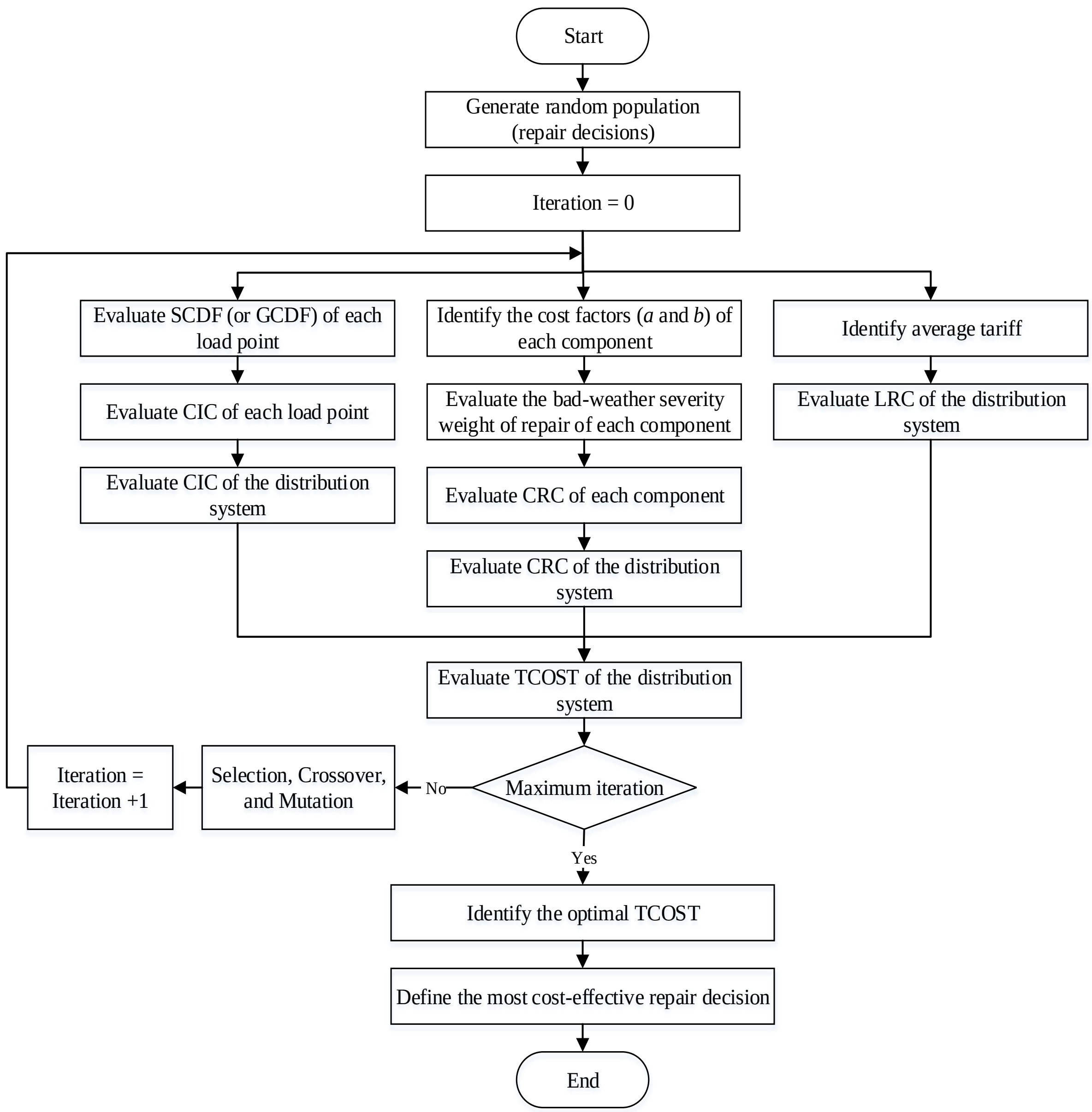


Fig. 5-3: The Procedure of Finding the Most Cost-Effective Repair Decision Using GA

5.2.2 Optimal System Reliability Level

In addition to the benefit of effectively allocating repair resources, the DMARM model would also help determine the optimal system reliability level which the utility should target over the future time-horizon of one year. According to the risk cost analysis introduced in this chapter and based on the results of the optimization process, components that can be repaired in bad weather during the FD are identified and their FRR values are evaluated using equation (4.11) whereas the FRR values for the remaining components are evaluated using equation (4.12). These values represent the optimal FRR of the components and are accordingly used to re-evaluate system reliability indices. Distribution reliability indices evaluated using optimal FRR values represent optimal system reliability level.

5.3 Summary

The concept of DMARM model is introduced in this chapter. In addition to the four stages of PRAM method, DMARM model is comprised of two more stages. The additional stages are risk cost analysis and optimal system reliability level. In the risk cost analysis, an optimization problem using GA is developed. The main objective of this optimization problem is to investigate the cost-effectiveness of performing repair activities for distribution system components that may experience failure events due to bad weather conditions. The outcome of the optimization represents the most cost-effective repair decision by identifying, in a cost-effective manner, which components can be repaired during bad weather and which components should wait to be repaired until the weather improves. Based on that repair decision, reliability indices are re-evaluated in order to identify the optimal reliability level of the system.

Chapter 6

Application of FOPRA Approach on Distribution System

6.1 Introduction

In this chapter, the proposed FOPRA approach is numerically illustrated using a case study. In the case study, a comparison between the indices obtained using the proposed approach versus the indices obtained using the commonly used conventional method is presented. The application of FOPRA on a distribution system is described in this thesis for both weather-based predictive reliability assessment method (PRAM) and decision-making repair model (DMARM). A sensitivity analysis is conducted to show the impact of different weather forecast data on the evaluation of reliability indices and the decision of repair.

6.2 Case Study

This section describes a numerical illustration of the proposed approach using the urban distribution system connected to bus 2 of the Roy Billinton Test System (RBTS) [67] shown in Fig. 6-1. The system consists of four feeders: F1, F2, F3, and F4 feeding 22 load points. The total number of components NC = 56 components is comprised of 14 feeder sections (S), 22 lateral distributors (D), and 20 transformers (T). The feeders are operated as radial feeders; however, they can be meshed using the normally open points to recover a disconnected load in the case of a component failure. A load point could be disconnected as a result of the failure of the transformer at the load point, the lateral distributor, or any section in the feeder. Disconnect switches are installed in the feeders to isolate the faulted section, thus allowing the service in healthy sections to be restored. Fuses are installed at the tee-point in each lateral distributor to protect other load points from being interrupted in the case of a distributor failure. Faulted transformers are replaced and the associated replacement time is used to represent their average repair time. The average time for switching and isolation is 60 minutes.

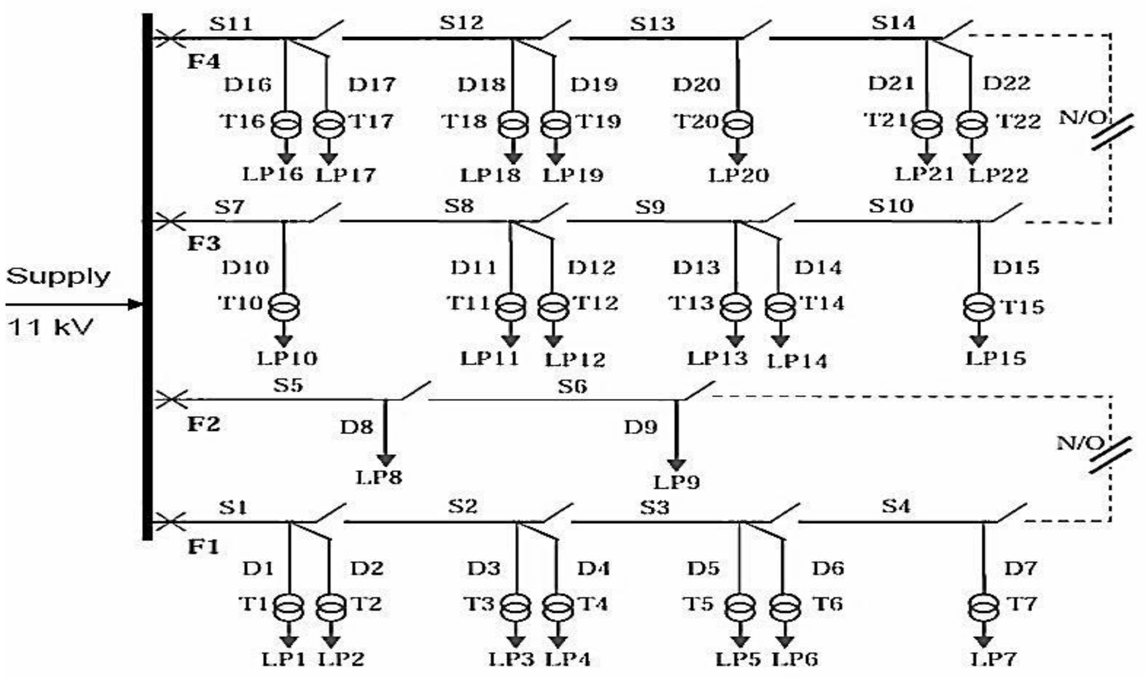


Fig. 6-1: A Typical Urban Distribution System

6.2.1 Weather-based Predictive Reliability Assessment Method

The PRAM method introduced in this thesis has four main stages, as explained in Chapter 4. The future month of the year in which the process of predictive reliability assessment starts is chosen in this chapter to be the month of December. As defined in Chapter 4, this month is referred to as the forecasted month, or FM. Thus, the FFR and FRT are evaluated for each component in the system based on weather forecast data of a typical forecasted day, FD, of December. The FFR and FRT are used in conjunction with the historical failure rate and repair time data of the months January through November to evaluate components EFR and ERT. Components EFR and ERT are used subsequently to evaluate load-point indices and distribution system indices.

6.2.1.1 Data Initialization

6.2.1.1.1 Weather Data

Assume that two bad weather conditions B_1 and B_2 are historically recorded as causing weather-related failures for system components and that their average durations are T_{B1} = 10 h and T_{B2} = 4 h, respectively, while the average duration of normal weather T_N = 300 h.

6.2.1.1.2 Outage and Customer Data

All failure rate and repair time data of the components are obtained from [67]. The average failure rate of a feeder section or a lateral distributor is 0.065 failures per year-km, whereas the average failure rate of a transformer is 0.015 failures per year. The average repair time of a feeder section or a lateral distributor is 5 hours and the average replacement time for a transformer is 10 hours. The lengths of line segments are given in Table 6-1. Based on the outage data, distribution system components can be categorized into four groups as shown in Table 6-2. The average failure rate and repair time values of the lines and transformers are presented in Table 6-3. For lines and transformers, the proportions of failures occurring during B_1 and B_2 as well as the proportions of failures occurring in every month are assumed and given in Table 6-4 and Table 6-5, respectively. Customer data are given in Table 6-6.

Table 6-1: Line segment lengths

Length (km)	Feeder sections	Lateral distributors
0.75	S1, S2, S3, S5, S7, S10, S12, S13.	D6, D11, D13, D16, D21.
0.60	S4, S6, S9, S14.	D1, D4, D10, D15, D17, D18.
0.80	S8, S11.	D2, D3, D5, D7, D8, D9, D12, D14, D19, D20, D22.

Table 6-2: System component groups

Group	Components
Group 1	S1, S2, S3, S5, S7, S10, S12, S13, D6, D11, D13, D16, D21.
Group 2	S4, S6, S9, S14, D1, D4, D10, D15, D17, D18.
Group 3	S8, S11, D2, D3, D5, D7, D8, D9, D12, D14, D19, D20, D22.
Group 4	All transformers

Table 6-3: Average failure rate and repair time data of lines and transformers

Components	λ (f/yr)	r (h)
Group 1	0.04875	5
Group 2	0.039	5
Group 3	0.052	5
Group 4	0.015	10

Table 6-4: Proportions of failures occurring in every bad weather condition

Proportions of Failures (bad weather)	Lines	Transformers
PoF_{B1} (%)	40	20
PoF_{B2} (%)	30	15

Table 6-5: Proportions of failures occurring every month

Proportions of failures (monthly)	Lines and transformers	Proportions of failures (monthly)	Lines and transformers
$PoF_{January}$ (%)	15	PoF_{July} (%)	6
$PoF_{February}$ (%)	15	PoF_{August} (%)	8
PoF_{March} (%)	4	$PoF_{September}$ (%)	10
PoF_{April} (%)	3	$PoF_{October}$ (%)	10
PoF_{May} (%)	3	$PoF_{November}$ (%)	10
PoF_{June} (%)	6	$PoF_{December}$ (%)	10

Table 6-6: Customer data

Load point	Number of customers	Customer type	Average demand (MW)
1, 2, 3, 10, 11	210	Residential	0.535
12, 17, 18, 19	200	Residential	0.450
8	1	Small user	1.000
9	1	Small user	1.150
4, 5, 13, 14, 20, 21	1	Institutional	0.566
6, 7, 15, 16, 22	10	Commercial	0.454

6.2.1.2 Historical Reliability Assessment

The historical failure rates in normal weather and bad weather for all components are evaluated on an annual basis using equations (4.1) and (4.2), respectively. The bad-weather severity weight of failure of B_1 and B_2 for each component can be found using equation (4.3). The results are tabulated in Table 6-7.

Table 6-7: Data analysis for lines and transformers

Components	λ (f/yr of normal)	λ (f/yr of B_1)	wf_{B_1}	λ (f/yr of B_2)	wf_{B_2}
Group 1	0.0153075	0.6123	40	1.1480625	75
Group 2	0.012246	0.48984	40	0.91845	75
Group 3	0.016328	0.65312	40	1.2246	75
Group 4	0.010205	0.0942	9.23	0.176625	17.3

The historical failure rates from each month for all components are evaluated on a monthly basis using equation (4.6) and presented in Table 6-8.

Table 6-8: Monthly failure rate values

Months	Number of days	λ (f/month)			
		Group 1	Group 2	Group 3	Group 4
January	31	0.007174899	0.00574	0.007653	0.002208
February	28	0.007943638	0.006355	0.008473	0.002444
March	31	0.001913306	0.001531	0.002041	0.000589
April	30	0.001482813	0.001186	0.001582	0.000456
May	31	0.00143498	0.001148	0.001531	0.000442
June	30	0.002965625	0.002373	0.003163	0.000913
July	31	0.00286996	0.002296	0.003061	0.000883
August	31	0.003826613	0.003061	0.004082	0.001177
September	30	0.004942708	0.003954	0.005272	0.001521
October	31	0.004783266	0.003827	0.005102	0.001472
November	30	0.004942708	0.003954	0.005272	0.001521
December	31	0.004783266	0.003827	0.005102	0.001472

6.2.1.3 Weather Forecast

A typical day in the month of December is chosen to represent the FD. The criteria of choosing the FD is discussed in Section 4.3. For illustrative purposes, hypothetical weather forecast data for an arbitrary FD are presented in this section. The forecast period T_F is chosen to be 24 h (1 day), starting at midnight and ending at 11:59 p.m. on that particular FD. The weather forecast data can be obtained from the appropriate local weather forecast centre in order to determine whether B_1 and/or B_2 will occur during the designated 24 h window. For the sake of simplicity, the supposition is that all components are deemed to be exposed to the same weather conditions during any given time period. Weather forecast parameters and associated probabilities of occurrence are assumed and shown in Table 6-9. It can be seen from Table 6-9 for the particular 24 h time period that: α = 19 h, β_{B1} = 4 h, and β_{B2} = 1 h. It can also be noticed that γ = 0.

Table 6-9: Weather parameters and probabilities of occurrence

Time Period	Weather Forecast	*PoB* (%)
10:00 a.m. – 10:59 a.m.	B_1	50
11:00 a.m. – 11:59 a.m.	B_1	60
12:00 p.m. – 12:59 p.m.	B_1	70
01:00 p.m. – 01:59 p.m.	B_1	80
02:00 p.m. – 02:59 p.m.	B_2	50
Otherwise	N	Negligible

6.2.1.4 Effective Predictive Reliability Assessment

Component forecasted reliability indices, FFR and FRT, are evaluated for each component in the distribution system. A set of analytical equations and MCS algorithms, presented in Section 4.3.4, can be used to evaluate FFR and FRT indices. To avoid repetition, only the FFR and FRT values obtained using analytical equations of line S1 located at feeder section F1 are validated using MCS. The FFR and FRT of all other components in the system are evaluated using analytical equations only.

6.2.1.4.1 Component Forecasted Reliability Indices

The FFR and FRT of all components are evaluated analytically using equations (4.10) – (4.14). Table 6-10 summarizes the calculations of component forecasted reliability indices.

Table 6-10: FFR, FRR, and FRT for lines and transformers

Components	λ^F (f/day)	Repair *can* be performed during bad weather		Repair *cannot* be performed during bad weather	
		μ^F (rep/day)	r^F (h)	μ^F (rep/day)	r^F (h)
Group 1	0.000283783	4.194	5.72	2.963	8.1
Group 2	0.000227026	4.194	5.72	2.963	8.1
Group 3	0.000302702	4.194	5.72	2.963	8.1
Group 4	0.0000623878	2.121	11.32	1.832	13.1

Table 6-10 shows that the FRT is longer when repair cannot be performed during bad weather with approximately 2 hours and 23 minutes for lines; and approximately 1 hour and 47 minutes for transformers. This increase in FRT values is due to the incorporation of waiting time into the evaluation of repair time until the weather improves before the commencement of repair activity. If the bad weather conditions that are forecasted to occur during the FD of December are historically recognized as low-probability-of-occurrence weather events, then these actual increases in repair time values would not necessarily be clearly manifested using averaged repair time values. This reflects the importance of recognizing the effect of such weather events in the evaluation of reliability indices.

Alternatively, MCS can be used to evaluate components FFR and FRT. Line S1 belongs to Group 1 components whose forecasted reliability indices are λ^F = 0.000283783 f/day; r^F = 5.72 h if repair can be performed during bad weather; and r^F = 8.1 h if repair cannot be performed during bad weather. Using the MCS algorithms presented in Section 4.3.4.2, the simulated values for both λ^F and r^F of component S1 are depicted and compared with the analytical values in Fig. 6-2 and Fig. 6-3 respectively. Scenario 1 represents a repair that can be performed during bad weather while Scenario 2 represents a repair that cannot be performed during bad weather. Similarly, the λ^F and r^F of all other components can be deduced using MCS.

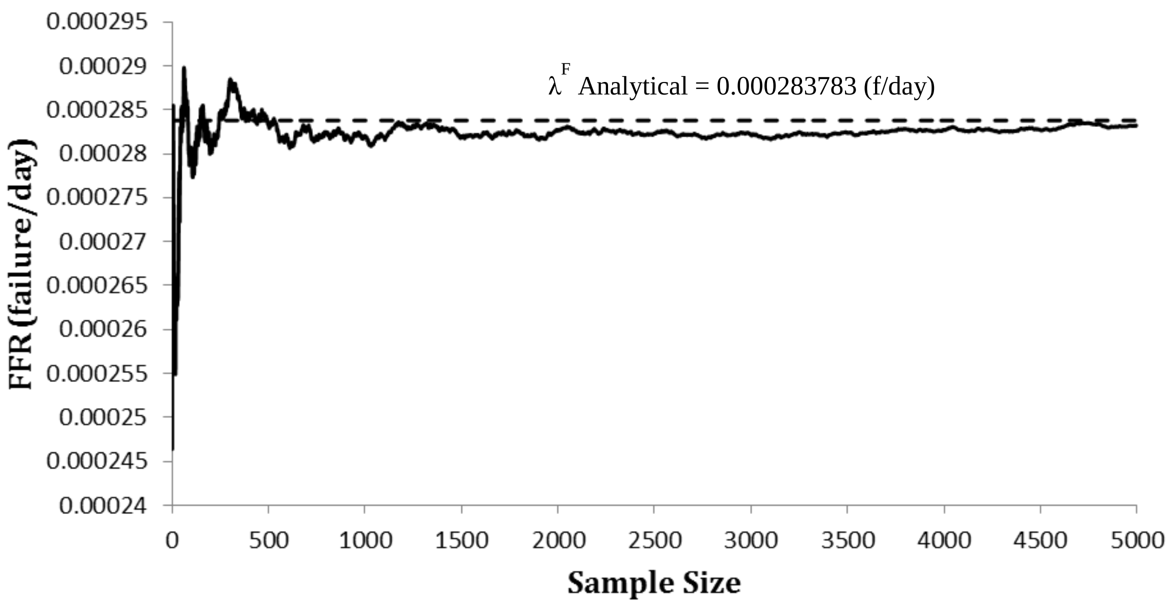


Fig. 6-2: Variation of λ^F for Line S1 with Number of Simulations

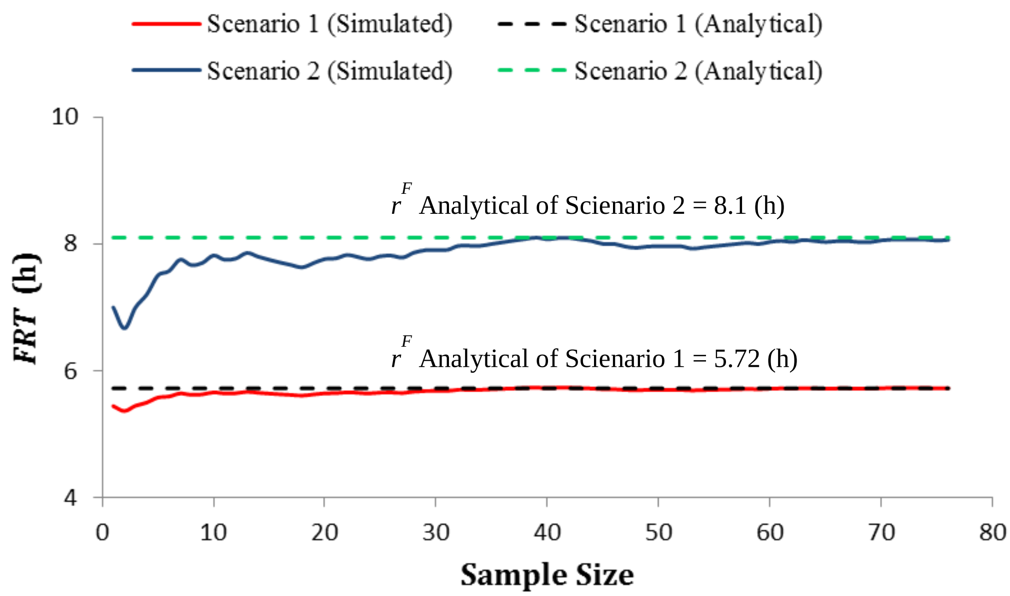


Fig. 6-3: Variation of r^F for Line S1 with Number of Simulations

6.2.1.4.2 Component Effective Reliability Indices

As previously determined at the beginning of this chapter, the month of December has been chosen to be the FM. Accordingly, the historical monthly basis failure rate values for the months of January through November for each component in the system are combined with their respective FFR and FRT to obtain the EFR and ERT for each component using equations (4.21) and (4.22) respectively. Line average repair time and transformer average replacement time values are used to represent their respective monthly repair time values. In Table 6-11, component EFR and ERT values are presented and compared with average failure rate and repair time values.

Table 6-11: EFR and ERT of lines and transformers

Components	Conventional method (average values)		Proposed method (effective values)		
	λ (f/yr)	r (h)	λ^E (f/yr)	Repair *can* be performed during bad weather	Repair *cannot* be performed during bad weather
				r^E (h)	r^E (h)
Group 1	0.04875	5.0	0.052840984	5.06	5.26
Group 2	0.039	5.0	0.042272787	5.06	5.26
Group 3	0.052	5.0	0.056363716	5.06	5.26
Group 4	0.015	10.0	0.015471112	10.11	10.26

It can be clearly observed in Table 6-11 that the effective reliability indices in this case are greater than that of conventional reliability indices due to including the evaluation of the effect of bad weather conditions that are forecasted to occur during the chosen FD of December. Nonetheless, effective reliability indices do not necessarily have to be greater than the conventional indices. In fact, they might be lesser or similar depending on the weather forecast data as they represent the effective weather-based prediction of component reliability behaviour. The EFR and ERT are used to evaluate load-point reliability indices.

6.2.1.4.3 Load-Point Reliability Indices

The approximate equation method for series systems, explained in Chapter 2, can be used in this case study to evaluate the load-point indices. Equation (2.11) can be used to evaluate load point failure rate whereas load point repair time and outage time can be evaluated using equations (2.12) and (2.13) respectively. For all load points, the EFR values are evaluated and compared with the average failure rate values obtained using the conventional method, as depicted in Fig. 6-4. It can be seen from Fig. 6-4 that there is a noticeable increase in the load-point failure rate values for all load points when component EFR values are used compared to the conventional average failure rate.

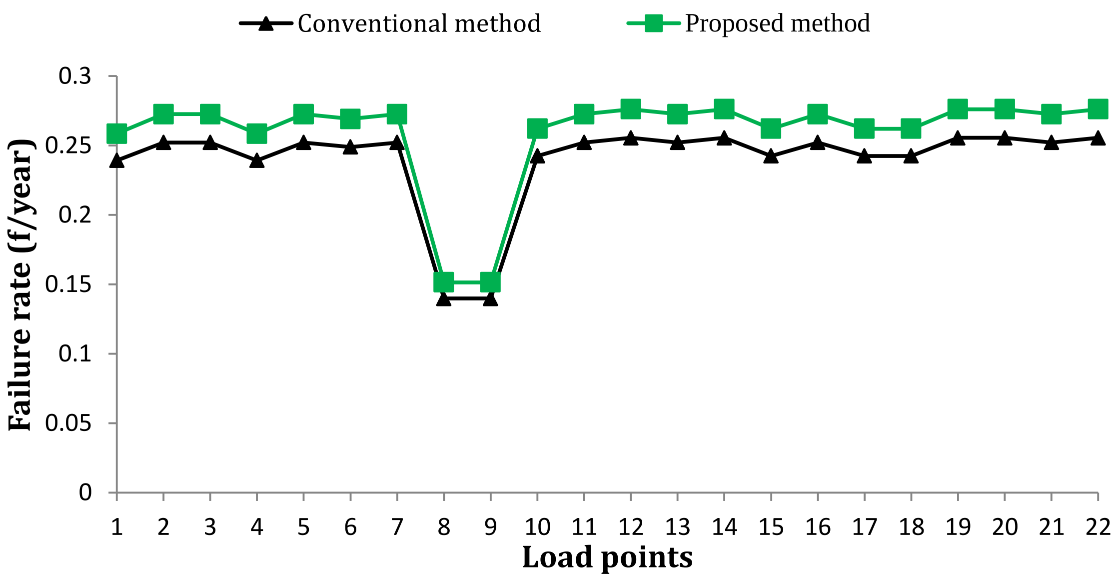


Fig. 6-4: Load-Point Failure Rates (conventional vs. proposed)

With regards to the evaluation of load point ERT, the two component repair scenarios are considered. The ERT values for each load point are evaluated for both repair bounds and compared with the conventional average repair time, as shown in Table 6-12. A slight increase in the ERT values is noticed in this case for all load points when repair can be performed during bad weather compared to the conventional repair time values. However, when components cannot be repaired during bad weather, the increase in the ERT values of load points is visible. For example, the proposed ERT value of load point 12 for the upper bound of repair indicates that a repair time that is 6 minutes longer than the conventional repair time might be required to restore the service for the 200 residential customers connected to that load point. For the same bound of repair, the repair time would be more than 11 minutes and 10 minutes longer than the conventional repair time for load points 8 and 9 respectively.

Table 6-12: Load-point repair times (conventional vs. proposed)

Load point	Conventional method (average value)	Proposed method (effective values)	
		Lower bound of repair	Upper bound of repair
	r (h)	r^E (h)	r^E (h)
1	3.03	3.04	3.12
2	3.13	3.14	3.23
3	3.13	3.14	3.23
4	3.03	3.04	3.12
5	3.13	3.14	3.23
6	3.11	3.12	3.20
7	2.98	2.99	3.07
8	3.88	3.93	4.07
9	3.60	3.64	3.77
10	3.00	3.01	3.09
11	3.13	3.14	3.23
12	3.16	3.17	3.26
13	2.93	2.93	3.01
14	2.95	2.96	3.04
15	3.00	3.01	3.09
16	3.13	3.14	3.23
17	3.06	3.07	3.15
18	3.00	3.01	3.09
19	3.11	3.12	3.20
20	3.11	3.12	3.20
21	2.93	2.93	3.01
22	2.95	2.96	3.04

For all load points, the effective annual outage time, U^E, is evaluated for both upper and lower bound of repairs and compared with conventional annual outage time, as illustrated in Fig. 6-5. Similar to the repair time, it can be noticed from Fig. 6-5 that for all load points the effective annual outage time obtained using the proposed method is higher than that of the conventional method for both bounds of repair. For instance, the conventional annual outage time of load point 12 is 48.40 minutes per year; however, when the proposed method to evaluate the outage time is applied using the effective annual outage time, the outage time is predicted to increase to 52.50 minutes per year or 53.97 minutes per year for the lower bound of repair and the upper bound of repair respectively. That is, based on the weather forecast data of the FD and historical reliability data, the 200 residential customers connected to load point 12 are predicted to experience an increase in the annual outage time ranging from 8.47% to 11.52% compared to conventional outage time. This predicted change in the annual outage time would not have been noticed without the incorporation of weather forecast data into the evaluation of reliability indices.

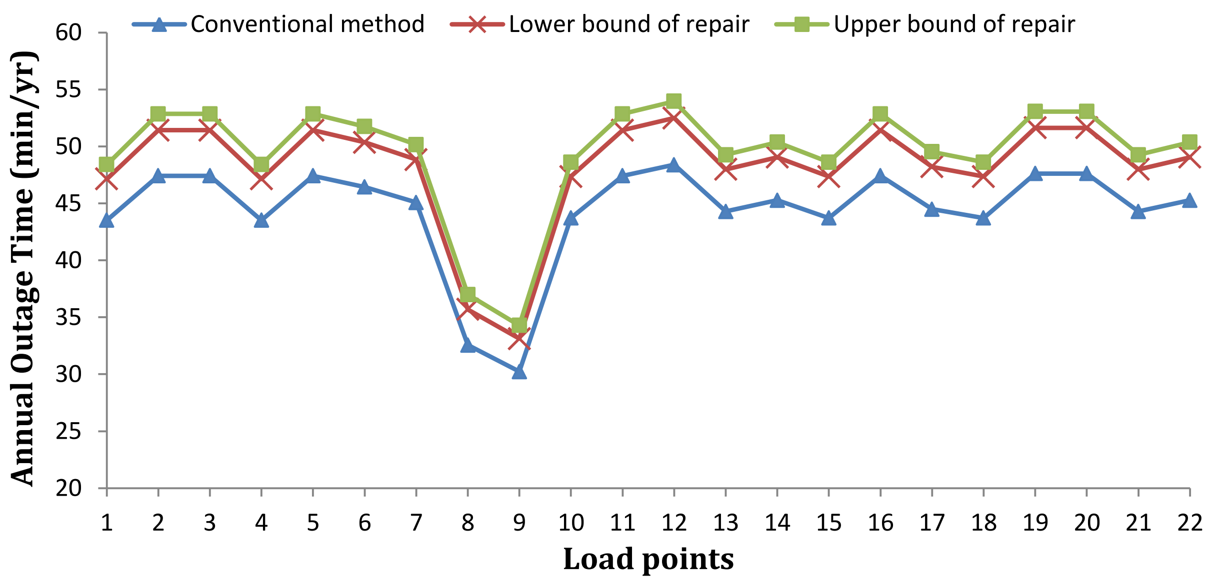


Fig. 6-5: Load-Point Annual Outage Time (conventional vs. proposed)

6.2.1.4.4 Distribution System Reliability Indices

These indices are evaluated using equations (4.23) – (4.28), and the results are compared with the results obtained using the conventional method, as shown in Table 6-13. In terms of comparison between conventional and proposed methods with regard to weather effect inclusion, the results clearly show that the indices are optimistic for the first method which, in turn, may result in misleading operational planning decisions. Indeed, the obtained results emphasize the significance of recognizing the effect of forecasted bad weather in the evaluation of overall system reliability indices.

In terms of comparing the results obtained for both repair scenarios of the proposed method, the benefit of reducing the outage time by allowing the repair to be performed during bad weather in the FD is obvious in most indices. For instance, the yearly ENS index could be reduced by up to 2.84% if all components can be repaired during bad weather conditions compared to postponing the repair activities until the weather improves.

Table 6-13: Customer- and energy-based indices of distribution system

Indices	Conventional method	Proposed method	
		Repair *can* be performed during bad weather	Repair *cannot* be performed during bad weather
SAIFI (interruption/customer yr)	0.2482	0.2683	0.2683
SAIDI (h/customer yr)	0.7656	0.8299	0.8527
CAIDI (h/customer interruption)	3.0844	3.0936	3.1788
ENS (kWh/yr)	8843.829	9598.9904	9871.6182
ASAI	0.999912606	0.999905265	0.999902657

6.2.2 Weather-based Decision-making Repair Model

6.2.2.1 Risk Cost Analysis

All components in the system are assumed to be eligible for both repair scenarios. Therefore, the full search space of all possible repair decisions is 2^{56}. The labour cost factor *a* and the constant cost factor *b* are assumed to be 250 ($/h) and 1,500 ($/repair) respectively for all components. The methodology of finding the CIC, CRC, LRC, and TCOST is discussed in detail in Section 5.2.1. The most cost-effective repair decision for system components is shown in Table 6-14. According to the results presented in Table 6-14, the repair activity is immediately performed to the components that can be repaired during bad weather as soon as they experience a forced failure regardless of the forecasted weather condition in which the failure event might occur, whereas repair activity must be postponed until weather improves if any of the components that cannot be repaired during bad weather experience a forced failure as they can only be repaired during normal weather.

The costs of CIC, CRC, LRC, and TCOST for the most cost-effective repair decision are shown in Table 6-15 and compared with the costs of upper and lower bounds of repair. When comparing the costs of lower and upper bounds of repair, the lower bound of repair has higher CRC because of the extra cost incurred due to performing the repair activity during bad weather. This is represented in the CRC equation by the bad-weather severity weight of repair. The postponement of performing repair activity until weather improves results in a longer interruption time which interprets the higher CIC for upper bound of repair. The most cost-effective repair decision is the decision that has the lowest TCOST by striking a balance between CIC, CRC, and LRC. The most cost-effective repair decision is found in this case study to be $53,089.67. By defining the most cost-effective repair decision, utilities can plan the allocation of their repair resources in advance which in turn can help maintain higher system reliability level in a cost-effective manner.

Table 6-14: Most cost-effective repair decision for system components

Repair decision	Feeder	Components
Repair *can* be performed during bad weather	F1	S3, S4, D6, D7, T6, T7
	F2	S5, S6, D8, D9
	F3	S10, D15, T15
	F4	S11, S14, D16, D22, T16, T22
Repair *cannot* be performed during bad weather	F1	S1, S2, D1, D2, D3, D4, D5, T1, T2, T3, T4, T5
	F2	None
	F3	S7, S8, S9, D10, D11, D12, D13, D14, T10, T11, T12, T13, T14
	F4	S12, S13, D17, D18, D19, D20, D21, T17, T18, T19, T20, T21

Table 6-15: Cost comparison between upper and lower bounds of repair vs. optimal repair

Repair decision	CIC ($)	CRC ($)	LRC ($)	TCOST ($)
All components *can* be repaired in bad weather (lower bound)	44,844.05	7,696.79	1,055.89	53,596.73
All components *cannot* be repaired in bad weather (upper bound)	46,175.51	6,443.23	1,085.87	53,704.618
Optimal repair	45,096.99	6,918.97	1,073.70	53,089.67

6.2.2.2 Optimal System Reliability Level

The optimal system reliability level that the utility should target can be determined by re-evaluating the distribution system indices based on the results of the optimization process obtained. Referring to Table 6-14, the FRR of the components that are designated as repairable during bad weather are evaluated using equation (4.11) whereas equation (4.12) is used to evaluate the FRR of the remaining components; these values represent component optimal FRR values. In the case study presented in this chapter, all components are connected in series; therefore, components FFR and EFR, load point effective failure rates, and SAIFI do not change regardless of the repair decision. However, in the case of redesigning some feeders to involve parallel components, all of these failure reliability indices are subject to change according to the repair decision considered. The optimal FRR values are used to find the optimal FRT which can subsequently be used to evaluate the optimal ERT. Table 6-16 presents the optimal FRT and ERT for system components.

Table 6-16: Optimal components FRT and ERT

Repair Decision	Components	Optimal FRT (h)	Optimal ERT (h)
All these components *can* be repaired during bad weather	S3, S4, S5, S6, S10, S11, S14, D6, D7, D8, D9, D15, D16, D22.	5.72	5.06
	T6, T7, T15, T16, T22.	11.32	10.11
All these components *cannot* be repaired during bad weather	S1, S2, S7, S8, S9, S12, S13, D1, D2, D3, D4, D5, D10, D11, D12, D13, D14, D17, D18, D19, D20, D21.	8.1	5.26
	T1, T2, T3, T4, T5, T10, T11, T12, T13, T14, T17, T18, T19, T20, T21.	13.1	10.26

Based on the component optimal ERT, load-point and distribution system indices are re-evaluated. In Table 6-17, optimal distribution system indices that represent the optimal reliability level of the system are tabulated and compared with those of the conventional method, and the lower and upper repair bounds of the proposed method.

Table 6-17: Comparison for customer- and energy-based indices of the system

Indices	Conventional method	Proposed method		
		Repair *can* be performed during bad weather	Repair *cannot* be performed during bad weather	Optimal
SAIFI (interruption/customer yr)	0.2482	0.2683	0.2683	0.2683
SAIDI (h/customer yr)	0.7656	0.8299	0.8527	0.8509
CAIDI (h/customer interruption)	3.0844	3.0936	3.1788	3.1721
ENS (kWh/yr)	8843.829	9598.9904	9871.6182	9760.9431
ASAI	0.999912606	0.999905265	0.999902657	0.999902862
TCOST ($)	N/A	53,596.73	53,704.618	53,089.67

The first column of Table 6-17 lists the indices used in this thesis. The second column gives the results obtained using the conventional method, with the main concern being that these conventionally evaluated indices do not represent the real behaviour of the system upon exposure to weather conditions as well as cannot reflect on reliability level of the system the profound effect of infrequent and improbable severe weather conditions. This concern is because that these system indices are evaluated based on component average failure rate and average repair time, both of which are statistical quantities obtained using historical data where the effect of weather is not apparent. In this case study, the results obtained using the conventional method give more optimistic results than the results obtained using the proposed method. The third, fourth, and fifth columns give the results obtained using the method introduced by FOPRA approach. The third and fourth columns give the results of system indices for lower bound of repair (all components can be repaired during bad weather) and upper bound of repair (all components cannot be repaired during bad weather) respectively whereas the fifth column gives the optimal results obtained from the risk cost analysis. The SAIFI does not change regardless of the repair decision due to the radiality configuration of the system in this case study. A significant improvement in terms of SAIDI, CAIDI, ENS, and ASAI can be seen when all components are assumed to be repairable during bad weather compared to the decision that all components cannot be repaired during bad weather. This improvement is due to the shortening of outage time by allowing the repair to be performed during bad weather. An investigation of the cost-effectiveness of repairing components during bad weather was conducted. The investigation involved examining all possible weather-based repair decisions using the GA in conjunction with the new concept of TCOST in order to determine the most cost-effective repair decision for system components. As pointed out in Chapter 5, the most cost-effective repair decision is the decision that has the lowest TCOST which is found to be as low as $53,089.67 and entails making the repair decisions presented in Table 6-14. Accordingly, the customer- and energy-based indices of the system are re-evaluated to determine the optimal reliability level of the system, represented in the fifth column of Table 6-17, that the utility should target in the future.

6.3 Sensitivity Analysis

In this section, the effect of weather forecast data on the evaluation of reliability indices and repair decision is examined. In addition to the base case study illustrated in the previous section, two additional case studies are presented in this section. While both of these case studies use the same data and assumptions given in the base case study, different weather forecast data of the FD are assumed. The base case study that has been illustrated in the previous section is referred to as Case 1 whereas the two additional case studies that are illustrated in this section are referred to as Case 2 and Case 3. Regarding the weather forecast data used in these additional case studies, Case 2 assumes relatively modest weather forecast data whereas extremely adverse weather forecast data are assumed in Case 3. The hypothetical hourly meteorological weather forecast data for Case 2 and Case 3 are presented in Table 6-18 and Table 6-19 respectively.

Table 6-18: Weather parameters and probabilities of occurrence (Case 2)

Time Period	Weather Forecast	*PoB* (%)
10:00 a.m. – 10:59 a.m.	B_1	20
11:00 a.m. – 11:59 a.m.	B_1	30
Otherwise	N	Negligible

Table 6-19: Weather parameters and probabilities of occurrence (Case 3)

Time Period	Weather Forecast	*PoB* (%)
10:00 a.m. – 10:59 a.m.	B_1	45
11:00 a.m. – 11:59 a.m.	B_1	55
12:00 p.m. – 12:59 p.m.	B_1	65
01:00 p.m. – 01:59 p.m.	B_1	70
02:00 p.m. – 02:59 p.m.	B_1	80
03:00 p.m. – 03:59 p.m.	B_1	90
04:00 p.m. – 04:59 p.m.	B_2	50
05:00 p.m. – 05:59 p.m.	B_2	50
06:00 p.m. – 06:59 p.m.	B_2	60
07:00 p.m. – 07:59 p.m.	B_2	75
08:00 p.m. – 08:59 p.m.	B_2	80
Otherwise	N	Negligible

Case 2 assumes weather forecast data of α = 22 h and β_{B1} = 2 h, as shown in Table 6-18, whereas weather forecast data of α = 13 h, β_{B1} = 6 h, and β_{B2} = 5 h are assumed for Case 3, as shown in Table 6-19. Both case studies assume $\gamma = 0$.

6.3.1 Weather-based Predictive Reliability Assessment Method (Sensitivity Analysis)

The FFR and FRT for all components are evaluated using equations (4.10) – (4.14) and tabulated in Table 6-20 and Table 6-21 for Case 2 and Case 3 respectively. It can be observed in Table 6-20 and Table 6-21 that components FFR and FRT change proportionally with the severity of weather conditions. That is, worse weather conditions mean higher FFR and longer FRT and vice versa.

Table 6-20: FFR, FRR, and FRT for lines and transformers (Case 2)

Components	λ^F (f/day)	Repair *can* be performed during bad weather		Repair *cannot* be performed during bad weather	
		μ^F (rep/day)	r^F (h)	μ^F (rep/day)	r^F (h)
Group 1	0.0000760133	4.703	5.1	4.364	5.5
Group 2	0.0000608106	4.703	5.1	4.364	5.5
Group 3	0.0000810808	4.703	5.1	4.364	5.5
Group 4	0.0000327531	2.355	10.19	2.286	10.5

Table 6-21: FFR, FRR, and FRT for lines and transformers (Case 3)

Components	λ^F (f/day)	Repair *can* be performed during bad weather		Repair *cannot* be performed during bad weather	
		μ^F (rep/day)	r^F (h)	μ^F (rep/day)	r^F (h)
Group 1	0.000725271	3.389	7.08	1.967	12.2
Group 2	0.000580217	3.389	7.08	1.967	12.2
Group 3	0.000773623	3.389	7.08	1.967	12.2
Group 4	0.000126635	1.742	13.78	1.395	17.2

Components EFR and ERT can be evaluated using equations (4.21) and (4.22) respectively. A failure rate comparison between the conventional method and the proposed method using the weather forecast data of Case 1, Case 2, and Case 3 for grouped components is depicted in Fig. 6-6. It can be observed that the EFR values for Case 3 are considered the highest values due to the worst weather conditions whereas EFR values obtained for Case 2 are considered the lowest values due to the relatively favourable weather conditions. The significance of incorporating the effect of forecasted weather conditions into reliability indices is quite obvious in Fig. 6-6 as the reliance on the conventional method could be misleading in some cases. The conventional method gives optimistic and over-optimistic failure rate values compared to the EFR values obtained for Case 1 and Case 3 respectively; however, relatively pessimistic failure rate values are given using the conventional method compared to the EFR values of Case 2. The observation that can be made about these values is that the evaluation of failure rate using the proposed method helps reflect the actual effect of weather on failure rate and consequently gives a more realistic indication to the failure behaviour of the component compared to the conventional method. The superiority of the proposed method over the conventional method to evaluate the failure rate is clearly identified by the inclusion of probable variability in weather condition into the evaluation of failure rate.

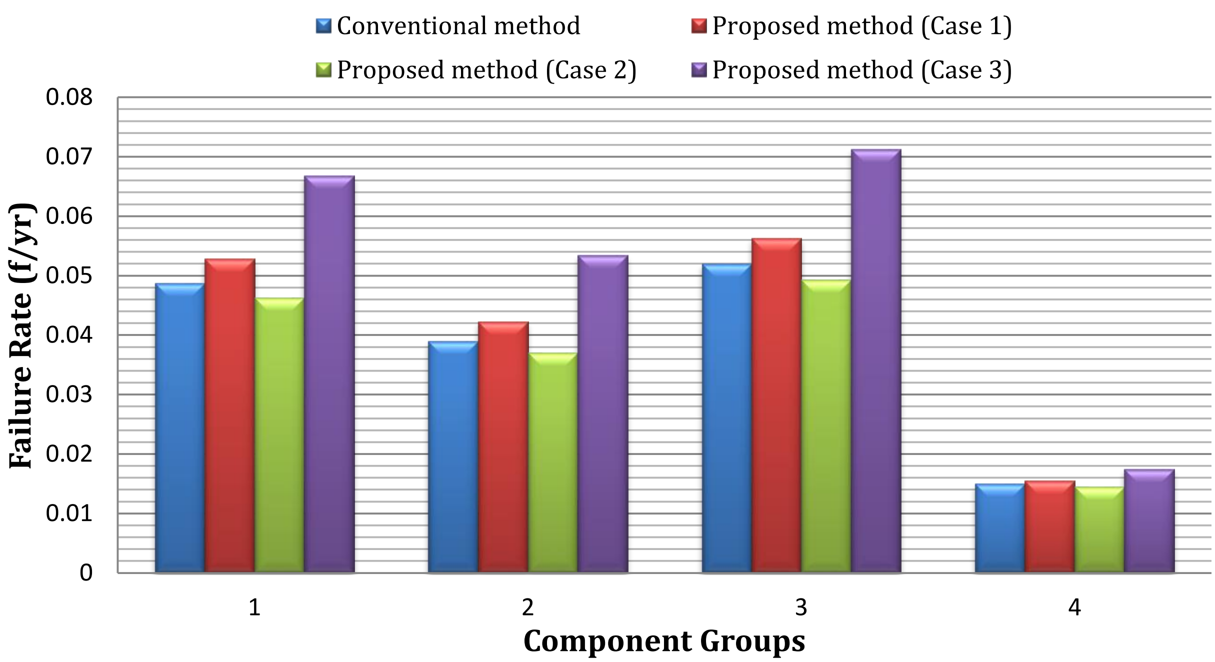


Fig. 6-6: A Failure Rate Comparison for System Components (conventional vs. all cases)

Likewise, a comparison between evaluation methods is conducted in terms of repair time (shown in Table 6-22). The main observation that can be seen from Table 6-22 is that the repair time increases as the weather worsens. When a bad weather condition is forecasted to occur, the conventional method always gives an underestimated indication of the actual repair time because incorporating the effect of forecasted weather is usually overlooked. For example, the effective repair time of Case 3 when repair cannot be performed during bad weather is longer by 12% and 6% than that of conventional method for lines and transformers respectively.

Table 6-22: Repair time of lines and transformers (conventional vs. all cases)

Components	Repair time (h)						
	Conventional method	Proposed method (effective values)					
		Repair *can* be performed during bad weather			Repair *cannot* be performed during bad weather		
		Case 1	*Case 2*	*Case 3*	*Case 1*	*Case 2*	*Case 3*
Group 1	5.0	5.06	5.01	5.17	5.26	5.04	5.6
Group 2	5.0	5.06	5.01	5.17	5.26	5.04	5.6
Group 3	5.0	5.06	5.01	5.17	5.26	5.04	5.6
Group 4	10.0	10.11	10.02	10.31	10.26	10.04	10.6

Using the approximate equation method for series systems, load-point reliability indices of Case 2 and Case 3 are evaluated and compared with the load-point indices of the conventional method and of Case 1. The load-point failure rate values are depicted in Fig. 6-7. The load-point repair time values for lower and upper bounds of repair are tabulated and compared with conventional repair time values in Table 6-23. Similarly, the effective annual outage time values for load points considering lower and upper bounds of repair are depicted and compared with conventional annual outage time values in Fig. 6-8 and Fig. 6-9 respectively.

The EFR values of load points evaluated using the proposed method are functions of the variation of weather conditions. Compared to the conventional load-point failure rate, Case 1 and Case 3 indicate a higher level of load-point failure rate while Case 2 indicates a lower level of load-point failure rate. Due to the extreme forecasted bad weather conditions that are assumed to occur during the FD in Case 3, the EFR values of the load points sharply increase compared to the values of the conventional method, Case 1, and Case 2. The conventional failure rate value of load point 12, for example, increases by approximately 36% in Case 3.

For components connected in series, load-point failure rate is dependent only on the failure rate values of load point components; however, load-point repair time is dependent on both the failure rate and the repair time of load point components, as expressed in equation (2.12). This relation interprets the variation of some load-point repair time values for lower bound of repair (shown in Table 6-23). For example, the repair time of load-point 2 for lower bound of repair of Case 2 is relatively longer than that of Case 1, although Case 2 has better forecasted weather conditions. For upper bound of repair, the repair time of load-point increases as the weather condition worsens and vice versa.

With regards to annual outage time, as pointed out earlier, the conventional method used to evaluate load-point annual outage time may not reflect the predicted annual outage time upon the exposure of system components to varying weather conditions. For both bounds of repair, the conventional method gives an optimistic indication for load-point outage time compared to Case 1 and Case 3; however, it overestimates the annual outage time if the weather conditions assumed in Case 2 are forecasted to occur.

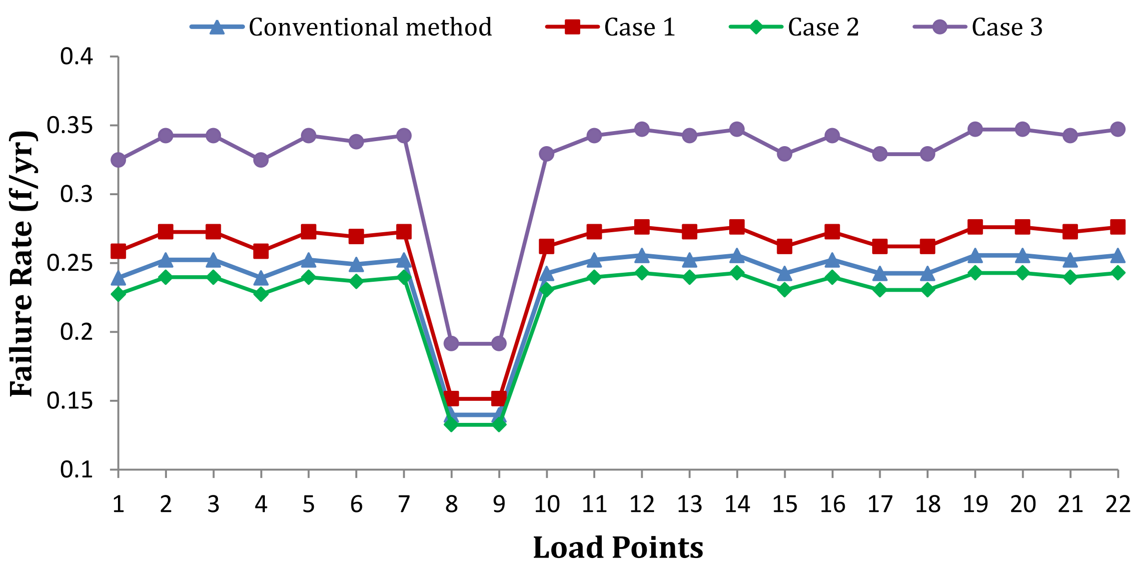


Fig. 6-7: Load-Point Failure Rates (conventional vs. all cases)

Table 6-23: Load-point repair times (conventional vs. all cases)

Load Point	Repair Time (h)						
	Conventional method	Proposed method (lower bound of repair)			Proposed method (upper bound of repair)		
		Case 1	*Case 2*	*Case 3*	*Case 1*	*Case 2*	*Case 3*
1	3.03	3.04	3.04	3.05	3.12	3.06	3.22
2	3.13	3.14	3.15	3.16	3.23	3.16	3.34
3	3.13	3.14	3.15	3.16	3.23	3.16	3.34
4	3.03	3.04	3.04	3.05	3.12	3.06	3.22
5	3.13	3.14	3.15	3.16	3.23	3.16	3.34
6	3.11	3.12	3.12	3.13	3.20	3.14	3.31
7	2.98	2.99	2.99	2.99	3.07	3.00	3.16
8	3.88	3.93	3.89	4.01	4.07	3.91	4.32
9	3.60	3.64	3.61	3.72	3.77	3.63	4.00
10	3.00	3.01	3.02	3.02	3.09	3.03	3.19
11	3.13	3.14	3.15	3.16	3.23	3.16	3.34
12	3.16	3.17	3.17	3.18	3.26	3.18	3.37
13	2.93	2.93	2.94	2.94	3.01	2.95	3.10
14	2.95	2.96	2.97	2.97	3.04	2.98	3.14
15	3.00	3.01	3.02	3.02	3.09	3.03	3.19
16	3.13	3.14	3.15	3.16	3.23	3.16	3.34
17	3.06	3.07	3.07	3.08	3.15	3.08	3.25
18	3.00	3.01	3.02	3.02	3.09	3.03	3.19
19	3.11	3.12	3.12	3.13	3.20	3.13	3.31
20	3.11	3.12	3.12	3.13	3.20	3.13	3.31
21	2.93	2.93	2.94	2.94	3.01	2.95	3.10
22	2.95	2.96	2.97	2.97	3.04	2.98	3.14

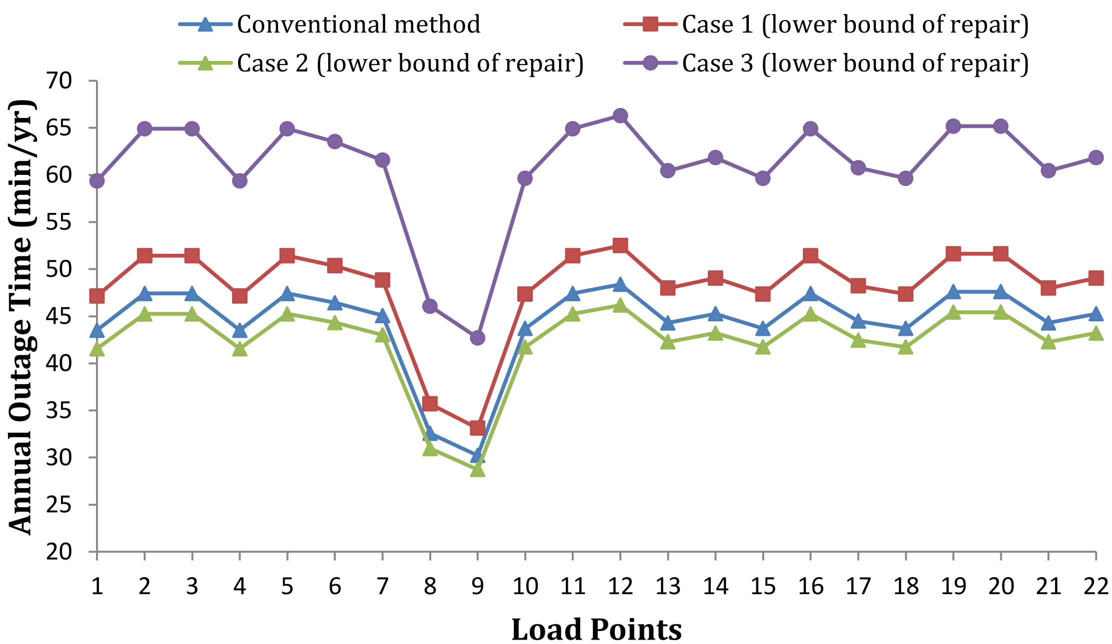


Fig. 6-8: Load-Point Annual Outage Time (conventional vs. lower bound of repair for all cases)

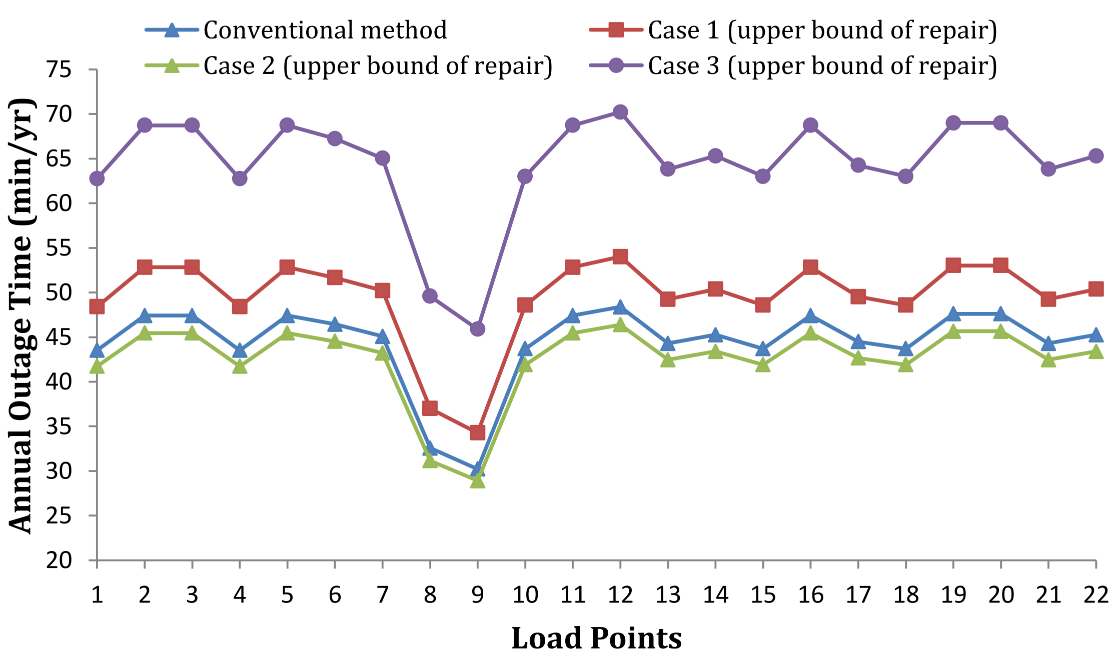


Fig. 6-9: Load-Point Outage Time (conventional vs. upper bound of repair for all cases)

In essence, overlooking evaluating the load-point reliability indices using the proposed method could result in overestimating or underestimating the reliability level of load points and hence may result in misleading identification of critical customers.

Distribution reliability indices are evaluated for the new cases and presented in Fig. 6-10 through Fig. 6-14. A conceptual representation to system SAIFI obtained using the conventional method and using the proposed method for all cases is depicted in Fig. 6-10. Since the effect of repair time is not incorporated in the evaluation of failure rate for series systems, there is no change in SAIFI level for any given case irrespective of the repair decisions. High SAIFI level can be noticed in Case 3 caused by extremely adverse weather conditions, whereas a noticeable improvement in SAIFI level can be seen in Case 2 due to the modest forecasted weather conditions. Regardless of the case study considered, SAIFI obtained using the conventional method does not reflect the real failure behaviour of the system. The conventional method gives a pessimistic indication when the system is forecasted to be exposed to the weather conditions of Case 2 whereas optimistic indications are given when Case 1 and Case 3 are considered.

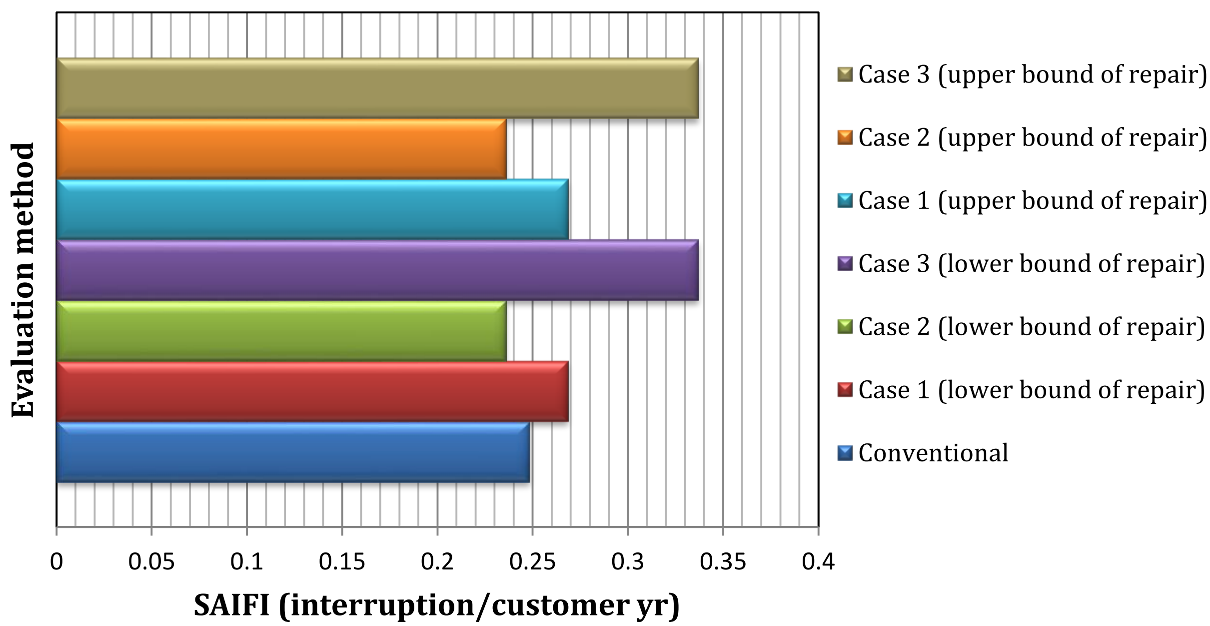


Fig. 6-10: System SAIFI (conventional vs. all cases)

System SAIDI varies according to the effect of both forecasted weather conditions and repair decision, as shown in Fig. 6-11. The SAIDI level of the system is in the highest level when the weather is extremely adverse and the repair cannot be performed during bad weather (Case 3: upper bound of repair). However, an improvement in SAIDI level is evident when repair can be performed during bad weather in the lower bound of repair in Case 3. Similar to SAIFI, SAIDI index obtained using the conventional method does not reflect the real interruption duration of the system due to the absence of incorporating into SAIDI the evaluation of the effect of weather as well as the effect of repair scenarios.

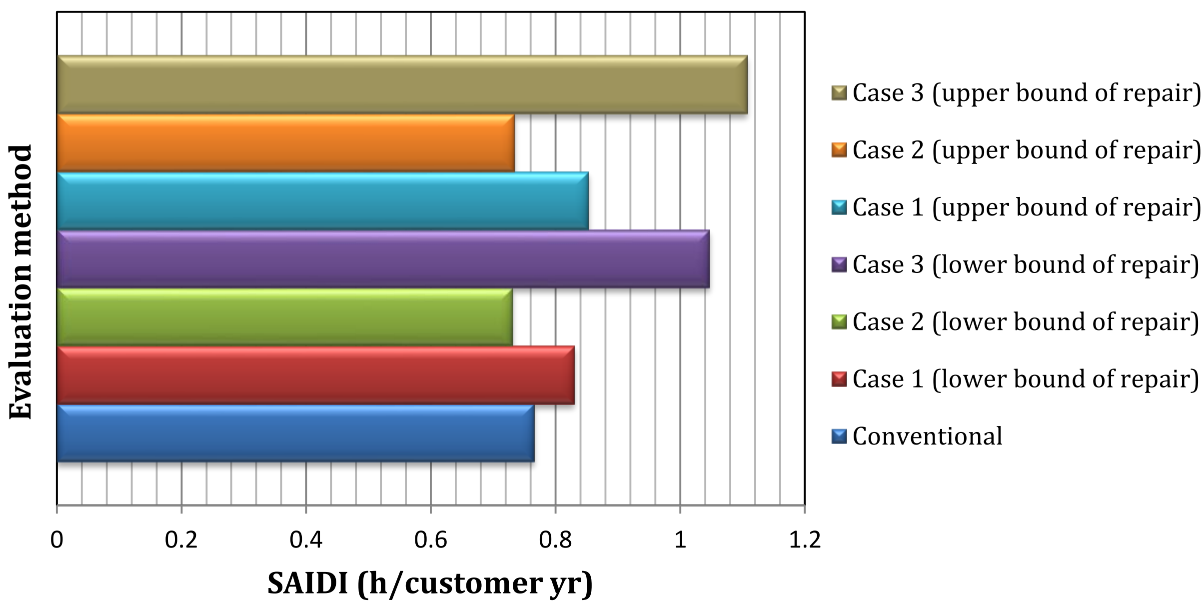


Fig. 6-11: System SAIDI (conventional vs. all cases)

Fig. 6-12 shows the CAIDI levels obtained using the conventional and proposed methods. It is clear how CAIDI is affected by the repair scenario considered. A considerable increase is evident in the CAIDI level obtained for the upper bound of repair in Case 1 and Case 3 compared to that obtained for the lower bound of repair. This increase is due to 1) the decision to postpone repair activities until weather improves for components that might experience failure events because of bad weather; as well as 2) the forecasted bad weather conditions that are assumed in these cases. The more severe the weather, the higher the CAIDI level. Due to the modest forecasted weather conditions assumed in Case 2, the difference in CAIDI levels between the values obtained for the upper and lower bounds of repair is relatively small compared to that of Case 1 and Case 3. System CAIDI that is evaluated using the conventional method gives optimistic result compared to all other cases.

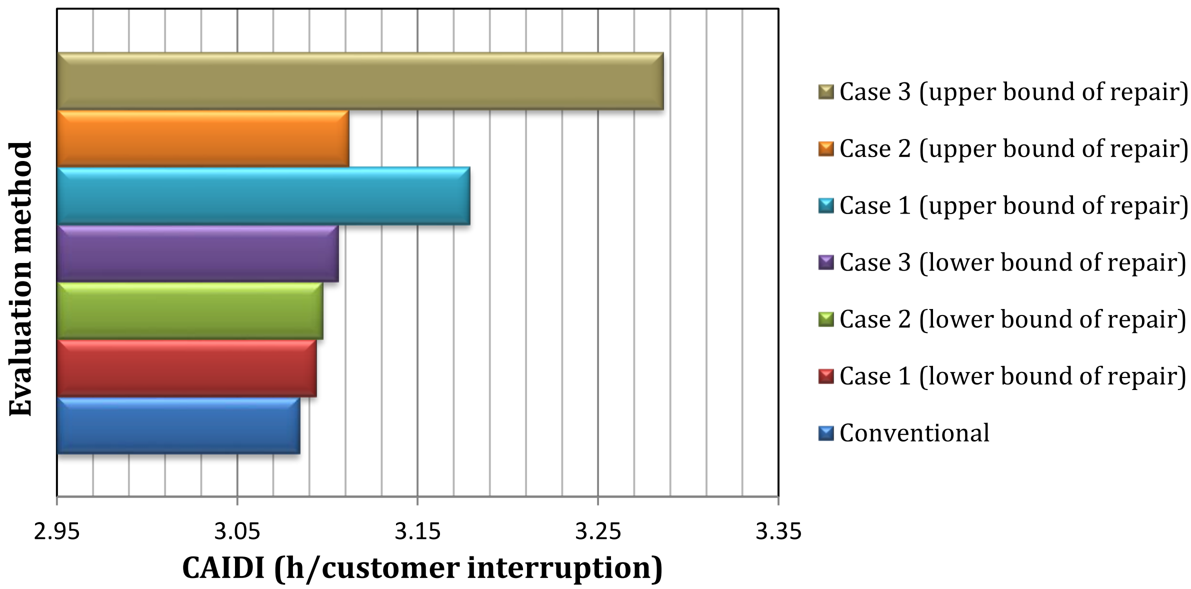


Fig. 6-12: System CAIDI (conventional vs. all cases)

The observations for system SAIDI can apply to the ENS index also since both indices are functions of the annual outage time. That is, system ENS is affected by both the repair decision that could be made and the weather condition to which the system components might be exposed. A comparison in terms of system ENS is depicted in Fig. 6-13.

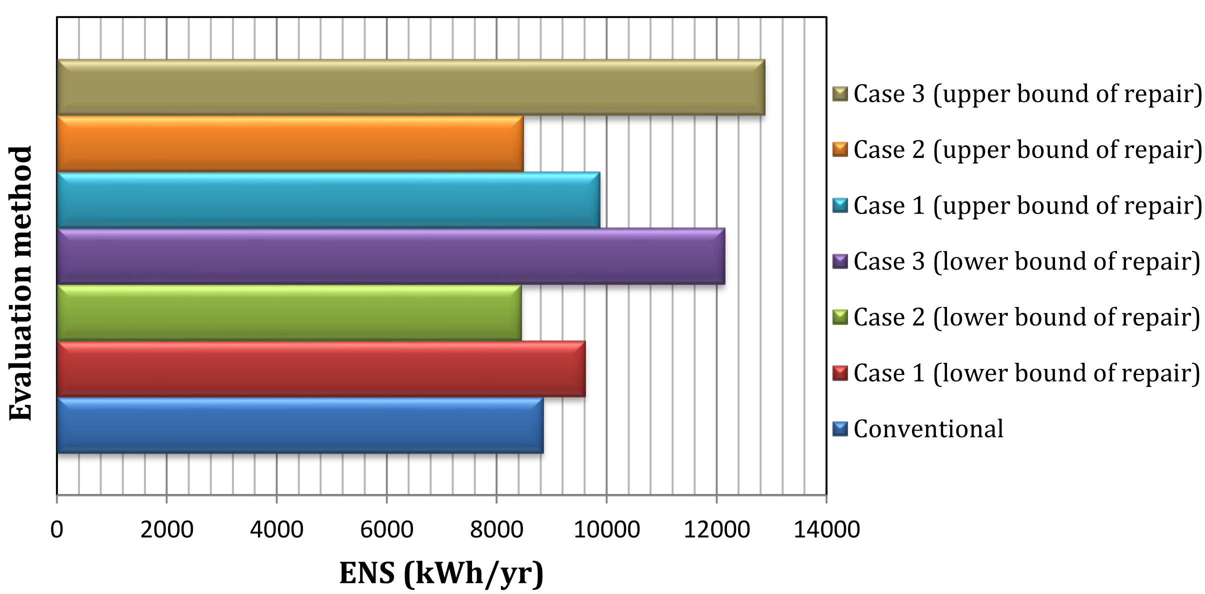


Fig. 6-13: System ENS (conventional vs. all cases)

The availability of the system is clearly affected by the repair decision and the weather conditions to which the system components are exposed, as shown in Fig. 6-14 for system ASAI. Fig. 6-14 shows how the decision of performing the repair during bad weather could positively affect ASAI levels. An improvement in ASAI levels is observed for all cases when repair can be performed during bad weather.

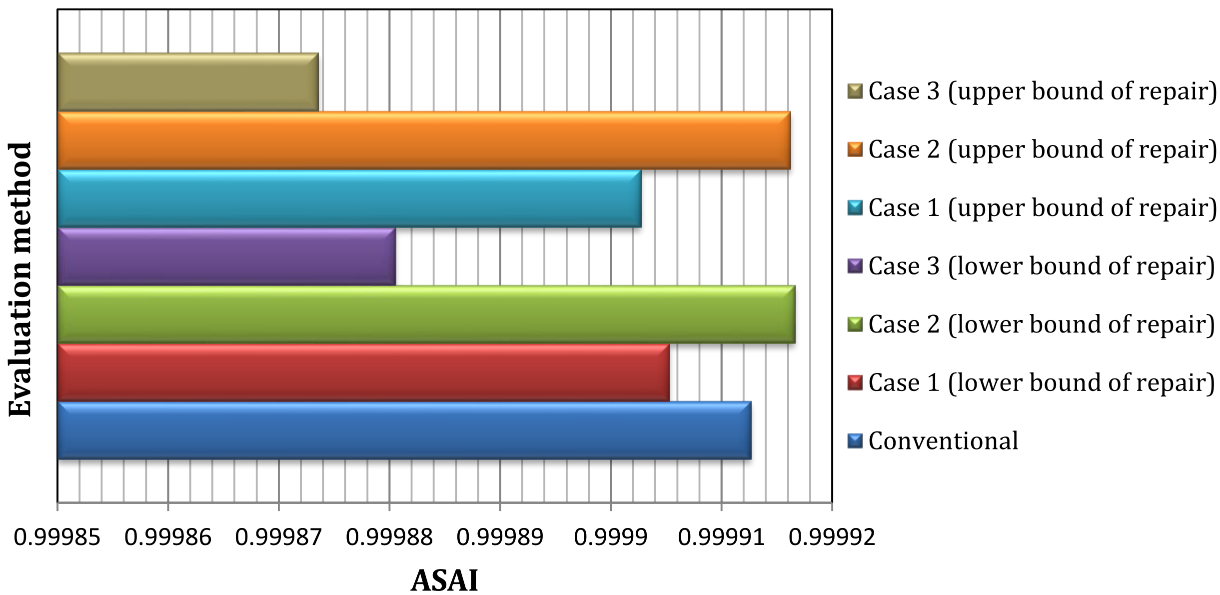


Fig. 6-14: System ASAI (conventional vs. all cases)

Regardless of the repair scenarios considered, distribution system reliability indices obtained using the conventional method may not be the most accurate indices to describe the weather-based predicted performance of the system. Thus, incorporating the effect of repair and weather forecast data has become crucial.

6.3.2 Weather-based Decision-making Repair Model (Sensitivity Analysis)

The same optimization process followed in Case 1 is applied in Case 2 and Case 3. Table 6-24 and Table 6-26 present the most cost-effective repair decisions for Case 2 and Case 3 respectively. Table 6-25 and Table 6-27 compare the optimal costs with the costs of upper and lower bounds of repair for Case 2 and Case 3 respectively. The optimal distribution reliability indices of the system are presented in Table 6-28 and Table 6-29 for Case 2 and Case 3 respectively. Table 6-30 presents the optimal distribution reliability indices obtained using FOPRA for all three cases and compared with the conventional indices.

Table 6-24: Most cost-effective repair decision (Case 2)

Repair Decision	Feeder	Components
Repair *can* be performed during bad weather	F1	S3, S4, D6, D7, T6, T7
	F2	S5, S6, D8, D9
	F3	S10, D15, T15
	F4	S11, S14, D16, D22, T16, T22
Repair *can only* be performed during normal weather	F1	S1, S2, D1, D2, D3, D4, D5, T1, T2, T3, T4, T5
	F2	None
	F3	S7, S8, S9, D10, D11, D12, D13, D14, T10, T11, T12, T13, T14
	F4	S12, S13, D17, D18, D19, D20, D21, T17, T18, T19, T20, T21

Table 6-25: Cost comparison between both bounds of repair vs optimal repair (Case 2)

Repair decision	CIC ($)	CRC ($)	LRC ($)	TCOST ($)
All components *can* be repaired in bad weather (lower bound)	39,228.82	5,754.54	928.07	45,911.43
All components *cannot* be repaired in bad weather (upper bound)	39,429.53	5,619.78	932.49	45,981.8
Optimal repair	39,266.23	5,670.88	930.70	45,867.82

Table 6-26: Most cost-effective repair decision (Case 3)

Repair Decision	Feeder	Components
Repair *can* be performed during bad weather	F1	T6, T7
	F2	S5, S6, D8, D9
	F3	T15
	F4	T16, T22
Repair *can only* be performed during normal weather	F1	S1, S2, S3, S4, D1, D2, D3, D4, D5, D6, D7, T1, T2, T3, T4, T5
	F2	None
	F3	S7, S8, S9, S10, D10, D11, D12, D13, D14, D15, T10, T11, T12, T13, T14
	F4	S11, S12, S13, S14, D16, D17, D18, D19, D20, D21, D22, T17, T18, T19, T20, T21

Table 6-27: Cost comparison between both bounds of repair vs. optimal repair (Case 3)

Repair decision	CIC ($)	CRC ($)	LRC ($)	TCOST ($)
All components *can* be repaired in bad weather (lower bound)	57,113.18	13,885.87	1335.29	72,334.34
All components *cannot* be repaired in bad weather (upper bound)	60,597.78	8,205.90	1415.45	70,219.13
Optimal repair	58,796.90	8,891.88	1401.00	69,089.77

It is evident that the components that are assigned for repair during bad weather in Case 1 are the same components that are assigned for repair during bad weather in Case 2, as shown in Table 6-14 and Table 6-24. This observation signifies the vital importance of these components to the reliability of the system. Nevertheless, when the weather worsens in Case 3, it would be more beneficial to postpone repairing some of these components until the weather improves, as indicated in Table 6-26. In terms of cost, the same observations from Case 1 are pointed out herein for both Case 2 and Case 3. Both CIC and LRC are high when repair cannot be performed during bad weather due to longer repair time whereas CRC is high when repair can be performed during bad weather due to the risk associated with performing the repair in unfavourable weather conditions.

Table 6-28: Comparison of customer- and energy-based indices of the system (Case 2)

Indices	Conventional method	Proposed method		
		Repair *can* be performed during bad weather	Repair *cannot* be performed during bad weather	Optimal
SAIFI (interruption/customer yr)	0.2482	0.2359	0.2359	0.2359
SAIDI (h/customer yr)	0.7656	0.7307	0.7341	0.7338
CAIDI (h/customer interruption)	3.0844	3.0973	3.1116	3.1105
ENS (kWh/yr)	8843.829	8436.972	8477.175	8460.929
ASAI	0.999912606	0.9999165	0.99991620	0.99991623
TCOST ($)	N/A	45,911.43	45,981.80	45,867.82

Table 6-29: Comparison of customer- and energy-based indices of the system (Case 3)

Indices	Conventional method	Proposed method		
		Repair *can* be performed during bad weather	Repair *cannot* be performed during bad weather	Optimal
SAIFI (interruption/customer yr)	0.2482	0.337	0.337	0.337
SAIDI (h/customer yr)	0.7656	1.0466	1.1075	1.1073
CAIDI (h/customer interruption)	3.0844	3.1056	3.2862	3.2857
ENS (kWh/yr)	8843.829	12138.95	12867.69	12736.35
ASAI	0.999912606	0.999881	0.999874	0.999874
TCOST ($)	N/A	72,334.34	70,219.13	69,089.77

Table 6-30: Comparison of customer- and energy-based indices of the system (all cases)

Indices	Conventional method	Proposed method (optimal)		
		Case 1	Case 2	Case 3
SAIFI (interruption/customer yr)	0.2482	0.2683	0.2359	0.337
SAIDI (h/customer yr)	0.7656	0.8509	0.7341	1.1073
CAIDI (h/customer interruption)	3.0844	3.1721	3.1116	3.2857
ENS (kWh/yr)	8843.829	9760.9431	8477.175	12736.35
ASAI	0.999912606	0.999902862	0.99991620	0.999874
TCOST ($)	N/A	53,089.67	45,981.80	69,089.77

In terms of ENS, for instance, it can be seen from Table 6-30 that the conventional method gives optimistic indication compared to Case 3 when the weather is extremely adverse and pessimistic indication compared to Case 2 when the weather is modest. The conclusion that can be made herein is that reliability indices obtained using FOPRA represent the real behaviour of the system other than the conventional indices which are just statistical quantities.

6.4 Summary

The proposed FOPRA approach is numerically illustrated in this chapter through a case study followed by a sensitivity analysis for two additional case studies. The results obtained show the significance of evaluating distribution system reliability indices using the proposed method instead of the conventional method. As a concluding remark, conventional indices are statistical quantities obtained from historical data and cannot reflect the actual performance of the system during specific operating conditions; however, the indices evaluated using the FOPRA approach reflect the actual weather-based performance of the system. Maintenance budget and component scheduled repair are more accurately estimated and better serviced using the new proposed FOPRA approach.

Chapter 7

Conclusion and Summary

7.1 Thesis Summary

This thesis proposed a new weather-based reliability analysis approach called forecasted power systems reliability analysis (FOPRA) approach. The proposed FOPRA approach aims to introduce a new philosophy to study the impact of weather on power system reliability. FOPRA approach is comprised of two main concepts:

- Weather-based Predictive Reliability Assessment Method (PRAM); and
- Weather-based Decision-making Repair Model (DMARM).

The PRAM method aims to develop a new methodology to evaluate reliability indices that can be used to predict the performance of the distribution systems in the future. PRAM involves four main stages:

1) Data Initialization: In this stage, a set of historical weather, outage, and customer data are identified.
2) Historical Reliability Assessment: In this stage the development of the equations used in the reliability assessment is carried out. These equations are then used to evaluate, for each component, the historical failure rates in normal and bad weather, the bad-weather severity weight of failure(s), and the historical failure rates during every month.
3) Weather Forecast: The weather forecast data that are forecasted to occur during the FD are collected and processed in this stage.
4) Effective Predictive Reliability Assessment: Two new sets of component reliability indices are formulated in this stage: component forecasted reliability indices and component effective reliability indices. Component forecasted reliability indices are evaluated based on the weather forecast data identified in the previous stage. Component effective reliability indices are evaluated using a new mathematical model that combines the component's forecasted reliability indices and both the component's historical failure rates during every month and the component's average repair time. Component effective reliability indices are used to evaluate load-point and distribution system indices.

The developed reliability indices evaluation method proposed by PRAM method is capable of indicating how the reliability level of the distribution system might change according to the variation of weather forecast data and the weather-based repair decision for system components. In other words, the reliability indices evaluated using the proposed PRAM method reflect the actual performance of the system.

On the other hand, the second part of the FOPRA approach, the DMARM method, developed a new procedure to investigate the cost-effectiveness of performing repair activities during bad weather conditions for distribution system components that may experience weather-related failure incidents. In addition to the four stages of the PRAM method, two additional stages are involved in DMARM model:

1) Risk Cost Analysis: An optimization problem was developed using the Genetic Algorithms (GA) to find the most cost-effective repair decision that achieves the minimum TCOST. Using the repair decision obtained from the optimization process, the allocation of repair resources can be made effectively.
2) Optimal System Reliability Level: Component, load point, and distribution system reliability indices were re-evaluated based on the results obtained from the optimization process of the risk cost analysis. These re-evaluated indices of the distribution system represent the optimal system reliability level that the utility should target.

7.2 Main Contributions

This thesis proposes a new weather-based reliability philosophy through the new forecasted power system reliability analysis approach (FOPRA). The main contributions of FOPRA can be summarized in the following points:

1. Extends the concept of predictive reliability assessment to involve predicting the benefit of reliability improvement for alternative weather-based repair decisions.

2. Introduces a new model to classify historical bad weather conditions. Every unfavourable weather condition that has been historically observed to cause noticeable forced failure for the component is classified as a separate weather state. This classification gives the reliability assessment more insight into and deeper understanding of bad weather's effect on reliability.

3. Introduces the concept of proportion of failures (PoF_m) occurring every month m. This new concept identifies the percentage of failures occurring every month which consequently can help to allocate historical failure events on a monthly basis.

4. Introduces the new term of bad-weather severity weight of failure (*wf*) to quantitatively express the severity level that a bad weather condition may pose on component failure rate.

5. Introduces a new method to decompose component average failure rate into a set of segmented failure rate values, each of which is expressed as the number of failures per month. This representation of failure rate over a short-term basis helps to identify the effect of improbable failure causes, especially those related to bad weather events. The introduced method develops a generalized form to evaluate component average failure rate during any month of the year.

6. Unlike all weather-based research works which have studied the effect of weather on reliability based on historical weather data, FOPRA approach takes into consideration the effect of both historical and forecasted weather data. Moreover, the uncertainty associated with weather forecast data is also considered. The incorporation of weather forecast data into reliability analysis helps to recognize the effect associated with ongoing changes to Earth's climate system and the consequent unpredictable variations in historical weather patterns.

7. Develops a new set of component reliability indices called forecasted reliability indices including forecasted failure rate (FFR) and forecasted repair rate (FRR). The evaluation of FFR and FRR is presented using analytical equations and MCS. Components FFR and FRR are developed in order to predict the performance of distribution system components upon exposure to weather conditions that are forecasted to occur over a predetermined forecast period. The FFR can help attentively recognize and highlight the instantaneous weather effect on failure rate value, especially for those low-probability-of-occurrence weather events.

8. Develops a new set of component reliability indices called effective reliability indices including effective failure rate (EFR) and effective repair time (ERT). Components EFR and ERT are evaluated using a new mathematical model that combines historical and forecasted component reliability indices. Unlike the conventional average failure rate and repair time, which are statistical quantities obtained from historical data, the new introduced indices of EFR and ERT help to demonstrate the actual weather-based performance of the component. Distribution system reliability indices evaluated using EFR and ERT represent the effective prediction of system performance.

9. Proposes a new decision-making repair model to investigate the cost-effectiveness of performing repair activities for failed distribution system components during bad weather conditions and

finding the most cost-effective repair decision for all system components. The introduced model can help utilities develop a weather-based crew dispatch management scheme that enables utilities to optimally and effectively allocate repair resources in advance.

10. Conducts a risk cost analysis through developing an optimization problem using Genetic Algorithms (GA). Instead of assigning one repair scenario to all components, the risk cost analysis conducted in this thesis helps to distinguish system components based on the contribution of each component to the reliability of the whole system which consequently results in the possibility of assigning different repair scenarios for the components. This provides the distribution system engineer at the utility the opportunity to schedule failed component repair in an intelligent and cost-effective manner.
11. Introduces a new reliability cost/worth index called total cost (TCOST), which involves all repair-related decision costs that the utility may incur. TCOST is comprised of three reliability cost/worth indices: customer interruption cost (CIC), component repair cost (CRC), and lost revenue cost (LRC). Both CIC and LRC have been already introduced in some references in the literature; however, they are modified by FOPRA approach to reflect the effect of effective reliability indices introduced in this thesis.
12. Introduces a new method to evaluate CRC, which aims to mathematically quantify the relationship between the cost of repair and the severity level of weather during which repair activity is performed.
13. Introduces the new term of bad-weather severity weight of repair (*wr*) to quantitatively express the severity level that a bad weather condition may pose on the process of performing repair activity and to express that effect in term of monetary value.
14. Uses the results obtained from the risk cost analysis to determine the optimal system reliability level that the utility should target.

7.3 Opportunities for Future Research

In addition to considering weather variability, the proposed FOPRA approach could be extended to consider the effect of other causes of failure including inherent component aging, for example. Repair activity is assumed in this thesis to be capable of being performed during any bad weather condition; however, further development opportunities exist to modify forecasted reliability indices to include a repair decision that allows performing the repair during some bad weather conditions and prohibits performing the repair during other bad weather conditions over the same forecast period. The major challenge associated with applying the FOPRA approach is obtaining accurate weather forecast data. Research developments in the science of meteorology would certainly be helpful in obtaining more accurate reliability indices.

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