Integrated System Model Reliability Evaluation and Prediction for Electrical Power Systems: Graph Trace Analysis Based Solutions

by

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ABSTRACT

A new approach to the evaluation of the reliability of electrical systems is presented. In this approach a Graph Trace Analysis based approach is applied to integrated system models and reliability analysis. The analysis zones are extended from the traditional power system functional zones. The systems are modeled using containers with iterators, where the iterators manage graph edges and are used to process through the topology of the graph. The analysis provides a means of computationally handling dependent outages and cascading failures. The effects of adverse weather, time-varying loads, equipment age, installation environment, operation conditions are considered. Sequential Monte Carlo simulation is used to evaluate the reliability changes for different system configurations, including distributed generation and transmission lines. Historical weather records and loading are used to update the component failure rates on-the-fly. Simulation results are compared against historical reliability field measurements.

Given a large and complex plant to operate, a real-time understanding of the networks and their situational reliability is important to operational decision support. This dissertation also introduces using an Integrated System Model in helping operators to minimize real-time problems. A real-time simulation architecture is described, which predicts where problems may occur, how serious they may be, and what is the possible root cause.

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“Persistence and perseverance will ensure your success”

To My Father
Changyin Cheng

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1 INTRODUCTION

1.1 Prelude

Electricity is a basic commodity that drives the economic productivity and prosperity of a society. Since the first generation of the U.S. power grid was successfully deployed in the twentieth century, electricity has become something that people have come to take for granted. Customers expect that electric power be available twenty-four hours a day, seven days a week, without any interruption.

Reliability of a power system is generally designated as a measure of the ability of the system to provide customers with adequate supply. It is one of the primary performance criteria of power systems. Major outages can have a significant economic impact on utility providers as well as the end users who lose electric service. The U.S. power system has been significantly affected by a wide range of outage events caused by incorrect planning, operational error, equipment failures, environmental conditions, adverse weather effects, and load conditions. Large-scale blackouts associated with the U.S. western interconnection in 1996 [1, 2] and with the northeast U.S. and eastern Canada [3] interconnection in 2003 emphasize the importance of reliability issues.

Due to the complexity of modeling and computation, it is a difficult task to analyze the entire grid configuration. Traditionally, functional zones are used to divide an overall power system into sub-systems under evaluation [4]. The functional zones depicted in

Figure 1.1 are generation, transmission, and distribution systems. Power generation combined with transmission is traditionally referred to as a composite system [5].

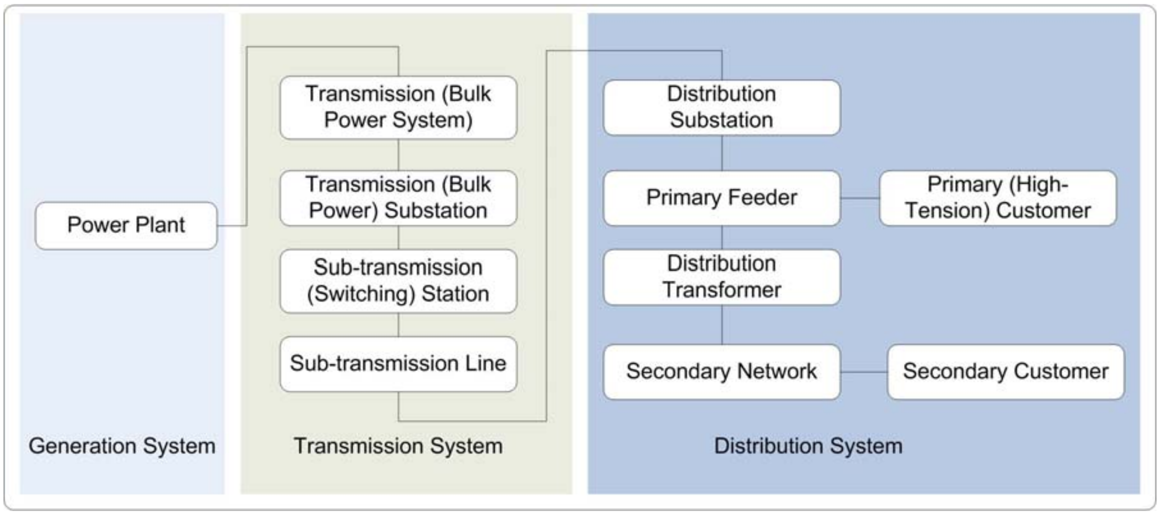


Figure 1.1 Typical Functional Zones of Reliability Analysis

In Figure 1.1, after the generator voltage (13.8~24 kV) is boosted for long distance transmission (340~765kV), the extra-high-voltage (EHV) transmission line transmits the energy to the transmission station. Following EHV transmission, the voltage may then be reduced (138 ~ 345kV), and energy transmitted to switching stations, where the voltage is further reduced to sub-transmission levels (34.5~138kV) [4]. At the distribution substation, the voltage is changed from sub-transmission level to primary distribution levels (4.16~34.5kV). Each primary feeder supplies its downstream network transformers, which reduce the voltage to secondary distribution levels (120~240V or 480V~4.16kV), and feed customers. Some large commercial or industrial customers are fed directly from feeder, subtransmission, or transmission voltage levels.

The reliability evaluation of transmission or composite systems analyzes the system failure events and estimates the chances of loss of load at major load points [6-8]. The reliability of distribution systems is based on individual customer service interruptions [9, 10]. Since the reliability studies described in this dissertation are customer service oriented, one of the analysis zones of the study includes the whole distribution system with extension to the sub-transmission lines and substations. For some of the networks analyzed here, the dominant causes of customer power interruptions are problems in secondary networks and faults in sub-transmission systems. Therefore, just considering the distribution system itself is not enough to accurately estimate customer outages.

The purpose of this dissertation is to design and build a Graph Trace Analysis (GTA) approach to providing comprehensive analysis view of power system reliability. Challenges and issues that have lingered in the traditional system modeling and reliability analysis are examined first, followed by an investigation of new changes and opportunities that come from the ongoing restructuring of the power grid. The concerns and needs from utility industry personnel are taken into account. Base on this background, two simulation tools aimed at reflecting the complexity of real-world needs are designed and implemented. The accuracy of the reliability assessment is enhanced by considering the time-varying characteristics of power systems, their operation status, and environmental conditions. The effects of the tools are examined with practical utility applications on large-scale systems and are also compared against actual field measurements of reliability.

1.2 Challenges in System Modeling and Reliability Analysis

The modeling and analysis studies associated with reliability evaluation are challenging, not only because of some of the system characteristics of the above proposed analysis zones, but also for persistent problems that have lingered in the energy industry for decades.

- ***Size***. The reliability evaluation of large utility systems can be daunting due to the sheer size of the model. Modeling the underlying distribution system, including each customer's service point, can result in a model containing millions of objects. Relatively scant attention has been given to distribution systems as compared to generation and transmission systems [11]. However, as the distribution system could be 80% larger than the transmission system, and occupies as much as 40% of the overall capital outlay of the total grid [12], it should receive adequate attention.

- ***Data***. The modeling and reliability analysis of distribution and/or transmission systems involves a large volume of various types of data and multiple system analysis algorithms. Examples of data include load, operation, planning, system design, system description, and reliability data. Examples of computer program algorithms include load flow, load forecast, network topology tracking and updating, and reliability analysis. Integrating the data into knowledge that is efficiently used by algorithms, and ensuring cooperation among algorithms are challenging tasks [13].

- ***Load***. The electrical load varies from hour to hour, day to day, and season to season. Each type of customer usually has different usage patterns. Residential, commercial, and industrial customers have different power demands and different peak demand times. This non-linear, time-varying characteristic has to be considered in order to obtain sound system evaluation results.

- ***Uncertainty***. The power system is vulnerable to many stochastic events. Random failures of control and protection devices, environmental disturbances such as high speed wind, lightning and severe storms, irregular load surges due to interruptions, and human errors all have impacts on customer outages.

- ***Fragmented Views***. In many utilities, the system and work information are not well coordinated. It is a very common phenomenon that different versions of data and naming conventions are used by different working groups for the same system information. The obvious result is that the system is not designed, planned, operated and managed in a coordinated way [12, 14]. For example, it often takes utilities days to months to determine the root cause of a major negative event from data and charts, simply because the person on duty at the onset of that root event couldn’t find the right information in a short time. As a result, the corrective action hadn’t been done in time to prevent further problems from happening. Therefore, a consistent model should be built and used by all parties.

Moreover, the model needs to be updated in a timely manner to reflect the actual field situation, as the power industry is a field intensive industry.

1.3 Changes and Opportunities

Some recent changes in the electric power industry have suggested the ever increasing importance of reliability analysis in the near future. The reliability analysis tools must keep pace with these changes:

- ***An unprecedented stressed power grid***. The U.S. power grid has continually grown larger and more complex during the past sixty years, with a trend that the load growth accelerates faster than capacity. Soon the country may experiences a capacity shortage. For the next decade, the predicted load growth rate is 3% per year, while capacity growth rate is only 0.7% per year, according to a Congressional Research Service report [15]. In addition, the load density keeps increasing with the movement of population from rural areas to metropolitan areas during the last fifty years [16].

- ***Distribution systems are as strained as transmission and generation systems***. The residential demand could be the largest portion of the peak demand among all classes of customers [17]. The growth factors of residential power consumption include population increase, more home appliances such as computers and air conditioners, and more power consuming appliances such as flat screen TVs. This, combined with commercial expansion and industrial construction, means the infrastructures that connect generators with consumers are nearing design capacity at many places [18, 19] .The situation may be even worse, as reported in official energy statistics from the U.S. government that hybrid electric vehicles (HEV) will dominate new light-duty vehicle sales by 2030 [20].

- ***Grid becomes more distributed and diverse***. The previous simple direct structure of centralized generation and distribution will give way to this trend. This also means greater need for coordination among system planning, design, operation, and management.

- ***Distributed generation (DGs) are being substituted for expensive construction in some circumstances***. To solve the imbalance between demand and capacity, one approach is to continue using the design approach of the first grid – that is building new central generating plants and transmission lines to ensure the peak load demand. The disadvantages are that the construction takes time and capital investment, which in turn will increase the cost to the customer. Also, this design will lead to idle plants that are in service a very short time, just long enough to meet the peak load demand [21]. In more and more places, the DG solution is both technically adequate and reasonably economical.

- ***Deployment of Smart Devices in the field and improved SCADA***. Many utilities in the U.S. already have a supervisory control and data acquisition (SCADA) system in operation and still continue to improve it. *Smart Grid* is the trend to build the next-generation power grid of generating distributed electricity. Through more data collection and better two-way communication, smart grid is able to provide a complete picture of customer power usage to a utility [21]. Thus, the balance of demand and supply is better monitored and adjusted. Smart grid also enhances the existing SCADA data quality and warning notification [12]. More intelligence is expected to be obtained by utilizing the improved SCADA data.

- ***Aging***. The power system infrastructure is aging rapidly. Much of the equipment is operating near, at, or beyond their life expectancy. How long they will survive is a question [22-24]. Without a good planned strategy of gradually replacing aging equipment, the cost may be high if they fail before replacement.

- ***Deteriorated Environment***. With global warming, pollution, and the associated local weather pattern changes, the overall environment of an electric power system keeps deteriorating. Factors such as high temperature plus high humidity in summer, dust due to pollution, and severe tropical storms account for major outages in many places in the U.S. [25, 26].

1.4 Voices from the Power Industry

The extensive experience of utility engineers, operators, managers, and other end-users such as counselors should be considered before an improved reliability analysis tool is designed. Some of the primary concerns voiced by the industry include:

- ***Information***

-“We can’t find the information when we need it at the right time. Often there is some inconsistency in charts and diagrams from different departments. Which of them is the correct one, or the most updated one?”

-“For consulting projects, often 90% of the project time is spend modeling the system itself, while only 10% is allotted to performing analysis and gathering results.”

- ***Real-Time***

-“We don’t know the actual real-time situation at present.”

Or- “We keep track of our network situation. But when a contingency comes, it’s still difficult for us to extract a complete and accurate picture of the network in a short period of time from the sea of data.”

-“We don’t fully understand how our network behaves.”

- ***Decision and Prediction***

-“When a summer heat wave comes, we know we can’t prevent bad things from happening. But how bad will it be? Will it affect critical customers? Where are the weak points in the system? Knowing these beforehand can help us prepare better.”

-“What is the root cause of the last big bad event? How should the network be improved to eliminate the root cause?”

-“When a contingency is under way and not yet cleared, is there a fast and efficient way to tell whether our last corrective decision is effective or not?”

1.5 Research Objectives

We are living at an exciting time, when the modernization of the next generation of the energy system is just beginning. The need for more comprehensive system modeling and reliability analysis is apparent. The approaches to design and build analysis tools are required to keep pace with the change, cope with the existing system characteristics, and meet the key needs of the industry. The envisioned features of the analysis and the major objectives of the approaches described in this dissertation are listed below.

- ***Improved System Modeling***.

A unified model is used to resolve the persistent problem of fragmented views, with the goal of better coordination among planning, design, operation, analysis, and management. The reliability characteristics of every component are embedded into the model.

- ***Efficient Computation***

The effectiveness of a computational method is strongly affected by the modeling strategy. A new approach to performing model-based computation is presented and applied to reliability analysis here, referred to as Graph Trace Analysis (GTA). GTA employs topology iterators [27], which allow a straightforward separation of component reliability parameter updating from the system reliability analysis computation itself. With GTA, the graph of a model is stored in a container, and then data, such as reliability characteristics, are attached to the graph on-the-fly using indices offered by the graph. After appropriate system model parameters are related to the graph, algorithms, such as load flow or reliability analysis, use the topology iterators offered by the graph to perform analysis calculations. Furthermore, distributed processing is used when multiple sets of system models need to be solved and the calculation results need to be coordinated. GTA, together with distributed computing, enables fast solutions of large-scale radial and looped systems.

- ***More Comprehensive Reliability Analysis***

In order to perform a comprehensive system analysis, component failures that drive customer level interruptions in both transmission and distribution systems are included into one analysis architecture. Aging, environment, weather, time-varying load, operation effects, and dependent failures are mapped onto analysis parameters that model the reliability. System components with a higher probability of failure are identified as a function of the model parameters. Corresponding contingencies may be analyzed, and system reliability assessed. Assessment may be given as system reliability indices or individual customer load point reliability indices, as well as the probability of losing substations.

- ***Improved Cascading Effect Simulation and Critical Customer Impacts***

Historically, major outages and blackouts have often been associated with cascading failure events [3, 28]. Using a sequential succession of dependent events to simulate cascading outages allows catching events which triggers catastrophes. This is also helpful in making better operational decisions to avoid the problems of losing high priority, critical customer loads.

- ***Real-Time Situational Awareness and Prediction***

Given a large and complex plant to operate, a real-time understanding of the networks and their situational reliability is important to operational decision support. Furthermore, instead of acting after weather and failures affect critical infrastructure and cause outages, performing forward-looking simulations based on real-time information would be beneficial. The backbone of the reliability analysis module is extended into an architecture that uses online weather conditions, SCADA measurements, and system operation status to foresee likely bad events beforehand. Events under interest are saved to a database, and a playback mechanism is provided to give "learn-and-improve" opportunities to let engineers, operators and managers understand their network behavior better, and make more informed decisions. Thus, an adaptive real-time monitoring and overall system status evaluation software environment is provided.

- ***Facilitation of Long-Term Planning and Short-Term Operation***

The analysis capabilities discussed above can be applied to long-term system planning as well as to short-term operation. Often, at the planning stage of utilities, different proposed alternatives need to be compared. Their performance and impact on the rest of the system are evaluated, including the change in system reliability. For short-term purposes of operation investigation and improvement, the system snapshots saved from the real-time module allow users to play with "what-if" scenarios by simulating alternative actions, or to find the root cause of a big event.

1.6 Work Summary

In summary, this dissertation describes a systematic approach toward electric power system reliability analysis, real-time monitoring, system situation assessment, and catastrophe prediction. Two analysis approaches are planned, designed, and implemented to improve advanced power system reliability assessment and to take advantage of opportunities from field challenges and changes.

The first analysis approach addresses the non-linear and time-varying difficulties of large-scale system modeling by applying a GTA-based approach. A reliability algorithm in terms of GTA notation for probabilistic solutions of large-scale system evaluation is developed. Software architecture for reliability analysis that can handle many of the complexities of the real-world is proposed. Both independent and dependent failures are incorporated into the analysis. Parameters of adverse weather conditions, heavy loading, and field operational conditions that contribute to component failure rates are identified. An integrated failure rate schema for both transmission and distribution systems is described.

With the analysis approach discussed here, the system analysis zone can be the transmission, sub-transmission, primary distribution, and/or secondary distribution, or some combination thereof. Thus, various types of reliability studies can be performed with the same analysis software architecture.

The analysis is extended into a real-time field application. This analysis integrates the functionalities of real-time grid monitoring, assessment, and reliability prediction. The analysis is based on a unified grid system model. It is designed to ensure that the model integrity is consistent with real-time SCADA measurements. The analysis takes into account network topology, on-line SCADA measurements, historical data, event storage, real-time system diagnosis, and reliability prediction. Distributed processing is used to boost the calculation speed to fit the real-time requirement. The results provided by the analysis help predict where problems may occur, how serious they may be, and what the possible root cause may be.

1.7 Dissertation Outline

There are seven chapters included in this dissertation. This introductory chapter defines the analyzing zones and reviews challenges and changes in the power industry. The objectives and features of this study are summarized here.

Chapter 2 is a literature review, which mainly encompass the reviews of the following areas: the need for integrated system modeling; outage types needed for a comprehensive reliability evaluation; comparison of existing reliability analysis methods; Monte Carlo simulation concepts and their application; reliability evaluation with DGs; and past works on real-time system monitoring and management.

Chapter 3 illustrates the outage causes and the influential weather factors based on a study of utility outage management system data. The time-varying features of component failure rates are reviewed. The design of an integrated component failure rate schema of transmission and distribution systems is given.

Chapter 4 presents GTA based reliability evaluation incorporating effects of weather, time-varying load, equipment age, wetness, and dependent failures associated with repaired components as factors that drive customer outage from sub-transmission to every customer in distribution system. Here the GTA implementation of the failure rate schema design presented in Chapter 3 is covered.

Chapter 5 gives five case studies based upon real power systems that were done using the reliability simulation method presented in Chapter 4. The first case study calculates reliability indices of aggregate networks. The second study gives reliability evaluation down to every customer load bus. The third study gives details of cascading failure analysis and system improvement according to it. The fourth case is a sensitivity study on how load and temperature affect system reliability. The last case is a transmission planning study based on reliability evaluation including the operation of DGs.

Chapter 6 extends the study scope into real-time applications. The needs of real-time reliability analysis and prediction are reviewed. A simulator architecture fitting distributed processing is proposed. Example analysis of predicted contingencies based on load, weather, and field measurement conditions which cause critical customer outages is given. Views to facilitate diagnosis are provided.

Chapter 7 presents the conclusion, lists the contributions of this work, and envisions possible future work.

2 LITERATURE REVIEW

The major purpose of this literature review is to address issues of how a system may be realistically analyzed. First, the hierarchical levels of power system reliability analysis are introduced, and the need for integrated system modeling is presented. This is followed by a review of outage types needed for a comprehensive reliability evaluation. Next, a review and comparison of existing reliability analysis methods is summarized. Monte Carlo simulation concepts and their application to power system reliability analysis are investigated. Then, the reliability evaluation with DGs is described. Past works on real-time system monitoring and management are summarized. Finally, conclusions are given to envision the importance of the work presented in later chapters.

2.1 Integrated Reliability Evaluation of Power Systems

The power system function zones described in chapter 1 are traditionally divided into three hierarchical levels as shown in Figure 2.1 [5, 29-31]. The reliability evaluation of hierarchical level I includes the generation system only. The generating capacity needs to be determined in order to satisfy the expected demand. The reliability evaluation of hierarchical level II includes generation and transmission systems, which is often referred to as the composite system or bulk power system. The transmission system has to be designed to ensure satisfactory energy transfer from generation plants to bulk load points [6-8, 32, 33]. The reliability evaluation of hierarchical level III includes all the three systems, and is rarely done due to the enormity of the problem.

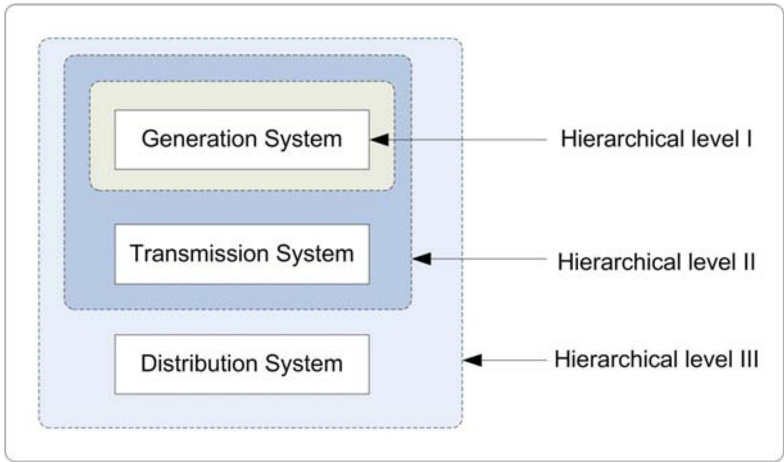


Figure 2.1 Hierarchical levels of Power System for Reliability Analysis

As stated in chapter 1, the study zones of this dissertation are transmission, sub-transmission, primary distribution, and/or secondary distribution, or some combination thereof. In this study, the combination of zones is referred to as an integrated system.

For many years, the distribution system design and analysis were decoupled from the transmission system development. The reliability studies of distribution systems are generally performed with the assumption that the transmission bulk points are fully reliable and have unlimited capacity. However, historical statistics demonstrate that problems initiated from the bulk transmission system can account for 24.4% of the end-customer interruptions [34]. Therefore, the evaluation result based on this general approach can only provide an optimistic view of the system performance.

Some past works [35-37] address this issue by using average failure rate and average annual unavailability values of the equivalent transmission system components, which are derived from an individual composite system reliability evaluation, as the inputs of the distribution system reliability study. The disadvantage of this approach is that it does not allow engineers to identify the root outage cause locations within the transmission system. Besides, these works normally use approximations to simplify system modeling [37] or failure rate calculations. This makes the evaluations derived theoretically correct but not able to deal with the time-varying characteristics of distribution systems as stated in chapter 1. In [36], an equivalent network is built by using minimal cut-set techniques as an approximation. It uses non-sequential Monte Carlo simulation to perform the reliability evaluation only at the peak load level. Therefore, the chronological effect of load conditions cannot be evaluated, nor can cascading failure effects. In [35], only first and second level contingencies are allowed, and the substation components are assumed fully reliable.

The reliability evaluation method described in later chapters aims to resolve the above problems by modeling and analyzing the integrated system. During integrated system modeling, if transmission/sub-transmission systems are included, the boundaries of transmission systems are treated such that the generation capacity is not constrained. The reliability studies are then used to examine the energy delivery capability to bulk load points for a transmission system only study or, to end-customers if the study zones include distribution systems.

2.2 Outage Types and Modeling

Component outages are the root cause of power system failure states. The first task in system reliability evaluation is to determine what component outage types are to be included into the risk assessment work. Component outages are generally categorized as independent outages and dependent outages.

2.2.1 Independent Outages

- ***Forced Outages***

Forced outages are defined as equipment outages occurring randomly and out of anyone's control [38]. The component state is usually represented with a simple two state model (up, down). Most of the forced outages in a power system are repairable outages, with each outage associated with a repair time of the outaged equipment [39]. Independent forced outages are the events included in contingency evaluations for most reliability evaluation techniques.

- ***Station Outages***

Station outages are forced outages caused by the failure of substation components, such as generators, transmission lines, and/or transformers. Though much research has been performed for the station itself [40-43], station originated outages are not included in most composite system reliability studies [5, 6, 44]. The traditional composite system reliability studies use individual bus-bars to model each substation, without any modeling of the configuration of the substation itself. However, as pointed out in [31, 45, 46], failures inside a station can contribute significantly to the unreliability of bulk load points in the composite system. Therefore, the topology and the sectionalizing devices of substations are modeled in the reliability work considered in this dissertation.

- ***Aging Effects***

For equipment in both transmission and distribution systems, it is known that the probability of equipment malfunctions increase with age. This is referred to as the aging effect [47]. The typical bathtub curves show that after the infant mortality, a constant, low failure rate exists during the equipment's useful life. Finally, the failure rate starts to increase exponentially until the component fails [9].

Previous studies have demonstrated that aging failures have a significant impact on system reliability. Therefore system aging effects should be included in reliability modeling factors. This is especially true for systems with aged equipment [48, 49] [22, 23]. Underestimation of the system risk could occur if we ignore the aging failure in reliability evaluations.

As the probability of aging failure increases as time passes, using the exponential distribution function to model it is not appropriate, since it implies a constant failure rate. Many papers have discussed using Weibull distribution functions to model aging failures. In [48], Li proposed a method to incorporate aging failures in reliability evaluation by treating aging failures with the same form as repairable failures. More Weibull model selection and adjustment on modeling aging failure is discussed in [50-53]. The shared disadvantage of these methods is the use of non-linear functions to solve the problems. Also, since typically exponential distributions are used to model most forced-outages, two distribution functions will need to be used if considering forced outages and aging failures together.

2.2.2 Dependent Outages

Like independent outages, dependent outages also have significant impacts on system reliability. Historically, major outages and blackouts have been related to dependent failure events [3, 28]. Most of these outages are not normally included in the traditional reliability evaluation of composite or distribution systems [23, 39, 54-56]. The concepts of these outages and their importance are reviewed here, with a brief discussion of the limitations of past studies.

- ***Common-mode Outage***

Common-cause outage is the outage of multiple pieces of equipment at the same time due to a common cause [57]. An example is a common environmental condition, such as lightning striking one transmission tower, causing several transmission lines connected to the tower to fail simultaneously. Common-mode outages may have a strong impact on system reliability. For example, redundant equipment is generally installed near the place or follows the same route of the operating equipment, so both of them are vulnerable to the same environmental hazard. In a common-mode outage of two pieces of equipment, the redundancy of the original design is removed. Thus, the effect of a common-mode outage has a higher probability to create new contingencies in the system. If a reliability study excludes the analysis of common-mode outages, the chance of several pieces of individual equipment failing simultaneously is very small, and cannot reflect the realistic situation.

- ***Component-group Outage***

Component-group outage is the failure of any component in a group of components leading to the simultaneous outage of all the components in that group [38]. The difference between common-cause outages and component-group outages is that the components in the former can have individual outages, while the components in the latter have to suffer outages together. A typical example of component-group outage is the failure of a component in a circuit segment leading to all other components in that segment losing power, because of the operation of sectionalizing devices to isolate the failure. Here, the definition of a circuit segment is the same as in [58], which is a group of equipment bounded with the same set of sectionalizing devices. The sectionalizing devices are important to the correct determination of reliability and system loading. However, much reliability work neglects the modeling of these, such as typical transmission systems models. The GTA concept introduced in Chapter 4 simplifies the modeling of sectionalizing devices and simulation of their operations.

- ***Cascading Outage***

A cascading outage occurs when the failure of a first component triggers the failure of a second component, and so on. As time elapses, the outage is sequentially propagated to more and more areas. The blackouts in U.S. history have often been associated with cascading outages [28, 59-61]. The failure of one transmission line can lead to the overloading of a second transmission line. When the auto-protection mechanism cuts off the second transmission line, this leads to more serious overloading problems on other lines and under voltage problems at some buses. Cascading effects have not been extensively included in traditional grid planning and operations [62]. Previous vulnerability assessments for cascading outages [60], and studies of analysis and control of major blackout events [61] demonstrate the importance of including cascading effects in the reliability analysis of power systems.

- ***Weather Dependent Outage***

Weather-dependent outages reflect the phenomenon of the failure bunching effect [63]. That is, the probability of component failures increases dramatically under adverse weather conditions. Unfavorable weather conditions, such as high speed wind, high temperature, or lightning, are not generally of long duration, but their impact on system reliability should not be ignored. However, a great number of past reliability evaluations only apply constant component failure rates, the value of which is based on historical outage statistics of the system.

Modeling the failure bunching effect has not been extensively studied. Considering the impact of weather on system reliability is generally done in two ways. The first approach uses correlation curves to predict the number of customers interrupted according to weather patterns, and adjusts reliability indices values accordingly [64]. The second approach adjusts component failure rates based on weather states [65-67]. The common weakness of these approaches is the weather state modeling.

The concept of weather-state modeling is proposed in [47, 67] and [68]. The weather conditions are only classified into one of two categories – normal or adverse weather. Accordingly, there are two component failure rate values associated with the two weather conditions. This trend is then extended by introducing more weather states or parameters during adverse weather conditions. The method of [69] uses storm duration and number of flashes; [70] uses wind speed and temperature level; [10] uses wind speed value to further categorize the severity of storms. These works only take into account storms as adverse weather conditions, while in reality other weather conditions such as (freezing) rain or heat waves also have significant impacts on the component failure rates. The impact of these failure rate influential factors will be introduced in Chapter 3. A comprehensive failure rate schema, which models component time varying failure rates according to detailed weather conditions, the type and age of the component, and load condition, is proposed there to serve partially as an improvement on weather dependent outage modeling.

2.3 Reliability Assessment Methods of Power Systems

The methods used in reliability assessments of power systems determine the accuracy of the results. Analytical and simulation approaches are the two types of techniques used in power system reliability analysis. Each approach has its merits and limitations. In this section, the concepts, assumptions, and typical applications of the commonly used methods in both techniques are reviewed. The limitations of analytical approaches are summarized as the reason to select the Monte Carlo simulation to perform the reliability analysis in this study.

2.3.1 Analytical Approaches

The analytical analysis methods use mathematical models to provide solutions to a reliability problem. Specific calculation results are obtained for a given set of system topology and input values. Some widely used methods are block diagram, event tree, cut sets, fault tree, state enumeration, and Markov modeling. Using reliability sets in calculation is also proposed in recent years. Their common problem is the frequent need to make simplifying assumptions and approximations.

- ***Reliability Block Diagram (Network Reliability Equivalent Modeling Method)***

This method utilizes modular concepts to reduce the overall system to a simple failure logic connection diagram, which only contains series and parallel components. The conditional probability approach is then used to calculate this series and parallel arrangements [71]. The application of this method usually needs to oversimplify component reliability parameters in order to transform the system into its functional layout. A typical example is to apply estimated failure rate values according to the number of pieces of equipment falling into each functionality group, such as protection, control, and monitoring groups [72].

- ***Event Tree***

An event tree of a system is a visual presentation of all events that may occur in a system [73, 74]. After an initiating event(s) is (are) selected, the possible consequences involving success and failure of the system components are deduced, and fan out as the branches of a tree. Each failure path represents a failure scenario that the system fails if all the components in this path fail. The size of the tree can be staggering for a large system. If each component can reside in either operating or failed status, a complete event tree of a system has 2^n paths for an n-component system. Therefore, reduced event trees are often used, sacrificing some precision.

- ***Cut Set***

A cut set contains a set of system components whose failure can lead to the failure of the system. The minimum subset of a cut set is called minimal cut set, which contains the set of components that must fail in order for the system to fail. Each cut in the cut set is in series with other cuts, with the components inside a cut combined using the principle of parallel components. As the failure path of an event tree is equivalent to a cut in the cut set, the minimal cut set can be derived to reduce the size of the tree. However, even the minimal cut set can still be prohibitively large for large systems. As a common case, exhaustive evaluation for precise results is often compromised with fast calculations by using approximations, such as neglecting cut sets greater than a certain value. This is based on an assumption that high order cut sets are much less probable than low order cut sets [73].

- ***Fault Tree***

Similar to an event tree, a fault tree is a pictorial representation of the failure logic embedded in the system. The top event of the tree, however, can only be a particular failure condition compared to that of the event tree. The branch events are then constructed as the essential events in order to lead to the top failure event. Therefore, this method is good at mission-oriented evaluation. It is applied particularly for safety assessments and not comprehensive reliability evaluations [38] [75].

- ***State Enumeration***

The state enumeration method tries to identify the events that have an adverse effect on system reliability, and evaluates the effects. Evaluating all possible contingencies is not practical and not required. The practical enumerative method utilizes contingency screening policies to reduce the number of states evaluated. A common approach is to evaluate the primary contingencies, whose outage frequencies exceed some predetermined value. Another approach is to use the contingency ranking method. It uses the severity level, such as overload condition of the contingency, for screening [44, 76, 77].

The limitation of this method is that the number of contingencies is large if the study system is large, even with the screening approaches [78, 79]. Moreover, it is not easy to accommodate the stochastic treatment of system loading. Usually, only a few selected load levels based on experience are used to perform the analysis [80]. Planned outages, such as maintenance events, are also not easy to integrate into this approach [81, 82].

- ***Markov Modeling***

Markov modeling is a matrix method that is applicable to memoryless systems whose components' probability distributions are constant hazard rates [31, 66, 83]. In order to perform the evaluation, the stochastic transitional probability matrix needs to be constructed. It is an $n \times n$ square matrix of an n-state system. As the system topology changes, the system transitional matrix needs to be re-constructed. Therefore, the application of this method is generally limited to simple system configurations.

- ***Reliability Set Calculation***

In [84], eight reliability sets are proposed in order to calculate the SAIDI [85] of individual circuits or feeders. The sets are defined based on the segments of the circuits. The system model is simplified to sets, with an average failure rate value of each segment. After that, the optimal placement of a DG for time–varying loads is examined. The major limitation of this method is that it only applies to radial system. Also, it assumes that only one failure takes place at a time, and thus does not handle multiple failures.

2.3.2 Simulation Approaches

The above review demonstrates that present analytical reliability techniques are not capable of modeling a large number of real system characteristics. For those analytical methods utilizing parallel and series network calculating principles, there are many realistic systems not easily separated into small independent subsystems [86]. All of the analytical methods that model detailed system states and/or enumerate among them have the common problem of system model size for large systems. Stiffness in calculation is also a problem when using traditional matrix methods. Additionally, using the Markov chains implies the events are memoryless, which often is not the case.

Compared with analytical approaches, the simulation or Monte Carlo approach is more universal. It provides a solution for complex problems that is not feasible for analytical methods [87]. The Monte Carlo method is widely used to simulate the stochastic behavior of systems and actual processes. The random number generator of the Monte Carlo simulation creates random variants that follow the distribution functions, even non-constant hazard rates. The simulation convergence is a fluctuating process, with the estimated outcome closer to the true value as sample size increases [63]. The convergence criterion usually uses the coefficient of variation of the output.

The Monte Carlo method can be further classified into non-sequential and sequential approaches. Non-sequential simulation is implemented by ignoring the event chronologies in the system. The state sampling method samples the states (up, down) of each component, and combines them to determine the system state. The state-transition sampling method uses system state transition and not the component states to calculate reliability indices [88]. The non-sequential methods cannot provide the interruption duration of system failure scenarios. In the case of simulating the chronological aspect of system operation, the sequential method (state duration sampling method) is needed. In this method, the chronological sequences of states (up, down) for each component in the system are generated, and combined to form the chronological sequence of system state [89-91]. Reliability indices are calculated based on the obtained system states by performing the necessary power system analysis, such as contingency analysis.

Based on the analysis above, the sequential Monte Carlo method is selected as the simulation approach used in this study. It is capable of handling the complexity of failure factors that may be integrated into the reliability model. Time-varying component failure rates due to weather or previous system states can be included in the evaluation. For example, non-sequential methods cannot reflect the scenario of previous contingency cases increasing the load burden of remaining feeders, resulting in a higher chance of more contingencies in the stressed network. Also, the sequential simulation allows use of historical hourly weather records to select appropriate component failure rates to be applied. In addition, as the subsequent events in cascading outages take place sequentially, utilizing the sequential method is a must in order to include cascading outages in the analysis. In summary, the sequential approach is preferable when complex operating conditions are involved [63, 92].

Most previous Monte Carlo based reliability analysis studies employ only a few load levels [38, 63, 91, 93]. Though chronological load profiles are employed for reliability analysis in [90, 92], only a six bus system is considered. In the later chapters of this dissertation, the proposed GTA-based Monte Carlo approach is applied to large utility systems that contain more than 10,000 customers or buses. Detailed customer information is attached to each load bus to generate customer class based load patterns. The difference in customer power consumption between weekdays and weekends is considered, which should not be ignored for some customers, such as industrial customers.

2.4 Reliability Analysis with DGs

As discussed in Chapter 1, as the trend of integrating more and more decentralized generation continues, it will transform the existing vertically operated power system into a horizontally operated one. Recent studies have predicted that DGs will account for a significant percentage of all new generation [94-96]. DG is favored in some new system designs, because it offers a more flexible way of balancing cost and reliability [17, 97, 98].

Past research on DG applications examines various topics. The investigation of the impact of DGs on adequacy and reliability assessment is discussed in [99-103]. The economical aspects of DGs are evaluated in [104]. A method of calculating and reducing power losses by using DGs is introduced in [95]. Extensive work has been conducted on the optimum placement of DGs and/or protective devices to improve reliability [84, 94, 105-108]. A common disadvantage of most of the above methods is that they can only be applied to radial systems.

The DG study discussed in this dissertation will focus on the problems that exist in the initial DG planning stage. Different system designs involving adding transmission lines or adding DGs are evaluated for both reliability and economic aspects. The reliability evaluation method can be applied to non-radial systems.

2.5 Real-Time System Monitoring and Management

Previous research has been performed on real time power system monitoring. [109] proposes a framework of real time congestion monitoring and management of power systems. However, no concrete implementation algorithm is given. The network topology error detection methods presented in [110-112] can be used to perform risk estimation or damage assessment. However, directly applying them to a complete power system without specific mission goals would not help with decision making. Furthermore, neural networks used in [110, 111] tend to propagate slowly in large systems.

In this dissertation, a new approach to system analysis, referred to as Graph Trace Analysis (GTA), is employed. GTA is used to implement an on-line power system risk assessment and monitoring scheme, which targets specific high priority customers or critical loads. The risk assessment indices provided by the monitoring scheme can be used by operations personnel to take action to improve critical load security. As part of this, operations personnel can direct the risk assessment monitoring scheme by setting mission priorities, which in turn affect the priority level of various load types throughout the system.

2.6 Conclusion

Although much research has been performed on the reliability evaluation of power systems, how large-scale realistic systems should be analyzed is still under investigation. The traditional, convenient assumptions of independent events and fixed component failure rates cannot model systems realistically. This literature review reveals some of the real problems that stress existing theoretical techniques. From there, insights are gained into the capabilities that an improved analysis approach should provide. Inaccurate reliability evaluations can result if dependent outages exist and are not taken into consideration. The sequential Monte Carlo approach is selected as the simulation method for this dissertation, because it fits the probabilistic nature of power systems, and can include various dependent outage scenarios. The later chapters of this dissertation propose and describe a GTA-based approach applied to integrated system models and reliability analysis. This approach is capable of considering not only independent, but also dependent outages. The analysis zones are extended from the traditional power system functional zones, with detailed simulations of station-originated outages. The impact of DGs on system reliability can also be evaluated. Simulation architecture of real-time system monitoring, reliability assessment and prediction is also proposed.

3 OUTAGE ANALYSIS AND INTEGRATED FAILURE RATE SCHEMA

3.1 Introduction

This chapter describes our motivation and activities in building an integrated failure rate schema of transmission and distribution systems. The first part of the chapter illustrates the reasons for including weather-related factors in component failure rate modeling. Typical outage causes and associated weather are then extracted based on our investigation of an eastern U.S. utility's Outage Management System (OMS). Three influential weather factors are identified. An example of a time-varying outage rate curve, along with the weather parameter changes, is also provided. Next, an integrated failure rate schema is proposed, which includes variation of component average failure rates along with the component operational status, weather conditions, and time. The schema fits GTA implementation, and is used to supply failure rate parameters for the reliability simulation studies performed in the later chapters of this dissertation.

3.2 Outage Causes and Weather Factors

Fast and proper responses to outages will improve the reliability of power systems. Many U.S. utilities have already had their own OMS for decades in order to manage and prioritize their restoration efforts. Since the OMS also holds historical outage records that can be used to find common causes of damage, it also supports the reliability analysis by providing outage statistics for better planning.

In this section, fourteen years of historical outage data from this U.S. an eastern U.S. utility is categorized to illustrate the typical causes and influential factors of storm-related outages in its area.

The data volume in an OMS database is large. An outage record may contain as much information as 83 fields. The essential data fields for understanding outage causes are outage ID, outage cause code, system/circuit ID, over or underground component, and weather condition code. The outage numbers and cause information are extracted from the above fields, and presented in Table 3.1. The categorized information is further plotted in Figure 3.1 to Figure 3.4 to illustrate the major categories among all causes.

Table 3.1 Overview of outage causes

System		Outage Causes										Total # of Outage
		Animal	Tree Contact	Over-load	Work Error	Equipment Failure	Lightning	Accident	Pre-arranged	Customer Problem	Other	
Overall System		40	8260	14	6	1472	2845	140	7	122	355	13261
Transmisson System		3	29	2	0	23	147	19	1	9	10	243
Distribution System	Overall System	37	8231	12	6	1449	2968	121	6	113	345	13018
	Overhead System	35	8224	11	6	1312	2575	89	4	109	330	12695
	Underground System	2	7	1	0	137	123	32	2	4	15	323

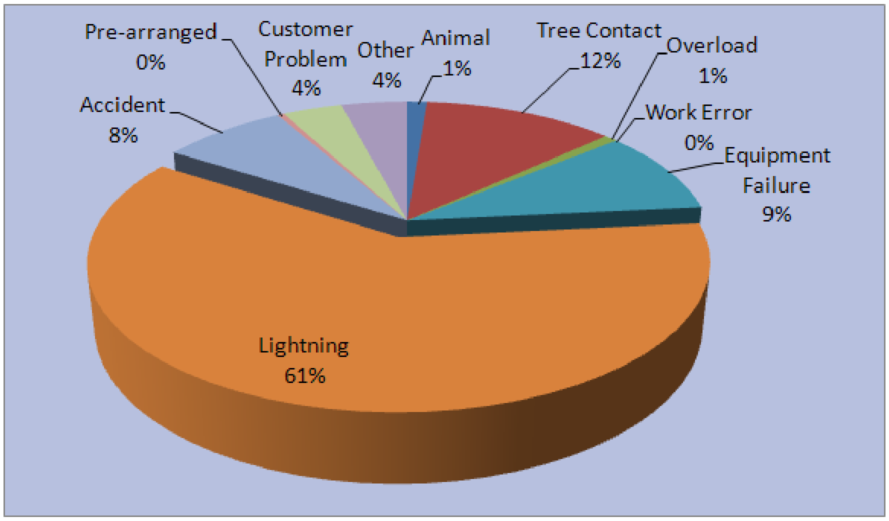


Figure 3.1 Outage causes within transmission system

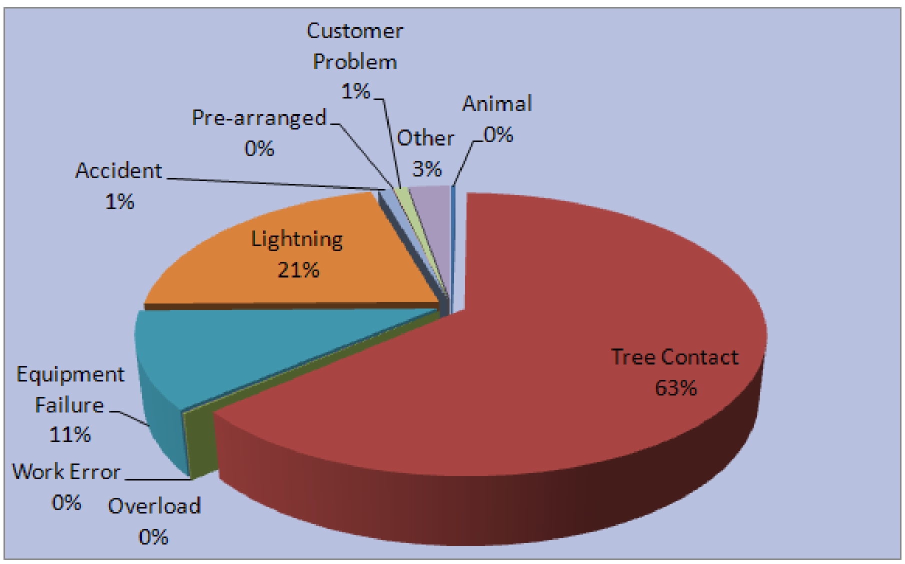


Figure 3.2 Outage causes within distribution system

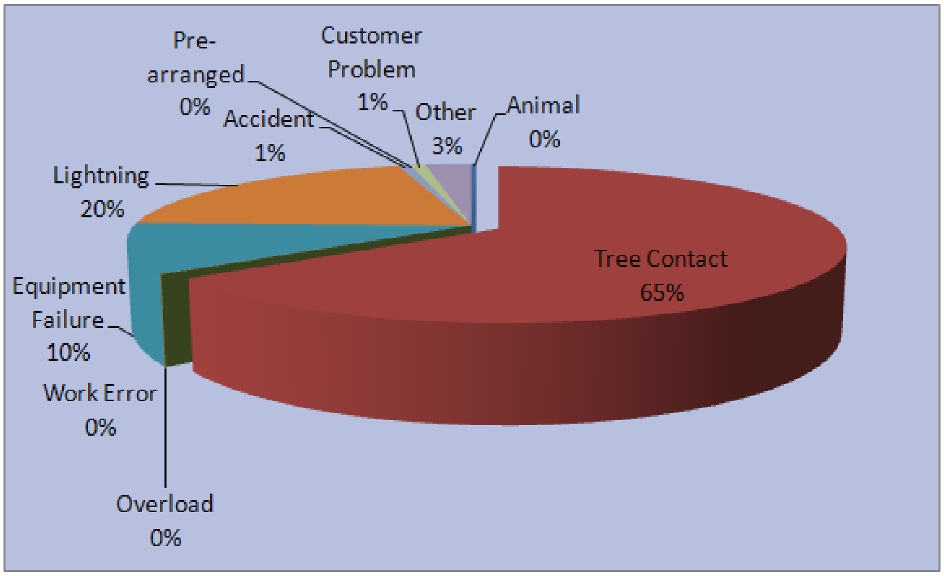


Figure 3.3 Outage causes within overhead components of the distribution system

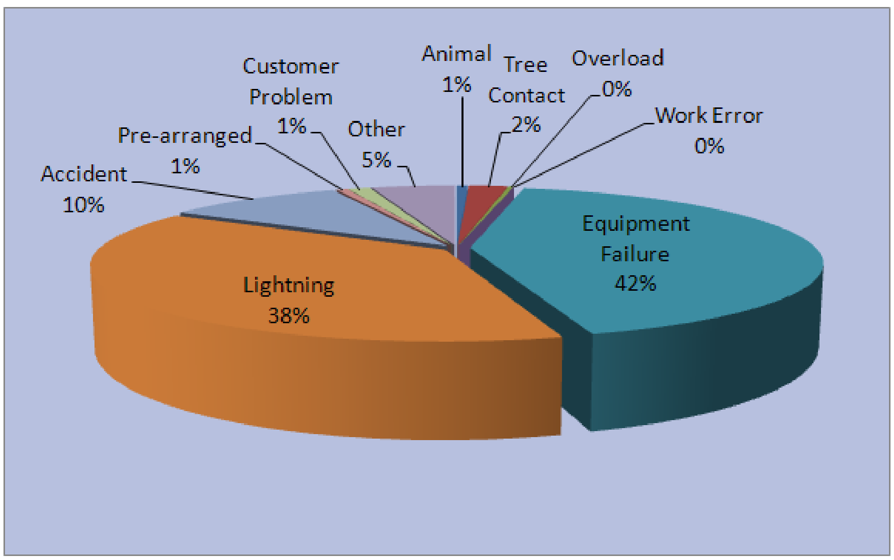


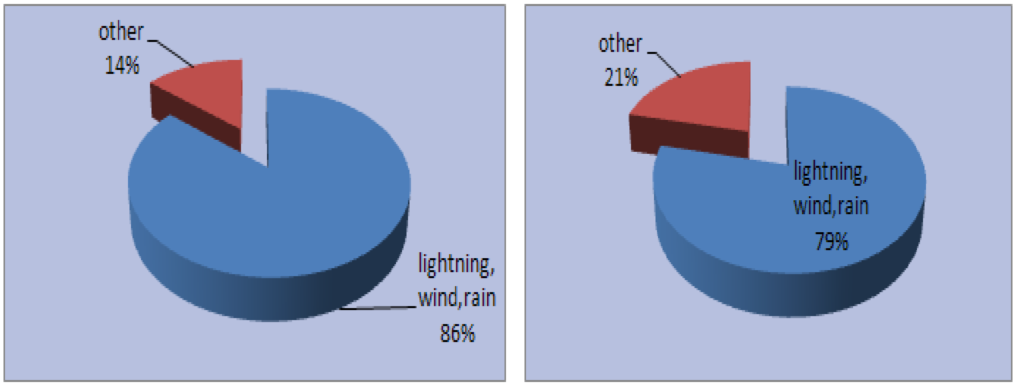
Figure 3.4 Outage causes within underground components of the distribution system

As Table 3.1 illustrates, for this utility the number of distribution system component outages dominates the total outage. Within the distribution system, the outages due to overhead distribution components significantly outnumber those due to underground distribution components.

Figure 3.1 and Figure 3.2 show that lightning, tree contact, and equipment failures are the three most essential causes of transmission and distribution component outages. Lightning ranks as the primary cause of transmission system outages, while tree contact is the biggest problem within distribution systems.

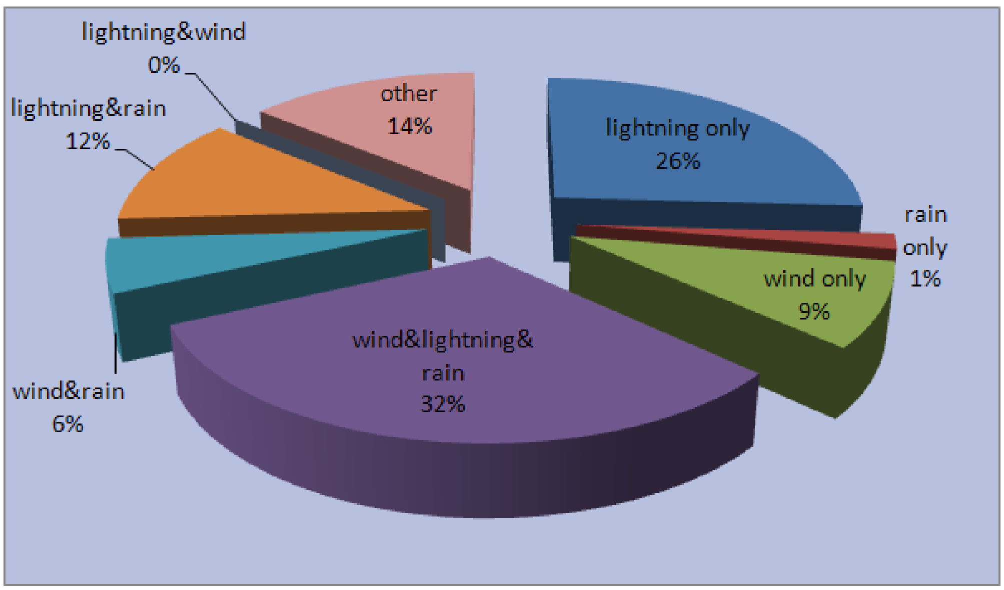
Figure3.3 and Figure 3.4 further break down distribution system outage causes according to underground and overhead components. The overhead system is strongly affected by tree problems, while equipment failure and lightning are the top causes of underground system component outages.

The weather conditions associated with each outage are examined further. Figure 3.5 shows that among all the outages, 86% of transmission system outages and 79% of distribution system outages occurred in weather conditions involving lighting, wind, and/or rain. A further breakdown (Figure 3.6) demonstrates consistency with the causes shown in Figure 3.1 and Figure 3.2. Lightning is the dominant weather factor for outages in the transmission system, followed by windy weather, which is a strong contributor to tree problems. Wind is the dominant weather factor for outages in distribution system, followed by lightning. Thus the adverse weather factors of lightning, wind, and rain should be considered because of their strong impact on component failure rates.

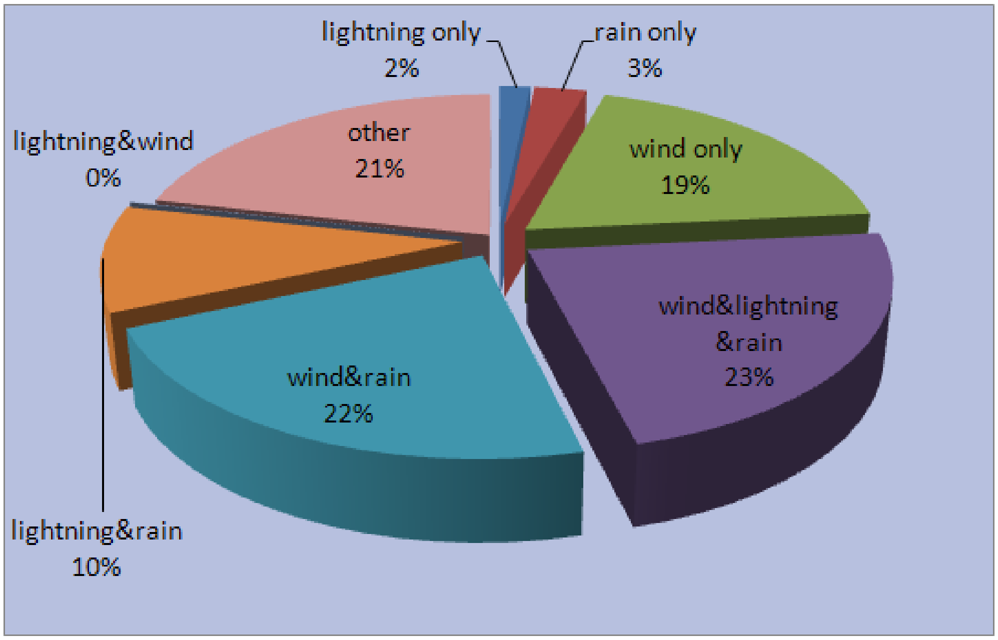


(a) Transmission system **(b)Distribution system**

Figure 3.5 Weather conditions associated with outages



(a) Transmission system



(b)Distribution system

Figure 3.6 Category splitting of lightning, wind, and/or rain associated with outages

Failure rates vary not only with different weather conditions, but also in time and location along with the movement of storms. A previous study [70] shows that the peak number of hourly outages appears in the first five to ten hours of a storm. Thus, when the end of a storm approaches, the cumulative number of outages gradually flattens out. Figure 3.7 illustrates the change of the number of outages over time. The sharpest slope of the curve denotes the actual outage peak hours, when the wind speed is often the highest.

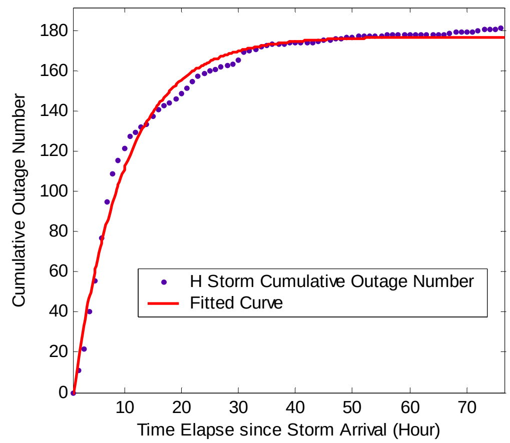


Figure 3.7 Curve Fit for Storm Cumulative Outages

3.3 Failure Rate Schema for Component Outages

An integrated failure rate schema needs to be constructed in order to incorporate factors that are known to drive customer level interruptions. The data provided in the previous section of this chapter demonstrate that adverse weather conditions increase the likelihood of component failure. Those factors affect components both in the transmission system and the distribution system, with different weights. As stated in chapter 1, one of the analysis zones of the studies in this dissertation includes the whole distribution system, with extension to sub-transmission lines and substations of a northeastern U.S. utility, which located at difference territory as the eastern utility in section 3.2. The traditional way of performing separate transmission and distribution reliability analysis, with two distinct component failure rate schemas, does not fit this case.

3.3.1 Essential Failure Rate Influential Factors

The U.S. power system has been significantly affected by a wide range of outage causing events, including localized factors different to each utility based on geographical location, meteorological conditions, system planning, network construction and distribution, policies of operations, and load characteristics. Based on the statistical significance tests [23, 24] and suggestions from senior counselors and engineers at a utility at New York, the most essential failure rate factors, including adverse weather effects, are categorized in table 3.2. Among these factors, some of them have never been identified and considered in the past reliability analysis works in chapter 2. The impact on reliability of each factor is also introduced in this section.

Table 3.2 Essential Failure Rate Influential Factors

Category	**Failure Rate Influential Factors**
Component Characteristics	component type, insulation type, age
Operation Conditions	voltage level, load level
Environmental Conditions	component installation environment (humidity condition)
Seasonal and Weather Conditions	summer, lightning, rain, high wind, heat wave, extreme heat wave, freezing rain, extreme cold
Other	testing condition, previous failure event

- ***Component Characteristics and Operation Conditions***

The typical failure rates are different based on the type of component, due to manufacturing methods and the electrical/mechanical mechanisms of the components.

The materials used to construct the components, such as paper insulated cable and solid insulated cable, also lead to differences in failure rates.

In this dissertation the age of a component refers to the number of years since the component was installed into the system. Starting at a certain age, which depends on the type of component, the failure rates of transmission transformers, network transformers, cables, and joints rise sharply [23, 24], denoting they have reached the wear-out stage. Within any one type of component, failure rates differ with components age. Often, failure rates begin to increase several years before the wear-out age has been reached. In this study, we use sets of age-categorized failure rates to model the rate changes in a typical bathtub curve [39].

Considering operation conditions, transmission line failure rates differ based on the voltage level. A feeder level study has demonstrated that, above a certain load threshold, the failure rates of joints and feeder cables increase [113].

A summary of component type based failure rate categories for components in the transmission and distribution systems under study is given in Table 3.3 and 3.4.

Table 3.3 Component type based failure rate categories for components in transmission system

Component Type	Failure Rate Category Based on Function, Characteristics and Operation Condition
Sectionalizing Devices	breaker, switch
Transmission Transformer	transformer(<10 years old), transformer(>=10 years old)
Transmission Lines	overhead line 345KV, overhead line 230/138/115KV, overhead line < 69KV, underground line 345KV, underground line 230/138/115KV, underground line <69KV
Others	Capacitor, reactor, phase angle regulator, substation bus

Table 3.4 Component type based failure rate categories for components in distribution system

Component Type		Failure Rate Category Based on Function, Characteristics and Operation Condition
Cable	Paper Insulated	cable section age < 40 years, age >= 40 years
	Solid Insulated	cable section age < 16 years, age>= 16 years
Joints	Paper Insulated	joint age [0,8],[8,16],[16,24],[24,32],[32,40], >40 years
	Solid Insulated	joint age [0,7],[8,12],>12 years
Stop Joints		stop joint age [0,9], [10,19],[20,29],[30,39],>40 years
Network Transformer		Transformer age [0,9], [10,19],[20,29],[30,39],>40 years
Sectionalizing Devices		switch, breaker, network protector, cable limiter
Others		substation bus

- ***Environmental and Weather Conditions***

Adverse weather conditions, such as a storm, have been recognized to have a strong impact on system reliability [38, 70]. Traditionally, the change of the component failure rate in adverse weather is modeled as two fixed normal-adverse weather rates as discussed in Chapter 2. Using sophisticated failure rates associated with detailed weather conditions to examine the influence of weather on failure rate changes has rarely been. Below is a summary of how the weather and environmental conditions impact the component failure rates of the utility systems under study.

  - Lightning, rain, and high wind – As described in section 1 of this chapter, we see lightning, rain, and high wind can significantly escalate the chances of failure.

  - Summer, high temperatures, heat waves, and load – For this New York U.S. utility, it has been observed that prolonged summer days with high temperatures result in a significant increase in the frequency of feeder failure. Multiple feeder contingencies are observed with increased customer load in hot weather conditions, thus putting the remaining feeders under stress once a contingency occurred in the network. The ambient temperature also increases in the manholes and ducts due to the thermal effects of sustained overloading in hot weather. Serious feeder problems may occur, accompanied by increased equipment temperature and load [23].

- Freezing rain and extreme cold – It was also reported that under icy and cold conditions, the propensity is high for failure of breakers and disconnect switches, as well as overhead lines [24].

- Humidity level – The environmental conditions such as the humidity level at the equipment location, have been found to affect equipment failure [23]. Thus, cables and joints in wet manholes that have water running through them are more likely to have problems.

- ***Other Factors***
  - Testing effect – Some power utilities do destructive tests for feeders before putting them back into service (restoration). They also have routine tests in the spring season for feeders that have a history of failure or have a high probability of failure. High voltage is applied on the feeder under test for a specific duration. The test has a significant impact on the feeder component failure rate during the following summer season.

  - Previous failure effect – An interesting discovery has been found in [24] that the transmission cable and breaker failure frequencies increase significantly within a few hours after a previous nearby failure event. Some possible causes include the previous failure overburdening other components nearby, or the intrusive repair [114] causing more trouble in the problematic area before the root outage is completely cleared.

3.3.2 Failure Rate Schema Proposed

A reliability study based on all of the above factors and numeric weather parameters is proposed here. The modeling of each component as an individual with a unique failure rate is impossible for the analysis of large-scale system. In the study here, the aim is to provide a reasonable variation of component average failure rates along with the component operation status, weather conditions, and time. All the data used in failure rates calculation come from the outage reports of this northeastern U.S. utility from 1992 to 2007.

3.3.2.1 Base Failure Rate

Given the wide range and possible combinations of all the influential factors, a core failure rate is first abstracted from the component characteristics, including component type ($Type$), component age (Age), and component insulation type ($InsulType$).

Next, the long-term seasonal effect is included by utilizing the outage statistical data under non-adverse weather conditions to provide two base failure rates: Summer base failure rate (F_{SB}), and non-summer base failure rate (F_{NSB}) expressed as functions shown in formula (3.1) and (3.2). Summer includes the three months of June, July, and August, while non-summer is the remaining months of a year.

$$F_{SB} = f(Type, Age, InsulType, SummerOutageStatisics) \quad (3.1)$$

$$F_{NSB} = f(Type, Age, InsulType, Non-SummerOutageStatisics) \quad (3.2)$$

3.3.2.2 Extended Failure Rate

The base failure rate is further extended to include the environmental conditions, and short-term changes such as hourly varying load and weather conditions. Testing and previous failure event effects are also integrated by introducing a series of multipliers as shown in Table 3.5. The final 12 categories of components failure rates are shown in Table 3.6. The GTA implementation of them will be explained in Chapter 4. Given the weather and load conditions at any hour, the reliability analysis tool described in Chapter 4 will decide which one of the twelve failure rates to use to fit the field conditions.

In order to reflect whether or not the weather conditions are prolonged summer days with high temperatures, the Average Weighted Daily (AWD) temperature [23] is used to examine heat wave and extreme heat wave conditions. The average wet and dry bulb temperatures every three hours are calculated for each day, among which a daily maximum value is found. Different weights are assigned to daily maximum averaged temperatures, with higher weights given to the more recent readings. In this way, the accumulation of high temperature effects can be assessed. The AWD temperature is the average of weighted temperatures for three consecutive days. When AWD temperature is equal to or higher than 80 degree, but less than 85 degrees, it is considered a heat wave condition. When AWD temperature is equal to or higher than 85 degrees, it is an extreme heat wave condition.

Table 3.5 Multipliers in Reflecting Changes on Failure Rates

Multiplier		Reflect Failure Rate Change on
Non-weather Related*	K_{load}	load condition
	K_{wet}	environment humidity (wet condition)
	K_{test}	high voltage destructive test
	K_{pEvent}	past transmission substation event happened within 6 hours of the current time
Weather Related**	$K_{lightning}$	lighting
	$K_{highwind}$	high wind (wind speed >= 20 mph)
	$K_{heatwave}$	Heat wave (AWD* [80^{o}F, 85^{o}F)]
	$K_{extremeheatwave}$	extreme heat wave (AWD 85^{o}F)
	$K_{free\sin grain}$	freezing rain
	$K_{extrememcold}$	Extreme cold (temperature <20^{o}F)
Notes	* If more than one of the non-weather factors applies, the applicable factors are multiplied together. ** Should more than one adverse weather condition prevail at a given time, only one weather multiplier will be applied. The order of precedence for the weather multipliers from highest precedence to lowest is: 1. lightning 2. freezing rain or rain 3. high winds (the first three reflect storm effect and have higher damage on the area under study, this is based on localized effect) 4. heat wave or extreme heat wave 5. extreme cold 6. summer or non-summer underlying failure rate.	

Table 3.6 Failure Rate Schema of Component

Failure Rate		Calculation Equation
F_S	Underlying failure rate in summer	$F_S = K_{test} K_{wet} K_{load} \cdot F_{SB}$
F_{SL}	Summer failure rate in lightning	$F_{SL} = K_{lightning} \cdot F_S$
F_{SR}	Summer failure rate in rain	$F_{SR} = K_{rain} \cdot F_S$
F_{SW}	Summer failure rate in high wind	$F_{SW} = K_{HighWind} \cdot F_S$
F_{SH}	Summer failure rate for Heat wave	$F_{SH} = K_{Heatwave} \cdot F_S$
F_{SEH}	Summer failure rate for Extreme heat wave	$F_{SEH} = K_{ExtremeHeatwave} \cdot F_S$
F_{NS}	Non-summer underlying failure rate	$F_{NS} = K_{test} K_{wet} K_{load} \cdot F_{NSB}$
F_{NSL}	Non-summer failure rate in lightning	$F_{NSL} = K_{lightning} \cdot F_{NS}$
F_{NSFR}	Non-summer failure rate in freezing rain	$F_{NSFR} = K_{FreezingRain} \cdot F_{NS}$
F_{NSR}	Non-summer failure rate in rain	$F_{NSR} = K_{rain} \cdot F_{NS}$
F_{NSW}	Non-summer failure rate in High Wind	$F_{NSW} = K_{HighWind} \cdot F_{NS}$
F_{NSC}	Non-summer failure rate for Extreme Cold	$F_{NSC} = K_{ExtremeCold} \cdot F_{NS}$

3.3.2.3 Map Weather Records to Adverse Weather Categories

In order to calculate the component failure rate, weather conditions from historical weather data must be mapped to the weather categories used by the failure rates in the reliability analysis. The proposed mapping for our analysis model is shown in Table 3.7.

Table 3.7 Mapping of Historical Weather Records to Weather Conditions

Historical Weather Record Condition	Monte Carlo Adverse Weather Category
severe thunderstorm	lightning
freezing rain	freezing rain
freezing drizzle	freezing rain
thunder snow shower	lightning
heavy thundershower	lightning
light thundershower	lightning
moderate thundershower	lightning
heavy rain	rain
light rain	rain
moderate rain	rain
thunder	lightning
Wind speed higher than 20 m/h	high wind
Temperature lower than 20 degree	extreme cold
AWD temperature higher than 80 less than 85 degree	heat wave
AWD temperature higher than 85 degree	extreme heat wave

3.3.2.4 Component Repair Time

After a failure occurs, the affected area of the failed component is isolated by protective devices. Then, the failed component is repaired before putting it back into the system for operation. The average repair time of every type of component should be considered in the reliability model. The proposed component repair time category used is shown in Table 3.8. The values of repair times are component type based, and will be used to calculate Time to Fail (TTF) parameters in Chapter 4.

Table 3.8 Component Mean Time to Repair Categories

Repair Time	Meaning of Repair Time (in hours)
Summer Repair Time	Average fault repair time in summer
Winter Repair Time	Average fault repair time in winter

4 INTEGRATED SYSTEM MODEL BASED GRAPH TRACE ANALYSIS FOR PROBABILISTIC EVALUATION OF POWER SYSTEM RELIABILITY

4.1 Introduction

There is still much work to be done on how to model and analyze large-scale realistic systems, as revealed from the summary on changes and challenges in the power industry in Chapter 1, and the literature review in Chapter 2. Old system models that provide fragmented views are detrimental to facilitating coordination and efficiency. In reliability analysis, the convenient assumptions of independent events and fixed component failure rates cannot reflect the realistic situation. As for the computation methods to achieve solutions, the traditional way of performing matrix calculations may lead to the complete reformulation of the problem whenever the system topology changes.

This chapter seeks to address these problems by first introducing the concept of an integrated system model. Next, the Graph Trace Analysis (GTA) method is described, and concrete ISMs of realistic systems built on this approach are illustrated. Then, traces and component sets created by graph tracing are explained, and the GTA algorithm for the Monte Carlo simulation is given. A software architecture for reliability analysis is proposed. A detailed GTA implementation of the integrated failure rate schema is then explained. Next, the issue of including dependent outages in the analysis is discussed.

And finally, considering time-varying characteristics of load, and calibrating the calculation by utilizing SCADA measurements, is introduced.

4.2 Integrated System Model

4.2.1 Motivation

No matter which approach is selected to perform a system analysis, a well-defined model of the facility is the foundation of the computational results. Besides system configuration and operational characteristics, concerns from the users also need to be addressed. The motivation of building an Integrated System Model (ISM) here is not only to allow long-term average reliability to be assessed, but also to achieve real-time monitoring and evaluation. The GTA analysis is described in this chapter and Chapter 5. Utilizing the features of ISM to perform real-time studies is further explained in Chapter 6.

The challenges in system network integrity, as well as real-time applications, spotlight the need of using an Integrated System Model (ISM) to perform system-wide analysis. Historically, in utility engineering, separate environments are used for system planning, reliability assessment, and real-time operations. The different naming conventions of the same device and data structures make it expensive and error-prone to maintain these models [14]. With such fragmented models, it is difficult to keep a consistent view of the system in order to maintain situational awareness. Furthermore, modeling management needs emerge when more participants attempt to mimic real-time plant-wide simulation environments with models that provide a consistent view of the system.

4.2.2 ISM Concept

The ISM model described here is a unified model for design, planning, operation, and control [115]. In the power systems modeled in this dissertation, one model integrates network, looped, and radial systems. The aim of this modeling method is to provide a consistent system view to operators, system planners, and reliability engineers. Various algorithms operating on the ISM model exist in a distributed processing environment, such that fast computation for real-time analysis can be achieved.

The ISM model is designed to handle system constraints either offline or in real time. The traditional system-wide analysis uses matrices to model large systems. These equations involve all levels of information from the laws of physics, to topology connections, and system level information such as the loading level. Handling real-time computations requires much coordination to track changing system conditions. To facilitate faster computation, the ISM model avoids a global view or tight-coupling in the model by employing a generic analysis paradigm with topology iterators [27]. The graph of a power system model is stored in a container [116], and real-time data are attached to the graph on-the-fly. The system components, topologies, and analyzing algorithms are then integrated into a flexible, expandable software framework [117]. Algorithms use the topology iterators offered by the graph to perform analysis calculations. Using iterators for maintaining topology and implementing algorithms with iterators makes the ISM model naturally structured for distributed processing.

The ISM model discussed in this dissertation is different from the Common Information Model (CIM) [118]. The ISM uses an edge-edge model for topology, where as CIM uses a node-edge model. CIM is a data exchange modeling standard that has been primarily used with transmission system models. Some recent research illustrates a trend to apply CIM to distribution systems [119]. According to this work, additional connectivity nodes need to be included in the CIM model. The ISM model is an object-oriented model based on graph theory. Topology changes in the model are handled locally because only topology iterators of components directly connected to the topology change need to be updated [116]. Because topology changes are handled locally, the graph trace (GTA) based reliability analysis solution times are not significantly affected by topology changes. The topology iterators of GTA provide a straightforward means of computationally handling dependent failure rates and cascading failures. These characteristics of iterators are important to the reliability analysis simulation considered here.

The construction of an ISM begins by constructing a plant model, which contains the physical layout and connectivity of the electric grid. Critical components are added at their locations. The location and connectivity information is generally imported from a GIS system. Each component carries unique identifiers that may be used to attach any number of additional data values, such as load or weather information.

4.2.3 Model Based Analysis

The reliability calculation in this dissertation uses GTA applied to an ISM model. Then, algorithms use the model iterators to compute the electrical processes. The analysis results are computed and transferred from one algorithm to another as if building blocks of a network. Algorithms are linked by dependencies. A higher-level algorithm depends on lower-level algorithms. For example, power flow relies on the results of impedance calculations and load estimation, while load estimation relies on load research statistics. Cases and data of interest during time-series analysis have a special storage, and are available for play-back.

4.3 Iterators and GTA on System Modeling

The integrated models under study are modeled with topology iterators. For any system modeled as a graph, a network container is used to hold the edges of the graph. There is a one-to-one correspondence between each edge in the graph and each item (often equipment, but potentially something constructed such as a connecting joint) modeled in the physical system. A component models an entity in the physical system for which across and through variable measurements are possible [120]. The model is implemented just in terms of edges. That is, iterators only return edges. The concept of nodes is not used in the implementation.

GTA is used to model equipment for which across and through variable measurements exist or structural equipment for which no measurements exist [116]. For example, voltage and current are across and through variables, respectively, of a two terminal electrical component. Every component handles its own across and through variable calculations following equations that describe the component's physical behavior. A system object is responsible for ensuring that system conservation equations are satisfied, which are: (a) the flux in and flux out of a multiple edge connection point are equal, (b) the across variables around a loop of edges sum to zero.

In GTA, a component object is synonymous with an edge in a container. Each edge has a unique index that may be used to attach any number of sets of attributes, such as reliability attributes, and any number of algorithm results, such as results from Monte Carlo calculations. This also provides a means to apply relational concepts to the in-memory layout of data. This results in efficient storage of data, because if many edges are really the same piece of equipment, they can all share one set of attribute values. The Monte Carlo simulation will make use of results from other algorithms that are run independent of the Monte Carlo analysis. This will be discussed further in the Architecture of Reliability Analysis section below.

The types of entities and the hierarchical relationships that are modeled in GTA are described by

$$Cmp \in Ckt \in Sys \in SS \tag{4.1}$$

where, *Cmp* represents a component in the model, *Ckt* is a set of components representing a subsystem (such as a substation or feeder), *Sys* is a set of subsystems representing a system, and *SS* is a set of systems representing a system of systems. Examples of SS may contain systems of transmission, primary distribution, and secondary distribution. Note that each subsystem has one and only one reference source. A subsystem is also referred to as a circuit in this study.

An example of systems stored in network containers is depicted in Figure 4.1. It is a transmission system contains 1209 transformers, 1793 sectionalizing/protective devices, 1501 bus bars, and 2980 lines/cables. A magnified example of a transmission switching station is shown on the upper right part of Figure 4.1. By modeling the detailed configurations of substations, station-originated outages are included in the studies. More containers used in the reliability studies will be introduced in detail in Chapter 5.

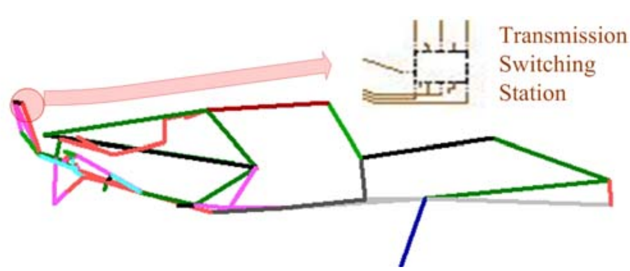


Figure 4.1 Network Containers Example

4.3.1 Graph Traces and Sets in Reliability Analysis

4.3.1.1 GTA Traces

In GTA-based analysis, topology iterators are used to traverse the objects of type component, i.e. edges in the container. Every component handles its own across and through variable calculations, including initialization and finalization calculations. Algorithms use iterators to access objects in the containers in order to implement data type independent programming. With this approach, an algorithm that determines flows throughout a system can be applied to either an electrical or fluid system.

The connectivity relationship among related edges is implemented by using four types of iterators in radial networks. They are forward, backward, feeder path, and brother iterators [27, 121]. Forward and backward iterators offer a way to perform a bidirectional traverse among the network components. The feeder path trace, using feeder path iterators, identifies the energy flow path from a given component to its reference source. A component can be supplied from multiple sources, but must have one-and-only-one reference source. The brother iterator of a given component defines the first component in its forward trace direction that is not fed by the given component relative to the given component's reference source.

For systems with loops, adjacent iterators and cotree edges are employed by GTA. An adjacent iterator marks connections across sectionalizing devices that may be used to create a cotree [27] connection. A cotree edge marks an independent loop for the graph, and thus may be used to break the independent loop by removal of the cotree edge from the graph.

4.3.1.2 Sets Created via Traces

GTA uses topology iterators to traverse the edges of the graph stored in a container [115]. Trace sets are generated by repeated application of iterators [122]. Nomenclature used for trace operations and set generation is presented in Tables 4.1 to 4. 4.

Let *Cmp* denotes a component. Its characteristics associated with the GTA based reliability analysis can be represented by using a 14-tuple as in (4.2), with the explanation of each element presented in Table 4.1.

$$Cmp = \{p,\ pS,\ f,\ b,\ fp,\ br,\ bCmpType,\ bMvStatus,\ bFail,\ fSetDev,\ fLostPwr,\ Load,\ CmpRel,\ CmpPri\} \tag{4.2}$$

Table 4.1 Nomenclature of pointers and attributes

Name	Meaning
p	Unique component identifier
pS	Reference source of the circuit the *p* belongs to
f	Forward topology iterator that returns forward component of *p*
b	Backward topology iterator that returns backward component of *p*
fp	Feeder path topology iterator that returns feeder path component of *p*
br	Brother topology iterator that returns brother component of *p*
adj	Adjacent topology iterator that returns the adjacent circuit component
bCmpType	Type of component – SOURCE, SECTIONALIZING DEVICE , LOAD, etc.
bMvStatus	Sectionalizing device moveable status attribute
bFail	Component failure status attribute – FAILED, NOT FAILED
fSetDev	Sectionalizing device open/closed status attribute – CLOSED, OPEN
fLostPwr	Component loss of power status attribute – ON, OFF
Load	Load attached to component
CmpRel	Failure rate of component, the value of which is affected by nine parameters as shown in formula (4.16)
CmpPri	Priority level of the component

Table 4.2 Nomenclature used to describe the variables/values used in traces

Name	Meaning
T_c	Current simulation period
FR_p	Failure rate of component *p* for weather and given loading condition
R	A random number in the range $R \in (0,1]$
TTF_p	Time To Fail for component *p*
Alg[p] → *variable*	Variable of the algorithm computing on *p*
pf[p] → *i*	Current *i* of power flow algorithm computing on *p*
pf[p] → *BuringThreshold*	Burning threshold of component *p* in the power flow algorithm
ra[p] → *RaIndex*	Reliability index of reliability analysis algorithm computing on *p*
LdEst[p] →*norminalVolt*	Nominal voltage of component *p* in load estimation algorithm computing on *p*
overload	Percentage of current overload of a component
K_{pEvent}	Failure rate multiplier associated with a past transmission substation event occuring within 6 hours of the current time
T	An interval of time
Note: The arrow operator → used in this chapter is from the Object Constraint Language (OCL) and is an overloaded operator here. When it is applied to a set, the operator applies the operation to every object of the set. When it isapplied to a component, the operator is used to select the value of one of the component's attributes.	

Table 4.3 Nomenclature of generated sets via traces

Name	Meaning
FT	Forward trace set over all circuits in *SS*
FTp	Forward trace set determined by starting at the component *p* to the end of the circuit that *p* belongs to
FC	Set of failed components in system
FPTp	Ordered set of components generated by using feeder path pointer *fp*, starting from *p*
$SID\_Upstream_{pFailed}$	Set of isolating devices to operate for a failed component *pFailed* that is located upstream (relative to the reference source) of *pFailed*
$SID\_Downstream_{pFailed}$	Set of isolating devices to operate for a failed component *pFailed*, that is located downstream of *pFailed*
$SID_{pFailed}$	Set of isolating devices to operate for a failed component *pFailed*
BTp	Ordered set of components generated by using the backward trace pointer *b*, starting from *p*
BRTp	Ordered set of components from *p* to its brother component by performing a forward trace
SNO	Set of new outaged components
SCAD	Set of outaged components due to cascading failures
SCCP	Set of customers that have lost power
SRS	Set of reference sources
CT	Set of co-trees [27]
PF	Set of power flow results
RA	Set of reliability analysis results
S_{pEvent}	Set of components whose failure rates are impacted by the past event

4.3.1.3 Essential Operations in Reliability Analysis

This section presents GTA set generation examples on essential operations in reliability analysis. Two essential operations in reliability analysis are locating failed components in the system and isolating the failures. The following two subsections use GTA notation to illustrate these operations. Note that GTA notation borrows from Object Constraint Language (OCL) [123], except in GTA "=" denotes assignment, and "==" denotes equality. A detailed explanation of basic operations of OCL can be found in Appendix A of this dissertation.

- ***Find Failed Components***

A forward trace set is operated on to select all components that have failed, and the failed components are placed in the set *FC* as given by

$$FC = FT \rightarrow select\ (\ p \rightarrow bFail == FAIL) \tag{4.3}$$

, where

bFail is the component failure status attribute.

Note that the arrow operator → from the Object Constraint Language is overloaded here. When applied to a set, such as *FT*, the operator applies the operation, such as *select()*, to every object of the set. When applied to a component such as *p*, the operator is used to select the value of one of the component's attributes.

- ***Isolate Failure***

Let *pFailed* represent a failed component to be isolated. A feeder path trace from *pFailed* is used to find the first moveable sectionalizing device p_1 in the feeder path, and this device is placed in the set *SID_UpstreampFailed*, as given by

$$SID\_UpstreampFailed = FPT_{pFailed} \rightarrow$$

$$select(\ p \rightarrow bCmpType == SECTIONLIZING\ DEVICE$$

$$and\ p \rightarrow bMvStatus{=}{=}UNLOCKED,$$

$$quit\ when\ STO_1 <> \Phi) \tag{4.4}$$

$$SID\_UpstreampFailed{=}{=}\{p_1\} \tag{4.5}$$

The additional sectionalizing devices to be operated to isolate *pFailed* are determined by performing a forward trace started at p_1 to find all the downstream moveable sectionalizing devices, placing them into SID_DownstreampFailed [115].

$$\begin{aligned} SID\_DownstreampFailed= FT_{p1} \rightarrow select(\ p \rightarrow bCmpType{=}{=}\ SECTIONLIZING\ DEVICE \\ and\ p \rightarrow bMvStatus{=}{=}UNLOCKED, \\ if\ p{=}{=}\ p_1 \rightarrow br\ \ then\ quit, \\ else\ p{=}p \rightarrow br\ ) \end{aligned} \tag{4.6}$$

The set of operable sectionalizing devices for *pFailed* is the union of *SID_UpstreampFailed* and *SID_DownstreampFailed*, as given by

$$SID_{pFailed} = SID\_UpstreampFailed\ \rightarrow union(SID\_DownstreampFailed) \tag{4.7}$$

The devices in *SIDpFailed* are then opened and locked in order to isolate the failed component, , as given by

$$SID_{pFailed}\ \rightarrow collect(\ p \rightarrow fSecDev{=}OPEN\ and\ p \rightarrow bMvStatus{=}LOCKED\ ) \tag{4.8}$$

4.3.2 Monte Carlo Simulation Algorithm

The GTA implementation of the six major steps of the sequential Monte Carlo simulation is described in this section.

Step 1: Forward trace checking for the failure of each component in system

A component p has a failure if time to fail of component p TTF_p falls into the current simulation period T_c, where TTF_p is calculated as

$$FT \rightarrow collect\left(TTF_p = -\frac{1}{FR_p}\ln(R),\ if\ TTF_p \in T_c\ \ then\ p \rightarrow bFail = FAIL\right) \tag{4.9}$$

, where

bFail is component failure status attribute.

FR_p is failure rate of component p for weather w and given loading

R is a random number in the range $R \in (0,1]$.

Step 2: Find failed component and isolate failures

Locating failed components is implemented with (4.3). Isolating failed component is implemented with (4.4)-(4.8).

Step 3: Check power flow for case of contingency

The power flow results of each contingency case can be obtained using the *PFI* interface shown in Figure 4.2. A cable burning condition can result in a cascading outage scenario.

A cable burns when the current of cable p is greater than the cable burn threshold *BurningThreshold* as expressed by

$$pf[p] \rightarrow i > pf[p] \rightarrow BurningThreshold \tag{4.11}$$

, where $pf[p] \rightarrow i$ accesses power flow results of current i for component p

Step 4: Restore failed component

Let *pFailed* denote a previously failed component for which the repair time has elapsed and the component returned to service. The restoration process utilizes the $SID_{pFailed}$ set to unlock and close the associated protective devices as

$$SID_{pFailed} \rightarrow collect(\ p \rightarrow fSecDev=CLOSE\ and\ p \rightarrow bMvStatus=UNLOCK\ ) \tag{4.12}$$

Step 5: Calculate reliability indices

The calculation is implemented by traversing the circuits and collecting and updating the customer outage information. Every specified reliability index is calculated using its own equations for each year of simulation. The set of reliability analysis results RA is obtained as

$$RA = FT \rightarrow collect\ (\ ra[p] \rightarrow RaIndex\ ) \tag{4.13}$$

, where $ra[p] \rightarrow RaIndex$ accesses the reliability index of p, which is calculated by the reliability analysis algorithm

Step 6: Check convergence criteria:

If $\alpha = \frac{\sigma}{E(X)} < \varepsilon$ *or Total simulation time* $\geq$ *max simulation time*

then quit

else go to the next simulation period and return to step 1 (4.14)

with $\sigma^2 = \frac{1}{N^2}\sum_{i=1}^{N}[X_i - E(X)]^2$ (4.15)

, where

α is the coefficient of variation of the reliability index

σ is the standard deviation of the reliability index

N is the number of simulation years

$E(X)$ is the expected value of the reliability index

X_i is the sample value of the reliability index in year i.

4.4 Architecture of Reliability Analysis

The modeling and reliability analysis of transmission and/or distribution systems involves a large amount of data and several interrelated algorithms. The proposed reliability analysis software architecture utilizing ISM and GTA is illustrated in Figure 4.2, which integrates network container, algorithms, and data into a generic programming software architecture.

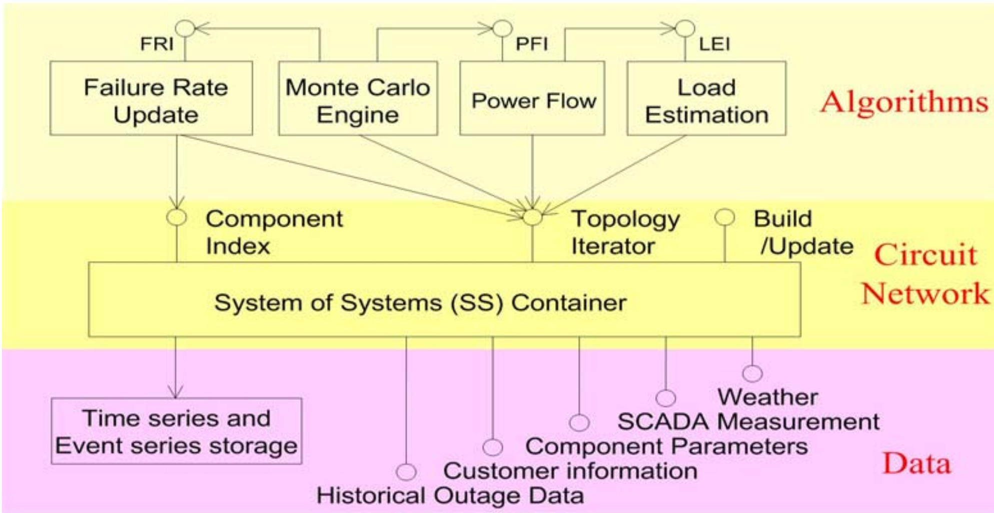


Figure 4.2 Architecture of Reliability Analysis Software

The Circuit Network layer in Figure 4.2 includes the container and a number of interfaces (the lollipop notation). The topology of systems under study is constructed and updated with topology iterators via the *Build/Update* interface. The *Topology Iterator* interface provides a way for algorithms to trace through components stored in the model container. As the traces are performed, the algorithms obtain data that is applicable to each component in order to perform calculations. The *Component Index* interface allows algorithms to attach their calculation results to components in the container.

The Algorithms layer in Figure 4.2 contains four algorithms and three interfaces. The algorithms are Load Estimation, Power Flow, Monte Carlo, and Failure Rate Update. The core of the reliability evaluation is the sequential Monte Carlo Engine. It uses the *FRI* interface to obtain component failure rates from the Failure Rate Update module. These failure rates are used by the Monte Carlo analysis to randomly fail components. Isolation and restoration operations are then simulated by using GTA algorithms to open/close protective devices. Consequences of contingencies, including cascading cable failures due to severe current overloads, are evaluated with power flow analysis via the *PFI* interface. Interface *LEI* allows power flow to utilize time-varying load estimation results. Violations of system constraints, such as cable overloads or low voltages, are reported. At each simulation hour of Monte Carlo, traces are performed via the *Topology Iterator* interface to collect customer interruption information.

The Data layer in Figure 4.2 contains five data interfaces and storage of time/event series data. The storage module collects events generated as time progresses, such as every contingency case generated by the Monte Carlo Engine. The *Historical Outage Data* interface provides component type based failure rates, repair times, and dependent failure rates multipliers determined by processing historical outage records. Interfaces of *Weather*, *SCADA Measurement*, and *Component Parameters* are used to provide weather conditions, system loading, and component parameters such as age and environmental conditions. The Failure Rate Update algorithm utilizes this data to update the failure rate of each component per simulation hour.

The customer information provided via the *Customer Information* interface in the Data layer is used to locate individual customers within the model, and also to determine customer attributes, such as class of customer, priority, and individual customer load data [124-126]. The Load Estimation algorithm makes use of individual customer loading data and SCADA measurements, where individual customer load estimates are calibrated with SCADA measurements so that customer load estimates agree with the energy flow measured into the system.

The reliability analysis is performed for each hour of a year, and as multiple years are simulated, multi-year weather and SCADA loading measurement patterns are repeated. Thus, if a ten year weather pattern from actual measurements is used, then the pattern will be repeated 100 times in a thousand year Monte Carlo simulation, where 8760 hours are analyzed every year. Hourly SCADA measurements of current and voltage are applied in a similar fashion to determine loading.

4.5 GTA Implementation of Failure Rate Schema

From the component failure rate schema proposed in Chapter 3, we know the failure probability of a component is not only related to its manufacturing quality. Adverse weather conditions affect system reliability [69, 70]. Existing feeder outages place remaining feeders under stress, increasing the probability of additional failures. Heavy, sustained loading increases the ambient temperatures in manholes and ducts, creating stresses on feeder cables and also increasing failure rates. Environment conditions such as moisture can cause failure rates to increase. Insulation testing by applying higher than normal voltages to cables can increase component failure rates. Equipmental age, especially in older systems, will affect failure rates [47, 127]. The component failure rate model used here includes seven parameters to determine failure rates FR and is expressed as

F_R = *f(Component Type, Age, Insulation Type, Environment, Voltage Level, Load, Season, Weather, Operating Condition)* (4.16)

In a previous study, a series of weather conditions was modeled, including lightning, high wind, heat wave, and icy conditions [70]. The Operating Condition parameter in (4.16) takes into account dependent failures. Note that with dependent failure rates, previously outaged equipment, such as a substation breaker, can cause the failure rates of nearby equipment in the substation to increase.

4.5.1 Static and Dynamic Failure Rates

From (4.16) illustrates that various input data are involved in the failure rate calculation. To improve the computational efficiency, especially taking into account the speed needed for real-time applications, the component failure rate updating computation is separated into two procedures.

Once the container in Figure 4.2 is built via the *build* interface, a static failure rate is calculated for each component based on its type, age, insulation type, installation environment, voltage level, and historical outage record. It is named static failure rate, because the parameters in (4.16) associated with it rarely change. Thus, there is no need to re-calculate it as long as the underlying data does not change. For example, the container may only need to be re-built once a year, following the annual reports of a utility. The static failure rate reflects the component characteristics that rarely change.

For other time sensitive parameters, such as weather, load and operating condition, a dynamic failure rate is used to catch these changes accordingly. The load estimation is based on profiles of class of customers, the results of which are further calibrated with SCADA measurements. During the sequential simulation, the Monte Carlo Engine in Figure 4.2 calls the failure rate update engine to update the component failure rates according to these parameters.

4.5.2 GTA Implementation

The objects, data, and their relationships in the GTA implementation of the failure rate schema proposed in Chapter 3 are depicted in Figure 4.3. Outage records with no prevailing adverse weather conditions are used to calculate base component failure rates in summer (June, July, and August) and non-summer separately. Component outages are grouped by parameter component type $Type$, component age Age, and component insulation type $InsulType$, which are modeled as attributes in component object Cmp as shown in Figure 5. The base summer and non-summer failure rates of a component, F_{SB} and F_{NSB}, are expressed as

$$F_{SB} = f(Type, Age, InsulType, SummerOutageStatistics) \quad (4.17)$$

$$F_{NSB} = f(Type, Age, InsulType, Non-SummerOutageStatistics) \quad (4.18)$$

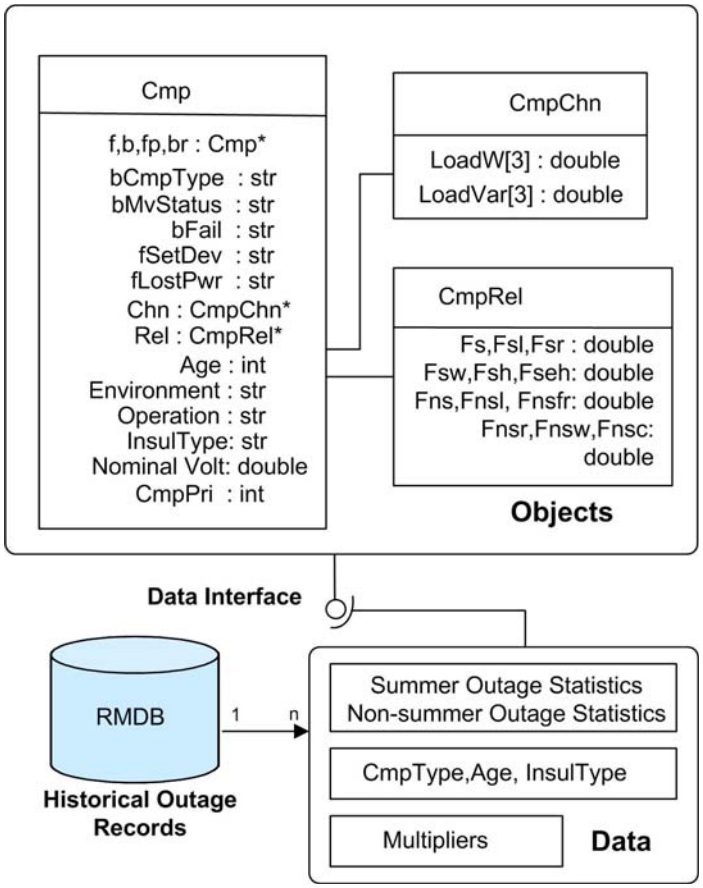


Figure 4.3 GTA implementation of failure rate schema

The base failure rate is then expanded by introducing a set of multipliers, the values of which are extracted from RMDB for each table associated with one type of component in Figure 4.3. The *CmpRel* object then uses multipliers in Table 3.5 of the corresponding type of component to expand the base failure rates into twelve weather-based failure rates, as described in Chapter 3. During the sequential Monte Carlo simulation, given the weather and load condition at any hour, the Monte Carlo Engine in Figure 4.3 determines which of the above twelve failure rate to use, then calls the Failure Rate Update engine to update the failure rate value.

The failure rate update procedure is illustrated with an example here. For a component *p* of type cable, age 20 years, using paper insulation, and installed in a wet manhole, the Failure Rate Update algorithm in Figure 4.2 first obtains the component type and parameter information via a circuit trace. It also gets the component type base failure rate $F_{R\_Base\_Cable}$, as well as multiplier values of $K_{Age}, K_{PaperInsul}$, and K_{wet} of the cable insulation age, type, and environment, respectively. The static failure rate of this cable is then

$$F_{R\_static} = K_{Age} \cdot K_{PaperInsul} \cdot K_{wet} \cdot F_{R\_Base\_Cable} \tag{4.20}$$

The Failure Rate Update Module then uses the Component Index interface in Figure 4.2 to attach the above failure rate to the cable model. Unless the component parameters change, there is no need to update the static failure rate.

During the sequential simulation, the Monte Carlo Engine in Figure 4.2 calls the Failure Rate Update algorithm to dynamically update the component failure rates based upon the conditions for each hour of the simulation. For the same cable component used above, given the current hour situations are heat wave, loading level of 300 amps, and no past events during the past 6 hours, its hourly updated failure rate F_R is calculated as

$$F_R = K_{HeatWave} \cdot K_{load} \cdot F_{R\_static} \tag{4.21}$$

, where $K_{HeatWave}$ and K_{load} are multipliers corresponding to heat wave, and loading level, respectively.

4.6 Dependent Outage simulation

Inaccurate reliability evaluations can result if dependent outages exist and are not taken into consideration. Historically, major outages and blackouts are often associated with dependent, cascading failure events [3, 28]. The failure rate model used here takes into account not only simultaneous independent failures, but also scenarios of dependent failures.

4.6.1 Cascading Failures

A cascading outage represents a sequential succession of dependent events. It occurs when the outage of one component triggers the outage of another component, such as may occur when the failure of one cable causes another cable to become overloaded. Thus, the outage is experienced in a wider and wider area as cascading failures occur. The cascading outage simulation algorithm is depicted in Figure 4.4.

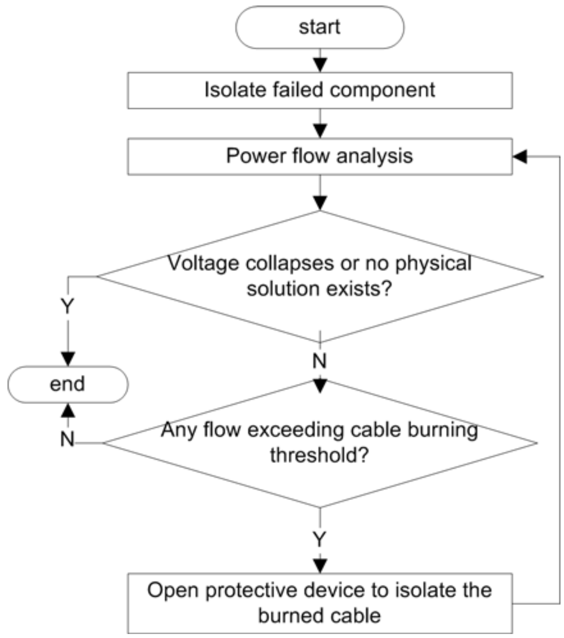


Figure 4.4 Cascading Outage Simulation Algorithm

The set of outaged components and customers that have lost power is found following each cascading failure by

$$SNO = FT \rightarrow select(pf[p] \rightarrow i > pf[p] \rightarrow BuringThreshold) \quad (4.22)$$

$$SCAD = SCAD \rightarrow union(SNO) \quad (4.23)$$

$$SCCP = SCAD \rightarrow select(\, p \rightarrow fLostPwr == TRUE) \quad (4.24)$$

, where

SNO is set of newly burned components

SCAD is set of outaged components due to cascading failures

SCCP is set of components with customers that have lost power

fLostPwr is component loss of power status attribute.

Figure 4.5 illustrates one of the cascading outages simulated in the secondary distribution system in Figure 1 (c). The outaged cables are shown in gray. This contingency involved the failure of three primary feeders.

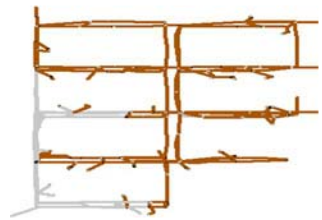


Figure 4.5 Cable Outages (Shown in Gray) Resulting from Cascading Failures

4.6.2 Failures Dependent upon Previous Events

From analysis of transmission system outage data, the actual number of component failures is clearly much higher than the value expected within six hours of an earlier event [24]. To incorporate this phenomenon into the simulation, GTA traces are used to identify the transmission components as the set S_{dep} of components whose failure rate are updated for an interval of time T, , following a previous event. The value of T is six hour in this study. The finding of S_{dep} and the updating of component failure rates in S_{dep} is given by

$$S_{dep} = FT \rightarrow select(\ p \rightarrow LdEst[p] \ \rightarrow norminalVolt > TanstVolt) \tag{4.24}$$

$$S_{dep} = FT \rightarrow collect(\ p \rightarrow FR_p = \ K_{pEvent} \ * p \rightarrow FR_p\ ) \tag{4.25}$$

, where

KpEvent is the outage multiplier associated with the past event.

TanstVolt is the voltage level of transmission system components

4.6.3 Component-group Outage

A group of components that are outaged due to the failure of any component in the group corresponds to a segment in the network [38]. That is, if any component in the group is isolated, all components lose power. The isolation may be performed automatically with protective devices, such as breakers or limiters. Further modifications to the isolated segment may occur by manual operation of sectionalizing devices. The method of determining a segment for component *p* is the same as the isolation process described in GTA Monte Carlo simulation algorithm, step 2.

4.7 Time Varying Load with SCADA Calibration

In order to properly analyze the performance of circuits, accurate estimation of power consumption is important. In the simulation here, customer information is used to perform customer class based load estimation with load patterns [124, 125]. The estimation results are improved by calibrating them with SCADA measurements. An hourly load scaling factor *SF* is calculated as

$$SF = \frac{\sum_{i=1}^{N} KVA_{Feeder}}{\sum_{j=1}^{M} KVA_{LoadBus}} \tag{4.26}$$

,where

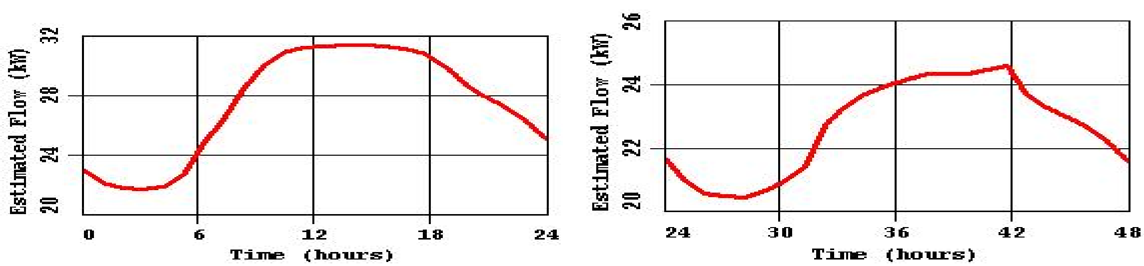
KVA_{Feeder} is the feeder loading measurement from field measurements

$KVA_{LoadBus}$ is the load estimation of a load bus

N is the total number of feeders

M is the total number of load buses.

Figure 5 demonstrates an example of the chronological load curves for a load bus used in the simulation, which considers the different mix of customer classes at the bus. Load research statistics are applied to billing cycle, kWHr consumption to estimate kW and kVar values for a given hour, day type, month, and weather condition. The calculated results of each algorithm reside in-memory and are shared with other algorithms as shown in Figure 4.2.



(a) Load Pattern for Weekdays **(b) Load Pattern for Weekends**

Figure 4.6 January Load Curve for an Example Load Bus

5 CASE STUDIES

5.1 Introduction

This chapter discusses five case studies based upon real power systems that were done using the reliability simulation method presented in Chapter 4. The first case study calculates reliability indices of aggregate networks. The second provides an evaluation of reliability evaluation down to every customer load bus. The third study gives details of cascading failure analysis and identification of system weak points. The fourth case is a sensitivity study on the ways in which temperature and load affect system reliability. The last case is a transmission level reliability evaluation including the operation of DGs.

5.2 Aggregate Networks Reliability Evaluation

5.2.1 Systems under Study

The purpose of this case study is to demonstrate the impact of the proposed approach on system level reliability evaluation. The ISM containers used in this study include the whole distribution system with extension to sub-transmission lines and substations.

A container of a transmission switching station is shown in Figure 5.1. It is extracted from the transmission system container shown in Figure 4.1. Based on the utility's historical records, the boundaries of this station connected to the transmission system are treated with the assumption that the generation capacity always meets the load demand. The switching station and its downstream distribution area station are connected with seven sub-transmission lines. All substation breakers are modeled and are used in simulating reconfigurations due to failures.

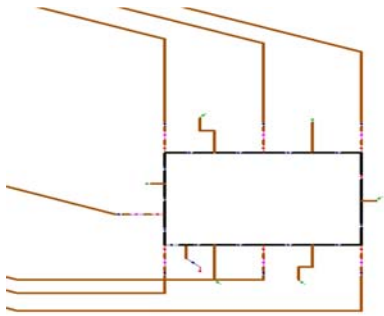


Figure 5.1 Transmission switching station

A primary distribution system with an area station and twelve feeders is depicted in Figure 5.2 and Figure 5.3, respectively. Each colored path in Figure 5.3 denotes the route of a feeder. There are a total of 218 network transformers fed by this primary network. Sectionalizing and protective devices, such as breakers, switches, protectors, and limiters are modeled. The sectionalizing and protective devices are important to the correct determination of reliability and system loading.

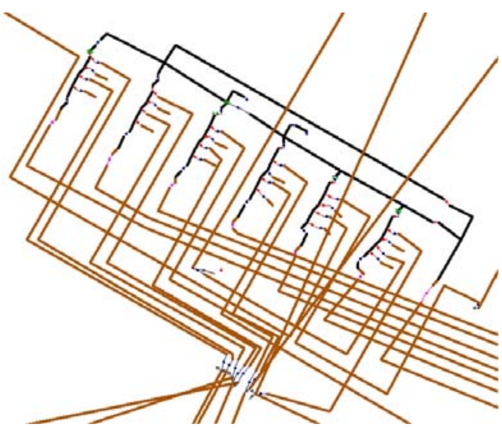


Figure 5.2 Distribution area substation

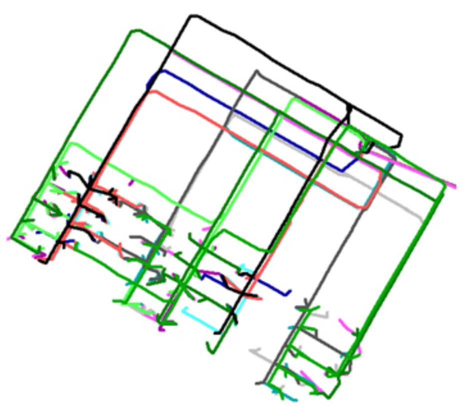


Figure 5.3 Primary feeders

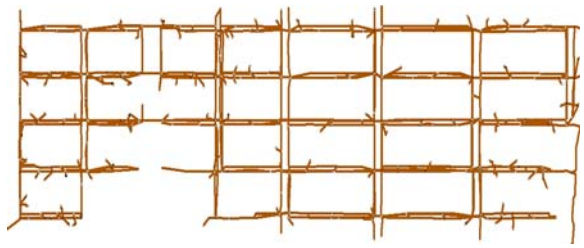


Figure 5.4 120V aggregate network container

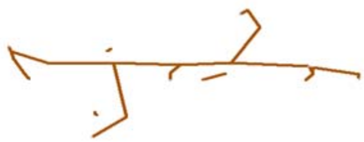


Figure 5.5 Example of high tension customer aggregate network container

The secondary distribution system supplies two different customer voltages, 120V and 480V, respectively. The 120V system is a heavily meshed network as shown in Figure 5.4. There are also sixteen individual 480V (high tension) networks scattered like islands in the secondary system, with one of the examples illustrated in Figure 5.5. These aggregate load areas are referred to here as Aggregate Networks.

In the secondary networks, customers are supplied at each customer load bus, with one of the load bus examples shown in Figure 5.6. The customer class information is summarized in Table 5.1. There are a total of 15,055 components and 10,387 customers included in the above containers.

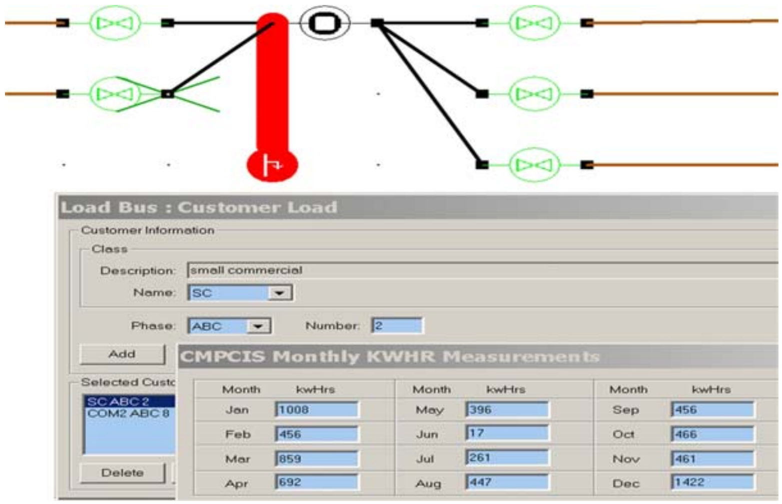


Figure 5.6 Example of customers attached to a load bus

Table 5.1 Customers in Containers

Customer Class	**Number of Customers**
Commercial Annual kWHr < 2500000	664
Commercial Annual kWHr > 5000000	21
Commercial Office	8
Constant All Day Load	121
Education	7
Hotel	11
Multi-Dwelling	87
Religious	13
Residential	7715
Restaurant	183
Retail	158
Small Commercial	1399
Total	**10387**

5.2.2 Aggregate Networks Analysis

5.2.2.1 Performance Indices

The study zones of this study include detailed modeling of end-customer information, and the system evaluation goal is also customer service oriented. SAIFI and SAIDI are the two most popular system level reliability indices used for customer service oriented studies [36]. SAIDI is an abbreviation of System Average Interruption Duration Index. It represents the average interruption duration per customer served per year. SAIFI denotes the System Average Interruption Frequency Index. It is the expected number of interruptions per customer per year. The calculation of SAIDI and SAIFI are shown in (5.1) and (5.2) respectively.

$$SAIDI_{SYS} = \frac{sum\ of\ customer\ \text{int}\, erruption\ durations}{total\ number\ of\ customers} \tag{5.1}$$

$$SAIFI_{SYS} = \frac{total\ number\ of\ customer\ \text{int}\, erruptions}{total\ number\ of\ customers} \tag{5.2}$$

The subscript *sys* in the above equations denotes that individual reliability indices can be calculated for each aggregated network, and only considers the customers served by the network. There are a total of 18 aggregate networks defined in the secondary distribution system containers. The whole secondary distribution system can be viewed as the largest aggregate network, with the 120V and 480V networks as individual aggregated networks.

5.2.2.2 Simulation Results

The input data used for this case study includes four years of historical weather records, and one year of chronological SCADA measurements for each feeder. Component based failure rates are derived from utility outage reports between 1992 and 2007. Component age, environment, and customer information are embedded as container properties.

Prior to performing the system level reliability analysis, the Monte Carlo simulation was validated against a small sample of historical failure rate field data. For the system under study, Table 5.2 shows a comparison between feeder contingencies predicted by a 10000 year sequential Monte Carlo simulation and ten years worth of field data. It should be noted that the available field data represents a very small sample. Contingency level 1 corresponds to the failure of a single feeder; contingency level 2 corresponds to the concurrent failure of two feeders, and so forth. The simulated contingencies display the same trend as the field data. The comparison indicates that the simulation is reasonable.

Table 5.2 Feeder Contingency Frequency Comparison of Field Data and GTA Model

Contingency Level	**10 Years Worth of Field Data (f/y)**	**GTA Model - 10000 Years of Simulation (f/y)**
Single Contingency	8.1	14.540
Double Contingency	1.0	0.9563
Triple Contingency	0.1	0.0467
Quadruple Contingency	0.0	0.0018

Table 5.3 presents the analysis results for each aggregate network for 10000 years of simulation. The results show that among the 480V isolated networks, networks 1, 3, 4, and 7 have worse reliability behavior than the 120V network. The 120V network has a

heavily meshed topology, which provides much redundancy. The failing of a few secondary main cables may not lead to customer outages, or may just impact nearby customers if no cascading failure occurs. However, the 480V networks 1, 3, 4, and 7 are all radial systems, constructed by many long cable sections. They have only one or no adjacent circuits connected by sectionalizing devices. Therefore, a problem with any one of the cables in these networks would lead to the whole circuit shut down, which affects a large portion of the customers served by these networks. The remaining 480V networks have better reliability behavior than the 120V network. A common feature of the topology of these networks is similar to that of the 480V isolated network 14. In this network, several network transformers from several different feeders support one customer through a very short cable.

Table 5.3 Reliability Evaluation of Each Aggregate Network

Aggregate Network	Number of Input Feeders	Number of Transformers	Number of Customers Served	SAIDI*sys* (hr/cus)	SAIFI*sys* (f/cus)
120V Secondary Network	12	140	9661	0.006947	0.003691
480V Isolated Network 1	5	5	6	0.010966	0.005933
480V Isolated Network 2	5	6	25	0.005995	0.003244
480V Isolated Network 3	10	11	400	0.043835	0.023716
480V Isolated Network 4	6	6	93	0.014554	0.007874
480V Isolated Network 5	4	4	76	0.003465	0.001875
480V Isolated Network 6	4	4	59	0.002402	0.001300
480V Isolated Network 7	5	5	6	0.008163	0.004417
480V Isolated Network 8	4	4	56	0.004251	0.002300
480V Isolated Network 9	4	4	3	0.002218	0.001200
480V Isolated Network 10	3	3	2	0.004618	0.001600
480V Isolated Network 11	4	4	9	0.002957	0.001600
480V Isolated Network 12	6	6	6	0.002310	0.001250
480V Isolated Network 13	3	3	6	0.002156	0.001167
480V Isolated Network 14	4	4	1	0.000000	0.000000
480V Isolated Network 15	4	4	22	0.002999	0.001623
480V Isolated Network 16	4	4	22	0.003352	0.001814
Secondary Distribution System	12	218	10453	0.008334	0.004446

5.3 Reliability Evaluation Down to Load Bus

5.3.1 Purpose of the study

The power system infrastructure is constantly changing. Expansion planning may need to be performed to add new devices and facilities, which may change the configuration of circuits. The purpose of this study is to demonstrate the capability of the proposed approach for comparing the features of alternative designs, and giving the system planner numeric guidance on selecting the final design.

5.3.2 Case Introduction

In this case study, the reliability of new design approaches for adding low voltage grid customers in the heavy meshed secondary network in Figure 5.4 is evaluated. The systems under study include all systems in Figures 5.1 to 5.5, from the transmission system down to each customer in the secondary distribution system. Both transmission cable and transformer failure events are simulated.

In Figure 5.7 the block on the lower left corner of the secondary network is magnified to give a view of the area where new customer configurations are to be considered. There are eight locations, marked by red circles inside the observation window, where customer reliability is suspected to be impacted by design changes.

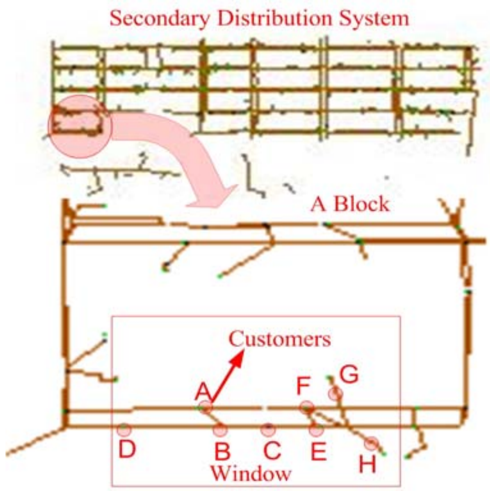


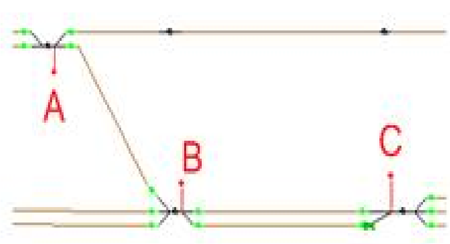
Figure 5.7 Observation Window

The purpose of this study is to evaluate the reliability changes for customers inside the observation window due to the addition of a new customer with a peak load of 700kVA at location B. Monte Carlo simulations are performed to determine the reliability of the following customers:

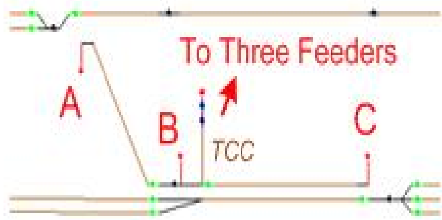
- *New Large (NL) Customer:* A new customer near location B with a peak load of 700kVA.
- *Relocated Network (RN) Customers*: Network customers located at locations A, B, and C that are eventually moved to an isolated network with the new large customer (see cases below).
- *Non-Relocated Network (NRN) Customers*: Network customers on the block where the new isolated customer is added but which are not moved to the new isolated network. In the observation window in Figure 5.8, these customers are at locations D, E, F, G, and H.

Four cases that are evaluated:

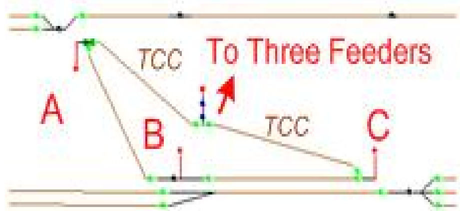
- *Base Case*: The existing configuration as in Figure 5.8(a) is used without addition of the *New Large Customer (NL)*. This establishes the existing reliability.
- *New Customer with Un-configured System*: Same configuration as in Figure 5.8(a) but with the *New Large Customer* added at location B.
- *Configured System without Loop*: The Relocated Network customers are moved to a new isolated network as shown in Figure 5.8(b), with the *NL* customer added. Existing secondary cables are used to construct the connection among A, B, and C. Three 1000kVA network transformers nearest to the points A, B, and C are selected to feed the isolated network. A new *Network Transformer Connection Cable (TCC in Figure5.8 (b))* is used to supply the *Relocated Customers* fed from the new isolated network with three feeders.
- *Configured System with Loop*: This case study modifies the Configured System by using two *Network Transformer Connection Cables* to form a loop, as shown in Figure 5.8 (c).



(a) Un-Configured Network



(b) Configured Isolated Network



(c) Configured Isolated Network with Loop

Figure 5.8 Circuit Configurations

5.3.3 Performance Indices

Instead of selecting SAIFI and SAIDI, CAIDI and CAIFI are chosen as the reliability indicators for this study, because they give details of the interruption statistics of each customer. CAIDI is abbreviation of Customer Average Interruption Duration Index. It represents the average interruption duration for those customers served by the same load bus per year. CAIFI denotes for Customer Average Interruption Frequency Index. It is the expected number of interruptions of customers served by a load bus per year. The calculation of CAIDI and CAIFI is shown in (5.3) and (5.4) respectively.

$$CAIDI = \frac{Sum\ of\ Customer\ Interruption\ Durations}{Total\ Number\ of\ Customer\ Interruptions} \tag{5.3}$$

$$CAIFI = \frac{Total\ Number\ of\ Customer\ Interruptions}{Total\ Number\ of\ Customers\ Affected} \tag{5.4}$$

5.3.4 Simulation Results

The weather, SCADA measurement, and component failure rate data used in this study is the same as for the Aggregate Network Reliability Evaluation in this chapter. Table 5.4 presents the analysis results for 10000 years of simulation for each case. The results for customer locations A-C report the reliability of the *NL* and *RN* customers. The results for customer location D-H report the reliability of *NRN* customers.

Table 5.4 Reliability Evaluations for Customers inside Observation Window -CAIFI and CAIDI

Customer Location	**Number of Customers**	**Base Case**		**New Customer with Un-configured System**		**Configured System without Loop**		**Configured System with Loop**	
		CAIFI (f/y)	**CAIDI (hr/y)**	**CAIFI (f/y)**	**CAIDI (hr/y)**	**CAIFI (f/y)**	**CAIDI (hr/y)**	**CAIFI (f/y)**	**CAIDI (hr/y)**
A	1	0*	0*	0.0001	10	0.0015	1.8483	0	0
B	1(base case) 2(other cases)	0	0	0.0001	10	0	0	0	0
C	10	0.0002	5.5	0.0002	13.5	0.001	1.8483	0	0
D	1	0.0000	0.000	0.0002	13.500	0.0000	0.0000	0.0000	0.0000
E	2	0.0003	9.000	0.0002	13.500	0.0003	6.7500	0.0005	10.000
F	1	0.0002	5.500	0.0002	13.500	0.0002	1.0000	0.0002	1.0000
G	3	0.0031	2.084	0.0032	2.5760	0.0039	1.7917	0.0036	2.0000
H	2	0.0031	2.084	0.0031	2.6000	0.0029	1.8059	0.0032	2.0000

**No outages observed in 10000 year Monte Carlo simulation*

The results in Table 5.4 demonstrate that directly adding the new 700KVA load into the existing network results in a higher probability of customer outages under contingency scenarios, both to *NL* and *RN* customers at locations A, B, and C, and to nearby *NRN* customers such as at location D.

The results of using the isolated network without a loop show that the *NL* and *RN* customers at locations A, B, and C may expect to have shorter outage durations but more frequent outages. This is because the major cause of customer outage is due to the failure of the secondary cable instead of a feeder contingency. The reliability of nearby *NRN* customers is improved. A loop in the isolated network itself reduces the frequency of outages of the customers inside the isolated network.

A further interesting study sub-categorizes the feeder contingency and secondary main cable contribution to the reliability changes, as shown in Table 5.5. It demonstrates the major cause of customer outages in the observation window in each design configuration.

Table 5.5 Reliability Evaluations for Customers inside Observation Window - Separate Feeder and Main Cable Contribution to Reliability Problems

Customer Location	Number of Customers	Base Case		New Customer with Un-configured System		Configured System without Loop		Configured System with Loop	
		Feeder (%)*	Main (%)**	Feeder (%)	Main (%)	Feeder (%)	Main (%)	Feeder (%)	Main (%)
A	1	0%	0%	100%	0%	0%	100%	0%	0%
B	1(base case) 2(other cases)	0%	0%	100%	0%	0%	0%	0%	0%
C	10	100%	0%	100%	0%	0%	100%	0%	0%
D	1	0%	0%	100%	0%	0%	0%	0%	0%
E	2	100%	0%	100%	0%	100%	0%	100%	0%
F	1	100%	0%	100%	0%	100%	0%	100%	0%
G	3	17%	83%	32.7%	67.3%	3%	97%	11%	89%
H	2	17%	83%	33.4%	66.6%	2%	98%	12%	88%

** "Feeder %" means the percentage of the feeder contingency contribution to the total CAIDI value.*

***"Main %" means the percentage of the secondary main cable failure contribution to the total CAIDI value.*

From the results of the base case study shown in Tables 5.4 and 5.5, the original reliability of customers at locations A and B is high. This is primarily due to the original topology as illustrated in Figure 5.9, since no single main cable failure near the load produces an outage. Compared with locations A and B, customers at location C have a higher chance of suffering from feeder problems. For example, a contingency involving three major feeders can result in cable overloads for mains near location C. In this scenario, the limiters will automatically open to limit the damage of burned cables.

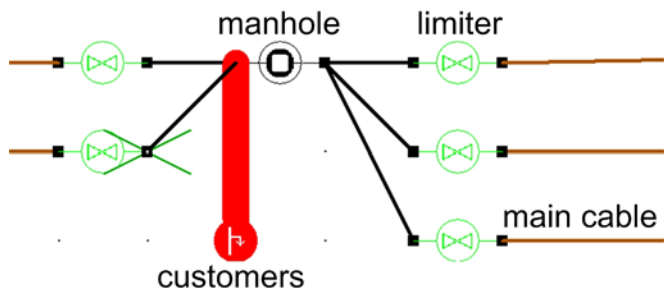


Figure 5.9 Example of Load Bus Little Influenced by Main Cable Failures

After adding a new large customer with a peak load of 700KVA at location B, the results from the case New Customer with Un-configured System, shown in Table 5.5, demonstrate that the customer reliability at locations A, B, and C suffers from feeder problems. With the unchanged circuit topology, the new customer load results in more overloads during contingencies. It is observed that feeder contingencies cause the customer outages for load buses near locations A, B, and C to also increase following the addition of the new load. Thus, the new customer load results in a higher risk for nearby customers being affected by secondary cable overloads.

In the case of a Configured System without a Loop shown in Table 5.5., the chance of customer outages caused by feeder contingencies at locations A, B, and C is dramatically improved. The failure of secondary main cables is now the main contributor to outages at locations A, B, and C. The results in Tables 5.4 and 5.5 also demonstrate that the reliability of nearby customers is likewise improved. Customers attached to load bus D benefit the most in this situation. The possibility of a feeder contingency causing an outage of either load bus G or H is much lower. On the whole, the customer outage duration is decreased, because the repair time of main cables generally is much shorter than feeder contingency repair times.

The analysis of the Configured System with Loop case in Table 5.5 demonstrates that the advantage of using the isolated network is that it can further decrease the average customer interruption duration for locations A, B, and C, since the outages are primarily due to failure of main cables. The fact that feeder problems do not cause trouble in the two configured designs of location A, B, and C indicates that this area has sufficient network capacity to support the existing load.

5.4 Cascading Failure Analysis

5.4.1 Case Introduction

The purpose of this study is to illustrate the details of cascading levels of cables burned in contingency situations, which is helpful in identifying the origin of the problems. The case under study is a third level contingency. Due to the failure of three components shown in green in Figure 5.10, three primary feeders, A, B, C, lose power as depicted by the pink lines. The contingency occurs at summer peak load condition.

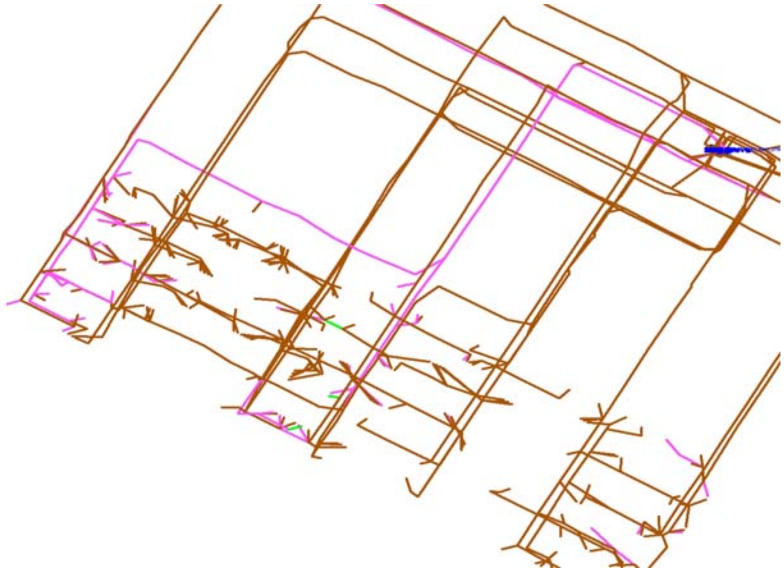


Figure 5.10 Primary Feeders Lost Power Situation

In this study, simulations are performed separately on two sets of ISM models of containers in Figures 5.1 to 5.5. The sources of data for the individual ISM models are utility reports of two consecutive years. The topologies of these two models are slightly different, which reflect the changes due to facility updates and augmentation. The difference in cascading behaviors between these two models is revealed, and the causes are investigated in order to validate the expanding and upgrading operations of the utility.

5.4.2 Results of Contingency in ISM models of Year 1

The power flow results in Figure 5.11 show the lower left corner of the secondary network is burned out. The origin of the burnout starts with the green cable that is identified and marked.

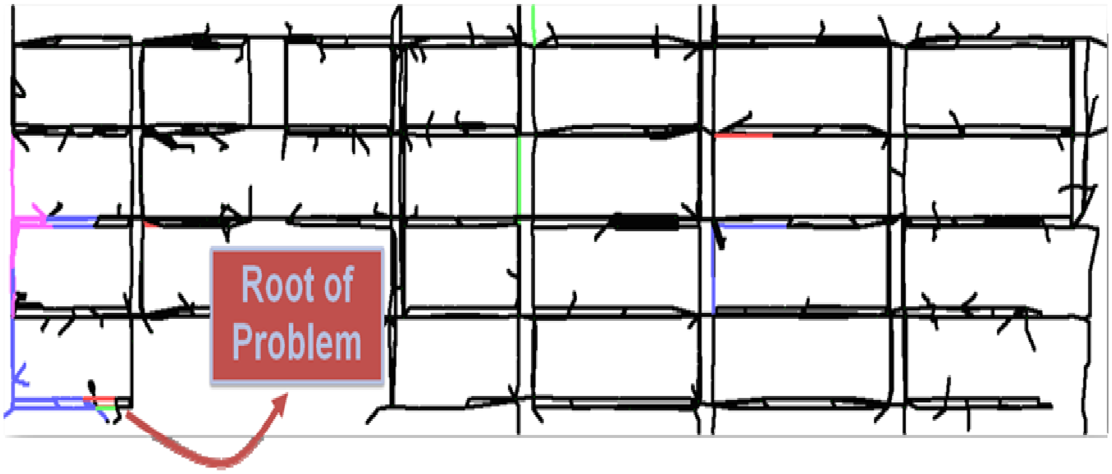


Figure 5.11 Cascading level of burned out cables*

*Black -	No Power Loss
*Green -	Power was Lost during 1st Level of Cascading
*Red -	Power was Lost during 2nd Level of Cascading
*Blue -	Power was Lost during 3rd to 5th Level of Cascading
*Pink -	Power was Lost during Cascading Levels higher than 5

5.4.3 Results of Contingency in ISM models of Year 2

The power flow results for this case are shown in Figure 5.12. Instead of burning out the corner, some cables are overloaded with less than 100% overload, including the small cascading effect origin cable in Figure 5.11. The overloaded cables, as well as the burned cables in the central part of the 120V grid, form the system weak points. They could become troublemakers in the future as customer loads continue to grow.

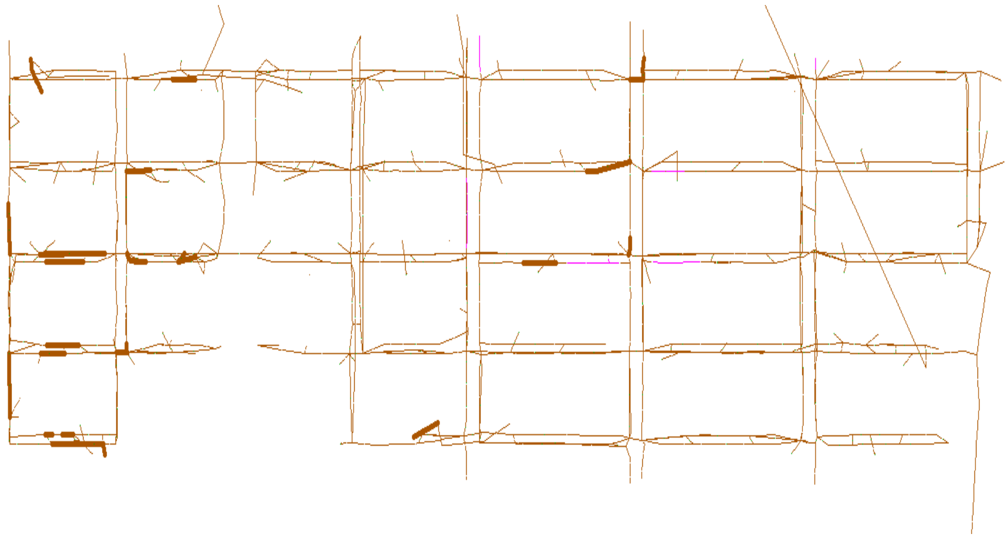


Figure 5.12 Cable Overloaded and Burned Situation**
**Brown Thick Line – Cables overloaded but less than 100% overloaded
**Pink– Cables burned

The burned cables are further studied by showing their cascading level in Figure. 5.13 It is observed that the original cable burn (shown in green) in the center of the 120V grid triggers the next cable burn events nearby (shown in red). The dropped loads of these burned cables are supported by the same single feeder. In this contingency case, loads have to be dropped to avoid further cascading burns.

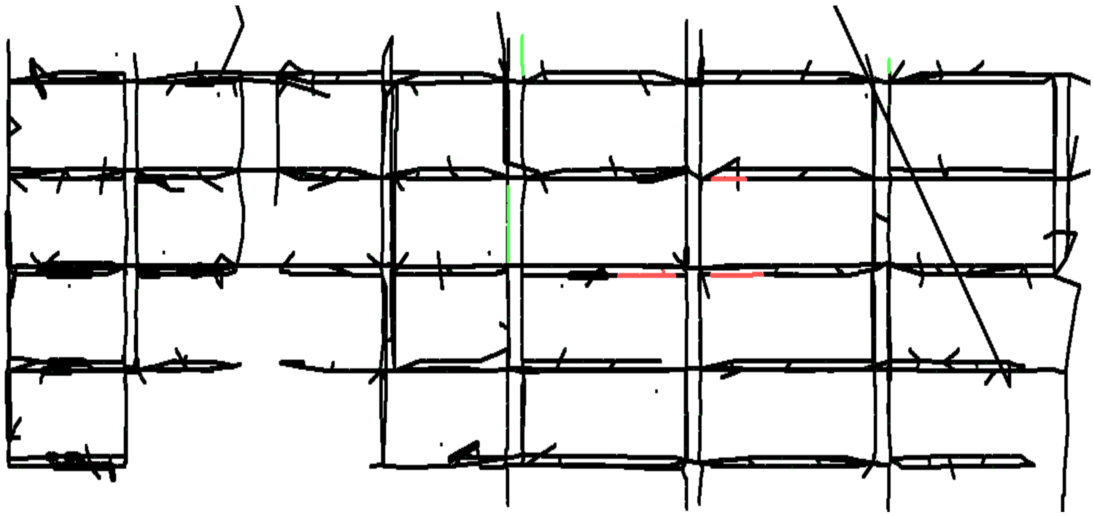


Figure 5.13 Cascading Level of Burned Cables***

***Black - No Power Loss
***Green - Power was Lost in 1st Level of Cascading
***Red - Power was Lost in 2nd Level of Cascading

5.4.4 Investigation of Result Differences between Two Case Studies

The difference is due to the topology changes in the secondary network of this utility between year 1 and year 2. The expanding and upgrading operations of this utility during year 2 include adding an additional main cable with a rating of 2034Amps as a redundant cable in parallel with the root problem cable in Figure 5.11. This greatly alleviates the cable overload condition in this area. Therefore, the cascading event caught in Figure 5.11 is eliminated for this particular contingency study.

Moreover, till the end of year 2, more network transformers (from 1000kVA to 2500kVA) are added into the primary system, with the ones associated with feeders A ,B, and C as summarized in Table 5.6. Thus the feeders support loads better.

Table 5.6 Transformers Added/Changed as the Difference between Two Year's Primary System

Transformer ID	Specification	Operation
FeederC_V7938	2500kVA	Added
FeederB_V7873	1000kVA	Added
FeederB_V1550	1000kVA	Moved from other feeder to FeederB
FeederA_V7944	1000kVA	Added

In summary, the difference between the ISM model contingency behaviors of two consecutive years demonstrates that the reliability of the secondary network improves from year 1 to year 2 for the contingency study. Instead of burning the corner out as in year 1, in year 2 only some cables burn in the middle of the 120V grid due to the failure of feeders in the central portion of the primary system.

5.5 Sensitivity Study

5.5.1 Introduction

This study measures the effect of changes in certain failure rate influential parameters on their impacts on the system reliability. For this particular metropolitan area, load growth is said to be the greatest single challenge of its energy infrastructures [19]. The situation becomes worse during high temperature days when over 6 million air conditioners are turned on in the service area. It is expected that about 900,000 additional units will be purchased in the next five years [18]. In addition, high ambient temperature itself is reported to lead to increased failure rates of components. One of the reported causes is that the cooling conditions of the cable ratings is no longer validated after high sustained temperatures, therefore the actual ratings are less than the manufacturer data as anticipated [23]. Also, contingency beyond system design criteria will place great strain on the remaining feeders with heat and sustained load. Therefore, load and temperature are selected as the parameters in this study.

5.5.2 Load Growth Effect

For the next five years, a conservative expectation of the load growth of the service area is 1.2 percent per year [18]. Table 5.7 below shows the change of contingency frequency due to this load growth over the next five years based on Monte Carlo simulation results. The increasing patterns of first to third contingencies are very consistent. The increasing patterns of higher contingencies are not that smooth. This is due to the fact of the very rare occurrence of high level contingencies.

Table 5.7 Load Growth Impact on Contingency Frequency

Year	Load Growth (%)	1st Contingency Frequency (f/y)	2nd Contingency Frequency (f/y)	3rd Contingency Frequency (f/y)	4th Contingency Frequency (f/y)	5th Contingency Frequency (f/y)
0	0%	14.5481	0.9563	0.0467	0.0018	0.0001
1	1.2%	15.0481	1.0043	0.0495	0.0019	0.0001
2	2.4%	15.6755	1.1150	0.0570	0.0026	0.0002
3	3.6%	16.1148	1.1653	0.0570	0.0021	0.0000
4	4.8%	16.8035	1.2703	0.0615	0.0021	0.0000
5	6.0%	17.1848	1.3345	0.0684	0.0022	0.0000

Table 5.8 below shows the change of SAIDI and SAIFI of the overall secondary network customers due to this load growth over the next five years. The percentage of SAIDI and SAIFI increase compared with those of year 0 is drawn in Figure 5.14. The overall trend

of increased SAIDI and SAIFI values is consistent. The average SAIDI and SAIFI increase is 1.37% and 1.2% per year due to the load growth.

Table 5.8 Load Growth Impact on Reliability Indices

Year	Load Growth (%)	SAIDI (hr/cus)	SAIFI (f/cus)
0	0%	0.008334	0.004446
1	1.2%	0.008443	0.004481
2	2.4%	0.008596	0.004563
3	3.6%	0.008629	0.004581
4	4.8%	0.008769	0.004655
5	6.0%	0.008959	0.004755

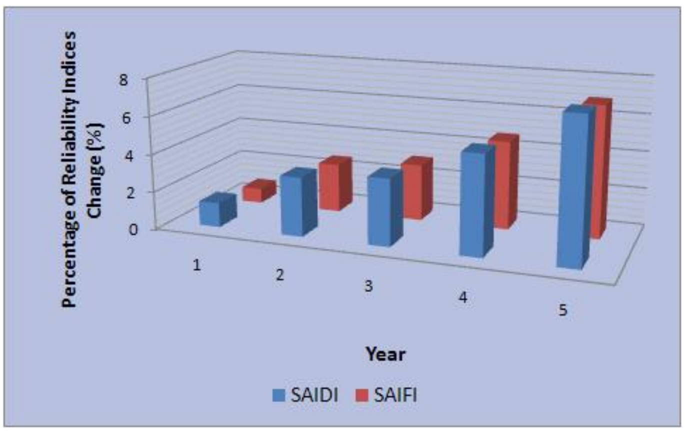


Figure 5.14 Load growth impact on percentage of reliability indices change

5.5.3 Temperature Rising Effect

The global warming effect cannot be ignored when we consider the impact of rising temperature on system reliability. There are many books that discuss the evidence of temperature rise, and try to forecast the climate change by the end of this century. Among them, [128] gives a range from 2.3 to 7.2 degrees F by the year 2100. [129] announces that 3.1 to 7.2 degrees F is the best estimate range of projected temperature increase. In the study here, we select a reasonable value of 5 degrees F as the expected temperature by the end of this century.

Table 5.9 below shows the change of contingency frequency due to this temperature change based on Monte Carlo simulation results. The increasing pattern of first to third contingencies are very consistent, while the trend is not that smooth in higher contingencies due to the rare occurrence.

Table 5.9 Temperature Rising Impact on Contingency Frequency

Temperature Rise (F)	1st Contingency Frequency (f/y)	2nd Contingency Frequency (f/y)	3rd Contingency Frequency (f/y)	4th Contingency Frequency (f/y)	5th Contingency Frequency (f/y)
0	14.5481	0.9563	0.0467	0.0018	0.0001
1	14.5713	1.0220	0.0464	0.0020	0.0000
2	14.9548	1.1700	0.0666	0.0023	0.0001
3	15.7102	1.4500	0.0771	0.0026	0.0001
4	17.0430	1.7900	0.0770	0.0022	0.0001
5	17.6647	1.6440	0.0831	0.0030	0.0002

Table 5.10 below shows the change of SAIDI and SAIFI of the overall secondary network customers due to this temperature change by the year of 2100. The percentage of SAIDI and SAIFI increase compared with those of the current year is drawn in Figure 5.15. The overall trend of increased SAIDI and SAIFI values is consistent. The average SAIDI and SAIFI increase is 1.84% and 1.53% per Fahrenheit degree rise. Since it may take about 20 years for the temperature to rise one degree, the overall impact of increased temperature on system reliability per year will be much smaller than the impact of projected load growth.

Table 5.10 Temperature Rising Impact on Reliability Indices

Temperature Rise (F)	SAIDI (hr/cus)	SAIFI (f/cus)
0	0.008334	0.004446
1	0.008468	0.004538
2	0.008574	0.004569
3	0.008748	0.004674
4	0.008994	0.004729
5	0.009245	0.004774

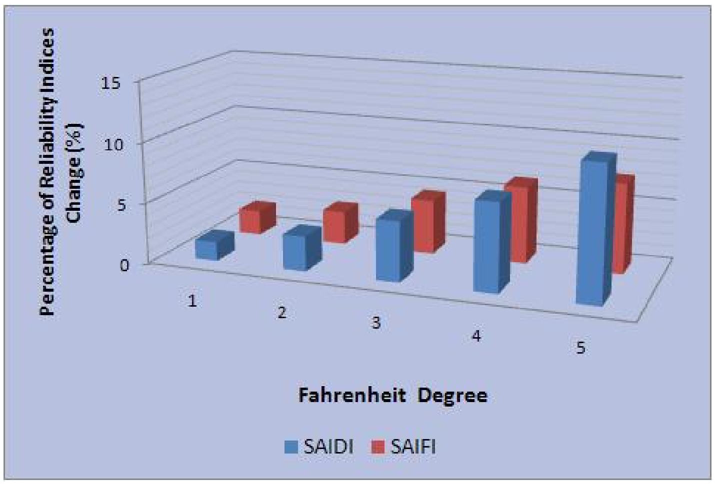


Figure 5.15 Temperature rising impact on percentage of reliability indices change

5.6 Transmission Planning with DGs

This study shows how to utilize GTA and ISM models on the initial DG planning studies. A detailed study of reliability based on time-varying load curve shapes can reveal the actual reliability after DGs are installed. However, it is generally sufficient for most initial planning studies that involve DGs to consider only the probability of forced outages in order to evaluate the likelihood of power insufficiency [97].

This study compares two alternative designs on expanding transmission system capacity to handle increasing peak load level. One involves DGs, and the other involves a new transmission line. The GTA based Monte Carlo simulation is able to analyze systems with distributed generators (DGs). Unlike big power plants, distributed generators usually do not need to be in service for 8760 hours in the year. In this study, the distributed generators are only operated during peak load conditions, so they are also called peakers. The uncertainty of the operating mode (on or off) of each DG is considered here, which is not easy to model using traditional matrix approaches because the matrix has to be re-constructed each time system status changes.

Figure 5.16 shows a cut set of a transmission system. It is a 120kV transmission network with approximately a 14000 MW peak load, where 4400 MW is from the central area (marked by the red square). There are six distributed generators in the black circled areas. In order to solve the load growth problem in the central area, two solutions are proposed:

A. Build a new 120kV transmission line to the central area, which is represented by the brown line in Figure 5.18
B. Add new distributed generation (DG) in the central area.

The Monte Carlo simulation is used to compare the reliability of the two designs. There are three cases that are evaluated:

- *Base case*: Original system without the new transmission line or new DGs.

- *New line case*: System with the new transmission line, but without any new DGs.
- *New DG case*: System with the new DG, but without the new transmission line.

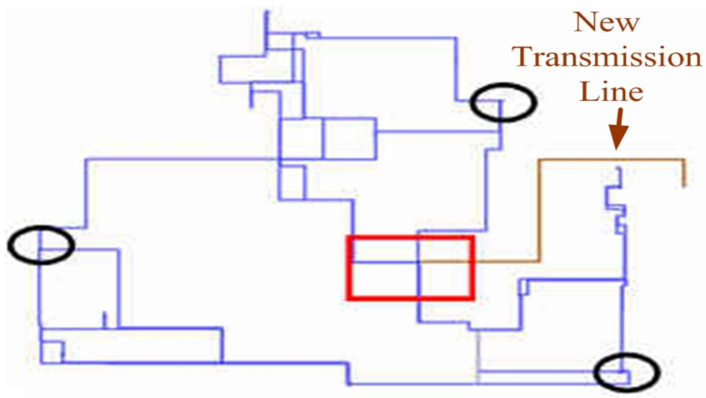


Figure 5.16 Transmission System with Central Load Growth Problem

In this simulation only forced outages are considered. The boundaries of the transmission system are selected based on the recommendation of senior utility engineers. All tie lines in the transmission system are modeled as voltage sources, connected to the system as a short line with transformer impedance. Generators are assumed to maintain constant output at the peak load, and are modeled as power injectors. The failure rates and average restoration times of lines and transformers are supplied based on utility historical outage records. The availability rates of DGs are based on manufacturer data.

Since there are no customers directly attached to the network at this level. The expected Duration of Load Curtailment is calculated, instead of CAIDI and CAIFI of customer oriented indices, at each aggregated load point. A load point can be a step down transformer or a trunk line at the boundary. There are 60 load points in the network.

Simulations are run for 100 years for each case. Table 5.11 shows the results of the simulations.

The cost of solution B is approximately 20% of solution A. Table 5.11 illustrates that building a new transmission line can increase the reliability slightly more than adding the DG, but at a much higher cost. If the main concern of this system expansion planning is that the capital cost of transmission expansion exceeds that of DGs, then DGs are the economical solution for this load growth problem.

Table 5.11 Performance Comparison between Adding Transmission Line versus Adding DGs

Case	**Expected Duration of Load Curtailment(Hr/Yr)**	**Absolute Performance Improvement**	**Performance Improvement Per $10,000**
Base Case	980	N/A	N/A
New line case	820	16%	0.128%
New DG case	870	11%	0.478%

6 REAL-TIME SIMULATION BASED RELIABILITY MONITORING AND FORECAST

6.1 Introduction

With load growth, aging systems, increased costs, and deregulation, public utility systems are experiencing increased stress. In order to continue to provide reliable service at affordable costs, utilities must look to developing more intelligence in the design and operation of systems. Utility systems may contain tens of thousands of transformers and thousands of miles of cables/lines. Given such large and complex plants to operate, a real-time understanding of the networks and their situational reliability is important to operational decision support.

Conventional reliability evaluation theory reflects the long-term average reliability level of an electric system. In real-time operations, analyzing the up-to-minute reliability level and predicting what might be wrong in the near future is important. Not only could this help operators to minimize problems, but it would also provide useful information to system planners on how to upgrade the grid.

This chapter describes an approach to electric power system real-time monitoring, system situation assessment, and reliability prediction. The simulation system is a collection of network topology, on-line measurement, historical data, event storage, analysis, and prediction that is assembled to achieve the following objectives:

- Provide a consistent system model to operator, system planner, and reliability engineer
- Ensure that the model integrity is consistent with real-time SCADA measurements
- Identify and predict where problems may occur, how serious they may be, and what the possible root causes may be
- Provide visualization for enhancing the situational awareness for system operators
- Provide a historical scenario reproduction mechanism to the system planners

6.2 ISM and GTA Applied to Real-Time Applications

It was discussed in Chapter 4 that a common situation in the power industry today is that every working group accesses and analyzes the same electric system, but with different models. The discrepancies among conventional separate models of different working groups have led to only a few circumstances in which the planning and real-time studies have provided the same solution [14]. Situational awareness is difficult to achieve because consistent views of the system cannot be kept by using fragmented models. Furthermore, modeling management needs emerge in which more participants attempt to mimic real-time plant-wide simulation environments with models that provide a consistent view of the system.

An essential requirement for monitoring and management of the real-time system is a fast and accurate mechanism to reflect the real-time field and operating condition changes, which have a strong impact on system reliability. Adverse weather, heavy sustained loading, and environmental conditions such as moisture level – all of these contribute to the failure probability of system components. System reliability may deteriorate greatly in certain special field conditions or operating modes. As described in the GTA Implementation of Failure Rate Schema section in Chapter 4, the dynamic failure rate calculation during a sequential simulation is able to catch the real-time field and operating condition changes.

The Integrated System Model (ISM) described in Chapter 4 is applied here in real-time applications. The component layer [117] is responsible for the "get/set functionality" of the reliability parameters. An example will be provided of shipping an ISM circuit model object from one processor to another, in the Simulator Architecture section below.

6.3 Real-time Assessment and Reliability Prediction

6.3.1 Simulator Architecture

The structure and the facilities of the simulator used in this real-time system assessment and reliability prediction are shown in Figure 6.1. A blade computer is used for distributed computation, where different processors run an instance of different algorithms such as Monte Carlo or contingency analysis, on the same circuit model in different states. The real-time simulation environment is seeking to identify the next event that will result in loss of service, where services may be prioritized as critical or non-critical.

The Data Acquisition process collects network topology, measurement, load, and weather from database servers and the Internet. The Model Validation process ensures the data used for system analysis is as accurate and up-to-date as possible. It detects topology changes, diagnoses whether any SCADA measurement readings are inaccurate or missing, and calibrates model loads to be consistent with the SCADA measurements. The validated circuit model is then shipped to a circuit queue to await further processing.

The Monte Carlo process obtains the forecasted weather online, and uses historical load patterns to forecast hourly loads for the next 24 hours. If contingencies already exist in the system, the circuit is directly shipped to the next queue to launch a fast assessment of the contingency. Otherwise, a sequential Monte Carlo simulation is performed to predict any contingency that may occur by utilizing the weather forecast and load data. A contingency case circuit model created by Monte Carlo is shipped to the next circuit queue to await processing by contingency analysis.

A set of contingency analysis processes is used to perform the contingency analysis. Each contingency analysis process extracts one circuit at a time from the circuit queue and uses power flow to perform the contingency analysis. Alerts concerning severe potential contingencies are provided to system operators. Time-stamped circuit models, along with power flow results are stored for future reference. The Controller in Figure 6.1 is used to coordinate the various processes.

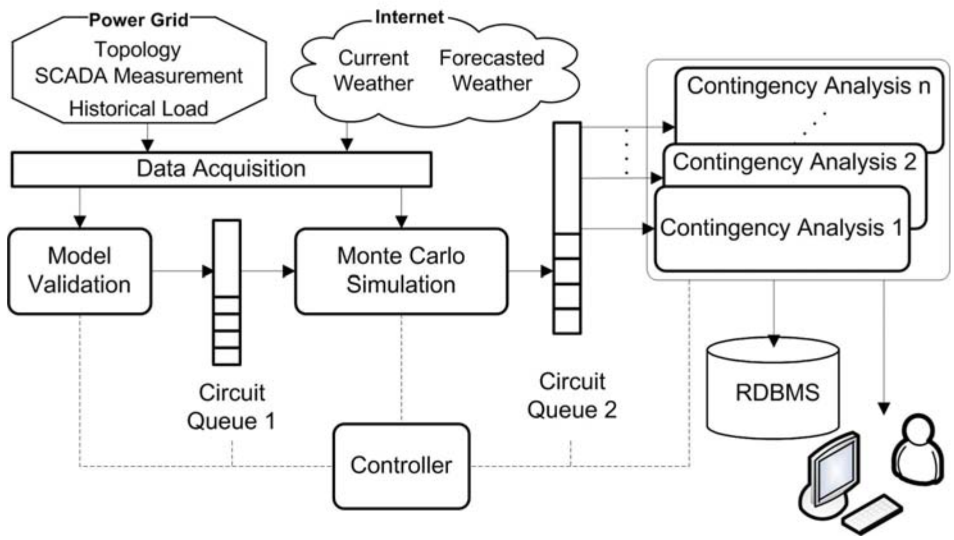


Figure 6.1 Real-Time Simulator Architecture

Each process of Model Validation, Monte Carlo simulation, and Contingency Analysis runs iteratively, and pushes and/or retrieves ISM containers to and from Circuit Queues. As an example, the flow chart of the iterative real-time Monte Carlo simulation is illustrated in Figure 6.2, with detail implementation of online weather data acquisition in Figure 6.3.

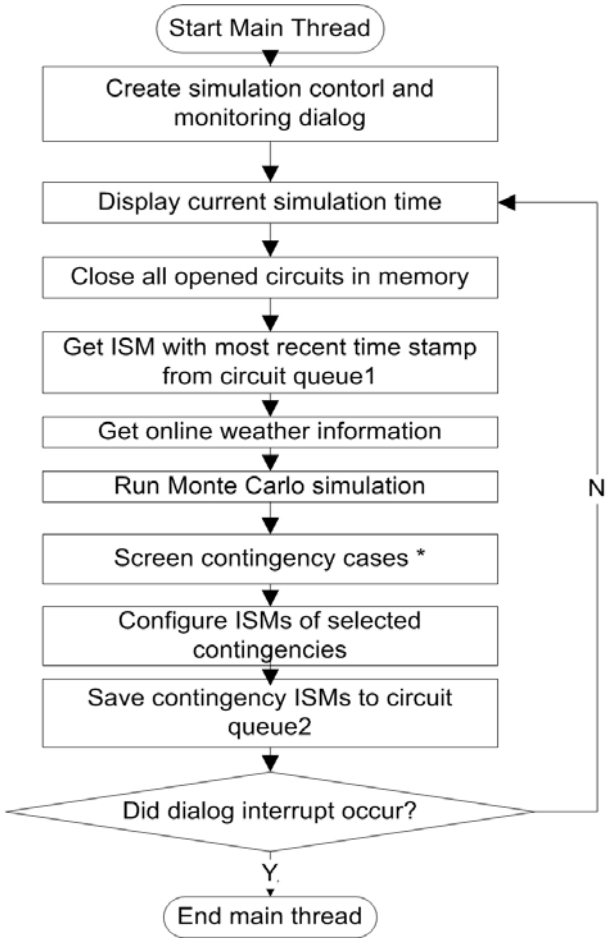


Figure 6.2 Iterative Real-Time of Monte Carlo simulation

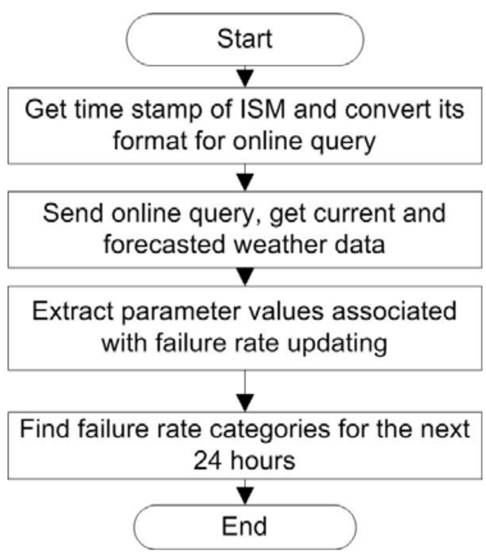


Figure 6.3 Online weather acquisition

6.3.2 System Assessment and Prediction

In order to maintain good real-time situational awareness, an accurate model that represents the behavior of the system is a necessity. Figure 6.4 shows how the real-time data and information flow in the simulation in order to evaluate model integrity and perform reliability calculations.

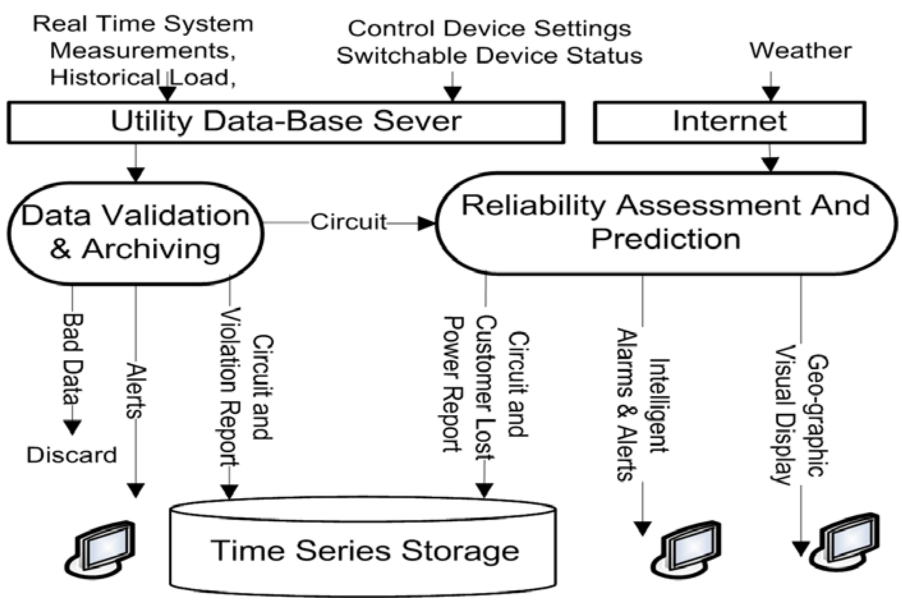


Figure 6.4 Real-time Data and Information Flow Overview

As loading has a strong impact on system reliability, accurate forecasting of the load is very important. SCADA measurements from the utility databases are used to tune the model to agree with real-time measurements. The SCADA data includes network transformer and primary feeder loading measurements. Device settings and status are used to update topology. Bad measurements are discarded by comparing each measurement with its historical statistical experience and a classical outlier rejection test is employed [130]. Loads are calibrated based on measurements, such that the difference between power flow calculation results for the tuned model and the actual measurements are less than pre-defined limits. Unusual changes in SCADA measurements are given as alerts. Low voltages or overloads at a customer service point are reported as system violations. The time-stamped, tuned circuit model is then available for reliability evaluation.

The reliability assessment and prediction module utilizes the current and forecasted system operating conditions to evaluate and predict the most credible contingencies that may occur within the next 24 hours. The dynamic failure rate update algorithm presented in Chapter 4 is used here to forecast the hourly changes in component failure rates. The goal is to identify the next event that will result in loss of service, where services may be prioritized as critical or non-critical. A geographic visual display helps to identify outaged customers. Alerts are provided for serious outage situations, such as cascading outages. The time series storage module stores SCADA measurements with their corresponding power flow calculation results. These data stores are used to update the model's statistical experience and are also available to system planners for offline processing.

Table 6.1 shows contingency analysis predictions compared with field measurements for a major primary feeder failure of a downtown network. The results show that the amps predicted by the contingency analysis have an average error of approximately 5%.

Table 6.1 Comparison of contingency analysis result with the field measurements

Feeder ID	SCADA Measurement (Amps)	Model Results (Amps)	Diff (%)
1	610	628.57	3.04%
2	566	612.11	8.15%
3	481	492.90	2.47%
4	418	459.53	9.94%
5	807	801.47	0.69%
6	0	000.00	0.00%
7	519	552.24	6.40%
8	606	654.36	7.98%
9	418	453.24	8.43%
10	470	489.31	4.11%
11	482	498.88	3.50%
12	488	515.20	5.57%
Average	**-**	**-**	**5.02%**

6.4 Visualization

Real-time system assessment and reliability prediction involves tremendous data processing for a system that contains tens of thousands of components. The traditional energy management system lists the contingency results in text oriented tables [131]. It is easy for the user to get distracted when mining important information out of long data lists. The challenge exists to deliver analysis results in a quick and intuitive manner. Here we describe an approach involving multi-view visualization, such that by using different but simple views, the operator can quickly understand the real-time situation, identify the root causes of problems, and arrive at analysis based control decisions.

6.4.1 Geographical versus Schematic views

A geographically based full-topology model like the one shown in the top layer of Figure 6.5 is built to provide an overview of the system. With the instant online alarm message described in Figure 6.4, this view can help the operator quickly capture the problematic area.

In order to assist the prompt control of a large and complex system, a small but equivalent system can be built by discarding the unnecessarily complexity of the geographical model [132],[133]. A schematic view of the system shown in the top layer of Figure 6.5 is illustrated in the bottom layer of Figure 6.5. It is an equivalent model that contains only the essential information needed to take effective corrective actions, including but not necessarily confined to substations, loads, control and protective devices. The status of each device in the schematic view is synchronized to the original geographical view, such that any control actions taken in the schematic view are reflected in the geographic view, and vice versa. Note that the schematic view can be automatically built from the geographically view.

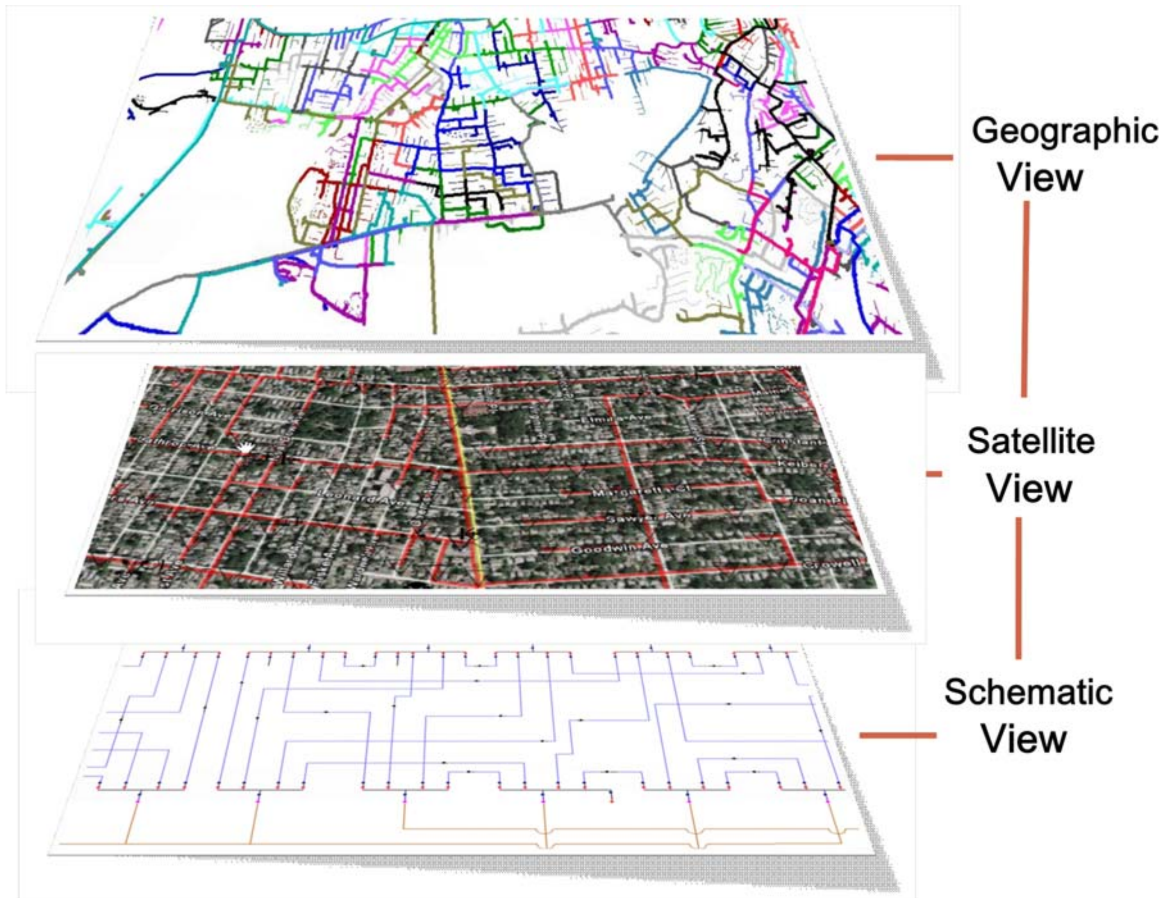


Figure 6.5 Visualization for diagnosis

6.4.2 Diagnostic and Satellite Views

In order to make the contingency analysis results listed in tabular/text displays more intuitive, visualization has been improved in recent years for displaying the percentage of overloads/outages, such as using dynamically sized pie-charts [134],[135]. However, for dangerous situations such as cascading failures, the number of components affected by the contingency could be excessive. It is not easy to discover the underlying problems in a quick manner by checking the pre/post contingency situation of every overloaded/outaged component one by one.

In order to facilitate the system diagnosis in a quick view, the cascading failure is simulated for every predicted, dangerous situation. Limit violations are checked. Burned out cables and customers that lose power in cascading failures are identified. The severity of the contingency can be quickly evaluated by how wide the affected area is and how many services are impacted. A similar visualization method as the cascading study case presented in Chapter 5 can be utilized. Therefore, mental connections between the failed components and the contingency caused by the violation are easily seen and understood. Detailed limit violation report are available for every component upon request.

Further planning can be performed by panning the problematic area into a satellite view. In the middle layer of Figure 6.5, a sub-set of the system (red lines) is overlapped with the real-time satellite image. The phenomenon that causes the potential trouble can be examined in this way. For example, nearby trees may need to be trimmed.

6.5 Impact on Critical Customers

The modeling and model maintenance needed to achieve real-time monitoring and risk assessment of critical loads are expensive. The plant model used for the risk assessment must predict field conditions with sufficient accuracy, and the topology of the model must be maintained continuously as components fail and/or as components are taken down for maintenance. However, for some critical loads, the risk assessment model investment would pay for itself many times over if even one major power outage is avoided.

The business costs of utility companies failing to meet the requirements of certain high priority customers can be very large. For power mill and pharmaceutical manufactures, a several minute outage is long enough to destroy semi-manufactured goods, the result of which may cost into the millions of dollars. Foreseeing risks in real time and taking appropriate preventive measures can avoid such losses, creating a win-win situation for utilities and their customers.

As listed in Chapter 4, the GTA implementation of the *CmpPri* attribute shown in Figure 4.3 can be used to identify the critical customers ISM container of the secondary network in Figure 5.4. Table 6.2 illustrates the critical customers in a network container, which is used in a real-time simulation application. Alerts can be given if any critical customers are affected in a contingency case. This may help initiate actions to evaluate reconfigurations, bringing on generation, and shedding of less critical load in order to restore the security of the critical load. Also, as a last resort, the decision may be to allow the power system itself to sustain life damaging overloads to maintain power to the critical load.

Table 6.2 Critical Customers in Network Container

Type	**Number**	**Priority level in ISM**
Hospital	1	Critical/Life support
Life Sustaining Equipment	11	Critical/Life support
Major Account	37	High Impact/Cost
Transportation	6	High Impact/Cost

6.6 Conclusion

This chapter describes an approach to power system real-time assessment and reliability prediction with the usage of a unified model. The validated SCADA measurements are used to update model topology and calibrate the loads in the model. A Monte Carlo simulation is used to predict the most probable dangerous situations that might occur in the short term. The results of contingencies are displayed in different views to achieve better diagnosis, planning, and control. Providing multiple, synchronized views, each view supporting display of analysis results, helps the operator to understand the up-to-the-minute situation. By replaying historical events in the ISM simulator, the system planner is provided with a “learn the system and improve it” planning environment.

7 CONCLUSION AND FUTURE WORK

7.1 Conclusion and Contributions

This dissertation describes research efforts concerning electrical power system modeling and reliability analysis. Although much research has been performed on the reliability evaluation of power systems, how large-scale realistic systems should be analyzed is still under investigation. The literature review reveals that the traditional, convenient assumptions of independent events and fixed component failure rates cannot model systems realistically.

This research makes efforts to move forward the past works towards the direction of addressing reliability needs directly from the consumer point of view. Previously, electric utilities use contingency and margin criteria for indirect reliability measures during planning and design. Generally, consumer oriented reliability evaluation indices such as SAIDI and SAIFI are not directly used in the design stage. However, given the complexity of the realistic system with constant facility additions and operating changes, directly use reliability values as numeric criterion on selecting a solution among potential alternative designs is expected to be a trend [97]. In this research, the expected reliability behaviors of realistic systems are computed by utilizing detailed analysis of their configurations and equipment information.

In this dissertation, a GTA based reliability analysis of electric power systems is presented, with extended analysis zones from the traditional power system functional zones. This approach allows handling the complexity of the real world, including dependent failure rates and cascading failures. The physical network of a large-scale system is modeled with containers and topology iterators, containing attributes from transmission system components down to each customer in the distribution system. Iterators are employed to handle topology connections and to reduce the computational overhead due to topology changes of failed components and protective device operations. A generic software architecture is presented such that the overwhelming amount of data needed in system reliability evaluation can be integrated together with algorithms and the network container.

The reliability evaluation of the utility system is performed with a sequential Monte Carlo Engine. Historical weather records are used as input to the engine. A failure rate schema is presented which considers not only independent failures but also dependent failures. The change of weather, load, environment, and operational conditions such as past events are used to dynamically update the component failure rates during the simulation. The simulation is performed with chronological load curves that depend on the customer classes at each load bus. Field measurements are used to calibrate estimated loads so that the time-varying characteristics of the loads are in agreement with the system power flow measurements.

Five case studies are performed to demonstrate the potential of the proposed approach on system evaluation, design, or planning. All systems understudy are large-scale realistic circuits containing combinations of radial and looped networks. The first case study calculates reliability indices of aggregate networks. The second provides an evaluation of reliability down to every customer load bus. The third study gives details of cascading failure analysis and identification of system weak points. The fourth case is a sensitivity study on the ways in which temperature and load affect system reliability. The last case is a transmission level reliability evaluation including the operation of DGs.

This dissertation also describes an approach to power system real-time assessment and reliability prediction using an Integrated System Model (ISM). SCADA measurements are used to update model topology and calibrate the loads in the model. Online weather and load information are utilized to predict credible contingencies that might occur in the short term. The results of contingencies are displayed in different views to achieve better diagnosis, planning, and control. This approach helps the operator's understanding of the up-to-minute situation. By replaying historical events, the system planner is provided with a "learn the system and improve it" planning environment.

The major contributions can be summarized as follows:

- An integrated failure rate schema is proposed. Component failures that drive customer level interruptions in both transmission and distribution systems are included into one analysis architecture. Here the analysis zones are extended from the traditional power system functional zones.

- GTA is used to implement simulation based solutions of reliability measures. Algorithms and trace operations associated with reliability analysis are described with GTA notations.
- Dependent outages are considered in the reliability analysis. Cascading failures are used to identify weak points of a system.
- The time-varying characteristics of the power systems are included into the analysis. The system reliability is analyzed as a function of time-varying load and time-varying component failure rates.
- A flexible software architecture for reliability analysis that integrates algorithms, data, and the power system network is proposed. Very different types of reliability studies can be performed with the same software architecture.
- A real-time simulator architecture aiming at online system monitoring and short-term reliability prediction is proposed.

7.2 Future Work

A comprehensive reliability assessment of power systems is a complex task that may involve many aspects. The assessment method, environmental and weather conditions, equipment operation status, reliability benefit over the cost of facility augmentation, real-time reliability monitoring and prediction are some of the related topics discussed in this dissertation. The following could be done as future work.

- Field testing of the real-time reliability monitoring and prediction simulator to evaluate its performance.
- Improvements in component failure rate modeling should be sought. Instead of using exponential distributions for failure rates, and using multipliers to reflect the rate changes, different distribution functions, such as curve fitting from histogram of outage data, can be applied to improve the reliability modeling of components.
- Implement cooperation with economic analysis. The reliability indices values calculated by the Monte Carlo engine can serve as one of the criterion inputs to perform a comprehensive economic study. Based on the priorities of the criterion chosen, different weights may need to be assigned to each criteria in order to obtain the most promising result.

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APPENDIX - GTA OPERATIONS

Table A.1 GTA Basic Operations Used In Reliability Analysis

Integer or Real	Integer or Real	a=b	Boolean	Equality
Integer or Real	Integer or Real	a<>b	Boolean	Inequality
Integer or Real	Integer or Real	a<b	Boolean	Less Than
Integer or Real	Integer or Real	a>b	Boolean	Greater Than
Integer or Real	Integer or Real	a<=b	Boolean	Less Than or Equal
Integer or Real	Integer or Real	a>=b	Boolean	Greater Than or Equal
Boolean	Boolean	a or b	Boolean	Or
Boolean	Boolean	a and b	Boolean	And
Boolean	Boolean	not a	Boolean	Negation
Boolean	Boolean	a<>b	Boolean	Inequality
Boolean	Anything	if a then b	Type of b or b’	If Then Else
String	String	a=b	Boolean	Equality
String	String	a<>b	Boolean	Inequality

Table A.2 GTA Operations on Collections Used In Reliability Analysis

a	b	Operation	Result Type	Effect
set	set	a->union(b)	set	All elements in either a or b, without repetition
set	any	a->including(b)	set	All elements of a with b added in if it was not in the set a
set	any	a->excluding(b)	set	All elements of a with b removed if it was in the set a
set	set	a-b	set	All elements of a not in b
set	set	a=b	boolean	True if a and b have identical elements, else false
set	set	a-b	set	All elements of a not in b
collection	expression	a->collect(b)	collection	The collection of results for the expression b applied to the elements of a
collection	expression	a->forall(b)	boolean	True if b evaluates as true for every element of a, otherwise false
collection	expression	a->exists(b)	boolean	True if b evaluates as true for at least one element of a, otherwise false
collection		a->size	integer	The number of elements in a
collection	any	a->count(b)	integer	The number of occurrences of b in a
collection	any	a->includes(b)	boolean	True if a includes b
collection	collection	a->includesAll(b)	boolean	True if a includes all the elements of b
collection		a->isEmpty	boolean	True if a is empty (i.e., has no elements)
collection		a->notEmpty	boolean	True if a is not empty
collection		a->sum	integer or real	The sum of the elements in a, all of which must be integer or real