Incorporating Time and Statistical Variations in Load Modelling for Reliability and Customer Interruption Costs Evaluations

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DECLARATION

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ABSTRACT

As society becomes more dependent on energy, a continuous supply of electricity is expected by the customers. Hence, reliability is an essential aspect in power systems planning and operations and therefore reliability studies are important in evaluating the robustness and the risks of failure in electric power systems. Furthermore, it is also essential to be able to quantify the costs of interruptions and therefore customer interruption costs studies are also necessary. In both studies, the modelling of load and reliability are required, while a cost model is also needed for the customer interruption costs evaluation. Thus, to obtain reliable and dependable indices, which power system planners and operators can use for their decision-making, an appropriate and accurate representation of the actual load demand interrupted during a power failure is necessary. Conventional methods have been integrated by using average values to represent the interrupted loads at the distribution points. But studies have shown that, although deterministic models are useful at identifying weaknesses and proposing reinforcements to the power system, they do not incorporate the effects of load variation whose behaviour directly affects the value of the calculated reliability indices. As time variation and uncertainty are important factors to consider in load modelling, time varying and stochastic methods are necessary to model the load variation. Hence a time dependent beta probability distribution model is proposed to represent the expected load interrupted. The beta PDF fits a variety of distributions and has a finite range (between 0 and 1) which can be easily fitted to any loads data. Furthermore this load modelling approach offers additional useful information, through the use of confidence/risk levels and probability distribution, which can associate a quantifiable degree of confidence or risk to the results. Therefore this dissertation investigates the impact of incorporating time and statistical variations in load modelling for reliability and customer interruption costs (CIC) evaluations, with the addition of the effect of reconfiguration and load growth on the power distribution system. A sequential Monte Carlo Simulation technique was used to simulate yearly interruptions of different load points in a test system (RBTS) and the simulations were performed in MATLAB software.

This study was carried out with two main objectives. Firstly to investigate different types of load modelling in reliability or CIC evaluations to obtain an understanding on how these evaluations are performed and identifying the benefits or limitations of existing models. Secondly to develop several load modelling approaches, including a time dependent beta PDF load model, which are simulated using an appropriate simulation technique and software. A comparison using historical load data based on South African residential customers and shops (used as commercial customers) with the different load models is performed and their impact on the calculated reliability or cost indices are analysed. The

analysis shows that the reliability and cost indices resulted in different values of varying degree as compared to the base case (average load model) when using reconfiguration with sufficient spare capacity. These differences are found to be more significant when reconfiguration with limited spare capacity is used. The analysis of the results also shows that each load modelling approach varies in simulation performance. The sensitivity of each load modelling technique compared to the base case varies over a wide range with decreasing and increasing percentage differences. In this particular study, the inclusion of time variation produced indices (EENS and ECOST) lower than the base case and this decrease is greater when the time intervals at which the time varying loads are simulated is shortened. Another observation is that in general the inclusion of statistical variation or uncertainty in the load produced indices higher than the base case. However, the increase in the number of steps in the case of the step load models causes a decrease in the values of these indices. The time dependent beta PDF load model incorporates both time and statistical variation in the load, which increases the accuracy of representation of the actual load. Additionally probability distributions illustrate the skewness of the indices and hence provide an idea on the spread of the indices and how they are dispersed. The probability distributions also provide important information such as the probability that the values in the distributions (EENS and ECOST) occur. Another useful feature when using statistical approaches is that the results can be associated with a degree of risk or confidence. The confidence level for instance indicates the degree of confidence that the index under investigation will be within a certain value (inclusive). Hence if the EENS obtained at 95 % confidence level is 254.67 MWh/year, then it means that the EENS can be less or equal to 254.67 MWh/year with a confidence of 0.95 (95 %). Another way to interpret this result is that there is a 5 % risk that the EENS will exceed 254.67 MWh/year. The probability distributions of the indices provide a clear picture of the system's behaviour to system planners on the range over which the indices extend and the probability that they occur, while the use of confidence/risk levels provide a number of combinations (EENS and ECOST values for various degree of confidence/risk) which is more meaningful in making rational planning decisions. Although higher confidence levels (or lower risk levels) in this study indicates that the EENS and ECOST may reach higher values, these values when used as reference for power system planning projects, also have a very low probability of occurring (when compared to the probability distributions of EENS and ECOST). There is no standard confidence/risk level used in practice as it depends on what degree of risk the electric utilities are willing to take. However it is clear that time and statistical variations in the load representation are needed to obtain reliable and informative results, and this can be achieved by using a time dependent beta PDF load model.

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GLOSSARY

CIC – Customer Interruption Costs

CDF – Customer Damage Functions

MCS – Monte Carlo Simulations

SAIFI – System Average Interruption Frequency Index

SAIDI– System Average Interruption Duration Index

CAIDI – Customer Average Interruption Duration Index

ASAI – Average Service Availability Index

ASIFI – Average System Interruption Frequency Index

ASIDI – Average System Interruption Duration Index

CCDF – Composite Customer Damage Function

SCDF – Sector Customer Damage Function

ENS – Energy Not Supplied

FMEA – Failure Mode and Effects Analysis

TTF – time to failure

TTR – time to restore

ECOST – Expected Interruption cost

EENS – Expected Energy Not Supplied, the expected number of MWh per year that a system must curtail due to inadequate generation

MWh – Mega-watt hour

IEAR – Interrupted Energy Assessment Rate

LOLE – Loss of Load Expectation, the expected number of hours per year that a system must curtail load due to inadequate generation.

PDF – Probability Density Function

Chapter 1

1 INTRODUCTION

This research investigates the impact of incorporating time and statistical variations in load modelling techniques in reliability and customer interruption costs assessments, with an emphasis on the use of probabilistic load models to represent the customer loads and provide sensible information in a reliability and CIC evaluation. The effects of reconfiguration and load forecasting (load growth) in the reliability or customer interruption costs evaluation are also looked at. These evaluations can then be used by power system planners to effectively choose their planning schemes for planning and future expansion projects for power systems.

1.1 Background

Brown, (2002), defines electrification as an important aspect of a country’s ability to develop economically as well as provide societal benefits. However, power systems are also expected to deliver electrical energy continuously to customers efficiently (at a competitive price), as well as effectively (provide reliable and good quality of supply) (Brown, 2002). In a power system scheme, events that can potentially disturb the system, such as overloading, lightning strikes, storms, corrosion and vandalism can occur (Gaunt, 2012). With the application of planning standards, maintenance programmes, system protection schemes and system control, disturbances can be minimized to enable the adequate operation a power system in such a way that the supply to the customers is only occasionally interrupted (Gaunt, 2012).

It is important to note that having power systems with extremely reliable supply to all customers are not economically viable, as in many outages, only a limited number of customers are affected (Gaunt, 2012). Outage durations depend on the time the utility takes to respond, remove or bypass the cause and any damaged equipment, and restore the network to an operational state (Gaunt, 2012). Poor planning, inadequate construction or maintenance, defective protection systems and human error in system operation contribute to the increased frequency, duration and extent of outages (Gaunt, 2012). The research undertaken in this dissertation concerns the reliability aspect of power systems and the study of different load model representations of the customer loads and their effect in a reliability and customer interruption costs assessment. Electricity is produced and delivered to customers through generation, transmission and distribution systems. Reliability can also be classified at different hierarchical voltage levels; mainly low, medium and high voltage levels. Generation systems operate at medium voltage level, transmission systems operate at medium and high/very high voltage levels while distribution systems operate at low voltage levels (Billinton & Allan, 1996; Brown, 2002; Brown, 2009).

Figure 1-1 below shows an illustration of a power system with many subsystems; in which the reliability depends upon generating enough electric power, and delivering it to customers without any interruptions in supply voltage. In developed countries, a majority of interruptions results from problems arising between customer meters and distribution substations. Since 90 % of all customer reliability problems are accounted for from distribution systems, improving distribution reliability is an important undertaking in improving customer reliability (Brown, 2002).

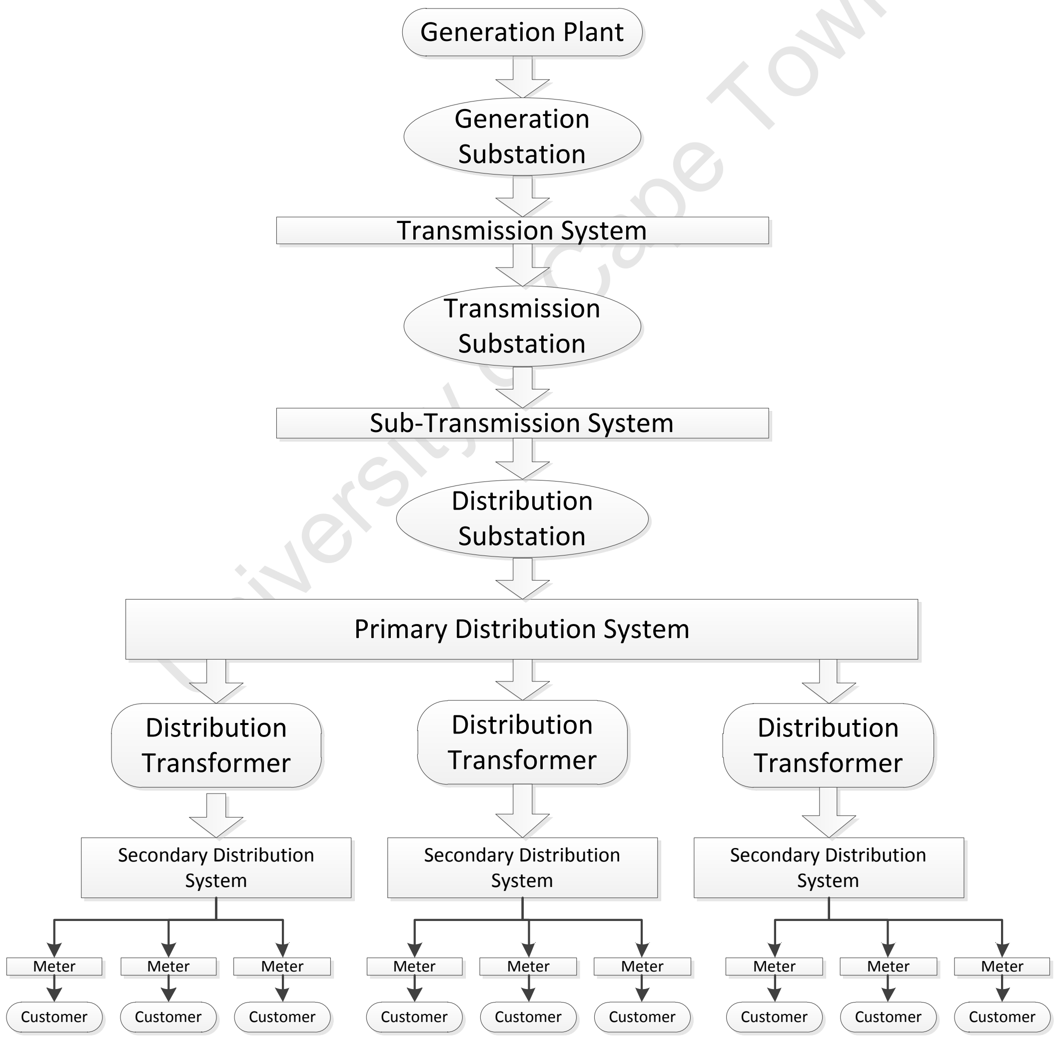


Figure 1-1: Block diagram based on an example of an electric power system scheme consisting of many subsystems (Brown, 2002).

Reliability evaluation of power systems is an intricate practice which requires the consideration of multiple factors, which affects a power utility's ability to supply its customers. Blackouts affect a country financially as well as disrupt daily routines of its inhabitants. In 2003, six blackouts occurring within five different countries affected more than 120 million people. The events occurred between July, 22 and September, 28 and the countries affected include the U.S.A., Canada, London, Malaysia, Mexico, Denmark, Sweden and Italy. In 2004, only three major blackout events occurred which affected several million people. Then, between 2005 and 2011, more than ten major blackout events occurred around the world each year (AP, CBC, The Guardian, 2003-2011). Even with the current technology, the risks of power outages are high and therefore the optimal reliability of power systems is important in reducing the risks or likelihood of power outages occurring. Some sources of interruptions can be attributed to a wide range of phenomena. These phenomena are described in detailed by Brown, (2002), and include the following:

- Equipment failures
- Animals
- Trees
- Severe weather
- Human factors

An example in the context of South Africa, the effects of blackouts have economic and socio-political impact on the country. The costs of interruptions are not only limited to the direct financial impact, but also the impact on Gross Domestic Product of the country, as production and commerce are major contributors to the GDP and constraints on output due to electricity interruptions cause a reduction in GDP. (Cross, et al., June 2006).

The dissertation will therefore look into the necessary information required to carry out reliability and customer interruption costs evaluations, with a focus on the impacts of load modelling in these evaluations when different models are implemented when reconfiguration and system load growth are considered.

1.2 Introduction to Reliability and Customer Interruption Costs Evaluation in Power Systems

To carry out an adequate reliability or customer interruption costs evaluation (CIC), one has to understand the principles surrounding the reliability of power systems and its financial evaluation. Chapters 2 and 3 provide detailed information on the subject as well as examples of such studies found in literature.

1.2.1 Definition of reliability

The reliability concept is defined in various ways. Reliability is defined by the International Standard, (ISO - International Standard, ISO 8402:1994), as “the ability of an item to perform a required function, under given environmental and operational conditions and for a stated period of time”. System reliability can be divided into system adequacy and system security as shown in Figure 1-2.

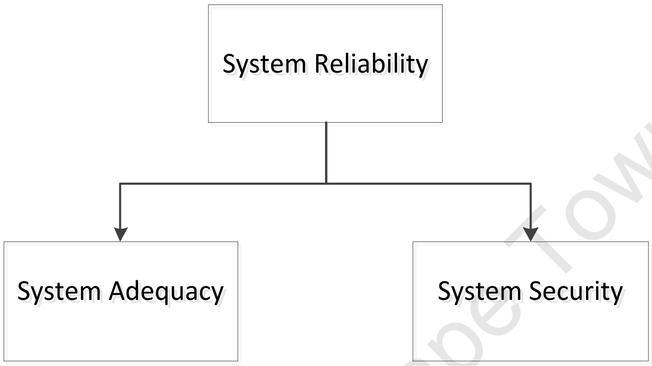


Figure 1-2: System reliability divided into system adequacy and system security (Billinton & Allan, 1996; Brown, et al., 1996; Brown, 2009).

System adequacy is defined as the ability of the system to supply its load while considering transmission constraints and scheduled and unscheduled outages of generation, transmission and distribution facilities (Khan & Billinton, 1993; Billinton & Li, 1994; Alvehag, 2008). *System security* is defined as the ability of the power system to withstand disturbances arising from faults or unscheduled removal of bulk power supply equipment (Khan & Billinton, 1993; Alvehag, 2008). Therefore, system adequacy involves the handling of static conditions while system security treats system dynamics or transient disturbances (Alvehag, 2008).

1.2.2 Static and Dynamic Approaches

When reliability assessments are involved in power systems, it invariably involves a consideration of system states and whether they are adequate, secure, and can be assigned an alert, emergency, or some designated status. This is particularly the case for transmission systems and it is therefore useful and convenient to discuss the importance and meaning of such states (Billinton & Allan, 1996). As mentioned in section 1.2.1, adequacy is generally considered to be associated with static conditions which do not include system disturbances.

The concept of adequacy, as described by Billinton & Allan, (1996), is considered to be the existence of sufficient facilities within the system to satisfy the consumer demand. These facilities include those necessary to generate sufficient energy and the associated transmission and distribution networks required to transfer the energy to the actual consumer load points (Billinton & Allan, 1996).

Security, however, relates to the ability of the system to respond to disturbances arising within that system. It is therefore associated with the response of the system to any disturbances it is subjected to, which include conditions causing local and widespread effects and the loss of major generation and transmission facilities (Billinton & Allan, 1996). To ensure that reliability can be calculated in a simply structured and logical fashion, only adequacy (static approach) is considered, as it is far easier to calculate and it provides valuable input to the decision-making process (Billinton & Allan, 1996).

Load modelling can also be investigated using different approaches such as the static or dynamic approach. An example of static and dynamic loads is provided in Figure 1-3.

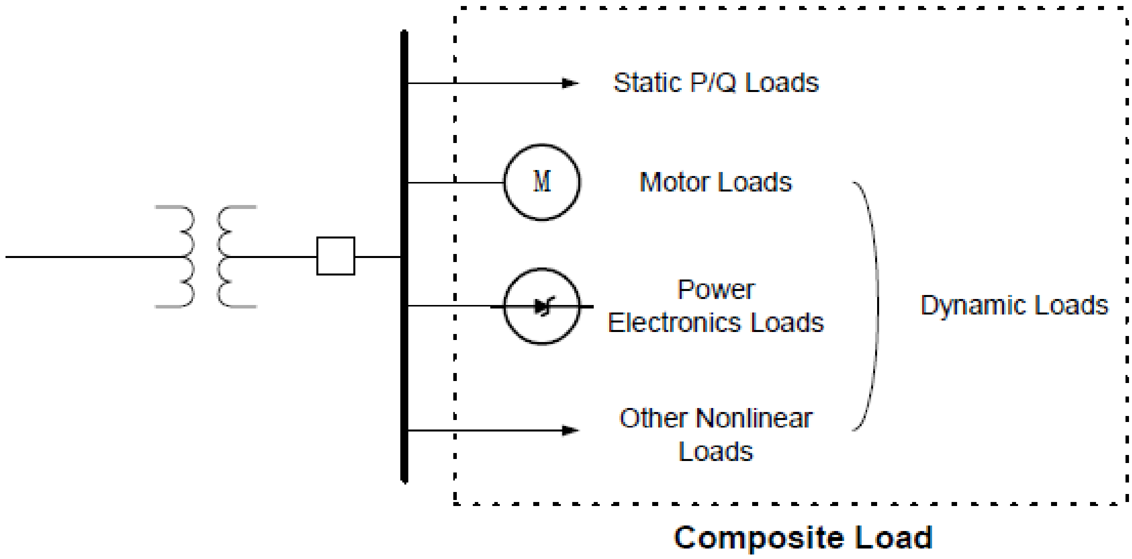


Figure 1-3: Composite load in a distribution system (Keyhani, et al., 2005).

For the purpose of this research, only load models based on static conditions are considered as composite or dynamic loads are of greater significance in power system stability analysis than in power system reliability evaluation.

1.2.3 Deterministic and Stochastic Methods

Reliability evaluation can be performed by deterministic or stochastic methods. Since deterministic models are useful at identifying weaknesses and proposing reinforcements to the power system (Veliz, et al., 2010), they are important as base case studies in reliability assessments. However, because the results do not incorporate the effects of load variation whose behaviour directly affects the value of the calculated reliability indices as described by Veliz et al., (2010), stochastic methods are valuable in incorporating uncertainty in the study. Load variation influences reliability assessment in the magnitude of load cut and in the values of frequency and duration (F&D) of supply interruptions (Melo, et al., 1992; Veliz, et al., 2010); and when combined with time dependency, the variability can be found at different time of the day, day of the week, or seasons. As explained earlier, it is essential that the calculated reliability indices take into consideration the behaviour of the load over the whole period of the analysis because the frequency, duration and magnitude of load cuts have an impact on the economic consequences of supply failure (Veliz, et al., 2010). Therefore, incorporating uncertainty and time dependency in the load model, allows a better accuracy of load representation in reliability evaluation and has relevance for moving towards more realistic reliability indices (Veliz, et al., 2010).

1.2.4 Analytical and Simulation Techniques

Billinton & Allan, (1996), point out that there are two main approaches in the calculation of power system reliability indices: mainly analytical and simulation. In the past, most techniques used have been analytically based and simulation techniques have taken a minor role in specialized applications. The main reason for this is because analytical models and methods have been sufficient to provide planners and designers, until recently, with the results needed to make objective decisions. Another reason was due to the amount of computing time that simulation techniques generally require (Billinton & Allan, 1996). With the improvement in technology (processing speeds and advanced simulation tools), there has been an increasing interest in recent years in modelling the system behaviour more comprehensively and in evaluating a more informative set of system reliability indices (Billinton & Allan, 1996).

Analytical techniques use mathematical models to represent the system and evaluate the reliability indices from such models using direct numerical solutions (Billinton & Allan, 1996; Billinton & Wang, 1999; Alvehag, 2008). They generally provide expectation indices in a relatively short computing time, however, assumptions are frequently required in order to simplify the problem and produce an analytical model of the system and this is particularly the case when complex systems and complex operating procedures have to be modelled. This results in the loss of some or much significance in the analysis and therefore simulation techniques are very important in the reliability evaluation of such situations (Billinton & Allan, 1996; Solver, 2005). Analytical techniques are mainly used to provide a measure of the mean or expected values of the load point and system reliability indices (Billinton & Wang, 1999; Solver, 2005) and this is the approach usually taught in university and industry based courses (Billinton & Wang, 1999).

Simulation techniques estimate the reliability indices by simulating the actual process and random behaviour of the system. The method therefore treats the problem as a series of real experiments and the techniques can in theory take into account virtually all aspects and contingencies essential in the planning, design, and operation of a power system. These include random events such as outages and repairs of elements represented by general probability distributions, dependent events and component behaviour, queuing of failed components, load variations, variation of energy input such as that occurring in hydro-generation, as well as all different types of operating policies (Billinton & Allan, 1996; Alvehag, 2008). For systems simulated over a long period of time, it is possible to study their behaviour and obtain a clear picture of the type of deficiencies that the system may suffer. This captured information allows the expected values of reliability indices along with their frequency distributions to be assessed. This comprehensive information gives a very detailed description, and hence an understanding of the system reliability

1.2.5 Customer Interruption Costs Scheme

Customer Interruption Costs (CIC) evaluation has significant importance in power system planning and operation for a power utility industry due to the growing interests and consideration of customer costs of power outages (Caves, et al., 1990; Tollefson, et al., 1991). This awareness has been motivated by the necessity to deliver cost effective customer service including an adequate cost-benefit framework which should contain both the marginal cost of supply and the marginal value of reliability (Koval, 1999). As utility industries continue on the path to deregulation, high levels of reliability are expected to be critical for the different categories of existing customers, mainly Residential, Commercial or Business (Suddeth, 1996) and also Industrial, Agricultural and Government and Public Offices. Cost of outages for business customers as well as the other customer groups is a key issue in the cost-effective management of electric utilities and these may take different forms for different customer types (Tollefson, et al., 1991; Tiedemann, 2004). While customers wish for improved reliability, reduced electricity prices are also one of their priorities and thus it is important to understand and consider the nature of this trade-off, which may vary for different customer types (Koval, 1999; Tiedemann, 2004). Customer interruption cost (reliability cost) and reliability worth of power system network reinforcement are very useful indices for making optimal planning and operation decisions (Neudorf, 1995; Wang & Billinton , 2002). Reliability of utility systems is estimated by their ability to maintain continuous service to the customers, however there are no completely reliable networks in practice and the issue arises as how to measure and quantify the reliability of service, make those measurements relevant, and finally classify and evaluate them (Nahman, 1997). Customer interruptions costs can thus be perceived as a function of the load model used, the reliability costs and the reliability worth. Figure 1-4 shows the basic models required for CIC evaluation.

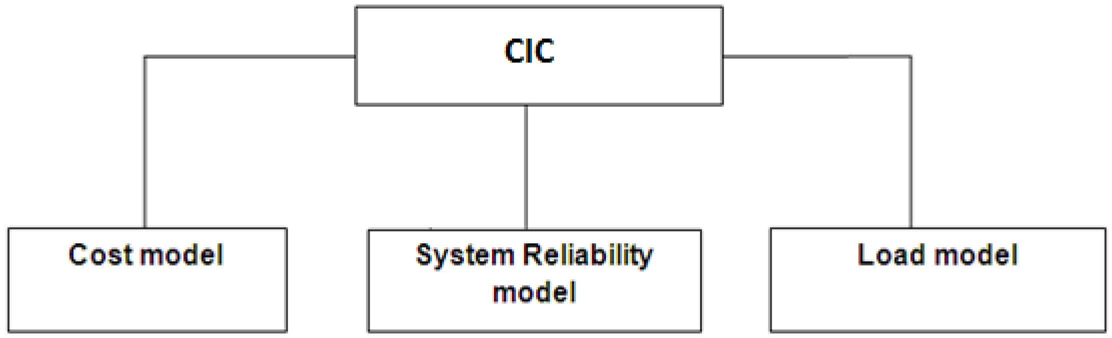


Figure 1-4: Customer Interruption Cost Model (Kariuki & Allan, 1996)

Detailed information about these models is available in Chapters 2-4. The cost and reliability models are of similar importance to the load model, however, the focus of this research is on the study of the impact of using various load modelling approaches when performing a reliability or CIC evaluation in a power distribution system.

1.3 Motivation for the Research

Load models in reliability evaluation can be classified as deterministic or stochastic as shown in section 1.2.3. In deterministic analysis the load is often seen as three levels: heavy, medium and light, and the load are considered on the same level during the whole period of the analysis (Veliz, et al., 2010). Although useful at identifying weaknesses and proposing reinforcements to the system, the results do not incorporate the effects of load variation, whose behaviour directly affects the value of the calculated reliability indices (Veliz, et al., 2010). Load variation influences reliability assessment in the magnitude of load cut and in the values of frequency and duration (F&D) of supply interruptions (Melo, et al., 1992; Veliz, et al., 2010).

The frequency, duration and magnitude of load cuts have an impact on the economic consequences of supply failure; therefore it is essential that the calculated reliability indices take into consideration the behaviour of the load over the whole period of the analysis (Veliz, et al., 2010). Adopting a load model that allows a better accuracy of load representation in reliability evaluation has a relevant importance for moving towards more realistic reliability indices (Veliz, et al., 2010). Zhu, (2007), also explains that the way the load model is represented has an impact on reliability studies including conditions such as equipment aging and reconfiguration (availability of alternative power sources). Therefore there is a need to consider the different factors affecting load variation such as time dependency and uncertainties.

1.3.1 Uncertainties and Time Dependency in Load Modelling

It has been established in 1.2.3 that stochastic methods are important in the reliability and CIC evaluation of power distribution systems. This is especially true in power distribution systems and a supporting statement highlighting the universal problem faced by power system planner in achieving optimal distribution network designs is that; “The largest source of uncertainty in low voltage (LV) distribution design is in the modelling of the design load”. (NRS 034-1, 2007). Therefore it is essential to use an appropriate load modelling approach in reliability or CIC studies to incorporate the uncertainties in load modelling. Furthermore, the variation of load with time should also be included in the study, as studies described in Chapter 4 show that the time of interruption of load has an effect on the calculated indices. Therefore there is a need of a load modelling approach which incorporates both the uncertainty and time dependency in load variation.

1.3.2 Probability Distribution Functions in Load Modelling

The use of probability distribution functions in the modelling of load takes into account the stochastic nature of customer electricity demand. In Davies & Paterson, (1962), ACE, (1981), and Herman & Kritzinger, (1993), a “Goodness of fit” was performed on various PDFs to assess how well they trend the load frequency histograms as PDFs can be fit on load frequency distribution histograms and these include the Weibull, Beta, Gaussian and Erlang PDFs. However, Herman & Kritzinger, (1993), showed the Beta PDF as the preferred choice for its ability to take on a variety of shapes as well as being limited to a finite range (between 0 and 1) which are attributes that are appropriate for the representation of residential load. Relevant work using the beta PDF approach is described in section 4.6.3 and the benefits of using probability distribution functions in load modelling are discussed in section 5.1.1, followed by the detailed description of the beta PDF load model used in this research in section 5.3.2.

1.3.3 Contribution of the Research

Looking into different load modelling approaches with a focus on probability methods in reliability and CIC evaluation provide an insight on the impacts of varying load models in such studies and outlines the advantages of incorporating time and statistical variations in the load to obtain a practical and an accurate representation of the results.

The dissertation outlines the research efforts in load modelling in reliability and Customer interruption costs evaluation of electrical power distribution system using several approaches. The contributions of this research are as follows:

- An analysis of existing load modelling approaches is performed and the selected load models are used for comparison in a reliability and CIC evaluation. Depending on the availability of load data and other information such as the type of reliability and cost data available, some approaches can be performed while others cannot or are not necessary. For instance, in the absence of historical load data, probabilistic methods are unlikely to be achieved, while in the presence of historical load data, the fuzzy load model becomes redundant, as they are useful to model uncertainty (possibilistic) when historical data are not available. Instead, probability methods (probabilistic) then become a more sensible alternative.
- Existing load modelling approaches are used and proposed load modelling approaches are developed, such that they can be implemented in a selected software (MATLAB) using an appropriate simulation technique (Monte Carlo Simulation). This provides a comparison of various load modelling techniques whereby the same framework is used for the simulation process and therefore provides a clear difference in results due to the approach used to model the load and not because of the process used to model the load.
- This study also applies a time dependent beta probability density function approach to model customer load demand during interruptions, by incorporating uncertainty and time dependency of the load. The time dependent beta PDF load model allows the display of the results in the form of probability distributions as well as associates the results with risk levels. This provides system planners with an additional tool for their decisions-making process. Other useful information, such as the probability distributions of the reliability or cost indices in the system can also be obtained, providing an insight on the shape or skewness of the distributions.

1.4 Hypothesis

When looking at electrification or expansion projects, system planners also look at the reliability aspect of the system and the associated costs when experiencing power outages.

The aim is to find a suitable load modelling approach to evaluate reliability and customer interruption costs, in an attempt to provide power system planners and power utilities with useful additional information for future decisions making on reliability improvements or future planning of their networks. Probabilistic methods provide a more useful representation of the customer load interrupted during an outage and consequently providing more dependable simulation results when evaluating the reliability or interruption costs. While uncertainty is important in load modelling, there is also a need to include time dependency of load in the model. This can be achieve through the use of a time dependent beta probability density function (PDF) load model which provides flexibility and a more useful representation of the load usage of customers for an electric utility, as most approaches used are usually based on an approximation of the load demand of customers during outages. Therefore power system planners are provided with detailed and useful information on the customer load, when interruptions occur, for the decision-making process.

The hypothesis is thus:

Time dependent probabilistic load models using a beta probability density function fitted to historical load data can be used to model customer's load demand while incorporating time and statistical variation, thus providing a better representation of the actual interrupted load.

1.5 Research Questions

So as to find the appropriate approach for the research, several research questions have to be asked so that the aim and purpose of the research can be identified. The research questions for this particular work are set as follows:

- What are the existing types of load modelling techniques currently available and which method best portray the stochastic behaviour of actual load?
- What additional or useful information can probabilistic load modelling techniques provide for power system planners and power utilities for practical purposes?
- Can the chosen load modelling approaches be implemented in a simulation program?
- Are there any evidence/results showing that the output of reliability or CIC studies are affected by the load modelling approach used? How is the impact of load models on reliability or CIC evaluations assessed?
- Does any load modelling approach help power system planners in particular to effectively make their planning decisions?

1.6 Research Objective

The objectives of this study are therefore to:

- Describe the current existing load modelling approaches available in literature.

- Distinguish the advantages of using probabilistic methods for load modelling in reliability and customer interruption costs evaluation instead of other load models found in literature.
- Identify and describe the benefits of using a beta probabilistic load model for reliability and CIC evaluation as opposed to other load modelling approaches.
- Using the information from literature and available data (NRS, 1995-2006), design a load model for a test system using the selected load modelling approach.
- Model the data to fit in the simulation program and Implement the model in simulation software.
- Compare simulation results with the results of other load modelling approaches using the same test system and software.
- Represent the results comprehensively using tables and graphs.
- Discuss the results obtained to validate whether the proposed load modelling approach provides coherent and useful information for the power system planners
- Describe, based on the results, how the load modelling approaches are beneficial to the power system planners.

1.7 Limitations

This research focuses on the load modelling aspect in reliability and customer interruption costs (CIC) evaluation in distribution networks of electrical power systems. The load research data available are based on residential customers in South Africa over several years (NRS, 1995-2006). However, the test system that is used contains a mix of commercial and residential customers. The data used to model the commercial customers have been taken from historical load data collected from shops which were also available from the NRS loads data (NRS, 1995-2006).

1.7.1 Benchmarking of Reliability Indices

Benchmarking reliability indices across utilities is problematic for a variety of reasons (Brown, 2002):

- Geography
- Data gathering practices
- Index definitions

- Major event exclusions

However, the concept of benchmarking is used in this research by applying available information onto a distribution test system. The reliability and cost information are applied on the same test system for each of the models developed and only the load modelling approach is changed. The base case, which is used as the benchmark, consists of the most basic reliability or CIC model where results are readily available for comparison. The load model used as benchmark/base case is the average load model, which is widely used in literature and is very simple to implement. The average load model is also used as a validation model in this study. The load data used for the load model is normalized to that of the test system (Roy Billinton Test System) used. The results obtained from simulations are then compared to that shown in the work by Billinton & Jonnavithula, (1996). Subsequent load models are then implemented and the results are compared to those of the base case/validation model.

1.7.2 Scope of Research

The scope of this dissertation includes power system reliability studies regarding system adequacy, and does not consider system dynamics and transient disturbances. Therefore the load modelling approaches employ static models and not dynamic models. Also, only unplanned (unscheduled) outages that are sustained for more than a few minutes are relevant in the assessments, and therefore the effects on the study of scheduled outages and power quality problems, such as voltage sags, are outside the scope of this research.

1.7.3 Modelling and Data Requirements

There are several problems that have made the modelling and analysis studies associated with reliability and CIC evaluation challenging as described below:

- ***Size***: The reliability or CIC assessment of large power systems tend to be challenging due to the huge amount of components to be considered. For instance, modelling large distribution systems, including each customer's service point, can result in a model containing an overwhelming number of objects (Pansini, 2007; Brown, 2009; Cheng, 2009). Therefore a smaller test system from the Roy Billinton Test System (RBTS) is used for the purpose of the evaluations.

- ***Data***: When modelling the load for the reliability analysis of distribution systems, a large volume of data is required for each type of customer in the system. For this dissertation, residential load data was available to be used in the load modelling approaches while load data for shops were adjusted to represent commercial customers.

- ***Load***: Electrical load can be modelled in different ways and the load data available must be shaped based on the load modelling approach to be used in the evaluation of reliability or CIC in power distribution systems.
- ***Standardization:*** The test system used in this work is provided with average load data for each load point in the system, which is very different from the load data made available by Herman and Gaunt (NRS, 1995-2006). Therefore to properly investigate the impact of stochastic load using the test system, first a validation model using the average load data of the test system needs to be reproduced. Then, once the simulation results obtained are close to those published by Billinton and Jonnavithula (1996), the NRS load research data (1995-2006), provided by Herman and Gaunt, are normalized to match the test system load data. This ensures that only the stochastic nature of the load affects the simulation results.

1.8 Outline of Dissertation

The following section explains how the dissertation has been planned:

Chapter 1 provides a background on reliability in power systems and introduces the importance of reliability and customer interruption costs evaluation in power systems. Reliability at different hierarchical levels in a power system is also discussed along with the impact of blackouts on power system networks and various sources of interruption. The reader is then introduced to the reliability and costs component such as reliability indices used in the evaluation. The fundamentals of load modelling in power systems are discussed as well as its importance in reliability and CIC studies. The hypothesis is defined and research questions are formulated. Objectives are set for the research and the limitations are specified. Finally the contributions and relevance of the research are mentioned and a list of publications provided. **Chapters 2, 3 and 4** contain the literature review on the work around reliability models, cost models and finally load models in reliability or CIC evaluations. **Chapter 5** introduces the reader to the theory and mathematical expressions developed around load modelling techniques used in this work along with an account of the usefulness of probabilistic modelling in reliability and customer interruption costs evaluation. **Chapter** 6 provides a description of the test protocol designed before proceeding with the creation of the algorithms, the programming and simulation phase. **Chapter** 7 describes the simulation methodology and algorithms used in this study as well as a description of the case studies used for simulation purposes. **Chapter** 8 shows the simulation results for each case study and a description/interpretation of the results. **Chapter 9** contains the conclusion, the answers to the research questions and the final observations followed by the list of references and **Appendices A - E**

1.9 List of Publications

Title	Reference
Load Modelling for Reliability and Customer Interruption Costs Evaluation	(Ip Cho, et al., 2010)
Impacts of using Average, Time Varying and Probabilistic Load Modelling on Customer Interruption Costs Evaluation in Power Systems	(Ip Cho & Awodele, 2011)
Impacts of Different Load Models on Reliability Evaluation in Power Systems	(Awodele & Ip Cho, 2011)
Investigating a Probabilistic Customer Interruption Costs and Energy Not Supplied Assessment for Electric Power Distribution Residential Customers	(Awodele & Ip Cho, 2011)
Comparison of Four Load Models for Reliability Evaluation Considering Reconfiguration Using Monte Carlo Simulation	(Ip Cho & Awodele, 2012)
Probabilistic Model Applied to load Modelling in Reliability and Customer Interruption Costs Evaluation	(Ip Cho, et al., 2013)

Chapter 2

2 OVERVIEW OF RELIABILITY ASSESSMENT

The following section provides a brief understanding of the work done around reliability evaluation in power systems. The components needed in reliability evaluations can be modelled using a deterministic or a stochastic approach. This section provides an understanding on how reliability assessments are carried out.

2.1 Reliability Metrics and Indices

The most basic aspect of reliability is *availability*, which is the probability of being energized. It is typically measured in per-cent or per-unit and its complement is unavailability, which is the probability of not being energized. Unavailability can be computed directly from interruption duration information. Other basic aspects of reliability include the failure rate, outage duration and frequency of failure (Brown, 2002; Billinton & Allan, 1996). Many other reliability index definitions are available and follow the IEEE trial use guide P1366. The most widely used reliability indices are averages that weight each customer equally. Customer-based indices are popular with regulating authorities since a small residential customer is as important as a large industrial customer. They have limitations, but are usually considered good aggregate measures of reliability and are very useful as reliability benchmarks and improvement targets.

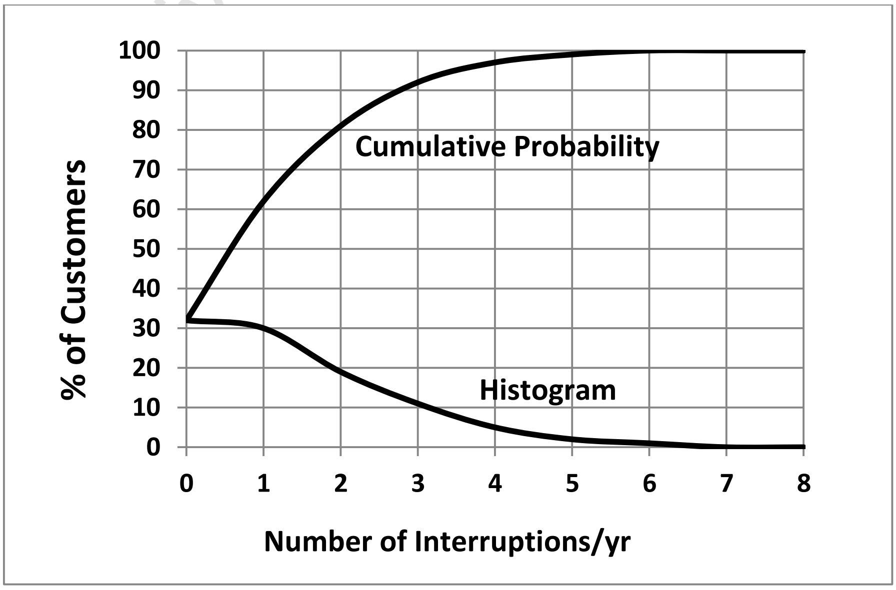


Figure 2-1: Probability distribution of interruption frequency for an area serving 27,000 customers in central Texas (Brown, 2009).

The definitions of customer-based indices are available in APPENDIX A.1 (Brown, 2009). Indices such as SAIFI and SAIDI reflect average system reliability but such measure may not have a high correlation to customer satisfaction, since few customers may actually experience average reliability. A better way to illustrate the information could be that, each reliability measure is plotted as a histogram to identify the percentage of customers receiving various levels of reliability. Figure 2-1 above shows the distribution of sustained interruptions for a 25 feeder area in central Texas. The histogram shows the percentage of customers that experience each number of sustained interruptions. The cumulative probability curve shows the percentage of customers that experience less than or equal to each number of interruptions. These types of curves are useful to examine variations in customer reliability and to identify the number of customers with relatively poor reliability. Figure 2-1 shows that 32 % of customers will not experience an interruption over the course of a year and about 99 % of customers will experience 5 interruptions or less.

The indices ($CEMI_n$ and $CEMSMI_n$) defined in APPENDIX A.2 are not widely used, but offer a useful alternative to SAIFI and MAIFI for utilities looking for more flexible measures of reliability without incurring the complexity of histograms and cumulative probabilities (Brown, 2002). Other indices used for reliability and customer interruption costs evaluation also include the energy not supplied (ENS), the average energy not supplied (AENS), the expected interruption cost (ECOST) and the interrupted energy assessment rate (IEAR) as shown in APPENDIX A.4 (Billinton & Wang, 1999).

When computing reliability indices, electric utilities often exclude interruptions caused by storms and other major events. Since the definitions of major events vary widely, comparison of reliability indices between utilities is very challenging. Some examples of major event definitions are provided in Brown, (2009). The views about when the exclusion of major events from reliability index calculation is appropriate differ from a customer's perspective to that of the utility. For the customers, it should not matter whether interruptions occur during mild or severe weather and reliability targets should be set to maximum societal welfare. On the other hand, from the utility's point, power systems such as distribution system are not designed to withstand extreme weather such as earthquakes, floods, forest fires, hurricanes, ice storms and tornadoes. Considering these events would require substantial rate increases, and therefore reliability measurements and improvement efforts should focus on non-storm performance. In addition, there tends to be more tolerance from customers during severe weather, as the cause of the interruption is apparent and utility response is highly visible (Brown, 2002; Brown, 2009).

2.2 Reliability Analysis for Three Functional Zones in Power Systems

Modern power systems are complex, highly integrated, and very large. However, even large computer installations are not powerful enough to analyse realistically and exhaustively all of a power system, as a single entity. This problem can be solved by dividing the overall power system into appropriate sub-systems which can be analysed separately. It is very unlikely as a necessity or even desirable to attempt analysing a system as a whole; as not only will excessive amount of computation be required, but the results are likely to be so vast that it will be challenging, if not impossible, to draw meaningful interpretation from them (Billinton & Allan, 1996). A convenient approach for dividing the system is to use its main functional zones as in the generation systems, the composite generation and transmission (or bulk power) systems, and the distribution systems (Billinton & Allan, 1996; Alvehag, 2008). These can then be used as the basis for dividing the materials, models, and techniques. Each of these primary zones can be subdivided in order to study a subset of the problem. Particular subzones include individual generating stations, substations, and protective systems (Billinton & Allan, 1996). The concept of hierarchical levels (HL), such as in (Billinton & Allan, 1996), was developed in order to establish a consistent means of identifying and grouping functional zones as illustrated below.

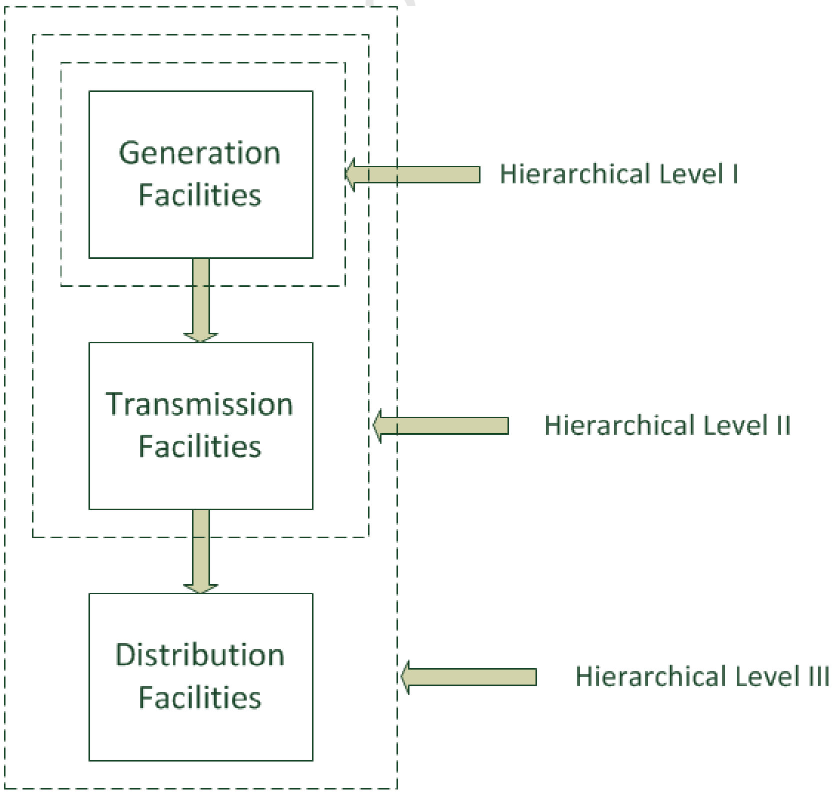


Figure 2-2: Hierarchical Levels (Billinton & Allan, 1996; Brown, 2009).

The first level (HLI) refers to generation facilities and their ability on a pooled basis to satisfy the pooled system demand, the second level (HLII) refers to the composite generation and transmission (bulk power) system and its ability to deliver energy to the bulk supply points, and the third level (HLIII) refers to the complete system including distribution and its ability to satisfy the capacity and energy demands of individual consumers (Billinton & Allan, 1996).

Although HLI and HLII studies are regularly performed, complete HLIII studies are usually impractical because of the scale of the problem. Therefore assessments are generally done for the distribution functional zone only (Billinton & Allan, 1996). Although failures in generation and transmission will affect distribution reliability, reliability assessments of distribution systems are often treated separately from the other zones (Billinton & Allan, 1993; Alvehag, 2008). One major justification of this simplification can be explained by the majority of outages seen by customers occurring in the distribution system, and reliability indices will not vary much if failures in the generation and transmission system are included in the analysis (Billinton & Allan, 1993; Alvehag, 2008). Therefore the focus of this study is on distribution systems.

2.3 Basic Data Requirements for Reliability Analysis

The reliability model describes the component failure and restoration process that follows (Alvehag, 2008). Components in a power system are prone to fail due to aging (wearing-out) or due to a technical fault. Other additional factors, such as wind, lightning, snow and temperature conditions, can increase the likelihood of a component failure (Billinton & Allan, 1996; Alvehag, 2008; Brown, 2009) Reliability models can also include the impact of severe weather, where components experience the same catastrophic environment and multiple failures are common (Alvehag, 2008). Failure rates and restoration times can be modelled using deterministic or stochastic approaches. Generally, severe weather occurs during certain times of the year, which therefore suggests that the failure rate of a component becomes time-varying (Solver, 2005; Alvehag, 2008)The restoration times will be dependent on the failure cause, for example, a repair process of overhead lines cannot start until extreme winds have calmed (Alvehag, 2008). Due to the availability of crew, which vary with time of day and day of the week, the restoration times can also be considered as time-varying as well. Therefore the main information needed to conduct a reliability analysis is the failure rates and restoration times (or outage duration). Restoration times include switching time (SwT), replacement time (RpT), repair time (RT) and reclosing time (RcT). Switching operations, for example on lines, are usually faster than repairing operations.

2.4 Failure Mode and Effect Analysis (FMEA)

Preliminary preparations for any analytical calculations or Monte Carlo simulations require a preparatory step. For any failed component leading to a failure event, the affected load points need to be identified and the nature of the outage time for each load point (e.g. reclosing time-RcT, switching time-SwT, replace time-RpT, or repair time-RT) must be determined (Billinton & Wang, 1999; Alvehag, 2008). Based on the protection system, network configuration and maintenance philosophy, some load points will be affected only by a switching time for a particular failure event while others will suffer an interruption for the whole replacement or repair time of the failed component (Alvehag, 2008). By using the failure mode and effect analysis (FMEA) method, these outage events can be identified. In the FMEA method, the different possible types of component failures are included as separate failure events (Billinton & Wang, 1999; Solver, 2005; Alvehag, 2008).For example, a transformer experiencing either a temporary or a permanent fault is seen as two separate events in the FMEA method (Alvehag, 2008). Therefore for independent failure events, it is essential that a failure event that occurred first is cleared before the second failure event can occur. It is important to note that events affecting different components may overlap (Alvehag, 2008). It is also necessary to note that mapping for an entire distribution system can be the most tedious part of a reliability analysis. APPENDIX B provides the illustrations of the FMEA method applied to a distribution system (RBTS).

2.5 Examples of Reliability Models in Power Systems

This section provides examples of different types of reliability models used in literature in the reliability evaluation of power systems. Although the focus of this research is on load modelling, it is necessary to understand how to model reliability as well as how different models affect the calculated reliability indices.

2.5.1 Deterministic Reliability Models

For simplification, power system reliability is commonly modelled using constant values of failure rates and restoration times and if a constant failure rate is used, it implies that the time to failure (TTF) is exponentially distributed (Billinton & Allan, 1996; Alvehag, 2008). The failure rates and restoration times of most components are dependent on time varying factors (Alvehag, 2008) and uncertainties which can be modelled by using probability distributions (Li, et al., 2008). Therefore, the use of deterministic reliability models provides some valuable information but does not provide an accurate representation of reliability information used in reliability evaluations. Deterministic models such as the average reliability model provide only a single customer risk dimension without the underlying probability distributions (Li, et al., 2008).

2.5.2 Time Varying Reliability Models

Alvehag, (2008), mentions that more advanced modelling attempts accounting for aging of components, maintenance actions, elevated rates during severe weather conditions and time-dependent patterns, have been made (Billinton & Acharya, 2006; Billinton & Allan, 1996; Billinton, et al., 1993; Retterath, et al., 2005; Radmer, et al., 2002) and what all these attempts have in common is the assumption that the failure rate is time-varying. Alvehag, (2011), proposed a new reliability model which considers both the failure rates and restorations time of overhead lines as direct functions of weather intensity. The reliability model used in this study is limited to the mean values of reliability indices so that only the stochastic nature of the load model is the varying factor in the evaluation.

2.5.3 Fuzzy Reliability Models

Nahman, (1997), presents a method for the evaluation of the reliability of a network and its nodes by using fuzzy logic to formulate criteria for reliability evaluation and grading on a percentage scale. Nahman, (1997), explains that the reliability of a network or a node is evaluated as high, medium and low. To obtain a more precise quantification of the reliability, a reliability scale extending from 0 to 100 % is used and membership functions (MFs) of grades *g* in the sets of high, medium and low reliability are defined in the work by Nahman, (1997).

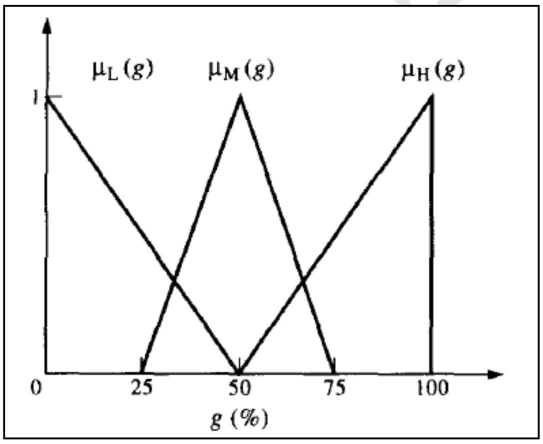


Figure 2-3. Membership Functions of Reliaiblity Grade (Nahman, 1997).

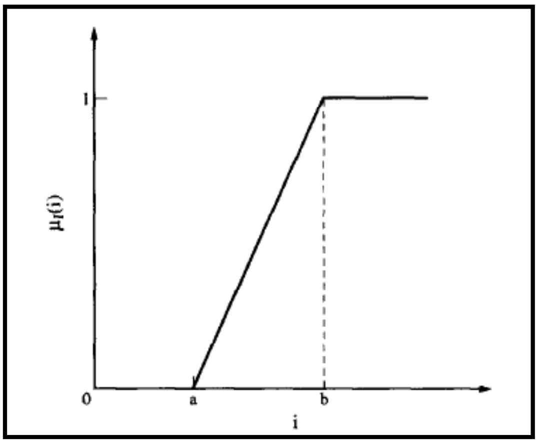


Figure 2-4. Member Function of reliability index I in the set of unacceptable values (Nahman, 1997)

The MFs overlap partially which can be explained by the nature of assessing linguistic attributes such as high, medium and low; i.e. some grades can be evaluated as being both low and medium, or being both medium and high to different degrees (Nahman, 1997). In a number of applications the principal concern involves the long term behaviour of a network and for the majority of customers the impact of service disturbance can be quantified by overall annual duration *D* and the frequency *F* of service interruptions (Nahman, 1997). The index *D* can be determined from the steady-state unavailability.

Therefore,

$$D = TU \dots\dots\dots (2.1)$$

Where *T* = a year period expressed in appropriate time units (e.g. hours).

The general shape of the *MF* of reliability index *I* in the set of unacceptable values is shown in Figure 2-4 (Nahman, 1997). Parameter *a,* determines the threshold value of index *I* up to which the index is not considered to be unacceptable to any degree and index *I* magnitude exceeding *b*, are evaluated as unacceptable to the highest degree (Nahman, 1997). Parameters *a,* and *b,* should be specified for both indices *F* and *D*, and for each node individually, depending on the type and number of the associated customers, and their specific requirements and needs (Nahman, 1997).

For commercial and, especially residential consumers the reliability of service is most appropriately evaluated by linguistic terms in such networks, reflecting the subjective response of interviewed consumers, as well as past experience of network designers and operators (Nahman, 1997). Thus, it can be concluded that the fuzzy logic is an adequate theoretical basis for network reliability assessment in most applications (Nahman, 1997). Therefore, the fuzzy reliability model offers an alternative method in modelling reliability indices in the absence of historical data, while still providing a better representation of the reliability of a power system than deterministic models.

2.5.4 Probabilistic Reliability Models

Average (mean) values for are usually used to represent the reliability information in conventional reliability evaluation methods (Wangdee & Billinton, 2005; Li, et al., 2008). Although average values are valuable information, they only provide a single customer risk dimension without the underlying probability distributions (Wangdee & Billinton, 2005). Wangdee & Billinton, (2005), and Li et al, (2008), describe the probability distributions of reliability indices as a more appropriate representation as they provide additional valuable information and a more complete understanding of the power system behaviour. However, there can be limitations in creating such probability distributions for individual components when there are inadequate statistical records (Li, et al., 2008).

The work by Wangdee & Billinton, (2005), illustrates the development of probability distributions for bulk electric systems reliability performance indices using sequential simulation. The detailed explanation to this approach is available in (Wangdee & Billinton, 2005). The results, in Table 1 in (Wangdee & Billinton, 2005) which displays simulated results for two consecutive years, show that the performance indices vary annually because of the random bulk power system behaviour.

Table 2-1. Expected values of SAIFI, SAIDI and DPUI for the original RBTS at different system peak loads **(Wangdee & Billinton, 2005)**

Peak Load Level	**179 MW**	**188 MW**	**197 MW**	**206 MW**	**215 MW**
SAIFI (occ./yr)	0.51	0.85	1.37	3.14	6.48
SAIDI (h/yr)	3.30	4.60	7.20	12.10	25.60
DPUI (system-min)	51.70	68.70	102.50	168.00	359.80

The expected values of SAIFI, SAIDI and DPUI (delivery point unavailability index) shown in Table 2-1 above, are based on five selections of system peak load levels while the probability distributions of these indices are illustrated in Figure 2-5 below. Although it can be seen that the reliability indices increases as the system peak load is increased when looking at the expected values, the reliability-index probability distribution analysis provides a pictorial representation of the annual variability of these parameters around their mean values (Wangdee & Billinton, 2005). Knowing the range of a predictive reliability index is frequently needed as well as the likelihood that a certain value will be exceeded (Wangdee & Billinton, 2005). In some cases, the system can be found to be “very” reliable”, however the probability distribution is highly skewed (Billinton & Allan, 1996; Wangdee & Billinton, 2005) and in such cases, the average value is very close to the ordinary (zero) axis (Wangdee & Billinton, 2005). It is valuable to look at the distribution tail values even though they may occur very infrequently, as these events can have serious impacts on the system (Wangdee & Billinton, 2005).

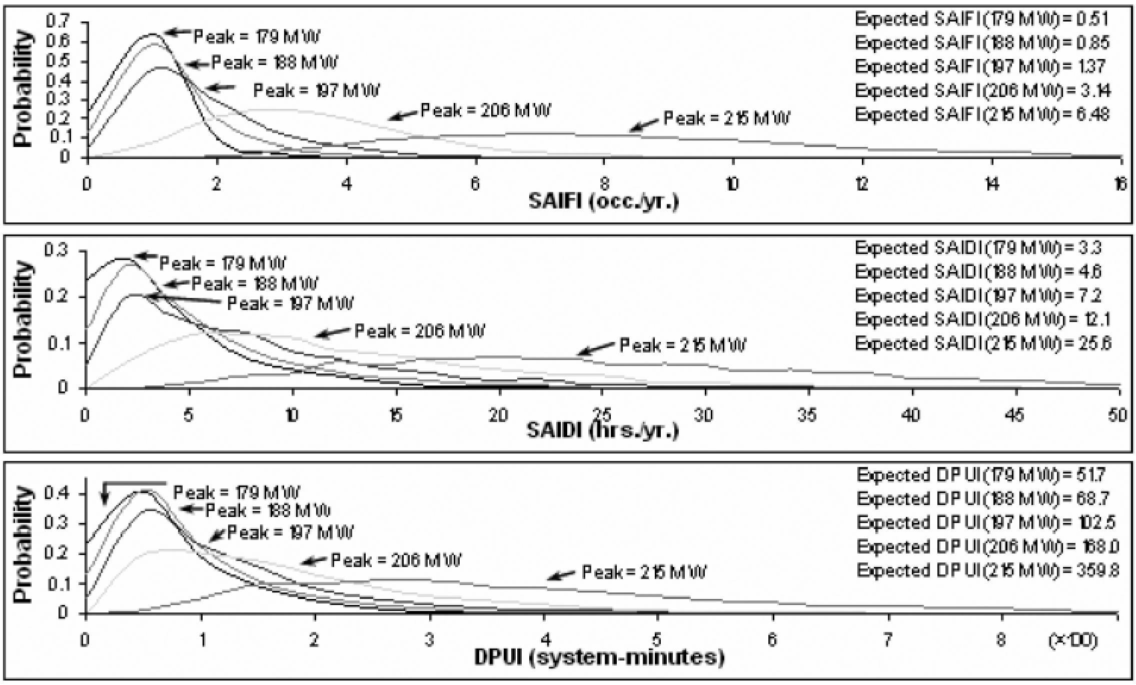


Figure 2-5. Performance-index probability distributions of the original RBTS at different system peak load **(Wangdee & Billinton, 2005)**.

Wangdee & Billinton, (2005), also analyse bulk electricity system reinforcement using the reliability-index probability distributions and the results show various degree of improvement for the different system peak load levels, and the degree of uncertainty (dispersion) is significantly decreased by reinforcing the system with the addition of a transmission line between Bus 5 and Bus 6 of the RBTS. This concept of reliability-index probability distribution analysis is a useful supplementary tool in risk management of future potential risk arising within the system (Wangdee & Billinton, 2005). The risk assessment tool developed in (Wangdee & Billinton, 2005) using probabilistic methods offers power engineers and risk managers a more deeper knowledge of their bulk electric system, and helps them identify system risk with higher confidence in their decision-making (Wangdee & Billinton, 2005). It also offers additional perception, through the resulting information, on when to conduct system improvement and reinforcements so as to reduce potential risk and uncertainty (Wangdee & Billinton, 2005).

Herman & Gaunt, (2010), propose the use of a probabilistic approach for a customer interruption cost study by accommodating the time-dependency of interruptions, which predicts the probability of such interruptions and of their cost. Herman & Gaunt, (2010), explain that interruptions are characterized by the duration and frequency of the occurrences and that these characteristics are commonly described by the reliability indices

– SAIDI and SAIFI. These indices are expressed as average values per annum; however, many interruptions have specific time dependence (Herman & Gaunt, 2010). Therefore this suggests that the description of duration and frequency should include when the interruption may occur. Also Wangdee & Billinton, (2005), recognize this phenomenon and use weighting factors for different times of the day. Herman & Gaunt, (2010), therefore explain that besides the statistical description of duration and frequency, the description should be enhanced by including time-dependent interruptions. The time-dependency incorporated in the work by Herman & Gaunt, (2010) is characterized by a 4 by 4 matrix represented in Table 2-2.

Table 2-2. Interruption intervals for duration and frequency **(Herman & Gaunt, 2010)**

S/I	**00 - 06**	**06 - 12**	**12 - 18**	**18 - 24**
Season 1	μ_{11}, σ_{11}	μ_{12}, σ_{12}	μ_{13}, σ_{13}	μ_{14}, σ_{14}
Season 2	μ_{21}, σ_{21}	μ_{22}, σ_{22}	μ_{23}, σ_{23}	μ_{24}, σ_{24}
Season 3	μ_{31}, σ_{31}	μ_{32}, σ_{32}	μ_{33}, σ_{33}	μ_{34}, σ_{34}
Season 4	μ_{41}, σ_{41}	μ_{42}, σ_{42}	μ_{43}, σ_{43}	μ_{44}, σ_{44}

Table 2-2 shows the association of both duration and frequency indices with seasonal and time-of-day intervals. Herman & Gaunt, (2010) explain that the seasons need not coincide with the natural yearly seasons, nor be of equal duration, but should instead be categorized according to their vulnerability to interruptions. Although Table 2-2 shows equal time periods during the day, they can also vary (Herman & Gaunt, 2010). The duration and frequency indices are not modelled by using the average values, but instead Herman & Gaunt, (2010), use statistical parameters to represent these values. These parameters could be the mean and variance, as shown in Table 2-2, or possibly Beta PDF parameters (Gaunt, et al., 2009; Herman & Gaunt, 2010). The overall approach results in the probabilistic financial impact assessment of interruptions, which provides an appropriate basis for decision-making (Herman & Gaunt, 2010).

Chapter 3

3 OVERVIEW OF CUSTOMER INTERRUPTION COSTS (CIC) EVALUATION

This section contains several customer interruption cost models available from literature and therefore provides an insight on what information is required to conduct such a study on power systems. Some examples of CIC evaluation of power systems are then described.

3.1 Reliability Cost-benefit (worth) Concept

As the electricity industry is moving towards deregulation and more consideration is given to customer choice; electric utilities give more importance to the reliability of electricity supply that influences customer's purchasing decision. Also modernization of societies increases the dependence on cost-effective reliable electric power supply, and unreliable supply services can be very costly to both the utility and the customers (Chowdhury & Custer, 2004). When very large number of capital and investments are required for system planning and expansion, a rational means of decision making must be provided on the requirements of changing the supply reliability levels experienced by customers. Utility costs and the costs incurred by customers associated with interruption of service must be incorporated in the system planning practices (Chowdhury & Custer, 2004).

The reliability cost assessment has become a well-established practice in some developed countries of the world and hence the data obtained is recognised and approved. In contrast assessing the reliability worth of a utility service (benefit of reliability) is still not well acknowledged, although considerable amount of work has been achieved worldwide. This is because the analysis of the worth of service reliability is more difficult and a subjective task which makes direct evaluation not feasible (Navjot Kaur, et al., 2004).

All power interruptions lead to some sort of significant economic losses for electric utility customers, which vary with customer type, seasons, time of the day, day of the week and month of the year. Hence customers who are likely to suffer significant economic losses during power outages require the highest reliability of service that the utility can supply. Thus for efficient operation, it is important for the utilities to achieve a balance between the economic investment of improving service reliability and the economic viability and benefits that these improvements bring to the customers (Navjot Kaur, et al., 2004).

Moreover, it is essential to be able to justify capital investment, operating expenditures and maintenance costs based on the benefits gained by the customer and the utility. One major problem that electric utilities face today is that as the infrastructure of the electricity grid ages, there is a rapid increase in demand whereas the infrastructure expansion is constrained by limited resources, environmental factors and other social concerns in an uncertain deregulated system. These conditions have in effect resulted in a need for more extensive validation to account for new system facilities and upgrades in production and distribution of electricity (Chowdhury, et al., 2004).

Reliability planning has the objective to balance the utility's investment cost and the interruption costs experienced by the customers (Navjot Kaur, et al., 2004). Investing in reliability helps in balancing these costs so that the overall cost of service reliability, investment cost from power utility and customer interruption, is minimised (Navjot Kaur, et al., 2004). Figure 3-1 shows the relationship between service reliability and the utility investment costs and customer interruption/damage cost (Billinton & Allan, 1993).

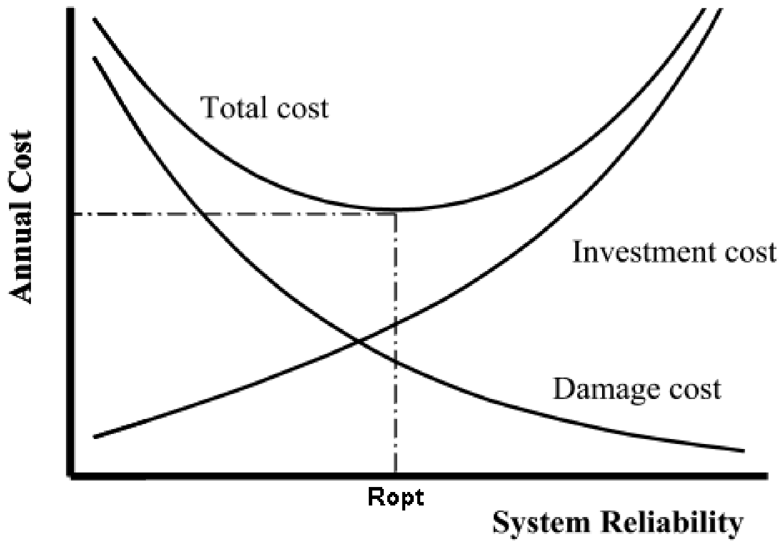


Figure 3-1: Reliability cost and reliability worth concept (Billinton & Zhang, 2001).

The total cost curve is obtained by combining the customer cost curve and the utility cost curve. On the left hand side of this line, it can be observed that while investment cost for the utility is small, the reliability is also low and hence involves greater risks of power interruptions which will lead to higher customer cost. While on the right hand side of the line, the utility cost is high which means the investment in reliability is also higher, thus the customer costs are reduced.

Therefore the total cost is the sum of the project and the customer damage costs and this total cost displays a minimum, at which an optimum or target level of reliability is achieved

(Billinton & Zhang, 2001). Therefore a dashed line is drawn downwards from the point where the total cost curve is a minimum until it intersects the customer cost curve and the utility cost curve. Note that the line does not necessarily cross the point of intersection of the customer and utility cost curves but will usually be near this point. Thus, where the line intersects the curves can be seen as the optimum point (R_{opt}) where the utility customer will receive the least cost service and the reliability cost is minimized for the utility (Chowdhury, et al., 2004; Navjot Kaur, et al., 2004).

The cost/benefit approach uses the total cost as a basis for ranking the system expansion alternatives (Billinton & Zhang, 2001).

This approach can be formulated as:

$$\text{Total Cost} = \text{Investment Costs} + \text{Customer Damage Cost}$$

Where the *investment cost* includes the capital cost and the operation/maintenance cost, and the customer damage cost reflects the importance of unsupplied energy. The investment cost is of deterministic nature and can therefore be obtained using proven methods while the customer cost concept involves the combined value the customers are willing to pay to avoid load interruptions.

The *customer damage cost* is a function of interruption frequency, load lost, duration, location, and other social factors. Customer damage cost can be tangible, with inherent monetary values in some cases while in others, the costs are intangible and subjective, depending upon the type and timing of interruptions and the consumers affected (Billinton & Zhang, 2001). Calculating the customer damage cost (CDC) is an essential and complex task in reliability cost/benefit analysis. The method to calculate the CDC and the application of the method in system studies are discussed in section 3.2 below as well as the concept of customer damage function (CDF) and the data for calculating the CDC are usually obtained from customer surveys (Billinton & Zhang, 2001).

3.2 Methods to Evaluate Interruption Impacts on Electrical Customers

Finding the worth of service reliability is a difficult and subjective task. Direct evaluation is not considered possible. Interruption costs can be generally classified into direct and indirect costs. An essential and early requirement for any interruption cost evaluation procedure is to have some understanding of the nature and variety of the interruption impacts on the customer.

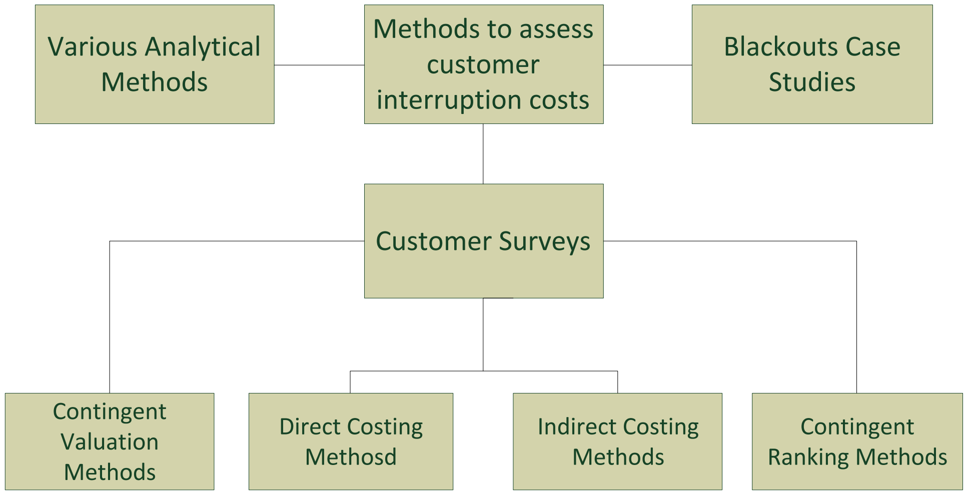


Figure 3-2: Methods to assess customer interruption costs.

Various methods, as shown in Figure 3-2 above, are available to evaluate interruption impacts on electrical customers and can be broadly classified in three categories, namely, indirect analytical evaluations, case studies of actual blackouts, and customer surveys. Although a single approach has not been universally adopted among electric utilities, variations of the customer survey method appear to be the favoured (Billinton, et al., 1993; Alvehag, 2008). Another addition to customer surveys is the contingent ranking methods which has also been used for the assessment of customer interruption costs (Carlsson & Martinsson, 2006).

3.2.1 Analytical Methods

Early approaches conventionally used for interruption costs assessment can be classified as analytical methods. Some of these techniques assume outage costs from a broad perspective and the associated global indices or variables. In simple terms, these methods analyse the interruption costs from a principally theoretical economic perspective. Although simple, its weakest part is the inability to provide assessments other than on a large geo-political scale (Billinton, et al., 1993). Residential customers proved to be the most difficult areas to quantify the interruption costs since it involves household and leisure activities. Assumptions have to be formulated so as to use one of the measurements criteria in the evaluation. Some methods use wage rates as a value basis, and others use lost leisure time or the hourly depreciation rates of all electrical appliances in the household becoming unavailable due to an outage. One of the major limitations of the analytical approaches is that the actual needs of the user are not reflected (Billinton, et al., 1993; Alvehag, 2008).

3.2.2 Case Studies of Blackouts

This method conducts after-the-fact case studies of particular outages and is limited to major, large-scale blackouts. Direct and indirect short-term costs can be assessed where direct costs generally include food spoilage, wage loss, loss of sales, loss of taxes and similar items while indirect costs include the emergency costs, losses due to civil unrest, and losses of governments and insurance companies. However many of these losses are difficult to attribute a monetary value and the indirect costs are usually much higher than the direct costs. Black-out case studies can provide valuable information but is often only relevant to the particular incident and therefore the costs cannot be generalized (Billinton, et al., 1993).

3.2.3 Customer Surveys

The purpose of the customer survey methods is to make the cost assessments more customer-specific and to attempt to understand the losses experienced by the customers due to the unavailability of the functions, products and activities that depend on electricity. Hence to fully understand this dependency, some information had to be obtained from the customers themselves (Billinton, et al., 1993). A range and combination of methodologies are generally used by researchers to improve the information available to system planners in an attempt to optimize system reliability. The customer survey category contains a range of methodologies and can be sub-divided into three divisions: contingent valuation methods, direct costing methods and indirect costing methods. Each has its advantage and disadvantages and is chosen by the surveyor depending upon the resources available and the type of customer that is to be surveyed (Billinton, et al., 1993).

3.2.3.1 Contingent Valuation Methods

These methods are essentially economic approaches that grew out of the awareness that electricity is used in a predetermined pattern by consumers. The pattern includes the time of day and season of year characteristics that the consumer has evolved to provide as great a benefit as possible. This pattern is interrupted by an outage, which eliminates, reduces or delays the activity dependent upon electricity. All consumers vaguely know how to alter their electricity consumption in response to changes in unit price. Therefore, consumers will reduce or increase consumption as the rate increases or decreases. This implies that some uses of electricity must be worth more than others and surely more than is presently paid for them. The difference between the amount paid for them and the worth to the user is called the "consumer's surplus" and it is a loss to the consumer when the supply is interrupted (Billinton, et al., 1993; Tiedemann, 2004). A measure of the interruption cost could be obtained if the value of this surplus to the consumer could be determined and therefore the contingent valuation methods are based on evaluating this surplus.

Table 3-1. Advantages and disadvantages of the contingent valuation method **(Billinton, et al., 1993)**

Advantages of Contingent Valuation Method	Disadvantages of Contingent Valuation Method
In both WTP and WTA, the customer is asked to make monetary choices related to reliability options, hence making decisions based upon his own need and conditions.	Actual customer valuations reveal that WTP values are significantly less than WTA values, resulting in the belief that electric service and its associated reliability do not perform as normal "markets".
This method provides data for reliability levels where the potential market options do not yet exist or where outage scenarios have not occurred.	Normally, consumers do not have a choice of suppliers, and therefore, their response may be governed largely by their concern for potential rate changes.
From the customer's viewpoint, it allows consideration of options without actually experiencing actual change in reliability, both improvements and reductions.	They may react to providing further money for a service they understood was already theirs, or even that electrical supply is their "social right".

The quantification can be made either through the consumer's willingness to pay (WTP) to avoid having the interruption, or the willingness to accept (WTA) compensation for having had the interruption. In theory, any increase in WTP or WTA relate directly to marginal increases in reliability. WTP and WTA amounts should be very similar for equal levels of reliability, since the only difference between them is whether the customer's initial or final state is used as the reference point (Billinton, et al., 1993; Tiedemann, 2004). Table **3-1** shows the advantages and disadvantages of the contingent valuation method. However, when the problems mentioned above are taken into account, valuations based on WTP and WTA are valuable measures and may serve as outside bounds for cost of interruption assessments (Billinton, et al., 1993).

3.2.3.2 Direct Costing Methods

Direct costing methods can be the most evident approach for determining the customer's interruption costs for a given interruption conditions. A worksheet is given to the respondent and asked to identify the impacts and evaluate the costs associated with particular interruption scenarios. The worksheet is usually well structured so as to know what should and should not be included in the cost estimate so the results are not ambiguous. Therefore this approach provides consistent results in those situations where most losses tend to be noticeable, directly identifiable and quantifiable. Thus its application is suitable for the industrial sector and for most large electrical users. It can also be effective in the commercial/retail markets but must be used carefully. Its major weakness lies in those areas where the impacts tend to be less tangible and the monetary loss is not directly identifiable, such as the residential sector (Billinton, et al., 1993; Tiedemann, 2004).

3.2.3.3 Indirect Costing Methods

Responses to indirect method questions or customer selected alternatives can also be used as a derivation to obtain an outage cost value. In this method, the evaluation of the replacement good is used as a measure of worth of the original good and is therefore based on the economic principle of substitution. This approach attempts to provide a means to reduce the problems linked with rate-related antagonism and the customer's lack of experience in rating the worth of reliability. The questions asked to the respondents are related to the context of their experience and these could include such approaches as: the cost of theoretical insurance policies to compensate for possible interruption effects, preparatory actions the respondent might take in the event of recurring interruptions or ranking a set of reliability/rate alternatives. They yield evaluations of the financial load that the customer would willingly bear to ease the effects of the interruption. The derived expenditures can be seen as the perception of the value of avoiding the interruption consequences by the respondent. Therefore, they represent an indirect estimate of their perception of the worth of reliability (Billinton, et al., 1993; Tiedemann, 2004).

Limitations in this approach is the possibility that the derived value is not an estimate of the worth and instead related to some other aspect or entity linked with the indirect approach; and there is the matter of concern of the question: how valid are the customer's perceptions? Although seemingly a sensible criticism, in fact it is not since the main reason for using customer's perception was to obtain customer's opinions and insights and therefore the customer's behaviour will be determined by his perceptions of value (Billinton, et al., 1993; Tiedemann, 2004).

3.2.3.4 Contingent Ranking Methods

In these methods, a choice experiment is performed and has mostly been used in the fields of transport, environmental and health economics and is a fairly novel approach in the field of assessing customer interruption costs due to power outages. It is usually applied in the residential sector, where households are given the choice of one out of two sets each connected to a specific cost. One of the choice sets generally consists of several different outage events which differ by duration and also by occurrence, both regarding time of day and season. The limitation in this approach is that it is not a simple task to formulate the choice sets and defining the cost attached to each choice set (Billinton, et al., 1993; Tiedemann, 2004).

It has been established that customer surveys offer the advantage that the customer is the best practical and reliable source to assess the costs associated with his condition and experience (Ali, et al., 1999) and since it is the customer who makes decisions regarding energy consumption, it ultimately becomes essential to the electric utility planners. This method can be tailored to gather particular information needed by the utility. Although this method comes with all the problems of questionnaire surveys along with the significantly higher cost and effort of conducting surveys, it is favoured by utilities for obtaining interruption cost data for planning purposes (Billinton, et al., 1993; Tiedemann, 2004).

3.2.4 Value of Lost Load (VOLL)

The VOLL is seen as the value an average consumer puts on an unsupplied energy in kWh. VOLL is considered to be the maximum cost an average customer would be willing to pay to avoid an interruption. On this basis, VOLL can be used to determine the approximate security levels for different parts of a system. VOLL can also be used for other applications such as to value the energy potentially not supplied to a transmission system. From the customer’s standpoint, their perceptions of reliability are influenced by (Kariuki & Allan, 1996),

a) The number of interruptions experienced

b) The duration of these interruptions

c) The costs incurred as a result of the interruptions

VOLL affects two scaling factors: the Capacity Payments Price Factor and the Capacity Payments Generation Price Factor. These two factors are used to scale capacity payments for demand and scheduled generation based on the level of the System Marginal Price and VOLL (Curtin & Doherty, 2007).

There is almost no market information on the value customers put on a unit of unsupplied electricity because most of them do not respond directly to real-time prices. This means that the value of reliability has to be derived by indirect methods. There are generally two methods used to derive an estimate of VOLL (Curtin & Doherty, 2007):

- ❖ By surveying customers directly on what value they would set on their electricity supply not being interrupted
- ❖ By using the pre-existing generation security standard and the fixed and variable costs of a new peaking plant to put an implicit value on lost load.

Surveys from customers directly are done to find what value they put on the reliability and continuity of their electricity supply. A few problems to be considered when using surveys to find out what consumers are willing to pay to avoid their electricity supply being interrupted are:

- ❖ Because security of supply has some ‘public good’ characteristics, consumers have an incentive to under-report true willingness to pay, hoping to ‘free-ride’ on any security improvements provided;
- ❖ Different consumers will have different levels of willingness to pay; and
- ❖ The same consumer will put a different valuation on his/her willingness to pay, depending on the timing of any interruption, its duration, the number of interruptions over a given period, whether there was any advance warning of an interruption and the weather conditions at the time of the outage.

While the VOLL is described as the value a customer is willing to pay to avoid power interruptions, the evaluation of customer interruption costs (CIC) provides a cost estimate of the unreliability of power systems. However the price that a customer is willing to pay for higher reliability is directly connected to the interruption costs created by power failures (Manikya Rao, et al., 2010).

3.2.5 Customer Damage Functions (CDF)

Data collected from questionnaires using the customer survey methodology can be analysed and compiled as a customer damage function for a particular function. The costs incurred due to supply outages can be modelled as a function of outage duration to obtain the Customer Damage Function (CDF). The latter can be determined for a group of customers within particular Standardized Industrial Classifications (SIC) and in these cases the interruption costs versus duration plots are known as Individual Customer Damage Functions (ICDF). Furthermore, the ICDFs of a given sector such as residential or commercial or industrial etc.; can be combined into a representative cost function for that sector referred to as a Sector Customer Damage Function (SCDF) (Billinton, et al., 1993; Chowdhury, et al., 2004; Navjot Kaur, et al., 2004; Chan & Milanovic, 2009). There are various ways to calculate the costs, but the most common indices are the demand normalized values calculated on an aggregated basis (Ali, et al., 1999).

Normalization is generally with respect to the customer's annual energy consumption (e.g. $/kWh) or annual peak demand (e.g. $/kW). The use of those normalized values has limitations, such as the availability of actual data for large users is better than smaller users and it is important to note that the normalized cost values in $/kW are not to be confused for the costs of energy not served. For these values to be costs of energy un-served; first, the interruption must have occurred during the peak demand and second, this peak demand must have been sustained for the whole duration of the interruption. Furthermore, deriving an estimate of the costs of un-served energy from the normalized cost values requires knowledge and application of the time-of-day load curves and frequency and duration distributions of the time of occurrence of interruptions for the service area in question (Billinton, et al., 1993; Chan & Milanovic, 2009).

Figure 3-3 below shows an example of the SCDF for residential, industrial, commercial and institutional customers as well as the composite customer damage function (CCDF).

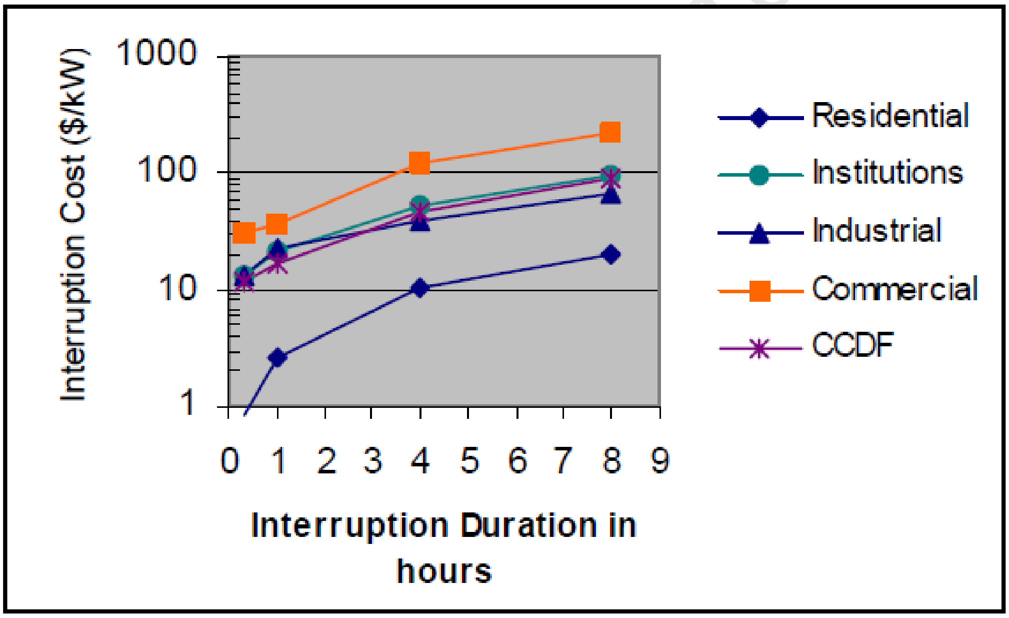


Figure 3-3: Sector Customer Damage Functions (SCDF) (Chowdhury, et al., 2004).

The sector damage function can be weighted based on the proportion of the peak load or energy utilization of the different element customer components to create a composite customer damage function (CCDF) for the service area of interest. The CCDF can then be used in system reliability cost/reliability worth assessment to determine the optimal level of reliability for the service area (Chowdhury, et al., 2004).

Several sources (Billinton, et al., 1993; Sadeka, et al., 1999; Chowdhury, et al., 2004; Navjot Kaur, et al., 2004; Chan & Milanovic, 2009; Dijerenge, 2009; Dzobo, et al., 2009) from literature offer a comprehensive insight on the importance, modelling and creation of customer damage functions. However the focus of this study is on the impact of load modelling approaches in reliability and CIC evaluation and customer damage functions for residential and commercial customers (Dzobo, et al., 2009) are used.

3.2.6 Factors Affecting Customer Interruption Costs

Customer interruption costs assessment is affected by various factors such as the stochastic nature of load usage by customer explained by the season factor and the activity factor, which have an impact on the results of the evaluation.

a. Customer Sectors

Several studies (Billinton, et al., 1993; Sadeka, et al., 1999; Chowdhury, et al., 2004; Navjot Kaur, et al., 2004; Chan & Milanovic, 2009; Dijerenge, 2009; Dzobo, et al., 2009) on reliability cost/worth in power systems have shown that the evaluation of customer interruption costs is affected differently from one customer type to another. Therefore customer sectors have an important role when modelling cost models in a customer interruption costs evaluation.

The study by Jonnavithula, (1997), provides a description of the customer characteristics of different customer sectors. Depending on the type of industry, industrial loads may have unique characteristics because of shift operations, etc. Large users and industrial customers have similar electricity use characteristics (Jonnavithula, 1997). Large industrial customers usually have a relatively large power demand remaining quite stable daily and from season to season and therefore have the most uniform demand for electrical energy (Jonnavithula, 1997). Smaller industrial customer, running only two shifts per day for example, with minimal or no weekend production, have lower demands during evenings and weekends. However, they exhibit a fairly constant demand during production hours (Jonnavithula, 1997). Jonnavithula, (1997), describes Commercial and governmental & institutional demand curves as relatively high but constant during the daylight hours of the normal business day and fall off during the night time hours. For commercial establishments, however, evening demand may fall off gradually due to the accommodation of evening shopping hours in many retail outlets and also show seasonal variations as result of space conditioning and seasonal differences in lighting, which constitute their major energy requirements (Jonnavithula, 1997).

Residential (Verzhbinsky, et al., 1984; Eto, et al., 1989) and agricultural customers show greater temporal variability in their electrical power demand than do commercial and industrial customers (Jonnavithula, 1997). For residential customers, in particular, demand is very strongly dependent upon seasonal weather variations and also exhibits very pronounced daily peak demands during the early morning and early evening, as a result of domestic uses of cooking equipment, hot water and lighting. The load profiles of the seven customer sectors discussed in the work by Jonnavithula, (1997), are also available for a typical day.

b. Activity Factor

While the customer interruption costs depend on the several factors, the time of the interruption, associated with the activities of the customers, is an important aspect to consider when carrying a CIC evaluation. The activities of the customer follow daily patterns as well as vary with the day of the week. The activity factor and seasonal factor as well as the number of customer factor and outage cost are used for a specific outage duration in the formulation of the interruption cost model (Alvehag, 2008). The activity factor can be seen as the activities that a customer performs daily that are dependent on electricity. Activity factor will vary from one customer to another, as residential, commercial, and industrial and other customer categories have different activities pattern (Alvehag, 2008; Dzobo, et al., 2009). Alvehag, (2008), describes activities pattern as a set of activities that follow a daily pattern and which also vary with the day of the week. Interrupted activities due to an interruption are inconvenient to the customers and its degree is available in surveys and is usually represented on an inconvenience scale (Alvehag, 2008).

c. Seasonal Factor

The variations of interruption costs with season are usually assumed to depend on loss of lighting and uncomfortable indoor temperature. The inconvenience due to uncomfortable indoor temperature is modelled in the work by Alvehag, (2008), to be linearly dependent on the difference between indoor and outdoor temperature. A simplification can be made such that the influence of the outdoor temperature on the season factor is modelled independent of the outage duration. However, it is arguable that customers would include this duration dependence when stating their interruption costs for a specific event for different durations in a survey. Uncomfortable indoor temperature depends on the climate and accordingly, customers can have electric heating and/or air conditioning.

3.3 Examples of Cost Models in Power Systems

This section presents some examples of available cost models found in literature. When performing a customer interruption cost evaluation, it is important to understand how different cost models can be used and how these models affect the study.

3.3.1 Deterministic Cost Models

Similar to the reliability models, cost models can also be modelled using deterministic methods. For example, the average cost model in the form of a customer damage function as shown in Figure 3-4 below, usually shows the average or aggregated interruption costs for particular interruption duration (Ghajar, et al., 1996; Midence & Vargas, 2007). These values provide a measure of the central tendency of sets of data for particular interruption duration and therefore they do not provide any additional information to the average estimate, such as the spread among the data or the shape of the distribution (Ghajar, et al., 1996). Several forms in which the aggregated or average cost model can be calculated for a particular duration include: the average cost per interruption, the aggregated consumption-normalized cost, the aggregated peak load-normalized cost, and the average peak-normalized cost (Ghajar, et al., 1996; Midence & Vargas, 2007). The basic concept of the deterministic CDF approach is to model the outage cost as a function of interruption duration. The average or aggregated outage cost for a particular duration can be calculated using equations (3.1) – (3.3) (Ghajar, et al., 1996; Midence & Vargas, 2007).

$$Average\ cost\ per\ interruption = \frac{\sum_{i=1}^{k} cost_i}{k} \quad (\$/int.) \ldots\ldots\ldots (3.1)$$

$$Aggregate\ consumption\ normalized\ cost = \frac{\sum_{i=1}^{m} cost_i}{\sum_{i=1}^{m} cons_i} \quad (\$/kWh) \ldots\ldots\ldots (3.2)$$

$$Aggregate\ peak - normalized\ cost = \frac{\sum_{i=1}^{m} cost_i}{\sum_{i=1}^{m} peak_i} \quad (\$/kW) \ldots\ldots\ldots (3.3)$$

Where,

$cost_i$ is the cost estimate in dollars,

$cons_i$ is the annual consumption in kWh,

$peak_i$ is the annual peak demand in kW,

k is the number of usable cost estimates,

m is the number of respondents for which both usable cost estimates and energy consumption values are available.

Midence & Vargas, (2007), also reach to the conclusion that the weakness in the average cost model approach is its disregard for the natural variability of the actual customer cost data. The following sections provide an insight on studies performed on reliability worth assessments using different types of cost models which incorporate time dependency and uncertainty so as to obtain a more realistic representation of the interruption costs of customers.

3.3.2 Time Varying Cost Models

A time varying cost model (TVCM) is presented in the work by Wang & Billinton, (1999), for seven customer sectors and used in an evaluation to demonstrate that different cost models result in different interruption costs which can lead to different planning and operating decisions. The time sequential simulation technique presented in the work by Wang & Billinton, (1999), is used to evaluate a distribution system and the results are compared with those from average cost model. The developed cost models (Wang & Billinton, 1999) are implemented in a computer program using time sequential technique. The effect of time varying cost models on customer interruption costs using the representative urban distribution system are illustrated in the work by Wang & Billinton, (1999). The results demonstrate that the system interruption cost can increase or decrease depending on the customer type and the shape of the cost model. The comparisons also provide distribution system planners with valuable information regarding selection of suitable cost models for optimum planning and operation decisions (Wang & Billinton, 1999).

3.3.3 Fuzzy Cost Models

In practice, uncertainty arises from the knowledge of the system performance as well as the goals of operation (Tomsovic, 2000). For example, the relative cost against reliability is not exact as the underlying models of the system also exhibit uncertainty through the approximations arising from the use of linearized models and other modelling approximations, parameter variations, costs and pricing, and so on (Tomsovic, 2000).

The study by Eua-arporn, (2005), is based on a probabilistic approach to evaluate the outage cost from the Interrupted Energy Assessment Rate IEAR) index. The conventional method to calculate IEAR is through the use of mean values, although customer damage information usually contains a fairly large deviation (Eua-arporn, 2005). To cope with the deviation of the data, Eua-arporn, (2005), applies fuzzy arithmetic to model the customer damage function which is consequently used in association with power interruption statistics to calculate what is described as a Fuzzy IEAR or FIEAR. Eua-arporn, (2005), presents the method used through the description of the basic concepts of fuzzy sets and fuzzy numbers, followed by its arithmetic and modelling of the customer damage function.

The fuzzy model, when compared with an average sector CDF, copes with large deviation of the customer damage cost perception (Eua-arporn, 2005). The fuzzy SCDF is modelled by a set of fuzzy number resulted from the fuzzy inference system (FIS), which is a process of mapping from a given input to an output using fuzzy logic (Eua-arporn, 2005). The FIS is used by Eua-arporn, (2005) to find the shape of fuzzy damage costs or possible distribution of the costs. A similar approach is used by Midence & Vargas, (2007), in their comparison of three customer outage cost models (aggregated or average, fuzzy and probabilistic cost models) which are used for the reliability worth assessment of a test system (RBTS).

The shapes of fuzzy costs are generated systematically under the designed IF-THEN rules which map a cost (input) to a membership value (output) (Eua-arporn, 2005). The generating process for the cost membership value is available in (Eua-arporn, 2005). The concept when developing the fuzzy model of SCDF is similar to the evaluation of mean SCDF, but instead the customer damage cost at specific interruption duration will be considered as fuzzy numbers. The membership value of each fuzzy number is generated by a defined set of rules (Eua-arporn, 2005). A composite CDF (CCDF) is then developed using the SCDF for the overall customers in a specific area or system (Eua-arporn, 2005).

In addition to the average CCDF, a fuzzy CCDF is developed and used to calculate the fuzzy IEAR (Eua-arporn, 2005). The IEAR is a factor that aggregates the monetary costs incurred due to electric power interruptions and is evaluated by suitably combining the CDFs with the probabilistic reliability calculation (Eua-arporn, 2005). Eua-arporn, (2005), highlights the need to acknowledge the high uncertainty in all the data concerned in reliability calculations and that using the proposed fuzzy model can provide more flexibility and perhaps better acceptance in its application especially under the present competitive environment.

3.3.4 Probabilistic Cost Models

Conventional CDFs for a given sector are easily developed and used but they do not portray the dispersed nature of the interruption cost data (Ghajar, et al., 1996). Similar to the load and reliability models, the customer cost models can also be represented probabilistically. For successful development of the probabilistic cost model or PCM, every customer response must be in one of the following forms: cost per interruption, consumption-normalized cost, or peak load-normalized cost (Ghajar, et al., 1996; Midence & Vargas, 2007). The principal idea applied to develop a PCM is to transform the whole cost data set from a surveyed specific duration into other data set, which is represented by a normal probability distribution using the normality transformation (Ghajar, et al., 1996; Billinton & Wang, 1999; Midence & Vargas, 2007). Hence, the inherent dispersion of the customer responses is handled in this way and incorporated within the customer outage cost (COC) model, and therefore the reliability worth assessment (Midence & Vargas, 2007). The normality transformation equations are (Ghajar, et al., 1996; Midence & Vargas, 2007):

$$y = \begin{cases} \dfrac{x^{\lambda} - 1}{\lambda}, & if\ \lambda \neq 0 \\ log(x), & if\ \lambda = 0 \end{cases} \quad \dots\dots\dots (3.4)$$

Where,

x = the original cost,

λ = the normality power transformation exponent,

y = the transformed cost

To convert to the corresponding actual customer cost *x,* the inverse function of the equation above is applied. The normality transformation (Ghajar, et al., 1996; Billinton & Wang, 1999) has two limitations which are (Midence & Vargas, 2007):

1) It applies only to continuous variables
2) It does not apply to zero-valued data

As mentioned by Midence & Vargas, (2007), to compensate for these constraints, zero-valued customer outage cost are extracted and treated separately. The remaining data are analysed using an iterative procedure that determines the value of λ which best transform the data set into a normal probability distribution (Midence & Vargas, 2007). The PCM for specific customer sector and outage duration is defined by four unique parameters: normality power transformation exponent, **λ**, the proportion of zero-valued data *Pz,* the characteristic parameters of the normal probability distribution; mean μ, and variance σ^2. The parameters that characterize the PCM for the industrial, residential sector are provided and described in the work by Midence & Vargas, (2007).

A similar approach is presented by Ghajar et al., (1996), to the CDF method of describing the interruption cost data, which is capable of recognizing the dispersed nature of the interruption cost data. In an investigation to test how well the aggregate or average values represent the entire survey response, interruption cost analyses conducted at the University of Saskatchewan showed that the monetary values for a given duration of interruption exhibited large variations and in some cases, the standard deviation was more than three times the mean value (Ghajar, et al., 1996). It is important to give some consideration to the variation of cost values about their means or expected values and the dispersion of the customer interruption cost data which should be implemented into the appraisal of electric service reliability worth (Ghajar, et al., 1996).

The aggregated peak-normalized costs ($/kW) used in the work by Ghajar et al., (1996) is shown in Figure 3-4 below. The outage costs represented in the first method are essentially average or aggregated values where each value provides a measure of the central tendency of a set of data for particular interruption duration (Ghajar, et al., 1996). However, these values do not provide any indication of the spread among the data (e.g. range, standard deviation) or its skewness (i.e. its deviation from a symmetrical distribution) (Ghajar, et al., 1996).

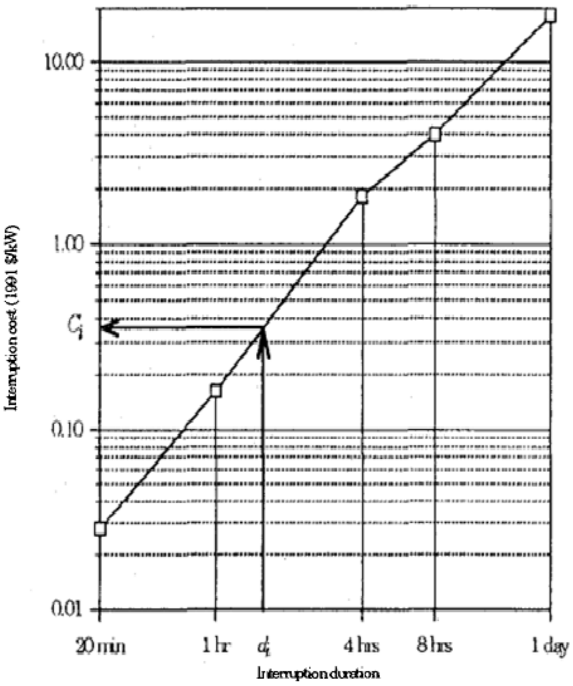


Figure 3-4. Customer damage function of the Canadian residential sector **(Ghajar, et al., 1996)**.

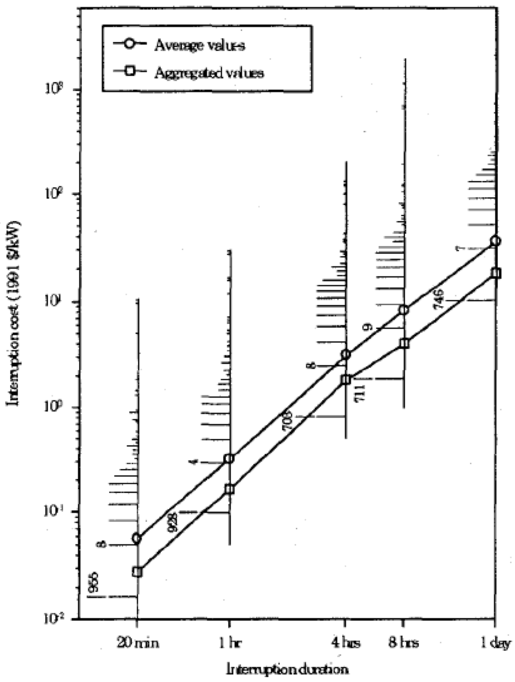


Figure 3-5. Comparison between the aggregated and mean peak-normalized cost data for the residential sector **(Ghajar, et al., 1996)**.

To illustrate the dispersion of interruption cost data for the residential sector, a number of basic statistics were derived by Ghajar et al., (1996), from the peak normalized costs and plotted in Figure 3-5 above. The clustering of bars in each histogram in this illustration is the result of using a logarithmic scale for the interruption cost axis (Ghajar, et al., 1996) and the shape of the histograms show the highly skewed nature of the outage cost estimates and the wide range of values that are possible for each interruption duration. Ghajar et al., (1996), suggest that the aggregate values represent conservative estimates of the true reliability worth for a given customer group and that it is evident that there is a need to develop an alternate approach to describing these costs.

Although easy to develop and use for the assessment of reliability worth, conventional CDF approach does not reflect the dispersed nature of interruption costs and its limitation lies in the interpretation of the entire customer outage cost data base (Ghajar, et al., 1996). Ghajar et al., (1996), and Midence & Vargas, (2007), propose similar probability distribution techniques which are capable of recognizing the dispersed nature of the interruption cost data. After the development of these distributions, an inverse transformation procedure for converting the transformed costs back to their original values is performed and can be used in a variety of reliability worth studies (Ghajar, et al., 1996; Midence & Vargas, 2007). Therefore, this technique, when used in reliability worth assessment, should provide a realistic and effective evaluation of the losses incurred by electrical users due to power failures (Ghajar, et al., 1996).

Chapter 4

4 OVERVIEW OF LOAD MODELLING APPROACHES USED IN RELIABILITY OR CIC EVALUATION

Performing a reliability evaluation requires a reliability model and a load model, while for CIC evaluation a reliability model, a load model and a cost model are required. This study involves the modelling of load using different approaches and analyses the impact of varying load modelling techniques in a reliability or CIC evaluation. This chapter provides an understanding on existing load modelling approaches, found in literature, which have been used for reliability or customer interruption costs evaluation. As discussed previously, loads can be described broadly as deterministic or stochastic approaches. Each approach can be sub-divided into various types of load modelling techniques.

4.1 Introduction to the Load Modelling in Power Systems

This section introduces the reader to the fundamentals of load modelling for power systems and provides a brief description of how loads can be perceived from a power system's point of view. The modelling of load for different hierarchical levels at low, medium and high voltages in a power system is also looked at.

4.1.1 Fundamentals of Load Modelling

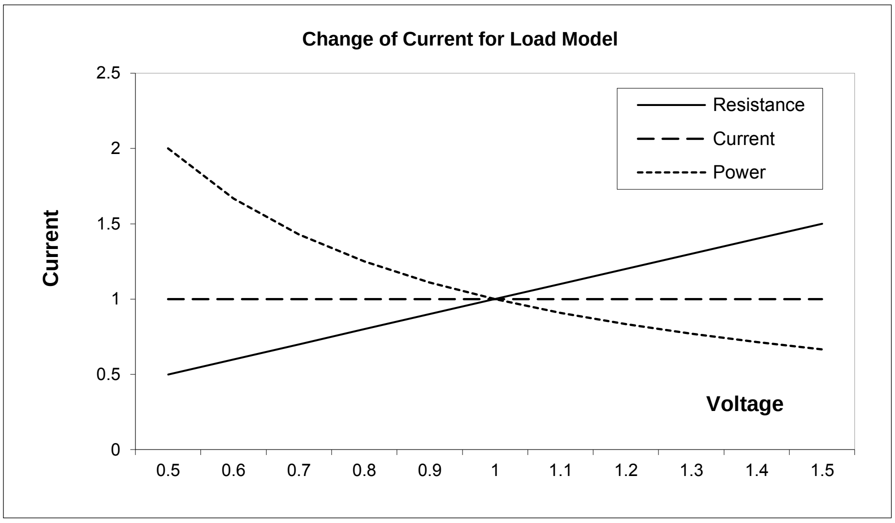
The basic understanding of load modelling is that common load models can be thought of (Kungwane, 1999):

a) A resistance connected to a network

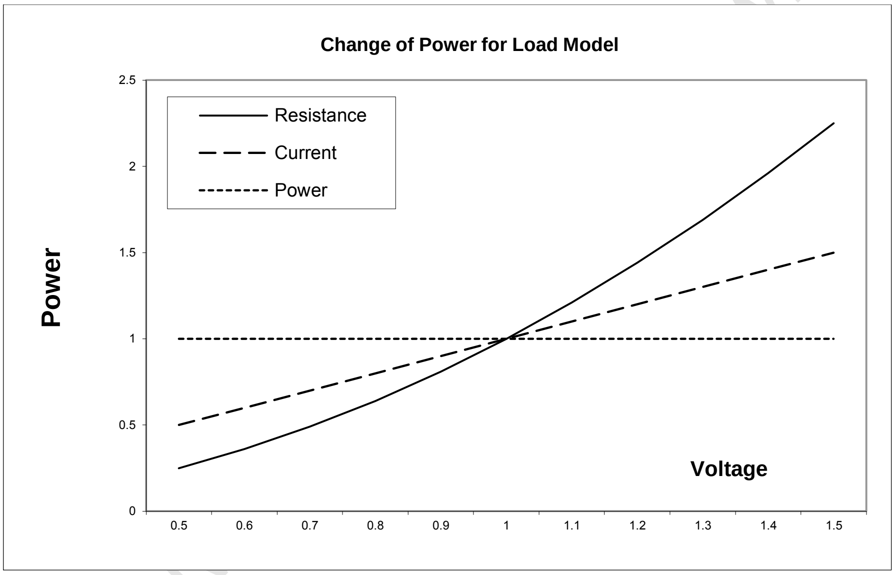
b) Current flowing from a feeder through a load

c) Power drawn from a feeder

The changes in current and power corresponding to changes in voltage are illustrated in Figure 4-1 below.



(a)



(b)

Figure 4-1: Change of load as voltage changes (Axes in p.u.) (Kungwane, 1999).

Kungwane, (1999), describes different types of practical load models, such as resistance loads, power loads, constant energy loads and constant current loads. Depending on how the load is modelled, the calculations of load parameters such as resistance, current, power, feeder resistance losses and power input to feeder differ accordingly to the load model and this affects the feeder size (Kungwane, 1999).

Kungwane, (1999), points out that load modelled as constant current to be an accurate representation of load behaviour in most practical cases and that load currents are easy to measure and the model allows simple calculations of feeder conditions. However there are few loads that have constant current characteristics but many of the most significant resistance loads are of the constant energy type (Kungwane, 1999). This research considers customer loads as load currents obtained from data collected by the NRS load research group from residential customers in South Africa and made available by Herman and Gaunt (NRS, 1995-2006).

4.1.2 Load Models for Hierarchical Levels in Power Systems: Low, Medium and High Voltage levels

Reliability planning can be dedicated to different hierarchical levels, mainly the generation level, the transmission level and finally the distribution level (Chowdhury & Custer, 2004). However, in the past the distribution level received less attention dedicated to reliability planning than generation and transmission levels because they require a vast amount of capital and potential outages in these segments could have widespread catastrophic economic impact on both utilities and customers (Chowdhury & Custer, 2004). Thus the distribution segment has become the weakest link between the source of supply and the customer point of utilization (Chowdhury & Custer, 2004).

Generation system reliability evaluation is considered to be an already developed area in power system reliability engineering in terms of both the modelling and numerical techniques (Singh & Chen, 1989). Several numerical techniques have evolved for efficient calculation of indices, such as LOLP (Loss of Load Probability), Frequency and Duration of loss of load, EENS (Expected Energy Not Supplied). Special considerations can also be incorporated in these techniques, such as scheduled maintenance, energy limitation of units, start-up failures, etc.

When load modelling is involved, the load supplied to the customers can be modelled probabilistically using a Beta probabilistic density function approach at the distribution level (Herman & Gaunt, 2008), while at the transmission level the load may be modelled stochastically using a Gaussian/Beta probability density function based on the particularity of the customer load profile (e.g. commercial) at this voltage level. This can be explained by the central limit theorem whereby, in the context of reliability, is described as a class of customers for which distributions can be approximated by the normal distribution.

As the commercial sector can be seen as many individual customers, a distribution of their load demand can be achieved. Also, commercial customers usually have constant demand curves during the daylight hours of the normal business day and fall off during the night time hours (Jonnavithula, 1997). Therefore load demand of commercial customers may be modelled using probability density functions. Finally at the transmission level, load supplied at this level could be modelled using a deterministic approach (e.g. an industrial customer uses a large amount of energy, however is seen as 1 customer).

4.2 Deterministic Methods

This section addresses different deterministic load modelling approaches used in literature. The deterministic approaches, in general, do not incorporate load variation using statistical values or methods. Wang & Billinton, (1999), describe the average load model, also known as a deterministic model (in this case the load is constant and known for an interruption event), as only an approximate representation of the actual load. A deterministic model, in mathematical term, is one in which every set of variables states is uniquely determined by parameters in the model and by sets of previous states of these variables and therefore, perform the same way for a given set of initial conditions.

Therefore, the average model is very simple to formulate and implement in simulations. For this reason, the average load model or deterministic models are often used in literature as a base case study to compare the results of other more complex and advanced modelling methods (Billinton & Jonnavithula, 1996; Wang & Billinton, 1999; Wangdee & Billinton, 2005; Eua-arporn, 2005). Other deterministic models used in studies (Veliz, et al., 2010) of power systems reliability are based on the assumption that the total load of the system remains constant in its peak value during the whole period of the analysis.

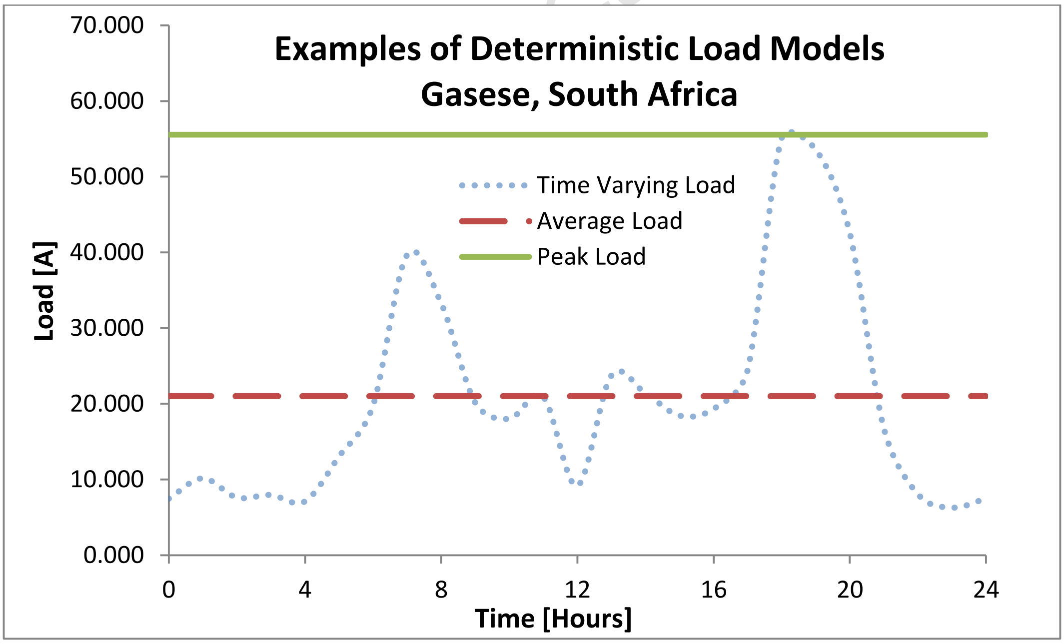


Figure 4-2: Examples of Deterministic Load Models for Gasese in South Africa data from the NRS load research group (1995-2006).

However, it is known that system load actually varies randomly and continuously in time and obtaining more realistic indices depends on a more accurate representation of the load (Veliz, et al., 2010). Figure 4-2 is generated using the NRS load research data from the

NRS Load Research Group, (1995-2006), and illustrates examples of deterministic load, modelled as average or peak load for the entire duration.

Another deterministic load model exists and uses approximate methods. In the study by Billinton & Wangdee, (2005), the *load data* consists of each customer having a unique load profile, but these data are however usually not available, as most metering is energy based. Nevertheless it is relatively easy to obtain the energy consumption and the average load for a specified time period. Billinton & Wangdee, (2005), explain that the individual customer load profiles for the feeder were not available for their study and also that generic load profiles that could be matched to the actual customers on the feeder were not available. Therefore, Billinton & Wangdee, (2005), modelled the individual customers on the feeder using representative sector load profiles such as residential, industrial, etc. The peak loads were estimated using load factors determined from the annual load profile of each sector and customer sector load profiles were therefore created for specific days in a year (8760 hours). In the studies by Wang & Billinton, (1999), and Billinton & Wangdee, (2005), the average load is used, but the studies are in essence different from each other.

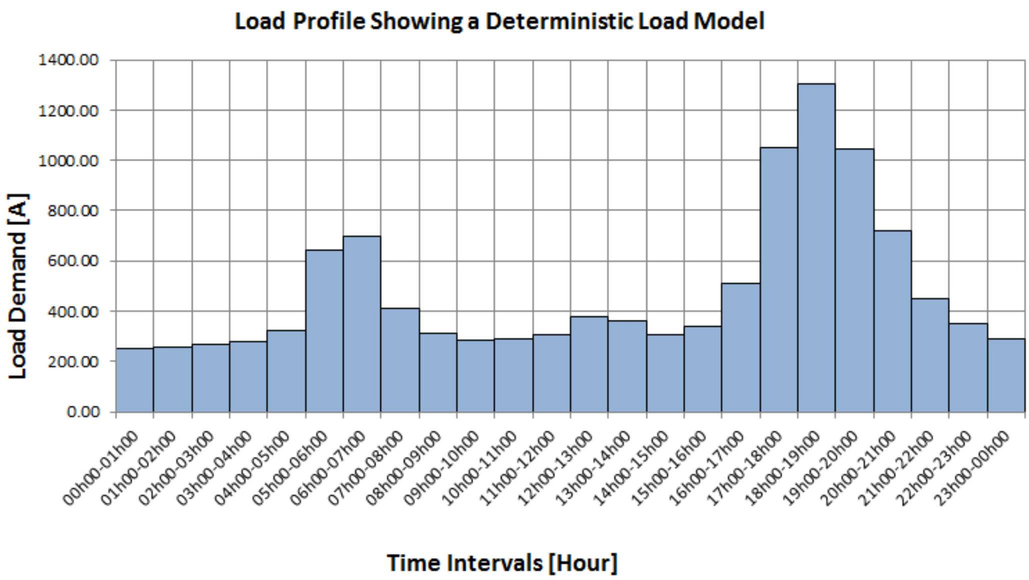


Figure 4-3: Load profile showing a deterministic time varying load model.

Another load modelling technique which can be considered deterministic is the time varying load model. If the average or the peak value is used in between intervals of time, then in essence, the model is deterministic as the same load values would be obtained for the same time interval. For example, Figure 4-3 above shows an example of a deterministic time varying load model, where the hourly load interval is the average load over the one hour interval.

However if the load at intervals of time are modelled using random load variations, then this approach can be considered stochastic. Therefore deterministic methods can be modelled in different ways in which the interrupted load is perceived (i.e. average or peak load (power), energy load, and so on).

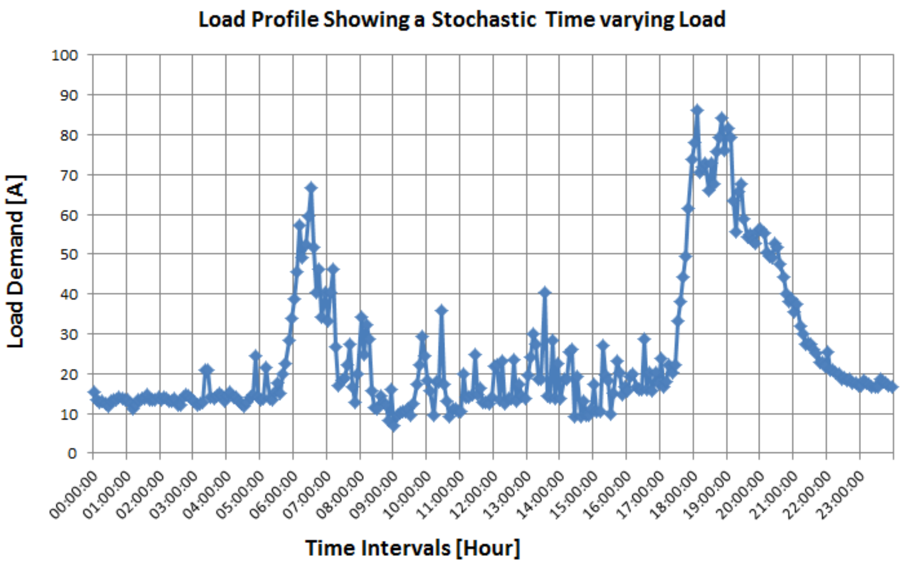


Figure 4-4: Load profile showing a stochastic time varying load model.

Figure 4-4 shows an example of load profile showing the load varying over time at hourly intervals. The hourly loads can be modelled stochastically to obtain a stochastic time varying load model. The next section provides several load modelling approaches used in reliability studies using time varying load models.

4.3 Time Varying Load Models

A time varying model is described by Wang & Billinton, (1999), as providing a more accurate representation of the actual load and can, therefore, be used in reliability or customer interruption costs evaluations to provide results which are more dependable. Wang & Billinton, (1999), use a time sequential Monte Carlo simulation technique for evaluating customer unreliability costs in distribution systems. Annual chronological load models for different individual customer sectors are developed and used for analysis. Random load fluctuations are combined with time varying load models (hence the model is stochastic) to identify the residual uncertainty associated with system load. A time varying load (TVLM) is presented in the work by Wang & Billinton, (1999), for seven customer sectors and used in an evaluation to demonstrate that different load models result in different interruption costs which can lead to different planning and operating decisions. The time sequential simulation technique, presented in the work by Wang & Billinton, (1999), is used to evaluate a distribution system and the results are compared with those from average load and cost models. A detailed customer load profile varies with customer type, location and time of the day, day of the week and week of the year. The procedure for the development of an hourly time varying load model consists of the following (Wang & Billinton, 1999):

1) develop a 24 hour daily load curve as a percentage of the daily peak load,
2) develop a 7 day weekly load curve as a percentage of the weekly load,
3) develop a 52 week yearly load curve as a percentage of the yearly peak load,
4) and finally determine the load *L(t)* for hour, *t* using the following formula:

$$L(t) = L_y \times P_w \times P_d \times P_h(t) \ldots\ldots\ldots (4.1)$$

Where,

L_y = the annual peak load,

P_w = the percentage of weekly load in terms of annual peak,

P_d = the percentage of daily load in terms of weekly peak load,

P_h = the percentage of hourly load in terms of daily peak.

The yearly seasonal representation in the load model used by Wang & Billinton, (1999), has been set as three categories: winter, spring/fall, and summer. The load profiles for 24 hours for three seasons are illustrated in the work by Wang & Billinton, (1999). The annual hourly load curve can be developed using the equation for *L(t)* above, after the annual peak load, weekly percentage, daily percentage and 24 hour load profile are determined. The developed load models (Wang & Billinton, 1999) are implemented in a computer program using time sequential technique. The effect of time varying load models on customer interruption costs using the representative urban distribution system are illustrated in the work by Wang & Billinton, (1999). Their results are thoroughly explained using graphical representations of the reliability indices such as ECOST and EENS at individual load points for both the average load and the time varying load models. Wang & Billinton, (2005), concluded that the use of average load provides a slightly inflated estimate of the system unreliability and a time varying load model provides a more accurate estimate. The comparisons also provide distribution system planners with valuable information regarding selection of suitable load models for optimum planning and operation decisions (Wang & Billinton, 1999).

A similar study by Zhu, (2007), describes the load demands in distribution systems as varying from time to time, and each class of customers follows a different load pattern.

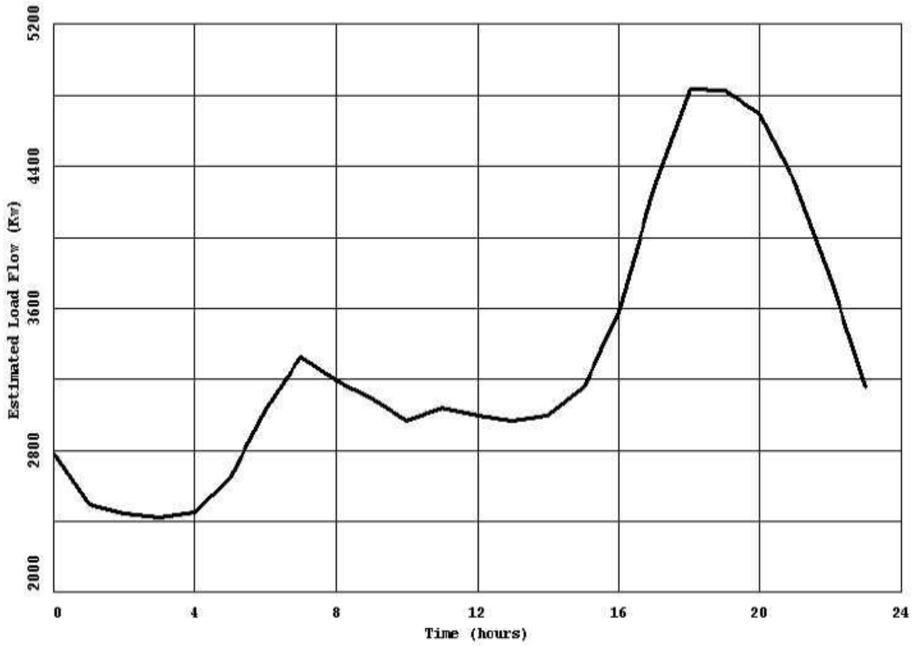


Figure 4-5. Daily Load Pattern of a Residential Load in a Weekday of January **(Zhu, 2007)**.

Figure 4-5 in the work by Zhu, (2007), shows the daily load change for a residential building in a weekday in January and the difference between the maximum load point and the minimum load point is significant, about 50 % of the peak load. Zhu, (2007), points out the applicability of a reliability analysis algorithm to a practical system is limited if only a constant load model is used.

Another study by Alvehag, (2008), describes load demand in distribution systems as varying with time and customer sectors due to their different load patterns. Alvehag, (2008), also describes he applicability of a risk assessment as limited if only a constant load is considered and therefore a load model which accounts for both daily and seasonal variations in load demand is considered in her work. The model proposed by Alvehag, (2008), also considers the different load patterns between weekdays and weekends and these variations in load are captured through load curves that depend on time of day, day of week, and outdoor temperature.

In the cost-benefit analysis of power distribution system by Wang & Billinton, (1999), the chronological variations in load are modelled to be deterministic. Alvehag, (2008), models the outdoor temperature to be stochastic, which means that extreme temperature conditions can be captured. Alvehag, (2008), states that the reported load curves are often valid in a certain temperature intervals and it is possible that the modelled outdoor temperature is below the lowest temperature interval or above the highest. It was established by Alvehag, (2008), that there is a linear relationship between energy consumption and outdoor temperature in Sweden where the study was conducted. Alvehag, (2008), also suggests that it is possible that a similar dependency is possible in case of high temperature in warm countries where air conditioning is prevalent.

Therefore Alvehag, (2008), suggests that the temperature dependency in case of very high or low temperatures can be implemented through a coefficient that moves the load curve vertically. Alvehag, (2008), considers only the case of low temperature due to the work being applied to the Swedish climate. The load model proposed by Alvehag, (2008), incorporates the linear relationship between load and temperature during very low temperature conditions, and thereby captures the loss of load and energy not supplied due to outages occurring on an extremely cold winter day.

Both studies by Wang & Billinton, (1999), and Alvehag, (2008), make use of a time varying load model whereby in the work by Alvehag, (2008), the study is focused on the impact of dependencies in risk assessment such as extreme temperatures, while in the study by Wang & Billinton, (1999), the time varying load model is used in a reliability worth analysis where the load model varies with time. However, both studies show that there is an impact on the results when a time varying load model is introduced as compared to a deterministic model.

4.4 Fuzzy Load Models

Several fuzzy models are used in literature and their applications in reliability studies are presented in this section. The principles of fuzzy set theory and the applications of fuzzy in power systems are provided by Song, (1997), and Tomsovic & Chow, (2000). An overview of the relevance of fuzzy techniques to power system problems is provided in the work by Tomsovic, (2000), and Baloyi, (2008). Some of the most useful capabilities and features provided by modelling in fuzzy set theory are as follows (Tomsovic, 2000):

- Representation methods for natural language statements,
- Models of uncertainty where statistics are unavailable or imprecise (i.e. intervals of probability),
- Information models of subjective statements (e.g. the fuzzy information measures of vagueness and confusion),

- Integration between logical and numerical methods,
- Models for soft constraints,
- Models for resolving multiple conflicting objectives,
- Strong mathematical foundation for manipulation of the above representations.

Uncertainties are present in the reliability evaluation of power systems. Uncertainty can be modelled based on randomness, as in, stochastic models for random load variations (Tomsovic, 2000). The fundamentals of fuzzy mathematic are described in the work by Tomsovic, (2000). Fuzzy logic implements experience and preferences through membership functions (MF). The MFs have different shapes based on the designer's preference and experience (Tomsovic, 2000). Fuzzy rules may be formed that describe relationships linguistically using IF-THEN statements. There are, in general, four approaches to the derivation of fuzzy rules:

- from expert experience and knowledge,
- from the behaviour of human operators,
- from the fuzzy model of a process, and
- from learning

Linguistic variables allow a system to be more comprehensive to non-expert operators (Tomsovic, 2000). Fuzzy set theory has been used in reliability evaluation in a number of ways. For example, the modelling of peak load forecasting is possible by incorporating fuzzy load modelling in power system reliability assessment by using a fuzzy membership function, MF, described by Li et al., (2007).

Another method of fuzzy set theory is used in the work by Verma & Kumar, (2000), for the reliability assessment of bulk power systems. Uncertainties in load and generations are modelled as fuzzy numbers from fuzzy set and are presented by Verma & Kumar, (2000). The basic concepts of fuzzy set theory are described by Verma & Kumar, (2000), as well as the fuzzy approach to optimization. Verma & Kumar, (2000), use a fuzzy model for the load representation. Linguistic declarations of variables are translated into possibility distributions by assigning a degree of membership to each possible value of the variable (Verma & Kumar, 2000).

Possibility distribution refers to the mapping of a fuzzy variable on the [0, 1] interval and in power analysis, some loads and generations are found precisely and others are described in terms of "more or less" expressions (Verma & Kumar, 2000). To model such quantities, a trapezoidal possibility distribution is used and the fuzzy load at a certain bus that would exceed L^4, is always higher than L^1, and typically falls between L^2 and L^3. This model is illustrated in Figure 4-6, where the possibility distribution will have a value of 1 for the load values that are highly possible, and will drop as the possibility decreases (Saraiva, et al., 1996; Verma & Kumar, 2000). A zero possibility is assigned to the values that are rather impossible to occur, which are located beyond the two extremes (Saraiva, et al., 1996; Verma & Kumar, 2000).

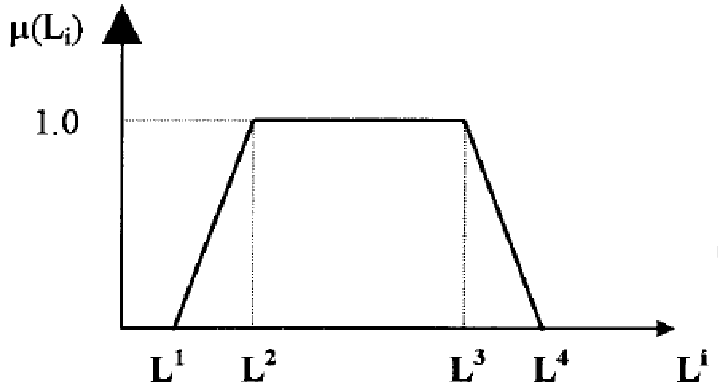


Figure 4-6. Load possibility distribution (Verma & Kumar, 2000).

In a planning process, load forecasting is very complex to deal with, and there has always been a need for tools that can be used in case of uncertainties such as the fuzzy set theory which provides an edge in modelling the systems having qualitative nature (Verma & Kumar, 2000).

The studies described by Li et al., (2007), Nahman, (1997), Eua-arporn, (2005), and Verman & Kumar, (2000), use the principles of fuzzy set theory and membership functions are generated by defined set of If-then rules. Although these studies present different ways of applying the fuzzy model in reliability or customer interruption costs evaluations, the techniques of fuzzy set theory are fundamentally the same.

However, the fuzzy load model (Verma & Kumar, 2000) only provides a load possibility distribution and is adequate when statistical data are unavailable. Also, in the work by Eua-arporn, (2005), the membership function is generated for the customer damage cost after using the customer's peak load in the calculation, while in the study by Verma & Kumar, (2000), the membership function is provided as a load possibility distribution. In studies where qualitative descriptions are important, fuzzy load modelling techniques can be very useful, but for quantitative studies where statistical or historical load data are available, a probabilistic study is more likely to be useful.

4.5 Hybrid Fuzzy and Probabilistic Load Models

This section introduces studies on combined (hybrid) fuzzy and probabilistic methods for power system reliability evaluation. The possibilistic and probabilistic uncertainties that are related in the method in which reliability evaluation are carried out considering a hybrid fuzzy and probabilistic model. A conceptual possibility approach using fuzzy set theory to manage the uncertainties in reliability input data of real power systems is presented by Kim & Singh, (2002). Kim & Singh, (2002), provide an algorithm to calculate the possibilistic reliability indices according to the degree of uncertainty in a given data set. A probability distribution function is transformed into an appropriate possibilistic representation using a probability-possibility consistency principle (PPCP) algorithm (Kim & Singh, 2002). The algorithm uses fuzzy classification theory to reduce the number of load data points by defining their closeness and assigning them to various clusters and then finding the distance between the clusters (Kim & Singh, 2002).

To demonstrate the capability of the algorithm proposed in the work by Kim & Singh, (2002), the IEEE-RTS with 32-generating units is used in a reliability study using the loss-of-load expectation (LOLE) index. The index of LOLE is typically used in planning decisions relating to additions of more installed generation (Kim & Singh, 2002). However, the authors describe that the approach is also suitable for risk calculations of operation and maintenance related decisions (Kim & Singh, 2002).

Using fuzzy clustering is described as enabling infinite number of membership values 0 and 1 to be assigned. This means that a single point load data can have partial membership in more than one class (Kim & Singh, 2002). The steps for iterative optimization algorithm for fuzzy clustering are described by Kim & Singh, (2002), and their case studies are presented as follows:

1) The single maximum load of 2850 [MW]
2) Load data for one week (given as 2650.0, 2850.0, 2793.0, 2739.0, 2679.0, 2194.5, 2137.5 [MW])
3) 8760 load data from IEEE-RTS

Three confidence levels, corresponding to different degrees of confidence, are used to transform possibility distribution of generating unit data using fuzzy theory. For each of these confidence degrees, the cumulative probability table of generating unit can be computed and the combination with load data allows the final possibilistic distributions on LOLE to be derived (Kim & Singh, 2002). A fuzzy classification theory is used to cluster large number of load data such as 8760. An example of LOLE distribution curves is illustrated by probabilistic and possibilistic function in Figure 4-7.

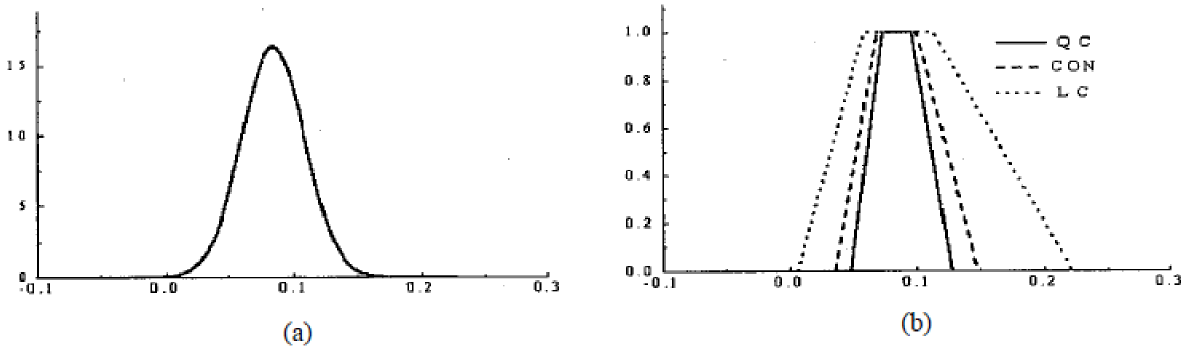


Figure 4-7. LOLE distribution curves depicted by (a) probabilistic and (b) possibilistic function (case of single maximum load) (Kim & Singh, 2002).

Kim & Singh, (2002), describe that in conventional probabilistic approach, the covariance matrix calculation is used to manage uncertainties in the evaluation of LOLE. However in their work by Kim & Singh, (2002), fuzzy set theory using Max-Min operation of fuzzy numbers has been introduced to manage the uncertainty, and fuzzy classification theory is also applied to reduce the number of load data and computation time. Large numbers of load data are used in the work by Kim & Singh, (2002), which are clustered into small number of classes using fuzzy partition matrix and the cluster centres representing each class along with their membership are used in a fuzzy calculation for the LOLE evaluation.

The results obtained by Kim & Singh, (2002), show that the computation time has been significantly improved through efficient fuzzy arithmetic operation, and the economic usage of the computer storage area also shows the feasibility of the algorithm used. Kim & Singh, (2002), mention that the algorithms have shown to be promising in the applications that have probability density functions, then either the probabilistic approach may be applied, or the data may be changed into possibilistic representation, and the fuzzy set approach may be used. However when large amount of data is not available, the construction of a possibilistic representation for including uncertainty may be easier and more desirable (Kim & Singh, 2002).

The work by Li et al., (2007), and Li et al., (2008), considers two types of uncertainties in load forecasting: the one that can be characterized by a probabilistic distribution model; and the other one that cannot be characterized by a probabilistic distribution model. In the case of the latter, the use of Fuzzy model is usually used to represent the uncertainty in peak load forecast and can be applied in generation reliability assessment. In practice, many utilities forecast the most probable peak load with its high and low bounds. This is closely similar to the fuzzy concept since a standard triangle membership function for the peak load can be built with this information. Figure 4-8 shows an example of the fuzzy load model, in which the most probable peak is 2000MW with the confidence grade of 1.0, while the high and low bounds are 1800 MW and 2400 MW respectively, with the confidence grade of zero (Li, et al., 2007).

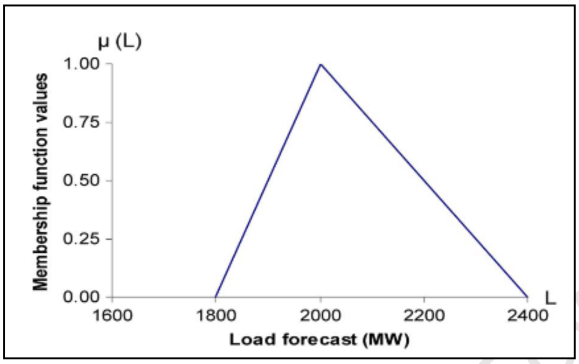


Figure 4-8: Membership Function of Peak Load Forecast (Li, et al., 2007).

In general, the high and low bounds are not in the same distance from the most probable peak, and therefore, the triangle membership function is not a symmetrical one (Li, et al., 2007). A load curve has to be considered in reliability evaluation and the annual load curve reflects the load levels at different time points during one year (Li, et al., 2007).

The annual load duration curve can be created using historical hourly load records, and then, a discrete probability distribution can be obtained to represent the load duration curve (Li, et al., 2007). In this model, each load level is a percentage with respect to the peak with a probability and is mathematically expressed as (Li, et al., 2007):

$$p(Load = L_i) = p_i(i = 1, \dots, n) \dots \dots \dots (4.2)$$

where,

L_i = the load level (% of the peak)

p_i = the probability of L_i

n = the number of load levels in the annual load duration

A discrete probability distribution model for the load curve was created using historical data and is given in Table 4-1 (Li, et al., 2007).

Table 4-1. Load Duration Curve Model (Li, et al., 2007).

% of Peak	Probability
100	0.00377
95	0.02260
90	0.05742
85	0.08664
80	0.08984
75	0.18368
70	0.16587
65	0.15126
60	0.09395
55	0.10240
50	0.03858
45	0.00400

The reliability assessment method (Li, et al., 2007) is based on a regional system in Canada which has 104 buses and 167 branches with the total generation capacity of 4580 MW. According to the load forecast, the most probable peak load is 3588 MW with the high and low bounds of 4100 MW and 3200 MW respectively (Li, et al., 2007). With this information, the membership function of the peak load was built and is shown in Figure 4-9 (Li, et al., 2007).

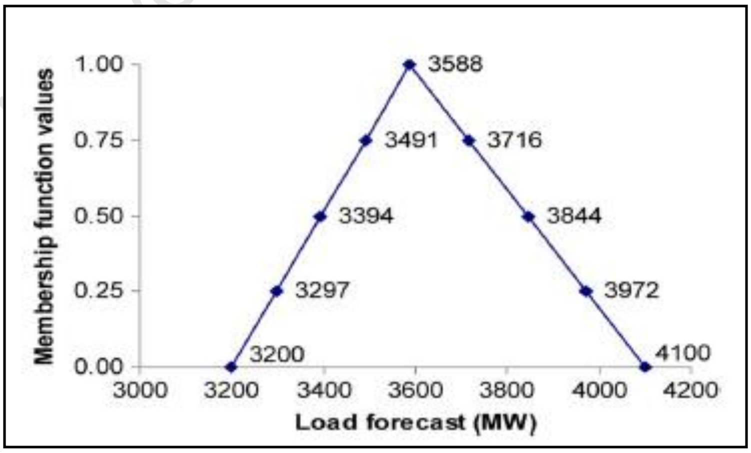


Figure 4-9: Membership Function of the Peak Load (Li, et al., 2007).

The membership functions of three reliability indices are obtained in (Li, et al., 2007) using the presented method and are shown in Figure 4-10 to Figure 4-12.

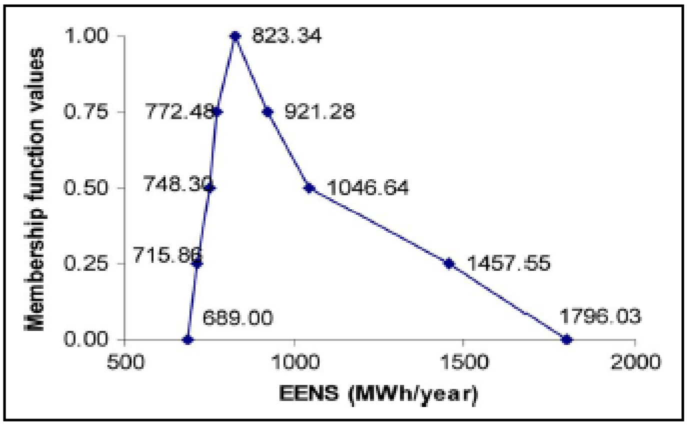


Figure 4-10: Membership Function of the EENS Index (Li, et al., 2007).

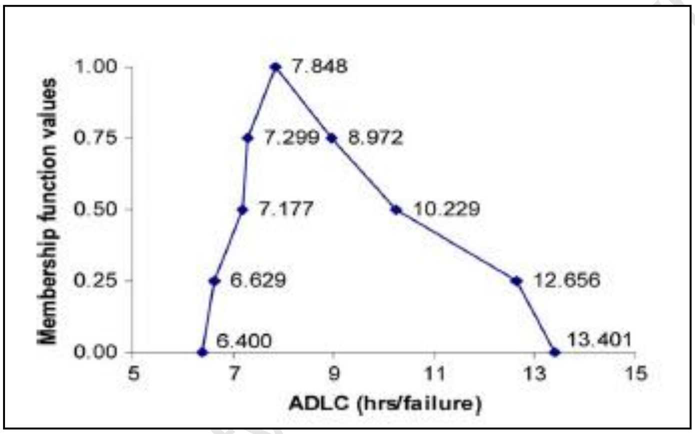


Figure 4-11: Membership Function of the ADLC Index (Li, et al., 2007).

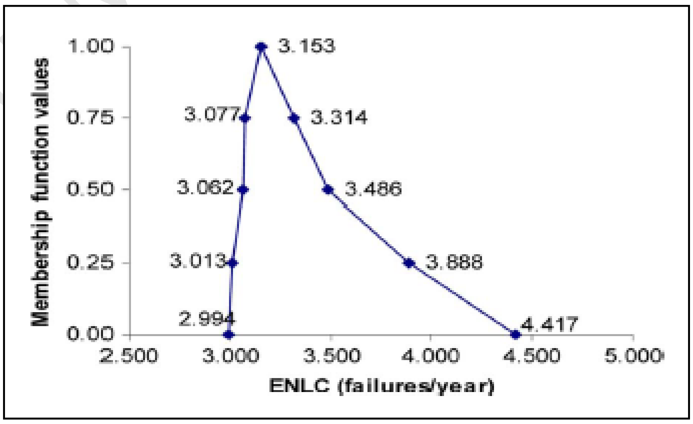


Figure 4-12: Membership Function of the ENLC Index (Li, et al., 2007).

The peak loads and reliability indices corresponding to five confidence grades ranging from 0 to 1 at 0.25 unit intervals are marked in the Figure 4-10 to Figure 4-12.These three indices are (Li, et al., 2007):

- The expected energy not supplied (EENS, MWh/year)
- The expected number of load curtailment (ENLC, failures/year)
- The average duration of load curtailment (ADLC, hours/failure)

The following observations are made in (Li, et al., 2007):

a) All the indices have a larger uncertainty range than the peak load.

b) The uncertainty ranges for the three indices are different. The EENS has the largest uncertainty, while the ENLC has the smallest uncertainty.

c) The uncertainty of the reliability indices is much more sensitive to the high side of the peak load uncertainty compared to the low side.

It can be concluded that the method using combined fuzzy and probabilistic load model in power system reliability assessment provides results that show a wider insight into impacts of load uncertainty on uncertainties of reliability indices in such evaluations (Li, et al., 2007; Li, et al., 2008). It can also be noted that the forecasted peak load is modelled using a fuzzy membership function and the load curve is modelled using discrete probability distribution, whereas component outages can still be simulated with a traditional Monte Carlo or numeration technique (Li, et al., 2007).

The work by Kim & Singh, (2002), and Li et al., (2007), explained in this section make use of hybrid fuzzy and probabilistic models which are different conceptually, but use similar fundamental fuzzy logic and theory of uncertainties. Although probabilistic methods are used by Kim & Singh, (2002), and Li et al., (2007), a discrete probabilistic distribution is used by Kim & Singh, (2007), which does not necessarily best represent the actual load of the customer. Also a load duration curve is used where the time at which an interruption occurs is not known and instead the load is represented as a percentage of the peak load for an amount of time (duration). Therefore, in a probabilistic model, where historical data is available, the use of probability distribution functions to model customer loads, which are dependent on the time at which an interruption occurs, is more likely to provide a better representation of the interrupted load.

4.6 Probabilistic Load Models

The following sections describe models that incorporate probabilistic load modelling techniques applied to reliability or customer interruption cost assessment. Probabilistic models are stochastic in nature and provide a measure of the likelihood of an event to occur. The presence of uncertainty has always been acknowledged by engineers in the study of engineering systems (Haldar & Mahadevan, 2000). In the past, conventional approaches were used to simplify the problem by considering the uncertain parameters to be deterministic and accounting for the uncertainties through the use of empirical safety/reliability factors (Haldar & Mahadevan, 2000). Deterministic methods do not provide sufficient information to achieve optimal use of available resources to maximize reliability in power systems while probabilistic analysis does provide this information for optimum design (Haldar & Mahadevan, 2000). Stochastic methods are described mathematically as one in which randomness is present, and variable states are not described by unique values, but instead by probability distributions. The use of probabilistic analysis is expected to provide additional information about how the system behaves, the influence of different uncertain variables on system performance, and the interaction between different system components (Haldar & Mahadevan, 2000). *Probability of failure* is usually used to describe the reliability of a power system and is linked with a particular performance criterion (Haldar & Mahadevan, 2000). An engineering system will usually contain a number of performance criteria, and a probability of failure is associated with each criterion (Haldar & Mahadevan, 2000). Load is an uncertain quantity, with a mean, standard deviation and so forth (Haldar & Mahadevan, 2000). The probabilistic model can be applied to load, cost or reliability models, and therefore several studies are available from literature.

4.6.1 Probabilistic Methods Using a Load Clustering Concept

Singh & Chen, (1989), present a load model based on a clustering concept which groups hourly loads based on their proximity resulting in nonequispaced load levels. The load model proposed by Singh & Chen, (1989), uses much fewer states as compared with conventional load models developed in equispaced discrete steps to obtain equivalent accuracy. The decrease in load states leads to more efficient calculations and a reduction in computation time (Singh & Chen, 1989). The study by Singh & Chen, (1989), is performed in generating system reliability evaluation which is a well-developed area in power system reliability engineering, both in modelling and numerical techniques. Singh & Chen, (1989), explain that conventional methods discretize the load model in equal steps and do not have the advantage of the load point clusters, which exploits the proximity of load point to group the hourly loads into suitable clusters.

The authors in (Singh & Chen, 1989) present an *equivalent load method* which attempts to avoid the convolution of two large models and for the computation of all the indices of interest, this method is described as more efficient than the conventional method. The drawback of this method is that it is only suitable for certain applications. For instance, the components of frequency of loss of load due to generation and load variations cannot be calculated separately using the equivalent load method, which are considered as vital information for more detailed models. The method presented by Singh & Chen, (1989), takes advantage of the proximity of load points to group the hourly loads into appropriate clusters, which leads to nonequispaced but fewer numbers of steps in the discrete state load model, and hence results in faster computations.

The general convolution procedure described by Singh & Chen, (1989), can be applied in a unit addition algorithm, an equivalent load method and in a cluster based load method, which are also thoroughly explained in their work. The concept of clustering proposed by Singh & Chen, (1989), utilizes the natural clustering of hourly loads and in their approach, the nonequispaced load levels coincide with the probability of actual loads, and therefore, the number of states in the load model can be reduced significantly without sacrificing accuracy. Singh & Chen, (1989), comment that clustering is performed based on similarities or distance. Singh & Chen, (1989), provide an example of the cluster model which was computed for the first week hourly load of the IEEE-RTS in Table 4-2 below.

Table 4-2: Cluster of hourly loads (5 clusters) (Singh & Chen, 1989).

Cluster	Initial Seed	Cluster mean	Frequency	Standard Deviation
1	2216	2135.83	32	79.2117
2	2456	2314.46	41	59.3734
3	1957	1728.51	39	83.8593
4	1179	1303.93	24	71.7628
5	1602	1489.78	32	57.0886

From the results obtained by Singh & Chen, (1989) in Table 4-2 above, column 4 lists the observed frequency of load in each cluster and the probability of each cluster load is calculated by dividing these numbers by the total number of observations (168). The fifth column provides the root mean square standard deviation and Table 4-3 below shows the probabilities associated with each cluster obtained by Singh & Chen, (1989).

Table 4-3: Probabilities of 5 clusters (Singh & Chen, 1989).

Cluster	Cluster mean	Probability
1	1303.93	0.143
2	1489.78	0.190
3	1728.51	0.232
4	2135.83	0.190
5	2314.46	0.244

After obtaining the capacity probability and frequency values of each state or cluster, Singh & Chen, (1989), then obtain the reliability by the convolution of generation system model and cluster load model. The convolution algorithms and equations are explained, and the state space diagram for the cluster load method is illustrated in the work by Singh & Chen, (1989).

Therefore the work presented by Singh & Chen, (1989), provides an efficient alternative method, known as cluster based model, for generating reliability evaluation. These nonequispaced load levels in their new model coincide with the high probability of actual loads, so the number of states in the load model can be decreased significantly without sacrificing accuracy. The decrease in the number of load states leads to higher efficiency in the computation time (Singh & Chen, 1989).

4.6.2 Probabilistic Methods Using Step Load Models

Jonnavithula, (1997), describes annual indices as more representative of the actual load model and they can be obtained by dividing the load duration curve into a finite number of steps. The annualized indices are usually calculated at the peak load level and are estimated by weighting the index obtained at each load level with the probability of being in that load level (Sankarakrishnan (Jonnavithula) & Billinton, 1995; Sankarakrishnan (Jonnavithula) & Billinton, 95 SM 512-4 PWRS; Jonnavithula, 1997). A chronological load model with 8736 points has been translated into the load duration curve by Jonnavithula, (1997), as shown in Figure 4-13.

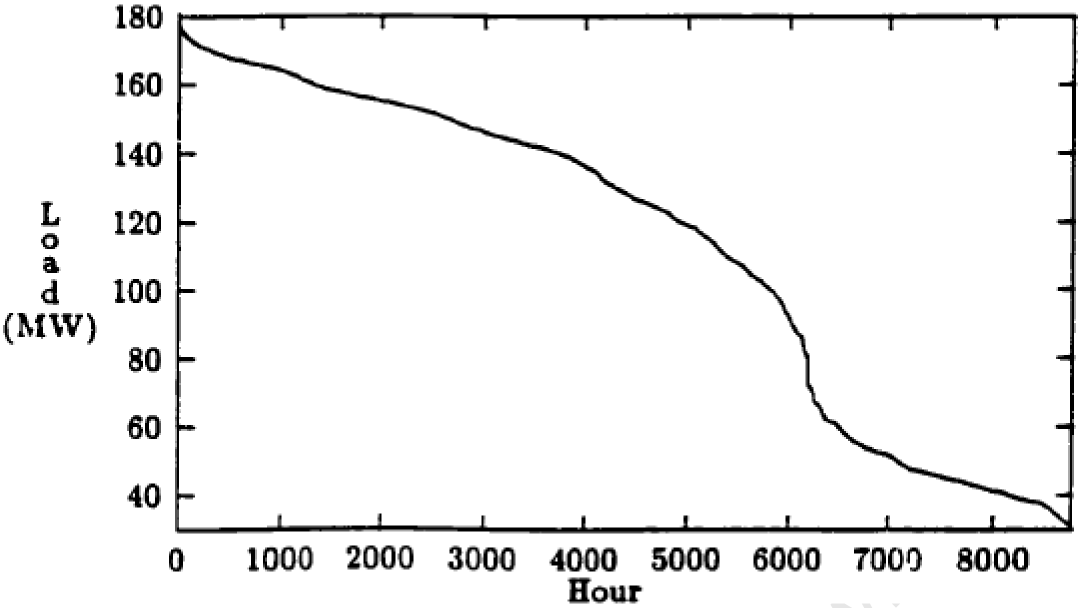


Figure 4-13: Load Duration Curve for the RBTS

The system is then analysed by dividing the load duration curve into a finite number of steps along the y-axis (load-axis) (Jonnavithula, 1997). Jonnavithula, (1997), separates the study into several cases, where in the first case; the load duration curve is divided into 10 uniform steps with a step load increment of 10 %. The 10 step load model used by Jonnavithula, (1997), for the RBTS is given in Table 4-4.

Table 4-4: 10 Step Load Model Data (Jonnavithula, 1997)

Step Level	Probability
100 %	0.13679
90 %	0.23993
80 %	0.14835
70 %	0.10588
60 %	0.05952
50 %	0.02049
40 %	0.06651
30 %	0.19998
20 %	0.02255
10 %	0

In a second case study Jonnavithula, (1997), divides the load duration curves into 15 non-uniform steps and this time, the higher load levels are divided into very fine steps while the lower load levels have a step load decrement of 10 % (Jonnavithula, 1997). In a third case, the load duration curve is divided into 70 steps with a step load increment of 1 % (Jonnavithula, 1997). The results shown by Jonnavithula, (1997), for the system indices show that dividing the load duration curve into non-uniform steps improves the process of obtaining estimates close to those obtained by the sequential method. Using a 10 step or 15 non-uniform step load model with the state sampling or state-transition sampling technique over-estimates the reliability indices (Jonnavithula, 1997). Case 3, with the load duration curve divided into 70 steps, produces estimates of the probability of load curtailed and EENS quite close to those obtained when using a sequential method as described in the work by Jonnavithula, (1997).

The work by Chowdhury & Custer, (2004), and Li et al., (2007), also make use of load duration curves in probabilistic reliability evaluation. In the work by Chowdhury & Custer, (2004), a value-based probabilistic approach for distribution system reliability planning is used in an attempt to locate the minimum cost solution where the total cost includes the utility investment costs plus the operating costs plus the customer interruption costs. Chowdhury & Custer, (2004), determine the optimal feeder and transformer loading required for its study by performing simulations to calculate the un-served energy costs for a total load served by an urban distribution substation. Simulations were run at different system load levels (100 %, 80 %, 70 %, etc) and annual un-served energy cost was calculated by weighting the results of each simulation by the percent of the year that each load level is present. The five-step load model used by Chowdhury & Custer, (2004) is represented in Table 4-5.

Table 4-5: Five-step load duration curve approximation (Chowdhury & Custer, 2004)

LOAD LEVEL	PROBABILITY
100 % (PEAK)	0.001
80 % - 90 %	0.025
70 % - 80 %	0.040
60 % - 70 %	0.097
<60 %	0.837

The annual un-served energy cost for a particular transformer and feeder loading scenario was then added to a charge for any unused transformer and feeder capacity to create the total annual cost of the loading scenario (Chowdhury & Custer, 2004). Li et al., (2007), also consider a load curve in probabilistic reliability evaluation and provide a mathematical expression for the model used. The load model used by Li et al., (2007) is further discussed in the section on combined fuzzy and probabilistic load model. While information can be obtained on reliability evaluation of a distribution system using probabilistic methods, knowing the probabilistic cost model and load model, the probabilistic approach can be further extended to customer interruption costs evaluation

Another study using step load models is presented by Billinton & Li, (1991), which involves the reliability analysis of composite generation and transmission systems using Monte Carlo simulation techniques. Two tests systems, the IEEE Reliability Test System (RTS) and a model of the Saskatchewan Power Corporation System (SPCS), are used for the evaluation and are conducted on a VAX-780 computer. A load duration curve is used as the load model, using the mean load as reference. In the case of the load duration curve, the more the number of steps which are taken, the more representative of the actual load model are the calculated annual indices (Billinton & Li, 1991).

However, Billinton & Li, (1991), explain that this can result in longer computation time and it is only necessary to use many steps in the load model to obtain accurate annual indices in the case of a composite system which is sensitive to the load curve. For a non-sensitive composite system, fewer steps can be used with an associated decrease in the required computing time (Billinton & Li, 1991). The ratios of generation-transmission adequacy indices for the two systems are computed and the results obtained by Billinton & Li, (1991), show that the IEEE RTS is very sensitive to the number of steps in the curve, while the SPCS model is non-sensitive to the number of steps in the load curve.

Annual indices are calculated using three load models which are applied to the two test systems. In model 1, the load is divided into 70 steps with a step load increment of 1 % while in models 2 and 3, the load curve is divided into 15 steps and 8 steps and the load increment of each step is 5 % and 10 % respectively (Billinton & Li, 1991).

The results obtained by Billinton & Li, (1991), show that the number of steps in the load duration curve has considerable influence on the calculated annual indices for the IEEE RTS which has very high ratios of generation-transmission adequacy indices (RGTAI) values. If the load curve is divided into fewer steps, the calculated annual indices can be quite inaccurate for sensitive composite systems such as the IEEE RTS.

The SPCS which has low RGTAI values is not very sensitive to the number of steps in the load duration curve and the 15 step approximate load model provides sufficiently accurate annual indices while the 8 step approximate load model provides relatively satisfactory results (Billinton & Li, 1991). As the SPCS is not sensitive to the number of steps in the load model, Billinton & li, (1991), point out that the annualised indices at the mean load level for the SPCS are reasonably close to the calculated annual indices obtained using the 70 steps load model (Billinton & Li, 1991). Billinton & Li, (1991), suggest that step load levels using load duration curve can have significant differences in the resulting reliability indices when the number of steps used is varied and if the system under study is sensitive to the load model.

4.6.3 Probabilistic Load Modelling Using Probability Density Functions

Gaunt et al., (2009), explain that in South Africa, extensive load measurements and research have produced load models for various classes of customers and that the Beta probability density function (PDF) load model is found to be the most appropriate for electrification design for small groups of customers. Gaunt et al., (2009), describes the load stochastically using a probability density function. A 12 year load research program was conducted in South Africa by the NRS Load Research Group, (1995-2006), and the results were used for the modelling of load. The most appropriate electrical and statistical models of residential loads were investigated and data loggers were designed and used to gather load measurements from a large number of domestic customers (Gaunt, et al., 2009). Load data consisting of at least 50 customers was collected at 5 minute intervals for periods of one or more years at each of more than 20 locations (Gaunt, et al., 2009). The most appropriate representation of the variation within a group of customers, at a given interval, was found to be the Beta PDF as presented in the work by Herman & Gaunt, (2008). Gaunt et al., (2009), explain that domestic customers have distinctive load patterns and these customers expect to have their load demand satisfied by the supply system at every time interval. Gaunt et al., (2009) found that, while the Beta probability distribution is useful for modelling small groups of customer loads, for larger numbers the grouped load current load variation will tend towards a Gaussian distribution with a group mean of μ_N and variance σ_N^2. Then the load variation may be described by Gaunt et al., (2009) as:

$$I_N = \mu_N + Z.\sigma_N \dots\dots\dots (4.3)$$

where Z is obtained from Gaussian tables (e.g. for a 90 % level of confidence, Z = 1.28). From the expression, it is clear that the variance has a large effect when N is small or equal to 1. The model in the work by Gaunt et al., (2009), allows comparisons to be made for a consistent level of adequacy and reliability of the total supply, and with an appropriate confidence in the modelling, giving greater meaning to the financial optimization of the combinations.

Herman & Gaunt, (2008), present a procedure derived for the probabilistic design of LV distribution networks in a developing country such as South Africa. Herman & Gaunt, (2008), investigates an approach for estimating load parameters in countries where a large load database is not readily available. The development and the application of a probabilistic design approach based on beta probability density function are described by Herman & Gaunt, (2008). The method estimates the beta parameters from the group after-diversity-maximum-demand (ADMD) for the customers.

Herman & Gaunt, (2008), explain that countries usually express the load per customer, for a given class, as the ADMD in kilovolt amperes (kVA) and that in all cases; a load model needs to be developed from statistical measurement.

In an electrical sense, loads may be represented as resistance, current or power and the form in which they are modelled have implications for both data gathering and the analysis of the network (Herman & Gaunt, 2008). Herman & Gaunt, (2008), mention that load representation as current sinks provides an acceptable and adequate model for the following reasons:

- It is the best representation of mixed loads typical for appliances of residential customers.
- The magnitude of the current-modelled load is independent of the voltage drop along a feeder or the distance from the source.
- The measurement of loads as currents can be carried out accurately and inexpensively.
- The current model is consistent with the observed behaviour of real loads. The current reduces with increased voltage, but to a lesser extent than would be expected of a pure resistance load.
- The representation of loads as power requires an iterative volt-drop calculation method.
- In traditional methods of volt-drop calculations in LV feeders, loads specified as powers are usually converted to equivalent load current at rated voltage.

The data collection used in the work by Herman & Gaunt, (2008), was performed by a data logger that meets the needs of the load survey with sampling intervals of 5 min. Figure 4-14 and Figure 4-15 show typical histograms of the load current distribution for a low-income group and middle- income group respectively at the time of the group's maximum demand (Herman & Gaunt, 2008). With the collection of a statistically sufficient number of load current samples, it is possible to identify the common interval in which the maximum demand for the group occurs as well as to determine the distribution of currents at the interval as represented in Figure 4-14 and Figure 4-15 (Herman & Gaunt, 2008).

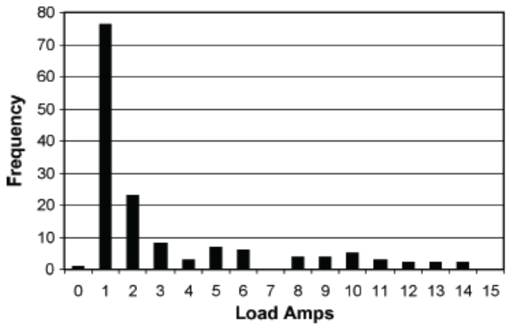


Figure 4-14. Typical histogram of the load current distribution for a low-income group at the time of the group's maximum demand.

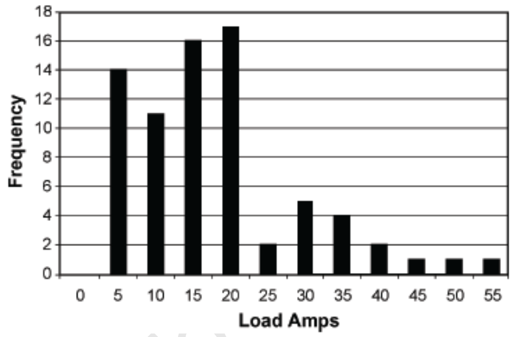


Figure 4-15. Typical histrogram of the load current distribution for a middle-income group at the time of the group's maximum demand.

From these examples, it is clearly seen that the probability distribution describing load currents is not symmetrical and can be very skew (Herman & Gaunt, 2008). However the distribution of currents in Figure 4-15 shows less skewness and more conformity within the group and therefore it is evident that the probability distribution functions chosen to represent the load currents of residential customers needs to represent mean, dispersion and skewness (Herman & Gaunt, 2008).

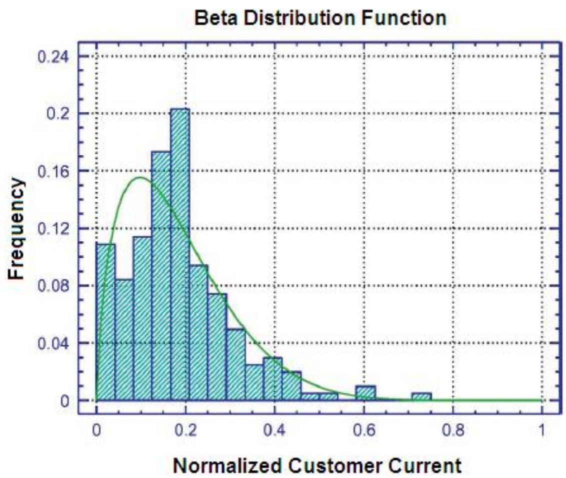


Figure 4-16. Beta PDF fitted to load current data **(Herman & Gaunt, 2008)**.

Extensive work has been done by Herman & Kritzinger, (1993) to identify the most appropriate probability distribution function (PDF) in representing the load current data and for a number of reasons, the Beta PDF was found to be the most suitable. Figure 4-16 shows a Beta PDF fit. The following reasons are used to explain the selection of the Beta PDF (Herman & Gaunt, 2008):

- The Beta PDF is constrained to a finite base in the same way that the load currents are confined between 0 and the circuit breaker limit, C. Therefore knowing the maximum allowable load current to the customer, a distribution can be fitted to the load currents;
- It can be negatively or positively skewed, hence providing an insight on how the load is distributed (frequency) along the lower, middle and upper values;
- Its parameters α and β can be easily found from data;
- It performs well in “Goodness of Fit” tests on real load data using both Kolmogoroff-Smirnoff and Chi-square tests;
- It is conducive to convenient statistical analysis since the moments are gamma functions;
- It can be incorporated into voltage drop calculations, eliminating the need to use diversity correction curves.

The mean and variation of the load current data are related to the Beta parameters as shown in the following equations:

$$E(X) = C.\frac{\alpha}{\alpha+\beta} \dots\dots\dots (4.4)$$

$$E(X^2) = C^2.\frac{\alpha(\alpha+1)}{(\alpha+\beta)(\alpha+\beta+1)} \dots\dots\dots (4.5)$$

Where E(X) is the mean of the load current, $E(X^2)$ is the variance of the load current and C is the circuit breaker limit in amperes.

In countries where residential load research is not a priority, Herman & Gaunt, (2008) present method to facilitate the use of Beta PDF in the absence of detailed load data.

In most countries, the design of LV distribution systems is based on an estimated after diversity maximum demand (ADMD) and the forecasting of this load value for an identified target group of customers has been the subject of many research projects (Willis, 1996). Average values alone do not provide information about dispersion or the shape of the probability distribution and very little though, has been written about the probabilistic distribution of residential loads (Herman & Gaunt, 2008). The correlation between variance (a measure of dispersion) and ADMD for various residential customer classes based on the large amount of data collected in South Africa was examined in the work by Herman & Gaunt, (2008). The focus was set, in particular, on the relationship between d, the demand in kVA and the coefficient of variation, γ (Herman & Gaunt, 2008). The coefficient of variation is defined as the ratio of standard deviation to the mean and is represented as follows:

$$\gamma = \frac{\sigma}{\mu} \ldots \ldots \ldots (4.6)$$

And with Vs the supply voltage,

$$\mu = \frac{d \times 10^3}{V_s} \ldots \ldots \ldots (4.7)$$

By assigning a common limiting value (the circuit breaker limit, C, in Amps) and using the expressions of mean and standard deviation for the Beta PDF, its α and β parameters can be determined as shown in the expressions below:

$$\alpha = \frac{\mu(C\mu - \mu^2 - \sigma^2)}{C\sigma^2} \ldots \ldots \ldots (4.8)$$

$$\beta = \frac{(C - \mu)(C\mu - \mu^2 - \sigma^2)}{C\sigma^2} \ldots \ldots \ldots (4.9)$$

Although the work by Herman & Gaunt, (2008), focuses in voltage drop calculations, the same approach of using Beta PDF can be applied as a load model in power systems for reliability and customer interruption costs evaluation.

4.6.4 A Summary of Probability Load Models

As seen in this section, various probabilistic modelling approaches were described at the generation, transmission and distribution levels and for load, reliability and cost models, which confirms that probabilistic methods can be successfully applied to both reliability and customer interruption costs evaluations. The methods described previously use different probability concepts to model the load, reliability or cost data, however for the purpose of this research, a modified step load model and beta probability density function (PDF) load model are selected to be used as case studies in customer interruption costs evaluation. An average load model and time varying load models are used for comparison. The average load model is used in the evaluation as base case for a comparative analysis with the other load modelling approaches.

4.7 Comparison of Selected Load Modelling Approaches

In the literature covered, a number of methods and techniques for the modelling of load, reliability and costs of power systems during outages have been reviewed. It is clear that two distinct approaches can be identified from literature, which can be categorised as deterministic and stochastic approaches with a time varying dependency in some cases.

Table 4-6 shows a comparison between the different types of load modelling approaches used for the reliability and CIC evaluation of a power distribution system in this study. The table differentiates these approaches by the type of approach, the presence of time variation, the type of load variability and the type of data required to model the load using each approach.

Table 4-6 Comparison of different load modelling approaches

Load Model	Type	Time Variation	Type of Load Variability	Data Required
Average	Deterministic	No	None	Mean Values
Time Varying	Deterministic/ Stochastic	Yes	Time/ Time with uncertainty values	Load Profiles
Step Probabilistic	Probabilistic	No	Uniform Distribution	Load Duration Curve
Fuzzy	Possibilistic	No	Membership Functions	Fuzzy Rules/Sets
Beta PDF	Probabilistic	Yes	Beta Distribution	Historical Load Data

As seen from Table 4-6 the beta PDF load model incorporates time dependency and load variation using a beta distribution. The beta PDF load model is further described in Chapter 5 in much more details, but this load model mainly consists of using historical load data to find the alpha and beta parameters which represent the shape of the distribution of customer loads. These parameters are found at hourly time intervals at each load point in the test system and are used in the simulation to generate random load distributions of individual customers at each load point.

4.8 Improving Reliability of Power System Using Reconfiguration

The reliability evaluation of power systems is affected by the availability of alternative power sources that can be connected to the interrupted load points if switching operations are available. Therefore the load modelling approach in a reliability analysis has an impact on the results when reconfiguration is considered. This section explains the effect of reconfiguration as well as the impact of system loading (load forecasting) in a reliability analysis.

4.8.1 Load Forecasting (Load Growth) – System Loading

System reliability, especially interruption duration measures such as SAIDI (system average interruption Duration Index) can be perceived as a function of system loading (Brown, 2009). For lightly loaded systems, system operators can freely reconfigure the system to restore customers who suffered a fault (Brown, 2009). Since equipment is loaded well under emergency ratings, there is no danger of equipment overloads from system reconfiguration (Brown, 2009). Some system reconfiguration options become constrained as the system becomes more heavily loaded and therefore deteriorates the SAIDI (increasing values) (Brown, 2009).

For equipment that are normally loaded above emergency ratings, no load transfers can occur and SAIDI is at its worst (Brown, 2009). It is valuable to compute system reliability for a range of loading levels since reliability varies as a function of load (Brown, 2009). An insight therefore can be obtained on how expected reliability will change according weather severity (e.g. a mild summer with low peak demand or a hot summer with a high peak demand) (Brown, 2009). Furthermore an understanding of how reliability will change with load growth can be obtained (Brown, 2009).

Reliability (SAIDI in hour/year) versus loading curves (0 % to 200 % of peak load) can be easily generated by multiplying the loads by a global scaling factor (Brown, 2009). It is generally sufficient to compute reliability for load levels ranging from 0 % to 200 % of the peak load, with steps ranging from 5 % to 25 % depending upon the resolution required (Brown, 2009). Figure 4-17 shows the change in reliability (SAIDI) versus loading curves for four actual US utility substations (Brown, 2009).

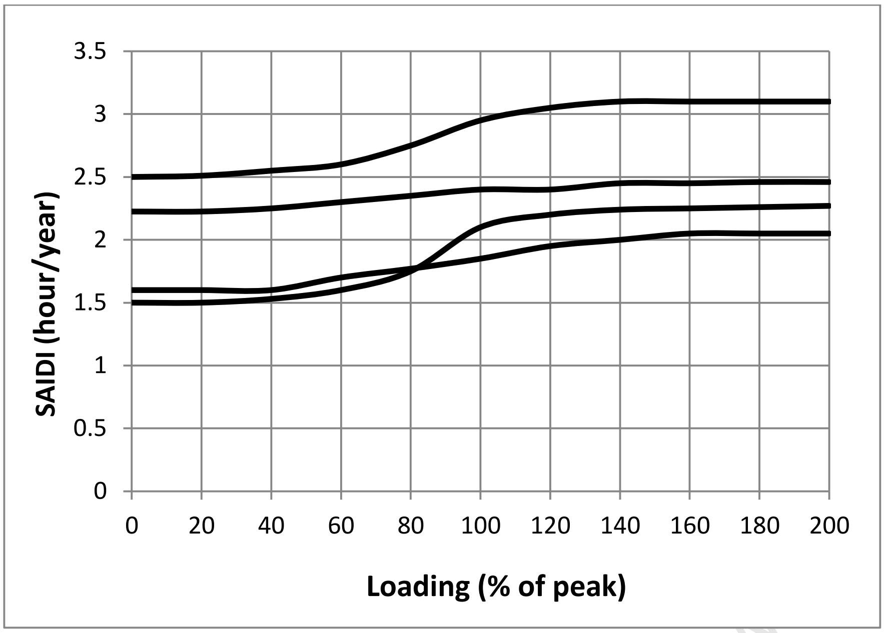


Figure 4-17: Reliability (SAIDI) versus loading curves for four actual US utility substations (Brown, 2009).

As seen in Figure 4-17, SAIDI increases with loading in each case, but the rate and degree of increase depend on a host of factors including the severity of peak loading, the number of normally closed switches, and the number of normally open switches (Brown, 2009). Therefore Figure 4-17 provides an insight on the difference in SAIDI performance between one utility to another and the change in SAIDI values with an increase in percentage loading of the peak load.

4.8.2 Effect of Reconfiguration in Reliability Analysis

Zhu, (2007), explains that the loading condition changes the system reliability in two different ways. Firstly, excess load speeds up equipment aging, while mild load may improve the life-span of an electric component. The second way concerns loading conditions which change the power interchange capability among the adjacent circuits (Zhu, 2007).

Power system networks are often interconnected by open tie switches or normally open switches as in the Roy Billinton Test System (RBTS) (Billinton & Jonnavithula, 1996). For many load points, there are alternative sources of power if switching operations are allowed and when an alternative source is available, whether the alternative source is able to supply power to a particular load point is determined by power interchange capability among the adjacent circuits (Zhu, 2007).

Therefore system reliability is affected by loading conditions, for a given configuration of the power system (Zhu, 2007). The reliability indices in relationship with the outage duration are likely to be affected when reconfiguration is considered, depending on the loading conditions, one or more load points may suffer switching times rather than repair/replace times, hence directly affecting reliability indices such as SAIDI.

Chapter 5

5 THEORY DEVELOPMENT

Mean values are very useful and are the primary indices of system adequacy in distribution system reliability evaluation (Billinton & Wang, 1999). However, the mean values do not provide any information on the variability of the indices. A Probability distribution, in contrast, provides both a graphical representation of the way the indices vary and important information on significant outcomes. Therefore probabilistic distribution based-models show the variation in the values and the lower and upper extremes. These extremes occur very infrequently and they can cause very serious system effects. These effects, which although can occur in practice, may be neglected in an evaluation if only average values are available (Billinton & Wang, 1999). The next section investigates the usefulness of probabilistic load modelling in reliability and CIC studies and the drawbacks or limitations involved, followed by a detailed descriptions of the proposed load modelling approaches in this work The general impression is that stochastic approaches applied to the load model used in reliability or CIC assessments can provide a more effective way of investigating their effect on the resulting indices. Therefore the advantages of stochastic methods over the deterministic approaches are discussed in this chapter.

5.1 Investigating the Usefulness of Probabilistic Modelling in Reliability and CIC Evaluation

In principle, average values (deterministic values) are an acceptable alternative to be used for reliability or CIC evaluations if the available data are limited to those values. Probability distributions of the relevant reliability indices can also be important in reliability cost/worth analysis for industrial customers with critical processes or commercial customers with non-linear cost functions (Billinton & Allan, 1996; Billinton & Wang, 1999). Average values, although an adequate indicator of values of the reliability indices or costs values in an assessment, are only approximations. In the load modelling concept, average values only represent the mean of a data set and do not provide realistic and good representation of the values in the data set. For instance, the average values alone do not show the skewness (measure of the asymmetry of the probability distribution of a real-valued variable) or values associated with risk levels obtained from a probability density function of the customer load interrupted during an outage. The following sections provide the advantages of using stochastic models over deterministic models.

5.1.1 Possible Advantages of Stochastic Models over Deterministic Models

Stochastic models provide a number of additional meaningful information over deterministic models. Deterministic models are generally designed using average or peak load values in the case of reliability or CIC studies in electric power systems. A time varying load model (TVLM) can be either deterministic or stochastic, depending on how the model is designed. TVLMs created using average values or peak values at intervals of time (e.g. 5min, 10min, 15min, 60min, etc.) are still considered as deterministic models as the load values generated do not change for the future states that fall in the same time interval. TVLMs combined with probability distributions of the customer loads within those time intervals are then considered to be stochastic, since the load values of future states generated differ from the previous states. It has been established in (Herman & Gaunt, 2008) that the beta PDF is an excellent statistical approach to represent customer loads in a power distribution system. Therefore any advantages related to probabilistic model are made in reference to the beta PDF approach. A number of advantages for stochastic models over deterministic models are described below:

Uncertainty: This terminology applies to predictions of future events, to physical measurements already made, or to the unknown. Uncertainty is generally described as a state of having limited knowledge where it is impossible to exactly describe the existing state, a future outcome, or more than one possible outcome. Power systems are vulnerable to many stochastic events such as random failures of control and protection devices, environmental instabilities (e.g. high speed wind, lightning and severe storms), irregular load surges due to interruptions, and human errors (Cheng, 2009). All of these factors have an impact on customer outages and their stochastic nature should be part of the evaluation. In reliability analysis, uncertainty can be branched into possibility and probability approaches.

Possibility Theory: This deals with certain types of uncertainty and is an alternative to probability theory (Dubois & Prade, 2001). It is an extension of the fuzzy sets theory and fuzzy logic and uses min/max or [0, 1] values to describe degrees of potential surprise (Zadeh, 1978). In the absence of statistics or data, the possibilistic approach using fuzzy set theory in reliability analysis is adequate to take into consideration the uncertainties inherent in these evaluations (Nahman, 1997; Li, et al., 2007).

Probability Distributions: In probability and statistical terms, a probability distribution assigns a probability to each of the possible outcomes of a random experiment (Everitt, 2006). Some examples include experiments whose sample space is encoded by discrete random variables, experiments with sample spaces encoded by continuous random variables where the distribution is a probability density function, and so on (Everitt, 2006). An example of a discrete probability distribution can be found in the step load model whereby discrete probability values are calculated for different load levels, while the beta PDF load model is an example of continuous probability distributions. A number of probability distributions are available in literature; however continuous probability distributions used in this work are mainly the uniform distribution and beta distribution.

Skewness: Skewness as described in probability theory and statistics is a measure of the asymmetry of the probability distribution of a real-valued random variable. The skewness value can be positive, negative, or even undefined. A negative skew, qualitatively, shows that the tail on the left side of the probability density function is longer than the right side and the bulk of the values (possibly including the mean) lie to the right of the mean (Dean & Illowsky, 2012). On the other hand, a positive skew indicates that the tail on the right side is longer than the left side and the bulk of the values lie to the left of the mean (Dean & Illowsky, 2012). A zero value indicates that the values are relatively evenly distributed on both sides of the mean, usually (but not necessarily) implying a symmetric distribution.

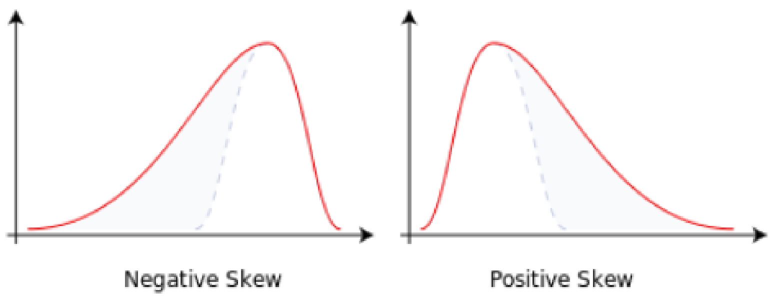


Figure 5-1. Example of a negative and positive skew **(Von Hippel, 2005)**.

In the case where the distribution is symmetric, then the mean is equal to the median and the distribution will have close to zero skewness (NIST/SEMATECH, 2012). Figure **5-1** illustrates an example of a negative and positive skew. For a beta distribution, which is used in this research, the skewness varies for different combinations of α and β parameters which can be obtained from data using general equations (Herman & Gaunt, 2008).

Skewness has many benefits in several areas as described in literature (Herman & Gaunt, 2008; Gaunt, et al., 2009; Herman & Gaunt, 2010). Many models assume a normal distribution whereby the data are symmetric about the mean and have a skewness of zero (Von Hippel, 2005). However in practice, data points may not be perfectly symmetric and therefore, an understanding of the skewness of the data set shows if the deviations from the mean are positive or negative.

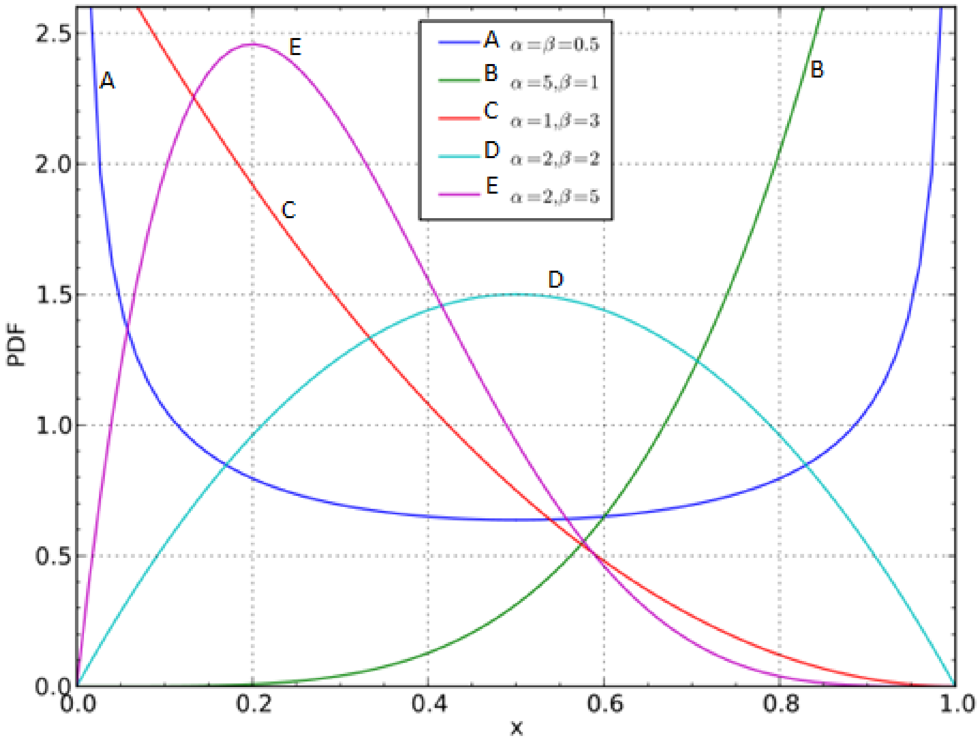


Figure 5-2. Example of a beta distribution for different combinations of α and β parameters **(Cross, et al., June 2006; Vedala, 2011)**.

Figure 5-2 illustrates an example of a beta distribution probability density function (PDF) for various combinations of α and β parameters. Therefore the beta parameters can be fitted to historical data that follow a wide range of shapes or skewness. This makes the beta distribution appropriate for historical power distribution system's load data which may differ in skewness when different types of customers are involved.

Percentage Risk or Confidence Levels: The concept of risk is a state of uncertainty where some possible outcomes have an undesired effect or significant loss. Its complement is the confidence level. In statistics, a confidence interval is an interval estimate of a population parameter and it is used to show the reliability of an estimate. It is an observed interval (principally different from sample to sample) that frequently includes the parameter of interest if the experiment is repeated (Kendall & Stuart, 1973; Cox & Hinkley, 1974). The confidence level or confidence coefficient determines how frequently the observed interval contains the parameter. For instance, if the value obtained at 95 % confidence level is 0.5, it means that a value of less or equal to 0.5 occurs with a probability of 0.95. This also means that there is a 5 % risk that the estimate of the population parameter will exceed 0.5. In a beta distribution the values of the data set are normalized to [0, 1] range in order to fit a beta probability density function to it (Kendall & Stuart, 1973; Cox & Hinkley, 1974).

5.1.2 Drawbacks and Limitations

The drawbacks that could potentially make stochastic approaches less desirable than deterministic approaches are the complexity in the modelling process and the integration in simulation software. Probabilistic models in reliability or CIC evaluation are limited to the availability of statistical data (mean, standard deviation, etc.) or the availability of a data set. Also probabilistic models can be more difficult to interpret than conventional models such as the use of average values.

5.2 Existing Load Modelling Approaches for Reliability and CIC Evaluation

This section provides the basic theory behind the modelling of each of the load modelling techniques used in this study on reliability and CIC evaluation in power distribution systems. Different types of load models described in literature have been selected and are described below before their implementation in a simulation program for reliability or CIC assessments.

5.2.1 Average (Deterministic) Load Model

The first load model used in this research is the average load which is deterministic and is extensively used in literature as the base case scenario. Historical load data, (NRS, 1995-2006), are normalized to the average loads, obtained from the study by Billinton & Jonnavithula, (1996), for the different load points of the RBTS, are used for this modelling approach. Therefore each load point has a single value which is used in a simulation program to evaluate the reliability or CIC indices and is described as follows:

$$LP(i)_{avg} = Load_i \ldots\ldots\ldots (5.1)$$

where,

$LP(i)_{avg} = the\ load\ at\ load\ point\ i\ for\ the\ average\ load\ model$

$Load_i = the\ average\ load\ value\ at\ service\ point\ i$

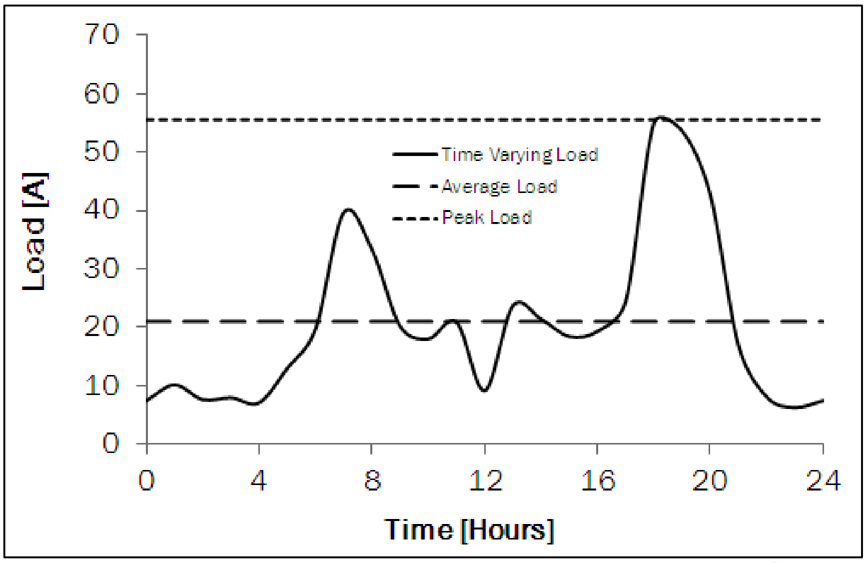


Figure 5-3. Example of a load profile indicating the average load, the peak load and the variation of load over 24 hour duration.

Figure 5-3 shows an example of a load profile showing the average load, the peak load and the variation of load over time. This illustrates the mean value used in the average load model while the actual load demand varies with time up to the peak load.

5.2.2 Time Varying Load Models

The time varying load model is divided into two sub-cases, one which uses average load (calculated from historical load data (NRS, 1995-2006)) over hourly intervals and the other, uses the actual load (obtained from historical load data (NRS, 1995-2006)) recorded at 5min intervals. The comparison in the two sub-cases of time varying load proposed is found in the time interval used for the evaluation. The first model averages the actual load collected at 5min intervals over an hour, and therefore the impact of averaging over time is sought in the evaluation as compared to the use of load data at shorter time intervals. The impact of averaging load data over an hour can be singled out to the loss of information on the load usage of customers within the hourly interval.

5.2.2.1 Load averaged at hourly intervals

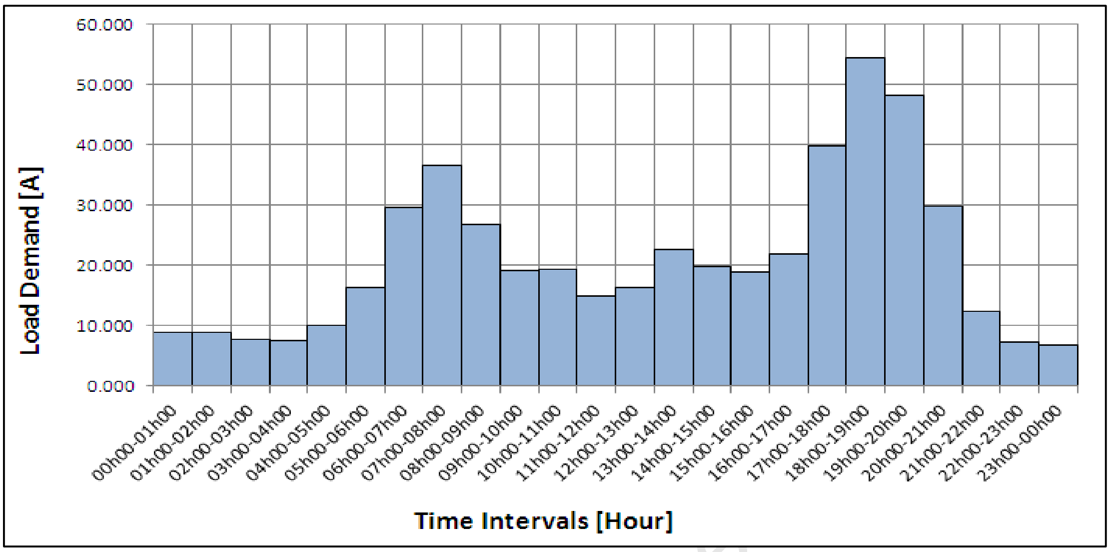


Figure 5-4. Average load at hourly intervals for a 24 hour load profile.

Figure **5-4** illustrates the average (deterministic) load at hourly intervals for a 24 hour load profile. The equation for the first time varying load model (hourly intervals) is defined as follows:

$$LP(i)_{TV} = (L_1 \quad L_2 \quad \ldots \quad L_h) \ldots \ldots \ldots (5.2)$$

where,

$LP(i)_{TV\_1hr} = the\ load\ at\ load\ point\ i\ for\ the\ time\ varying\ load\ model$

$L_h = average\ load\ at\ hourly\ interval\ h, where\ h = 1,2,3, \ldots ,24$

The time varying load model in this research uses 24 hour load profiles generated using available load data (NRS, 1995-2006) for each load point in the test system and represent the load at hourly intervals for each profile as a 1 by 24 matrix, where each column in the matrix represents the hourly intervals. The load at hourly intervals is the average load in that interval. The time of occurrence is randomly generated by using a uniform distribution, hence allowing interruptions to occur during each hourly interval with the same probability.

5.2.2.2 Load at 5 minutes intervals

The second time varying load model is similar to the first model, however shorter time intervals are used. The loads (NRS, 1995-2006) at 5 min intervals which are the actual load measured are set into a 1 by 288 matrix (24 hour) for each load point in the system. Each column in the matrix represents the load for a particular load point at 5 min intervals. The time of occurrence is randomly generated by using a uniform distribution, hence allowing interruptions to occur during each 5 min interval with the same probability.

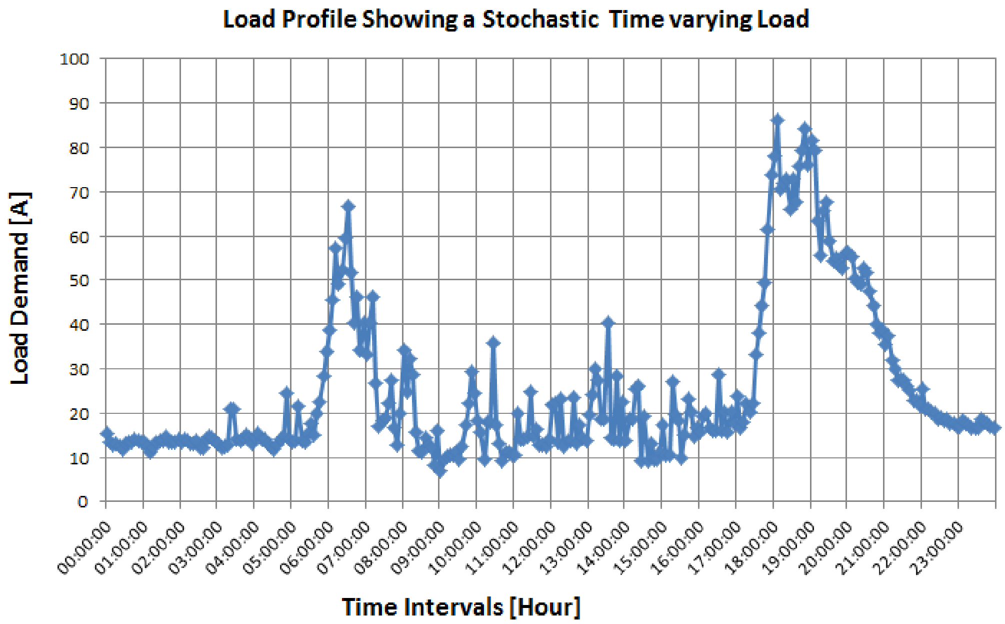


Figure 5-5. Stochastic load at hourly intervals for a 24 hour load profile.

Figure 5-5 above illustrates the load at 5 min intervals for a 24 hour load profile. The equation for the time varying load model is defined as follows:

$$LP(i)_{TV} = (L_1 \quad L_2 \quad \dots \quad L_h) \dots\dots\dots (5.3)$$

$LP(i)_{TV\_5min} = the\ load\ at\ load\ point\ i\ for\ the\ time\ varying\ load\ model$

$L_h = actual\ load\ at\ 5\ min\ interval\ h, where\ h = 1,2,3, \dots ,288$

By simulating the interrupted load using 5 min intervals, the time varying load provides a more accurate model of the interrupted load which is more representative of the actual load interrupted during a power outage. As seen in Figure 5-5 above, load varies with time, and the load variation in each hour interval may also be significant. Thus information about load variation is lost when using average hourly loads and therefore this method may not represent the actual load adequately. The use of the 5 min intervals may provide a more accurate representation than hourly intervals and the effects of using shorter time intervals should be seen on the expected energy not supplied and expected interruption costs which are obtained from simulations.

5.2.3 Step Probabilistic Load Using Load Duration Curves with Equal Percentage Load Intervals of the Peak Load

The step probabilistic load is modelled using a load duration curve which is obtained from the load profiles generated from load data for each load point in the test system. The step probabilistic load can be modelled in two ways.

The first step probabilistic load model defines equal intervals of the peak load (e.g. 0-20 %, 20-40 %, and so on), and to determine the probability of occurrence for each load level from the load duration curve. The probability is calculated by finding the duration for each interval, and dividing by the total duration. Therefore percentage load intervals are equally spaced with different probability of occurrence for a particular load point. The step (y-axis) load model is defined as follows:

$$LP(i)_{step(y)} = \sum_{i=1}^{No.of\ load\ levels} (L_i \times p_i) \dots \dots \dots (5.4)$$

where,

$LP(i)_{step(y)} = the\ load\ at\ load\ point\ i\ for\ the\ stepped\ probabilistic\ load\ model\ with$

$equally\ spaced\ load\ intervals\ of\ the\ peak\ along\ y - axis$

$L_i = the\ peak\ load\ obtained\ at\ load\ level, i$

$p_i = the\ probability\ of\ being\ in\ load\ level, i$

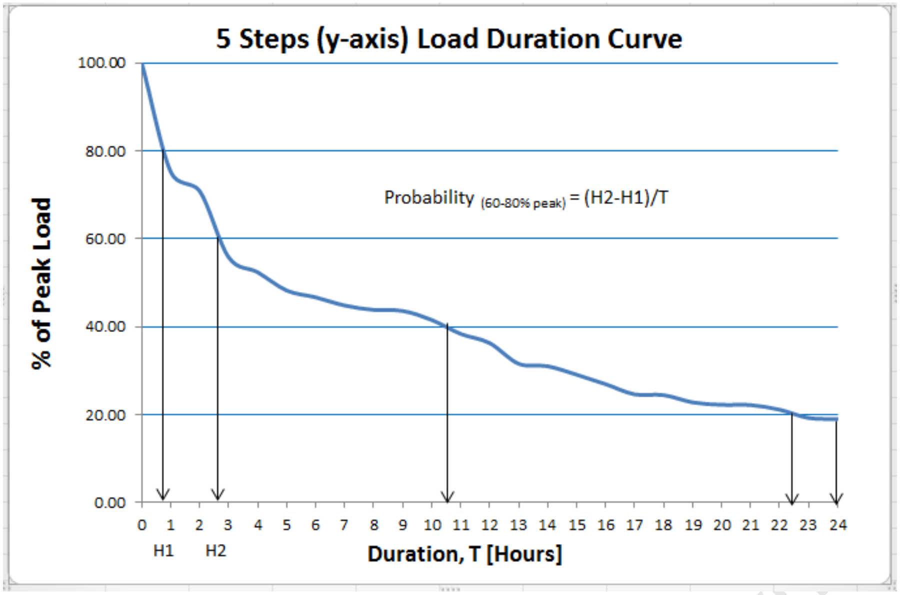


Figure 5-6. Percentage intervals of the peak load determined for each step of the 5 steps load model.

Figure 5-6 above shows an example of a 5 steps load duration curve with equally spaced percentage intervals of the peak load.

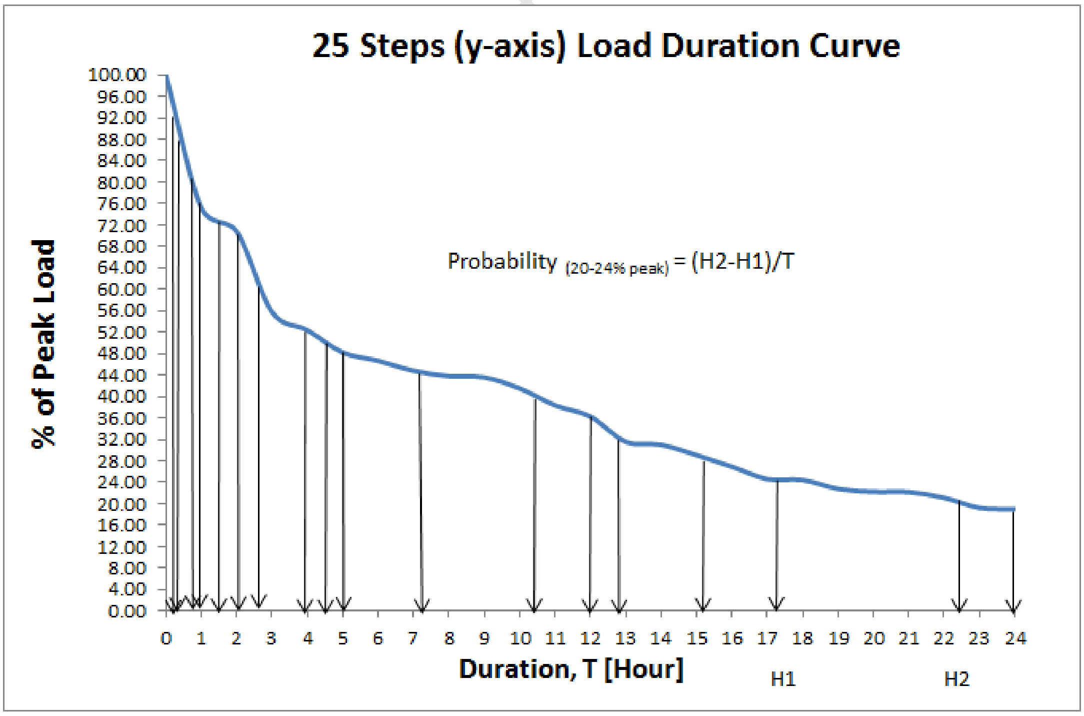


Figure 5-7. Percentage intervals of the peak load determined for each step of the 25 steps load model.

Increasing the number of steps (e.g. 25 steps, in this case the number of percentage intervals of the peak load), increases the accuracy of representation of the actual load as shown in Figure 5-7.

The probabilities are found for each percentage load levels of the peak and this information is used to model the load in a reliability and CIC evaluation in distribution systems. The probabilities for each percentage load levels, which are found from the load duration curve, are illustrated in Figure 5-8 and Figure 5-9.

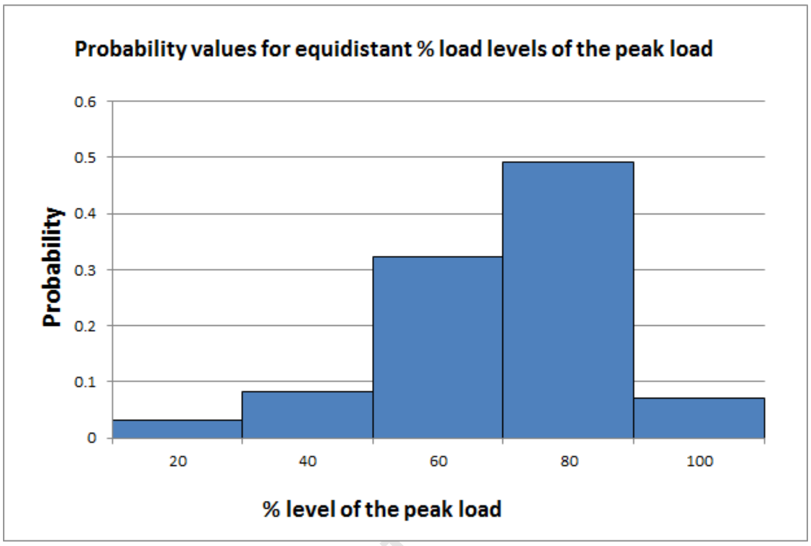


Figure 5-8. Probability determined for each percentage intervals of the peak load for a 5 steps load model.

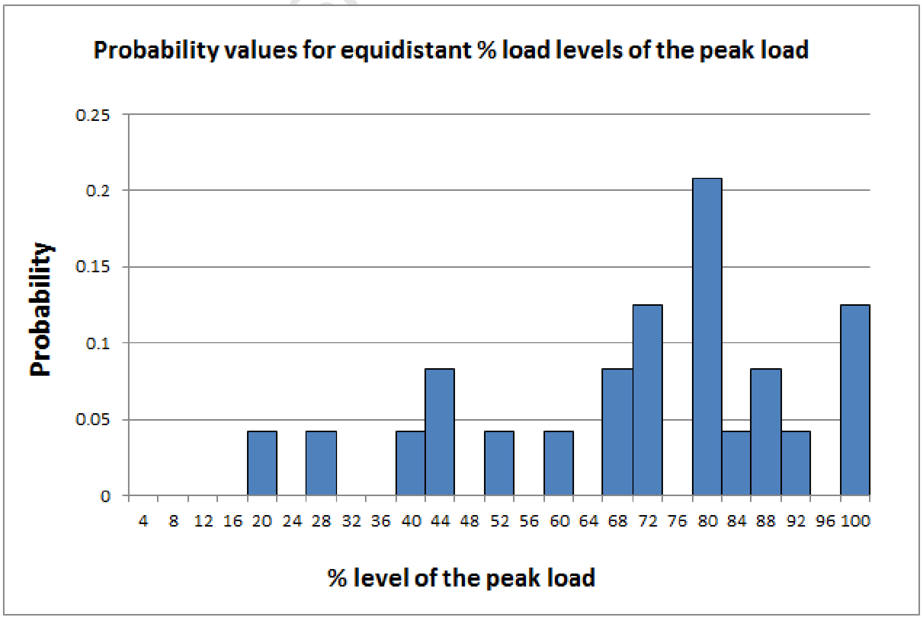


Figure 5-9. Probability determined for each percentage intervals of the peak load for a 10 steps load model.

5.3 Proposed Load Modelling Approaches for Reliability and CIC Evaluation

The following load modelling approaches are presented based on ideas around existing load models or approaches used in different areas of studies.

5.3.1 Development of a Step Probabilistic Load Using Load Duration Curves with Equal Probability of Loads at Equal Time Intervals

In the proposed model of step (x-axis) probabilistic load, equal probabilities are used for each load levels and are calculated by dividing the total duration into uniform intervals, and dividing the duration in each interval by the total duration. Then the percentage load level of the peak value is found for each probability. Therefore each percentage load level has equal probability of occurrence at a particular load point. This method provides a similar configuration to the time varying load models, in such a way that the x-axis is divided into 24 hourly intervals. However, the load chronology is kept in time varying load models whereas it is lost in step (x-axis) load model.

$$LP(i)_{stepped(x)} = \sum_{j=1}^{No\ of\ load\ levels} (L_j \times p_j) \ldots\ldots\ldots (5.5)$$

$LP(i)_{stepped(x)} = the\ load\ at\ load\ point\ i\ for\ the\ stepped\ probabilistic\ load\ model\ with$

$equally\ spaced\ load\ intervals\ of\ the\ peak\ along\ x-axis$

$L_i = the\ peak\ load\ obtained\ at\ load\ level, i$

$p_i = the\ probability\ of\ being\ in\ load\ level, i$

Figure 5-10 illustrates an example of a 6 steps probabilistic load model using a load duration curve generated from load data (NRS, 1995-2006) available.

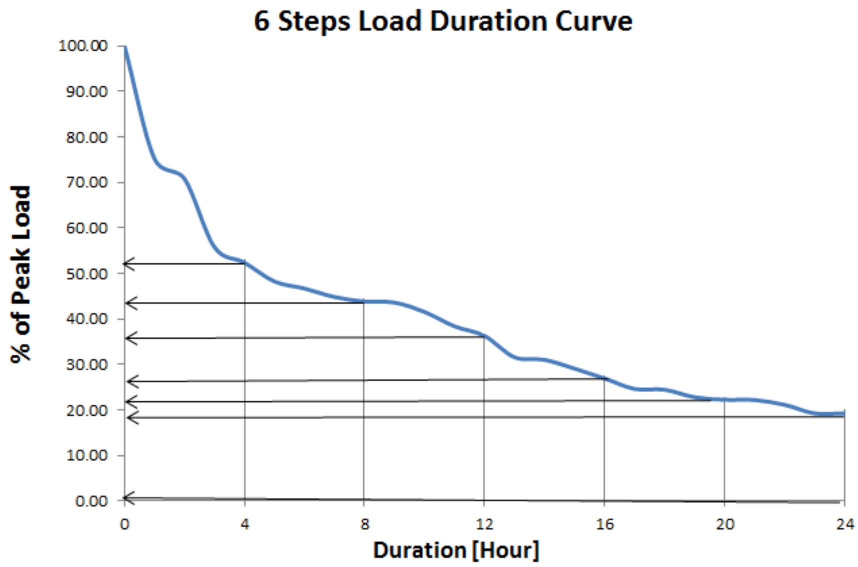


Figure 5-10. Example of a 6 steps load duration curve with equal probability.

The duration axis is divided in 6 equal intervals which represents the probability of occurrence of different percentage load levels of the peak. Increasing the number of steps (e.g. 24 steps), as indicated in Figure 5-11 below increases the accuracy of representation of the load.

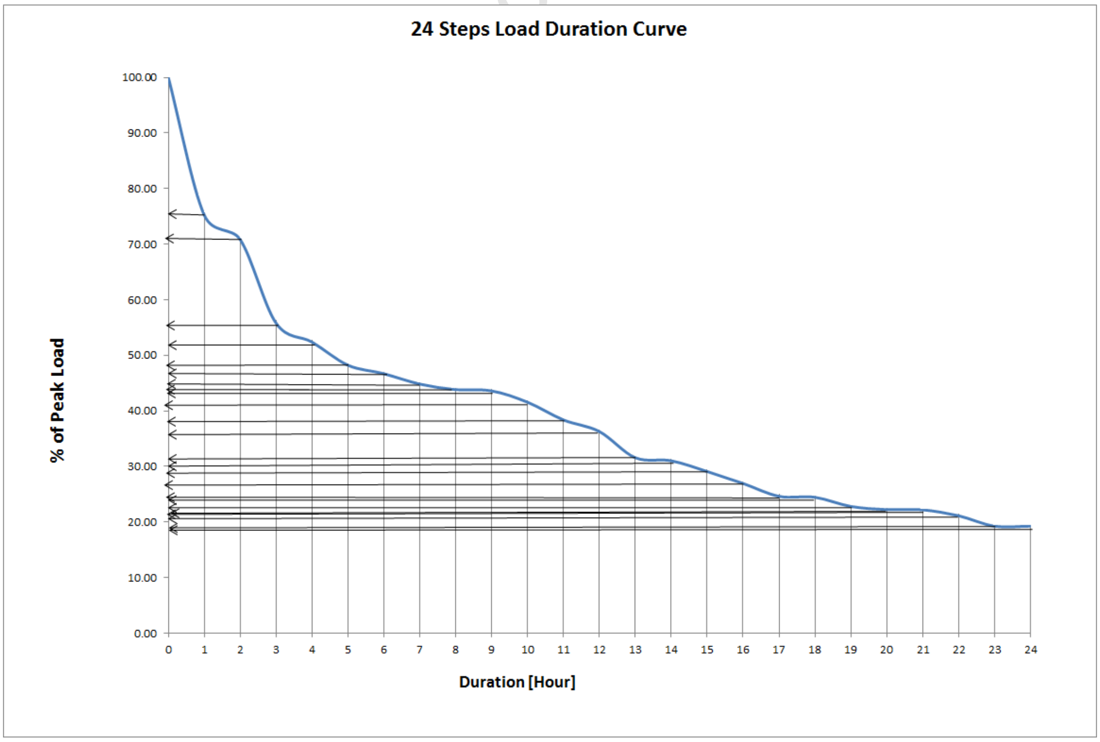


Figure 5-11. Example of a 24 steps load duration curve with equal probability.

The percentage load intervals of the peak are found for each probability and this information is used to model the load in a reliability and CIC evaluation in power distribution systems. The percentage load levels for each probability which are found from the load duration curve are illustrated in Figure 5-12 and Figure 5-13.

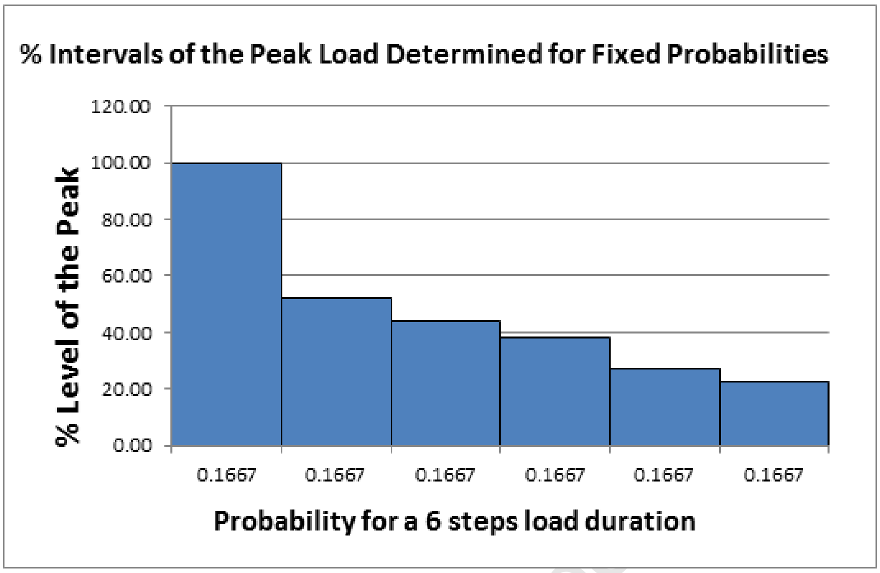


Figure 5-12. Six steps load duration curve with equal probability.

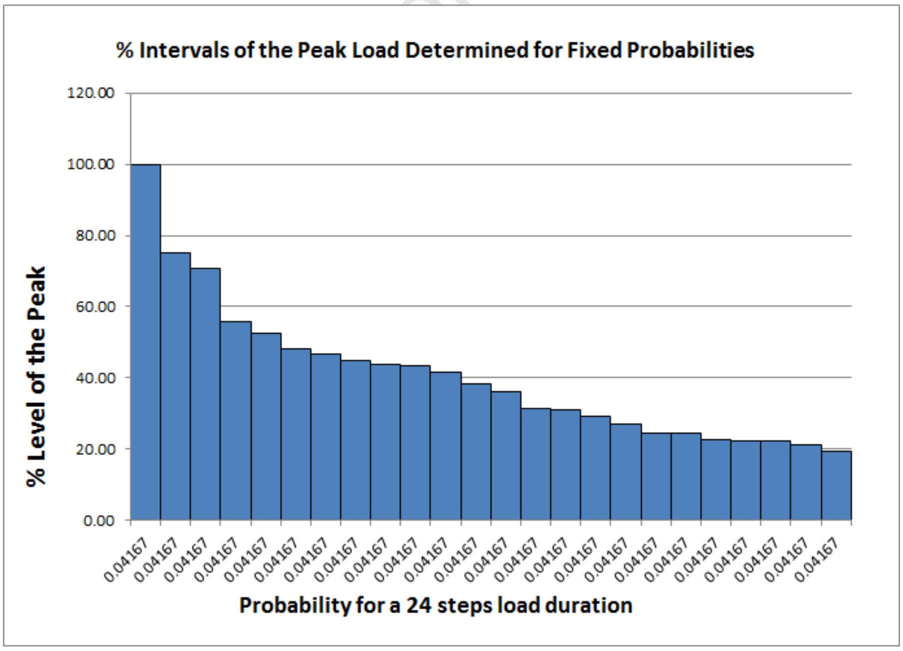


Figure 5-13. Twenty-four steps load duration curve with equal probability.

The step probabilistic load model using load duration curves with equal probability of loads at equal time intervals is a different method of load representation based on the existing step load model, which also uses load duration curves, but instead is modelled with equal percentage intervals of the peak load an varying probability values. The steps are divided into hourly intervals similarly to the time varying load model, however the chronology of load is not shown in this representation of load. This method can be used to compare the difference in modelling the load at hourly intervals without chronology with the time varying load model, which takes load chronology into consideration.

5.3.2 Development of a Beta Probability Density Function Model with Load Distributions

A combined time varying and beta probability density function fitted to the loads data is presented in this section. This load modelling approach demonstrates both the impact of load variation with time using two different time intervals and that of load uncertainty in the reliability and CIC evaluation of a test system. While load varies with time, it also varies stochastically. Therefore, the load at a particular time of the day will not be used the same way and by the same exact amount when considering the same customers. Therefore the beta PDF load model can be adequately used to model such uncertainties.

The beta PDF load model is divided into two sub-cases, where in the first sub-case, the alpha and beta parameters are calculated from the data set at hourly intervals for each load point in the system and in the second sub-case, the alpha and beta parameters are calculated using the actual load data taken at 5 min intervals.

Therefore in the first sub-case, a matrix of 44 (load points) by 24 (hours) elements is used to store the alpha parameters while another matrix of 44 by 24 elements is used to store the beta parameters. In the second sub-case, the alpha and beta parameters are stored in a 44 by 288 elements matrix separately.

When an outage occurs, a time parameter using a uniform distribution is generated to determine the time of the outage and the equivalent alpha and beta parameters are used for a particular load point to generate the interrupted load randomly using a beta probability density function. The individual loads using the beta PDF, are generated for each load point for the number of customers in the load point and the sum of these individual loads represented the interrupted load during a power outage.

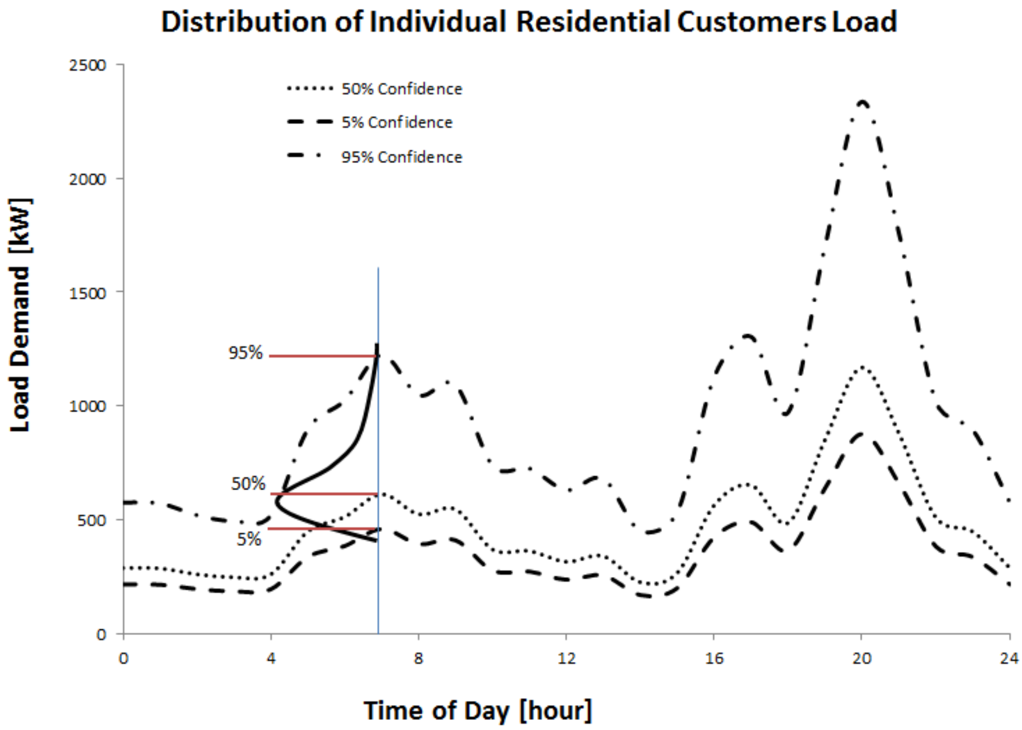


Figure 5-14. Beta PDFs with variation of individual loads.

Figure 5-14 above shows the variation of individual customers load at a particular time for a load point in the system. The customers load varies with time and also from customer to customer. Therefore using the beta PDF model, the interrupted load that is generated considers both the customer load interrupted when an outage occurs at the time of the interruption and also the pattern of load usage of individual customers at a load point.

5.3.2.1 Load Averaged at Hourly Intervals

These individual load values are generated randomly using the α and β parameters and the number of customers at a load point using the beta PDF and the summation of these loads gives the interrupted load at the service point as described below:

$$\alpha_{i,t} = \begin{pmatrix} \alpha_{1,1} & \cdots & \alpha_{1,24} \\ \vdots & \ddots & \vdots \\ \alpha_{44,1} & \cdots & \alpha_{44,24} \end{pmatrix} \dots\dots\dots (5.6)$$

$$\beta_{i,t} = \begin{pmatrix} \beta_{1,1} & \cdots & \beta_{1,24} \\ \vdots & \ddots & \vdots \\ \beta_{44,1} & \cdots & \beta_{44,24} \end{pmatrix} \dots\dots\dots (5.7)$$

$$LP(i)_{i,t} = \left(\sum betapdf(\alpha_{i,t}, \beta_{i,t}, N_i)\right) \times C_i \dots\dots\dots (5.8)$$

where,

$LP(i)_{i,t} = the\ load\ \ at\ load\ point\ i\ for\ the\ beta\ probabilistic\ load\ model\ at\ time\ h$

$\alpha_{i,t} = the\ alpha\ parameter\ for\ load\ point\ i\ at\ time\ t\ (in\ hours)$

$\beta_{i,t} = the\ beta\ parameter\ for\ load\ point\ i\ at\ time\ t\ (in\ hours)$

$N_i = the\ number\ of\ customers\ at\ load\ point\ i$

$C_i = the\ circuit\ breaker\ limit\ at\ load\ point\ i\ in\ Amperes$

5.3.2.2 Load at 5 Minutes Intervals

Similarly to the load at hourly intervals, the load at 5 min intervals is as follows:

$$\alpha_{i,t} = \begin{pmatrix} \alpha_{1,1} & \cdots & \alpha_{1,288} \\ \vdots & \ddots & \vdots \\ \alpha_{44,1} & \cdots & \alpha_{44,288} \end{pmatrix} \ldots \ldots \ldots (5.9)$$

$$\beta_{i,t} = \begin{pmatrix} \beta_{1,1} & \cdots & \beta_{1,288} \\ \vdots & \ddots & \vdots \\ \beta_{44,1} & \cdots & \beta_{44,288} \end{pmatrix} \ldots \ldots \ldots (5.10)$$

$$LP(i)_{i,t} = \left(\sum betapdf(\alpha_{i,t}, \beta_{i,t}, N_i)\right) \times C_i \ldots \ldots \ldots (5.11)$$

where,

$LP(i)_{i,h} = the\ load\ \ at\ load\ point\ i\ for\ the\ beta\ probabilistic\ load\ model\ at\ time\ h$

$\alpha_{i,h} = the\ alpha\ parameter\ for\ load\ point\ i\ at\ time\ t\ (in\ 5\ \mathrm{min}\ intervals)$

$\beta_{i,h} = the\ beta\ parameter\ for\ load\ point\ i\ at\ time\ t\ (in\ 5\ \mathrm{min}\ intervals)$

$N_i = the\ number\ of\ customers\ at\ load\ point\ i$

$C_i = the\ circuit\ breaker\ limit\ at\ load\ point\ i\ in\ Amperes$

Each element in the matrix represents the alpha or beta parameters for a particular load point for a specific time of the day.

5.3.2.3 Examples of Beta Distributions at hourly and 5 min Intervals

Figure 5-15a, b, c and d show the Beta distributions generated from Beta parameters of individual loads found for hourly averages and different readings taken at 5min intervals. The Beta parameters are determined for individual customers and can be used to randomly generate their distributions at different times.

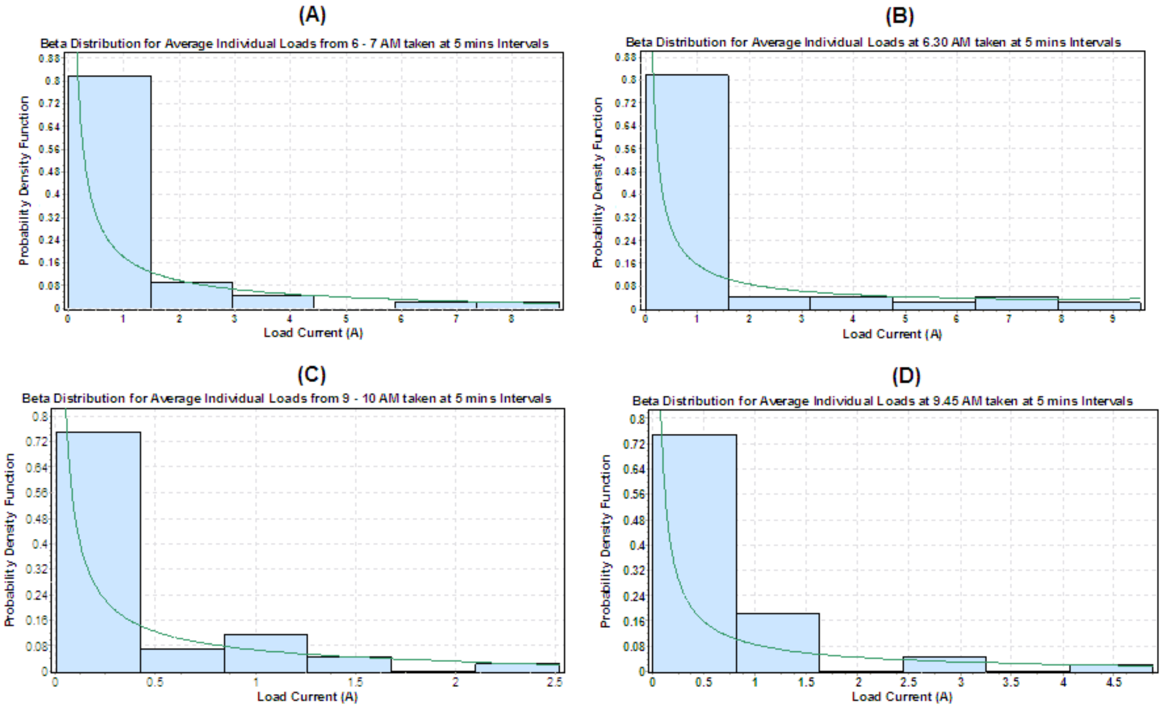


Figure 5-15. Beta Distributions for hourly average of individual loads and individual loads taken at 5min intervals.

Graphs (A) and (C) show the distributions of the individual customer loads using beta parameters calculated for the hourly average individual loads between 6-7am and 9-10am respectively. While all four graphs are extremely positively skewed, the tails vary in each case. Graphs (B) and (D) show the distributions of the individual customer loads using beta parameters calculated for individual loads taken at 5mins intervals. In graph (B), the distribution of the individual loads is for 6.30am while for graph (D), the distribution is generated from the beta parameters taken at 9.45am. These results not only show that the beta distributions of individual loads vary from one hour to another, but that also changes in the distribution of the individual loads can be seen at each 5 min intervals. Therefore it is necessary to model for both time intervals when investigating the impacts of load modelling in reliability or CIC evaluations of power distribution systems using this approach.

5.4 Motivation for the Selected Load Modelling Approaches

The load modelling approaches described in this chapter were selected based on several assumptions and requirements. The average load model, which has been widely used in previous studies on reliability and CIC evaluation, was selected as the base case and is used for comparison purposes. The time varying load model incorporates the variation of load with time which depicts peak and off peak load demand of customers. Load is not constant throughout time, and therefore it is important to incorporate this variation when proposing a load modelling technique. The step probabilistic load is used as a contrasting model to the time varying model, where the chronology of load is omitted but instead a load duration curve is used. Using the load duration curve, probability values can be associated with particular load levels of the peak demand. This provides a comparison when the variation of load with time is omitted while the stochastic nature of load is incorporated. The last load model considered is based on a time dependent beta probability density function, which incorporates both the variation of load with time and the uncertainty in load. Additionally this model can also associate risk or confidence levels to the resulting indices such as the energy not supplied or the expected cost of interruption.

Chapter 6

6 TEST PROTOCOL

This chapter concerns the general procedure to carrying out the study aiming at finding the impact of using different types of load modelling techniques (deterministic versus stochastic models) in a reliability or CIC evaluation. Different types of load models as described in chapter 5 are used in the analyses. The probabilistic approach is chosen over the fuzzy logic model as historical load data, which has been collected in South Africa over 10 years, is available from NRS load research group (1995-2006).

6.1 Preliminary Procedure

Many sources (Billinton & Li, 1994; Billinton & Sankarakrishnan, 1995; Billinton & Wang, 1997; Billinton & Wang, 1999) suggest that the sequential Monte Carlo simulation is suitable for reliability evaluation of power systems and allows the introduction of stochastic models and time variations. The initial procedure for comparing the impact of probabilistic load models with those of other load models is as follows:

- Describe briefly how the probabilistic load is modelled as well as the different load models used for comparison.
- Choose the reliability and cost models to be used in the reliability or CIC evaluation and the initial conditions and assumptions for these models (generally set as average models throughout the simulations unless stated otherwise).
- Choose a Practical/Test system for which the customer, reliability and load information are available and define your assumptions. For example the normalisation of the historical load data to that of the load data used in published results.
- Perform a failure mode and effect analysis (FMEA) on the test system to determine which load points are affected (suffers an outage) when a particular component/element in the system fails.
- Find a suitable simulation technique that allows all aspects of the load, reliability or cost model to be implemented. The simulation technique should be simple and fast enough to allow the integration of bigger power systems if necessary.

- Choose a simulation software package in which the simulation technique can be programmed and proceed with the integration of all the models required for the reliability/CIC evaluation of the Practical/Test system.
- Decide what will be the output in the results and how they should be represented for each of the different models under investigation.
- Find an adequate way of representing the results (tabulation, graphical illustrations, charts, etc.) which will allow for easiest and clearest comparison
- Validate the simulation program by implementing the information for which the initial results are available.
- Once validated, implement the different loads models in the simulation software using the simulation technique and the system's data.

6.2 Failure Mode and Effect Analysis of the Test System

A failure mode and effect analysis (FMEA) is performed for the RBTS in order to analyse which load points are affected when a particular component fails. The FMEA has been performed for Bus 3 of the RBTS and the results are tabulated in APPENDIX B.1 to B.8.

6.3 Description of the Load Models Used and Customer Data

The proposed methods for different types of load modelling approaches are described in chapter 4 along with their mathematical expressions. An average load model is used as the base case and the validation model. The average model is chosen as the base case as the test system chosen (RBTS) (Billinton & Sankarakrishnan, 1994), is provided with the average load information at each load point in the system along with the customer and reliability data which are available in **APPENDIX C**. The other load models used for comparison include a time varying load model, a step probabilistic load model (sub-divided into two approaches), and the beta probability density function (PDF) model. The historical NRS load research data made available by Herman and Gaunt (NRS, 1995-2006), is normalized to that of Billinton & Jonnavithula, (1996), so as to only have the variation in the load being the focus of the study.

6.4 Reliability and Cost Data Used

The information (customer, load point data, etc.) obtained from the work by Allan et al., (1991), and Billinton & Sankarakrishnan, (1995), for the Roy Billinton Test System (RBTS) are used in this work. APPENDIX C contains the reliability and system data for the RBTS used in this research which was obtained from the work by Allan et al., (1991). This information is used in a sequential Monte Carlo Simulation which is programmed in MATLAB. Examples of the reliability and system data used are the failure rates, repair times, switching times, etc. for different types of components such as transformers of various ratings, transmission lines/cables, etc. The cost data used for this study is in the form of customer damage functions for residential and commercial customer in Rand/MWh for different durations (e.g. 1 hour, 5 hours, etc.) and are available in APPENDIX C.

6.5 Load Data, Load Profiles and Load Duration Curves

This research on the impacts of load modelling techniques on reliability and CIC evaluation in power system, with a focus on probabilistic methods, was possible by the collection of NRS load research data made available by Herman and Gaunt from the University of Cape Town (NRS, 1995-2006). The load data collected are from residential customers in South Africa. This information is then used to generate load profiles and load duration curves for each residential load point (while load data for shops available from the NRS research load data were adjusted and scaled to represent commercial customers), which are needed for the different types of load models presented in this study. The historical load data (NRS, 1995-2006) was then normalized to the load information from Billinton and Jonnavithula (Billinton & Jonnavithula, 1996), such that only the variation in the load is captured in the study. Examples of residential and commercial load profiles and load duration curves used for this study are available in APPENDIX C.

6.6 Selection of a Simulation Technique and Software

Several studies on reliability and/or customer interruption costs evaluation have been carried out using the sequential and non-sequential Monte Carlo simulation technique (Billinton & Li, 1991; Billinton & Li, 1994; Saraiva, et al., 1996; Billinton & Wang, 1997; Billinton & Wang, 1999; Li, et al., 2008; Dijerenge, 2009; Veliz, et al., 2010), and therefore the Monte Carlo simulation approach is used in this study for the reliability and CIC evaluation of power systems with an emphasis on the impact of modelling the load using a probabilistic approach.

The software selected to implement to write the simulation program is MATLAB as it is readily available at the University of Cape Town. This software is powerful and flexible and allows the easy implementation of the Monte Carlo simulation. APPENDIX D – Monte Carlo Simulation provides a full description of the sequential and non-sequential Monte Carlo Simulation (MCS) techniques available in literature. While the general theory behind the MCS approach is presented, the step-by-step procedures outline the methodology comprehensively. Several methods are presented for both sequential and non-sequential MCS techniques. The sequential MCS approach is used for reliability and customer interruption costs evaluation and the methods described in APPENDIX D – Monte Carlo Simulation are used as the basis in formulating step-by-step procedures that accommodate different aspects (the different types of load modelling approach) required in the study.

APPENDIX E – Simulation Time Reduction Methods, contains several methods used in reducing the simulation time when using Monte Carlo Simulation (MSC) techniques. However the convergence approach is selected as it is easily implemented in the MSC techniques and also provides an efficient way to get the outputs after a number of iterations, through convergence to their expected values.

Chapter 7

7 SIMULATIONS METHODOLOGY

This chapter focuses on the method to investigate the impact of using the different load models in reliability and customer interruption costs evaluation by implementing different types of load modelling techniques presented in Chapter 5 in a simulation program, using Monte Carlo Simulation techniques in MATLAB. This study compares the results of the beta probability density function used for load modelling in a reliability and CIC evaluation, with results of the other approaches discussed in earlier.

7.1 Initial Assumptions and Considerations

To increase the accuracy of a reliability or CIC evaluation of a power system, several aspects have to be considered such as, activity factors, the time the failure event occurs, seasonal factors, etc. Additionally, the Beta PDF is chosen to fit the real load behaviour based on a study by Herman & Kritzinger, (1993), whereby a total of eight different describing functions (probability distribution functions) were fitted to domestic electrical load currents. In each case, the goodness-of-fit were analysed using chi-squared (X^2) and the Kolmogorov-Smirnov (K-S) tests (Herman & Kritzinger, 1993).

A similar study, where eight probability distribution functions are fitted to real load data, is performed. These ‘goodness-of-fit’ tests are carried out on real load data for residential customers using the Kolmogorov-Smirnov (K-S) and Anderson-Darling tests. Table 7-1 and Figure 7-1 below show the characteristics of the eight describing functions that are fitted to the real load data and their distributions respectively. In both ‘goodness-of-fit’ tests, the Beta function is situated in the middle of the group, ranked at number 4 (Anderson-Darling) and 3 (Kolmogorov-Smirnov) out of the 8 probability distribution functions.

Table 7-1: Describing function characteristics

	Distribution parameters	Anderson-Darling	Rank	Kolmogorov-Smirnov	Rank
Lognormal	σ = 1.8921 μ = -2.6556	1.28254	1	0.14751	1
Weibull	α = 0.58098 β = 0.16525	2.0472	3	0.18527	2
Beta	α = 0.20624 β = 1.2605	5.7425	4	0.18565	3
Gamma	α = 0.37312 β = 0.88387	1.9706	2	0.20186	5
Kumaraswamy	α1 = 0.28491 α2 = 1.5021 a = 0.0004 b = 3.9568	5.7472	5	0.19417	4
Exponential	λ = 3.0323	16.533	6	0.44073	6
Pert	m = 0.00401 a = 0.004 b = 3.0192	30.307	7	0.51752	7
Rice	v = 4.1534E-5 σ =0.44363	84.524	8	0.61843	8

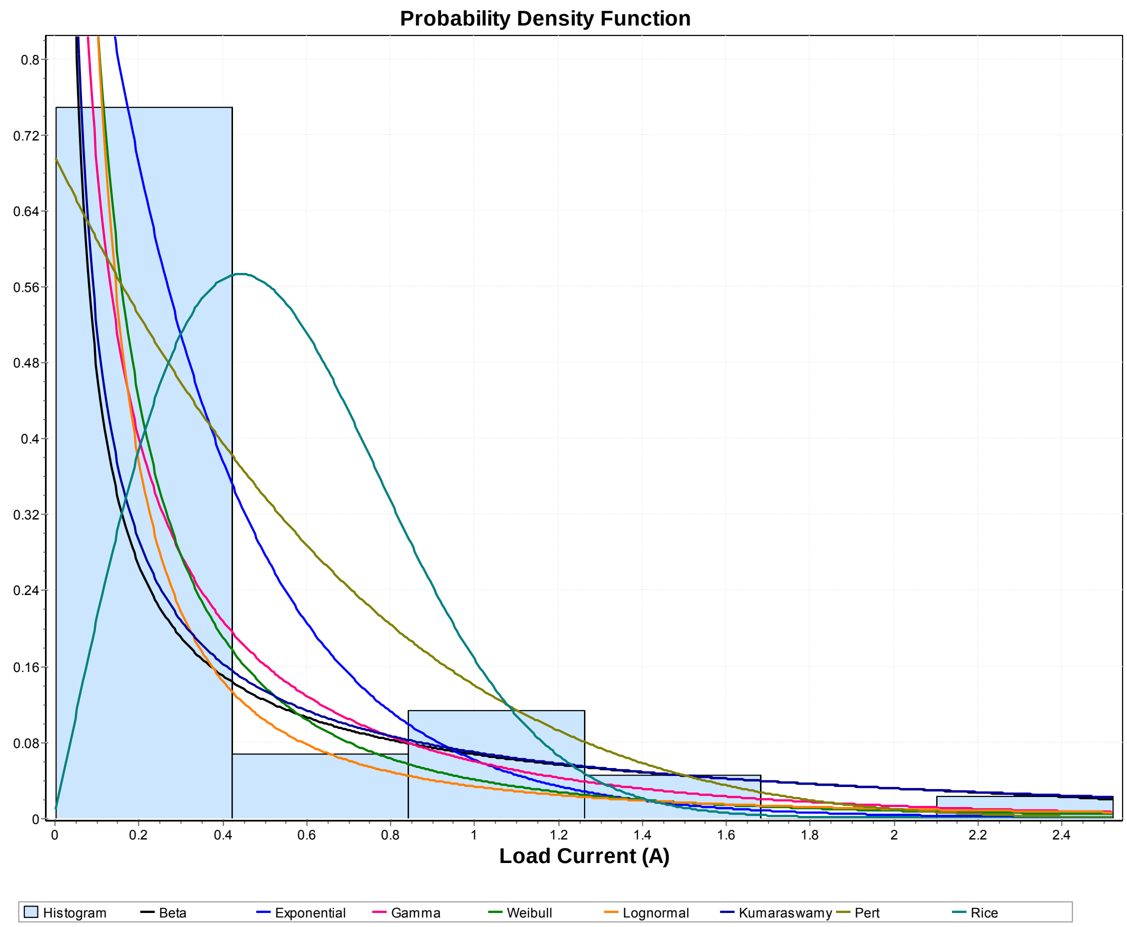


Figure 7-1: Probability distribution functions for the best four distributions fitted to the real load data.

In this particular study, the shape of the distribution/skewness of the load data used is very different to that of the results obtained in (Herman & Kritzinger, 1993) and (Cross, et al., June 2006). However these results suggest that the Beta function can be adequately fitted to these real load data and based on their findings, Herman & Kritzinger, (1993), explain that the Beta function is regarded as the most suitable for the following reasons:

1) It is clear that domestic electrical loads cannot be negative and cannot exceed the circuit breaker rated tripping current. Therefore the required distribution function should be bounded by zero minimum and a particular maximum value.

2) As the upper bound is reduced by the circuit breaker size, the distribution shape is altered and it can be either positively or negatively skewed. Only the Beta function can approximate this characteristic and is also has one of the best goodness-of-fit.

When looking at real load data which vary with of number of different distributions, the Beta function is the most suitable to fit the real load behaviour. This study is also supported by the results obtained from Cross, et al, (June 2006), in a preliminary investigation into the usefulness of the beta PDF in the context of reliability modelling in power systems.For the purpose of this study, several assumptions have to be considered and defined in the analysis. The following assumptions were made for Bus 3 of the RBTS for this work:

1) Bus-bars and circuit breakers are assumed to be 100 % reliable.
2) Feeders 1 and 2, 3 and 4, 5 and 6 and finally 7 and 8 are connected by normally open switches.
3) It is assumed that there are no back-up distribution 11/0.415 kV transformers, and therefore only the time to repair each failed transformer is taken into consideration (200 hours).
4) Reliability and cost models are modelled as average values. The study looks at whether there is any impact on the reliability or CIC assessment when modelling the load using different approaches. All of the other conditions (failure rates, customer damage functions, etc.) are left unchanged in each case while the load model is varied.
5) In the case of reconfiguration, once a faulted section is isolated, there is enough feeder tie capacity to serve the remaining sections for the sufficient spare capacity reconfiguration scheme, whereas an limited spare capacity reconfiguration scheme sets the available spare capacity to supply interrupted adjacent feeders to the average load of adjacent feeders.
6) Load growth (load forecasting) is taken into consideration and the results are shown as a separate study.
7) When simulating for random occurrences (e.g. time of occurrence), a uniform distribution is used to generate simulated values.

7.2 Test System Analysis

The test system used for this research is Bus 3 of the Roy Billinton Test System (Billinton & Jonnavithula, 1996), which is adequate to conduct overall system reliability at the distribution level. Only Bus 3 of the RBTS is used for this study and is shown in Figure 7-2.

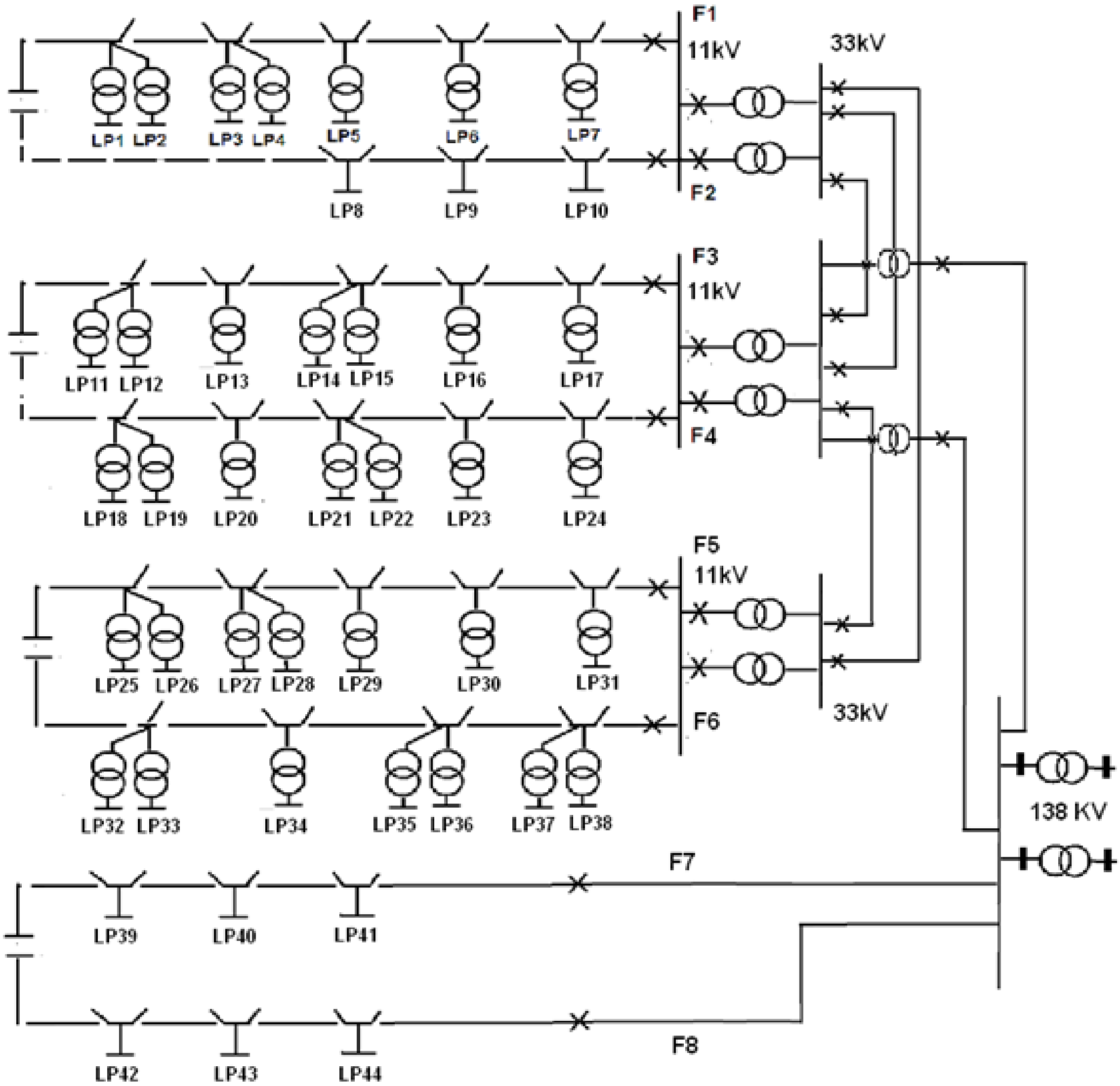


Figure 7-2: Bus 3 of the Roy Billinton Test System

The test system is thoroughly described in (Billinton & Jonnavithula, 1996) while additional data is available in (Allan, et al., 1991). The load and customer data available for the RBTS is used in the validation model (average load model), while the load and customer data (NRS, 1995-2006) used for the other approaches are normalized to that of the RBTS to obtain a suitable basis for comparison. Bus 3 consists of 44 load points and 8 feeders. Feeders 1 and 2, 3 and 4, 5 and 6 and finally 7 and 8 are connected by normally open switches. Therefore for any failure of one of the component in either of the feeder pair, the other feeder can supply the load points in the one which sustained the outage, hence causing that feeder to suffer interruption durations due to switching actions, which are much shorter than durations due to repairs. The load points in Bus 3 consist of residential and commercial customers as shown in Table 7-2.

Table 7-2 Description of Residential and Commercial Customers for Bus 3

Type of Customers	Load Points
Residential	1-7, 11-17, 18-24, 25-31, 32-38
Commercial	8-10, 39-41, 42-44

7.3 Calculating Load Point and System Reliability Indices

In the reliability analysis using a Monte Carlo Simulation technique, the operating and restoration histories of all components and load points are stored during the simulation and are used for the calculation of averages and distributions of the load point indices. The basic load point indices include the average annual failure rate, λ (failures/year), the average outage duration, r (hours/failure), and the average annual outage time or unavailability, U (hours/year) (Billinton & Allan, 1996; Brown, 2009):

In this study, the load point indices λ (failures/year), r (hours/failure), and U (hours/year) are calculated in the simulation in the following way:

$$\lambda_i = \frac{\sum_{j=1}^{n} F_{i,j}}{n} \ldots\ldots\ldots (7.1)$$

$$r_i = \frac{\sum_{j=1}^{n} R_{i,j}}{n} \ldots\ldots\ldots (7.2)$$

$$U_i = \frac{r_i}{\lambda_i} \ldots\ldots\ldots (7.3)$$

n = the total number of simulation years (n = 1000),

$\sum_{j=1}^{n} F_{i,j}$ = the total number of failures for load point *i* during all simulation years, n,

$\sum_{j=1}^{n} R_{i,j}$ = the total restoration times (repair or switching) for load point *i* during all simulation years, n,

The system indices are then estimated for each load point in the system and for the overall system using the following indices:

$$SAIFI = \frac{\sum \lambda_i \times Cust_i}{Cust_T} \ldots\ldots\ldots (7.4)$$

$$SAIDI = \frac{\sum r_i \times Cust_i}{Cust_T} \ldots\ldots\ldots (7.5)$$

$$EENS_i = \frac{\sum_{n=1}^{N} ENS_{i,n}}{N} \ldots\ldots\ldots (7.6)$$

$$ECOST_i = \frac{\sum_{n=1}^{N} COST_{i,n}}{N} \ldots\ldots\ldots (7.7)$$

$$IEAR_i = \frac{ECOST_i}{EENS_i} \ldots\ldots\ldots (7.8)$$

where,

$N = Number\ of\ simulation\ periods$

$Cust_i$ = the number of customers at load point *i*.

$Cust_T$ = the total number of customers in the system.

$SAIFI$ = the system average interruption frequency index

$SAIDI$ = the system average interruption duration index

$EENS_i$ = the expected energy no supplied for load point *i*.

$ECOST_i$ = the expected cost of interruption for load point *i*.

$IEAR_i$ = the interrupted energy assessment rate for load point *i*.

The system ECOST, EENS and IEAR can be obtained through the addition of the individual load point parameters.

N.B.: The energy not supplied is calculated by multiplying the load current data by the respective voltages and the outage duration incurred during an interruption. The cost of interruption is calculated by the product of the energy not supplied and the cost per kWh for specific outage durations obtained from customer damage functions.

7.4 Validation Model

The first step in validating the model is to check whether the simulation program is working as required. Therefore, the load, customer and reliability data used in the work by Allan et al., (1991), and Billinton & Jonnavithula, (1996), are implemented using the simulation procedure for the average load model as a simulation program and the reliability results are compared to that obtained in the authors' works. On validating the model through comparison of the simulated results to those provided in literature, the other load modelling approaches are then modelled using the same information and basic processes.

Note that in order to obtain a comprehensive study on the impact of varying the load modelling techniques in a reliability or CIC evaluation, the historical load data (NRS, 1995-2006) is normalized to that of the average values provided in the work by Billinton & Jonnavithula, (1996). Hence, any change in the results, will show the impact of varying the load model and will not be due to the use of different load information.

7.5 Reconfiguration and System Loading

The reliability of a power system is a function of system loading. This is particularly true for measures of interruption duration such as SAIDI or CAIDI (Brown, 2009). This study also considers the effect of reconfiguration and system loading on the reliability indices such as SAIDI. Based on the available capacity to supply adjacent load points, feeders which are connected, for example, by normally open switches, have an effect on the reliability assessment of these load points. For instance, given a fixed allowable spare capacity available on adjacent feeders during a power outage, over time the load demand tend to increase. Therefore the increased system loading, in this case, may reduce the reliability index performance (e.g. SAIDI). The results of the effect of system loading on reliability indices such as SAIDI, when fixed spare capacity is available to supply an adjacent feeder, is provided in Chapter 8.

7.6 Simulation Procedures and Flowcharts

The simulation procedure for each model used in the case studies is explained in the following sections. The procedure for the average load model is used as the base for the procedures for the other load models. In addition simulation flowcharts are also provided to illustrate the process which occurs in the program written in MATLAB.

7.6.1 Simulation Procedure for the Average Load Model

The basic simulation procedure for the load models developed follows the step by step procedure in (Billinton & Wang, 1999) using the sequential Monte Carlo simulation approach. Some of the steps are adapted to each load model and additional steps are included in some of the load models to accommodate for other information and conditions required in each approach.

Step 1 Generate a random number for each component in the system and convert these random numbers into time to failure (TTF) using the appropriate component failure probability distributions. The TTF is assumed to be exponentially distributed.

Step 2 Repeat step 1 for the desired simulation years. Simulation years, *n,* must be in the appropriate range to capture the outage events considered.

Step 3 Consider the components and obtain the load points affected by their failure using FMEA.

Step 4 If the TTF conditions are met, cumulate the number of failures for n years, and determine the outage duration and interruption costs and cumulate these parameters for n years respectively.

Step 5 Find the load point indices and system performance indices.

Step 6 Repeat steps 1-6 for the desired number of simulated period, *N*.

Step 7 If the stopping criterion is met, interrupt the procedure and find the load point and/or system simulation results for 1 simulation period using the number of simulation periods that occurred until the stopping criterion is triggered.

The simulation flowchart for the average load model is shown in Figure 7-3.

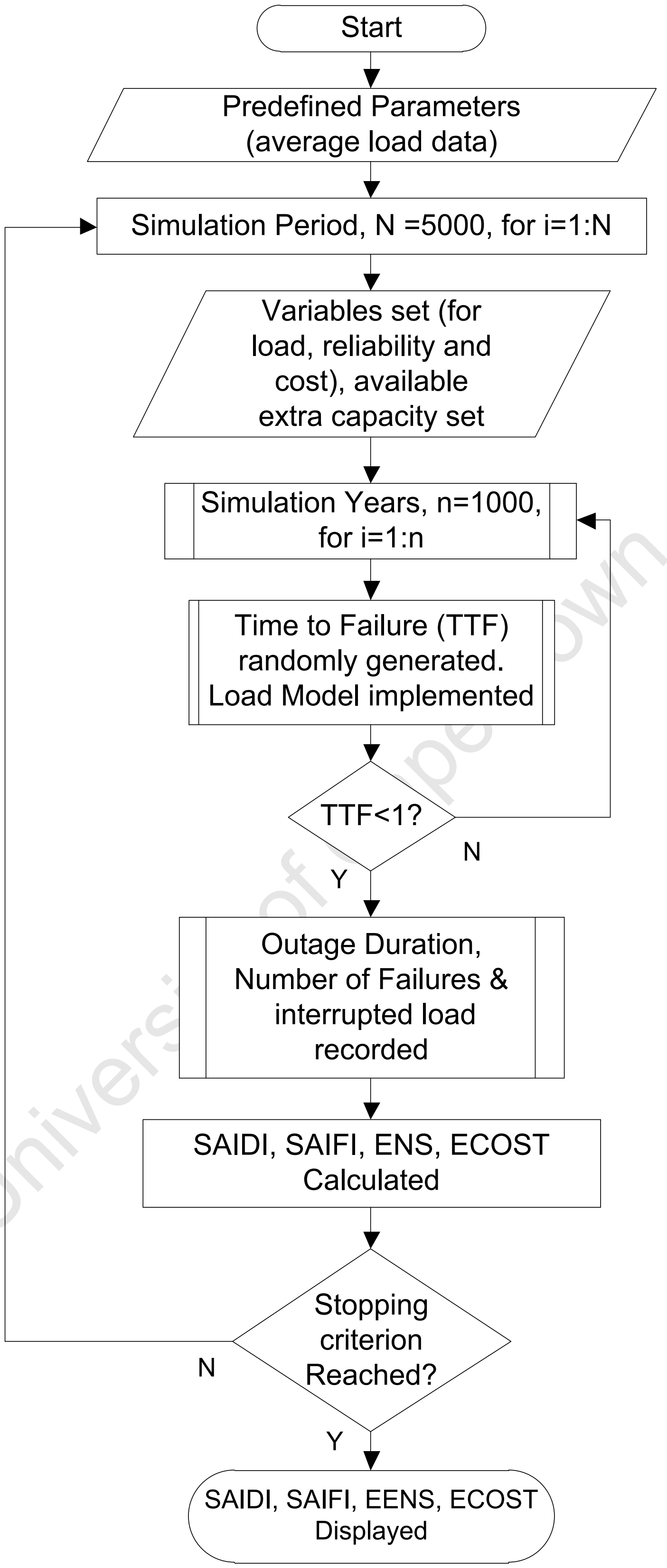


Figure 7-3: Simulation flowchart for the average load model.

7.6.2 Simulation Procedure for the Time Varying Load Model

The time varying load model incorporates one extra step where the time of occurrence of the failure is taken into consideration and determines the interrupted load at a particular load point.

Step 1 Generate a random number for each component in the system and convert these random numbers into time to failure (TTF) using the appropriate component failure probability distributions. The TTF is assumed to be exponentially distributed.

Step 2 Repeat step 1 for the desired simulation years. Simulation years, *n,* must be in the appropriate range to capture the outage events considered.

Step 3 Consider the components and obtain the load points affected by their failure using FMEA.

Step 4 Consider the time of occurrence of the failure, t, using a uniform distribution. The interrupted load at time, t, for a particular load point is used for calculation purposes.

Step 5 If the TTF conditions are met, cumulate the number of failures for n years, and determine the outage duration and interruption costs and cumulate these parameters for n years respectively.

Step 6 Find the load point indices and system performance indices.

Step 7 Repeat steps 1-6 for the desired number of simulated period, *N*.

Step 8 If the stopping criterion is met, interrupt the procedure and find the load point and/or system simulation results for 1 simulation period using the number of simulation periods that occurred until the stopping criterion is triggered.

The additional variable, t, is introduced in the flowchart as shown in Figure 7-4.

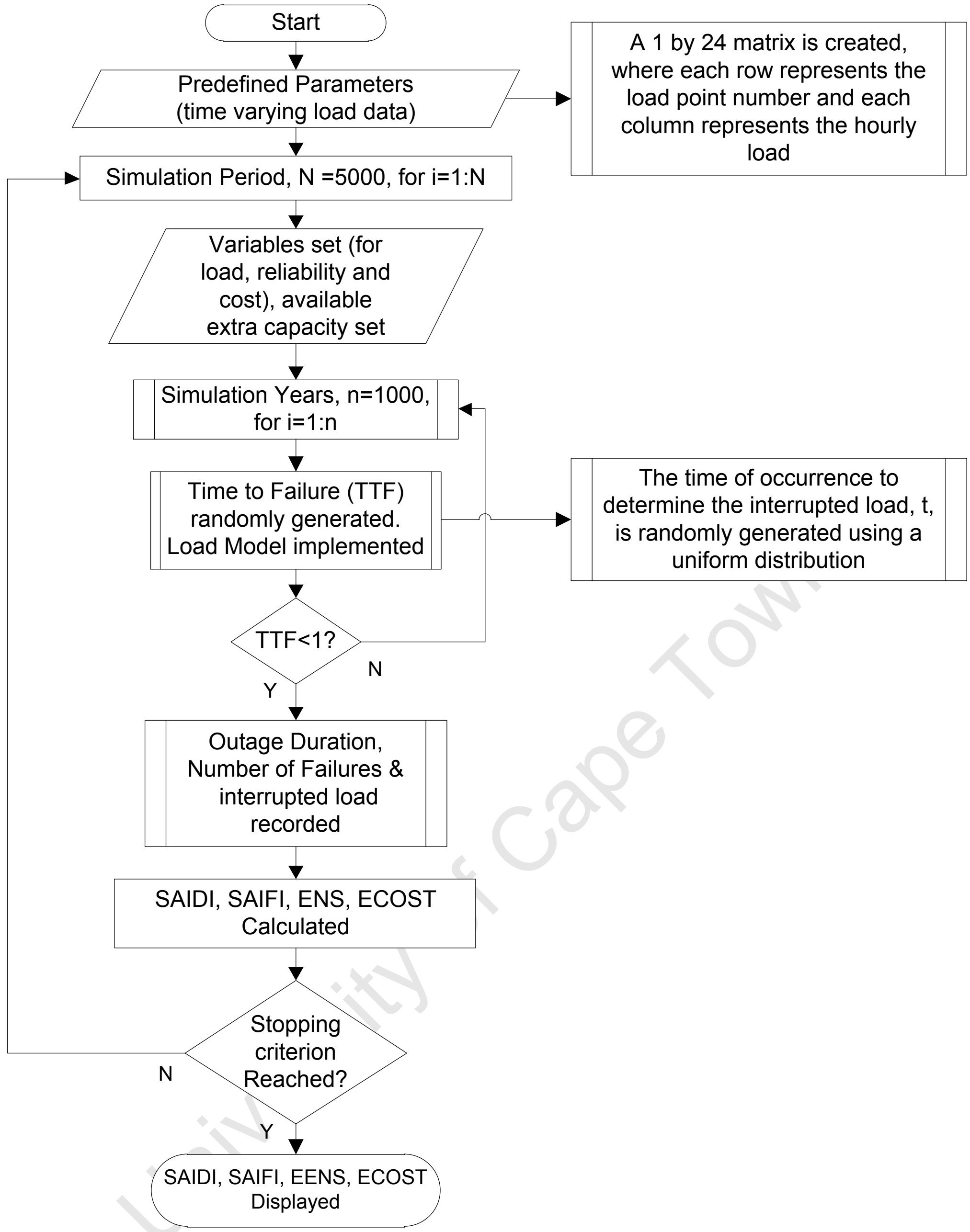


Figure 7-4: Simulation flowchart for the time varying load model.

7.6.3 Simulation Procedure for the Step Probabilistic Load Model

The step probabilistic load model is implemented in the simulation software using the same basic procedure as for the average load model, however the load is modelled differently as shown in Chapter 3. A uniform distribution is used to randomly generate where the interruption falls in the different load intervals. This procedure is valid for both variation of this method, that is, when having equispaced percentage load intervals and equispaced duration (which is used to calculate the probability of occurrence, hence equal probabilities).

The modified flowchart for the two version of the step probabilistic load model is shown in Figure 7-5.

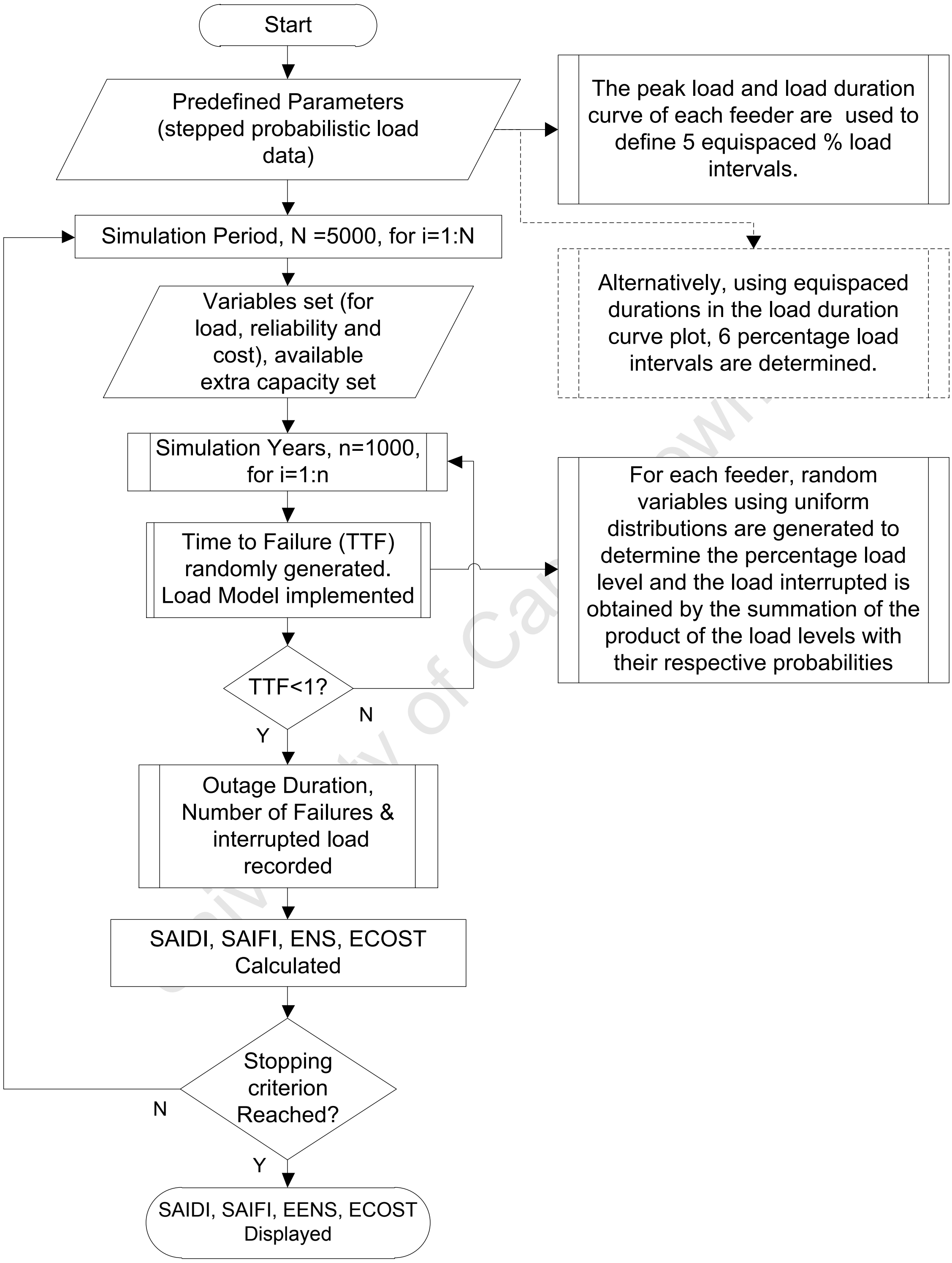


Figure 7-5: Simulation flowchart for the step probabilistic load model.

7.6.4 Simulation Procedure for the Beta PDF Load Model

The procedure for implementing the beta PDF load model is similar to that of the time varying load, except in the way the load is modelled and a few other variables.

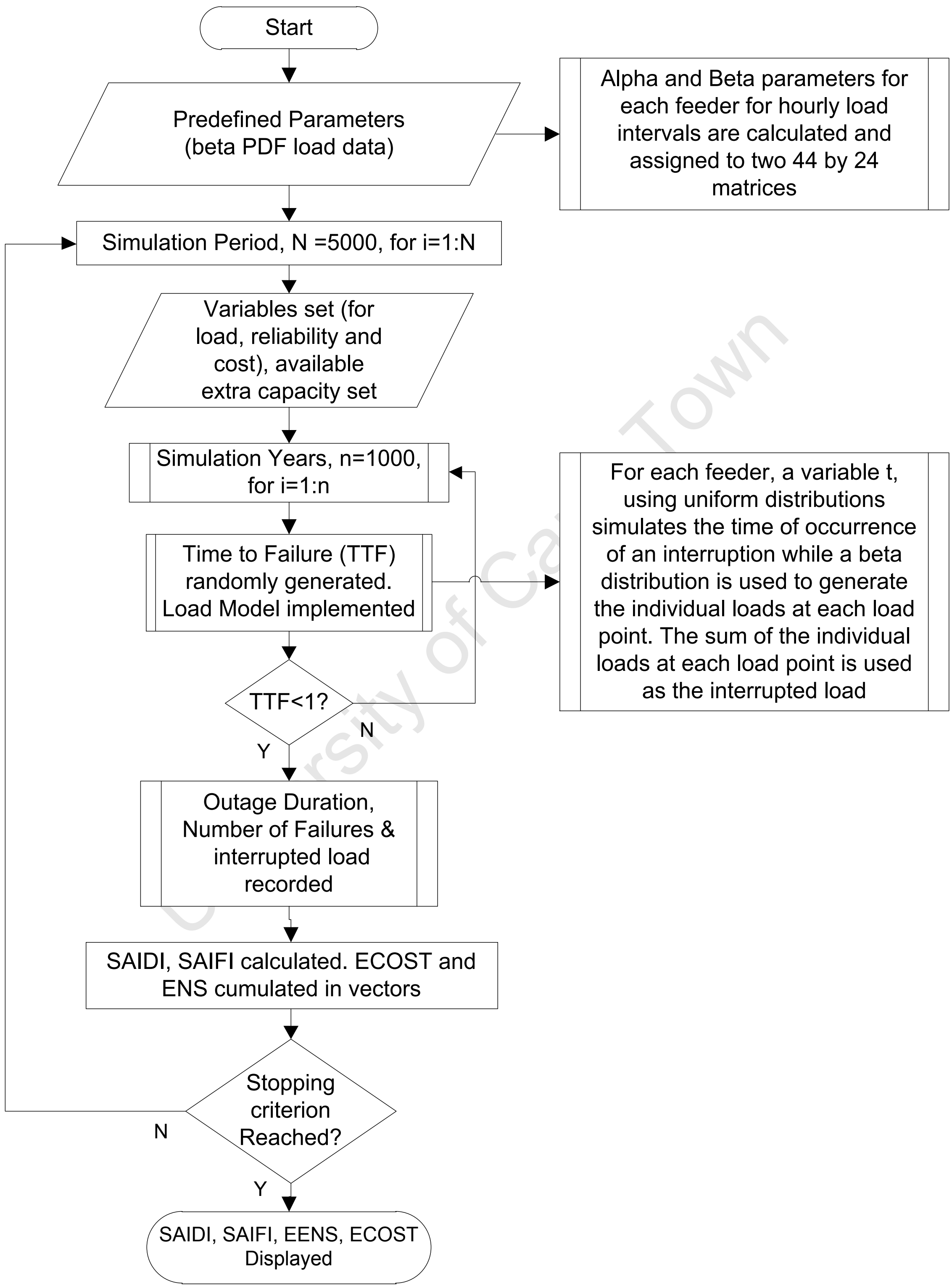


Figure 7-6: Simulation flowchart for the beta PDF load model.

While the time of the interruption is simulated by using a uniform distribution, the individual customer loads at each load point are generated by using a beta distribution from the alpha and beta parameters obtained at the time of the interruption. Then the interrupted load at a particular load point can be calculated by summing the individual loads generated in the simulation. The simulation flowchart for the beta PDF load model is shown in Figure 7-6.

7.7 Case Studies Description (Existing Models)

The case studies are defined in this section and the particulars are also described. Several case studies are set to investigate the impacts of using different types of load models in reliability and customer interruption costs evaluation. Other aspects of the effect of load on reliability assessments are also investigated, such as using reconfiguration and the consideration of load forecasting or load growth in the system.

7.7.1 Base Case: Average Load Model (Validation Model)

The base case study is also the validation model using the test system in the study by Billinton & Jonnavithula, (1996).

Reliability data: The reliability data used are the average values available in the work by Allan et al., (1991), and Billinton & Jonnavithula, (1996).

Costs data: The costs data used are the customer damage functions for commercial and residential customers obtained from the work by Dzobo et al., (2009).

Load data: The load data used are the average values obtained from the work by Billinton & Jonnavithula, (1996).

7.7.2 Case 1a: Time Varying Load Model

Case 1a consists of customer load that varies at hourly intervals. The loads data obtained from NRS load research group, (1995-2006), are used to generate load profiles which are then used to get the hourly loads for 24 hours duration. The load data are first normalized to that of the load information in the work by Billinton & Jonnavithula, (1996), so that only the impact of variation of load is the subject of the investigation. This also offers comprehensive comparison to already available results (Billinton & Jonnavithula, 1996).

Reliability data: The reliability data for case 1 is similar to the base case.

Costs data: Similar to the base case.

Load data: The load data used are the hourly average loads in a 24 hour load profile for each load point generated from the loads data (NRS, 1995-2006)

7.7.3 Case 1b: Time Varying Load Model

Case 1b is similar to case 1a, except for the load which is modelled using randomly generated load at 5 min intervals.

7.7.4 Case 2a: Step Probabilistic Load Model (5 steps y-axis)

Case 2 is based on another version of the step probabilistic load model with equidistant (equispaced) percentage load intervals of load duration curves at each load point. The corresponding durations are found for each percentage load intervals. The probability of occurrence is calculated by dividing the duration by the total number of hours in the load duration curve. Therefore each percentage load intervals has a varying probability. A uniform distribution is generated in the simulation to obtain the percentage load level of the peak that is interrupted for each probability value associated with it equidistant load interval.

Reliability data: Similar to the base case.

Costs data: Similar to the base case.

Load data: The load data used are percentage load intervals of the peak found for each of the probability values which are calculated by using the duration axis. A uniform distribution is used to randomly generate the percentage load levels of the peak load and the load interrupted is the sum of the individual products of each probability by their corresponding load levels. In this case the probability values are different while their corresponding percentage load intervals of the peak are similar to each other (equidistant).

7.7.5 Case 2b: Step Probabilistic Load Model (25 steps y-axis)

Case 2b is similar to case 2a, except for the number of steps used. In case 2b, a 25 steps load model is used instead of 5 steps.

7.8 Case Studies Description (Proposed Models)

The proposed load models are based on modified versions of existing load modelling techniques.

7.8.1 Case 3a: Step Probabilistic Load Model (6 steps x-axis)

Case 3a is based on a step probabilistic load model with equidistant (equispaced) duration of load duration curves at each load point. The probability of occurrence is calculated by dividing the duration by the total number of hours in the load duration curve. The corresponding percentage load intervals are found for each probability. Therefore each probability has a varying percentage load intervals. A uniform distribution is generated in the simulation to obtain the percentage load level of the peak that is interrupted for each probability.

Reliability data: Similar to the base case.

Costs data: Similar to the base case.

Load data: The load data used are percentage load intervals of the peak found for each of the probability values which are calculated by using the duration axis. A uniform distribution is used to randomly generate the percentage load levels of the peak load and the load interrupted is the sum of the individual products of each probability by their corresponding load levels. In this case the probabilities are of equal values while their corresponding percentage load intervals of the peak vary from each other.

7.8.2 Case 3b: Step Probabilistic Load Model (24 steps x-axis)

Case 3b is similar to case 3a, except for the number of steps used. In case 3b, a 24 steps load model is used instead of 6 steps.

7.8.3 Case 4a: Time dependent Beta PDF Load Model (1 hour Interval)

In case 4, the time dependent beta probability distribution function (PDF) load model is implemented in the simulation software as the load modelling approach. Historical data based on South African loads (NRS, 1995-2006) are applied to each of the load points in the test system. The alpha and beta parameters of the customer loads distribution are calculated for hourly intervals at each load point for 24 hour duration. Therefore a 44 (load points) by 24 (hours) matrix is obtained for alpha values and another is obtained for beta values for the test system. This approach incorporates both variation with time and the variation of customer load from one individual to another.

Reliability data: Similar to the base case.

Costs data: Similar to the base case.

Load data: The alpha and beta parameters are used to generate random interrupted loads when the time of interruption is determined using a uniform distribution. The interrupted loads at a particular load point is simulated using the beta distribution by taking the alpha and beta parameters at the time of interruption, obtained from the historical load data. Therefore, the proposed load modelling approach takes into consideration, both the time of interruption, as well as the distribution of the individual customer loads at a load point, at the time of the interruption. Then the sum of the individual loads is equal to the total interrupted load at the load point at a specific time of interruption.

7.8.4 Case 4b: Time Dependent Beta PDF Load Model (5 Min Interval)

Case 4b is similar to case 4a, except for the load which is modelled by using the alpha and beta parameters calculated at 5 min intervals.

7.9 Case 5: Effects of Implementing Reconfiguration and System Loading (Load Growth)

Case 5 investigates the effect of reconfiguration and system loading on reliability indices such as SAIDI (system average interruption duration index). Therefore the load data can be modelled as any of the approaches described in this work. Hence the impact of using the different types of load modelling techniques on the reliability indices such as SAIDI can be illustrated.

Reliability data: Similar to the base case.

Costs data: Similar to the base case.

Load data: For case 5, the different types of load modelling approaches are used to illustrate the effect of each model on the reliability indices such as SAIDI, when reconfiguration and system loading are taken into consideration.

Chapter 8

8 SIMULATION RESULTS & DISCUSSION

This chapter presents the simulation results of different case studies which have been set to investigate the effect of using different types of load modelling techniques on the reliability and CIC evaluation of a power distribution test system. The results are illustrated using tables and graphical representations of the output of the simulations performed in MATLAB and their significance in the context of reliability or CIC evaluation are discussed.

8.1 Base Case: Validation Model (Average Load)

The radial distribution system indices shown in the work by Billinton & Jonnavithula, (1996), for Bus 3 of the RBTS are compared to those obtained from the simulation results. The system indices including SAIFI, SAIDI and EENS, as described in APPENDIX A.1, are shown below.

Table 8-1: Comparison of system indices between expected results (Billinton & Jonnavithula, 1996) and simulated results

Index	Expected Results	Simulated Results	% Difference
SAIFI (fr/syst.cust)	0.3027	0.2963	-2.1143
SAIDI (hr/syst.cust)	3.4726	3.4567	-0.4579
EENS (MWh/yr)	66.6802	66.3569	-0.4848

The results in Table 8-1 above show good consistency between the expected and simulated results. The validation model is simulated to mimic the conditions used to obtain the results in the work by Billinton & Jonnavithula, (1996). Additionally the ECOST in Rand was calculated using a customer damage function as shown in APPENDIX C and the result obtained using the average load model shows that the system suffers an annual average interruption cost of R 5,707,200. It is also important to note that the reconfiguration scheme was assumed such that the alternate feeders, which are connected by normally open switches, are able to fully supply adjacent disconnected feeders at any time. The validation model serves as the base case and as a comparative test with the other load modelling approaches. Any noticeable change in the values of the indices (e.g. EENS) may then be attributed solely to the approach used to represent the load model.

8.2 Cases 1 - 4: Results for System Reliability and Cost Indices (Reconfiguration Scheme with Sufficient Spare Capacity)

Table 8-2 below shows the reliability and the interruption costs results obtained from simulations run in MATLAB using a reconfiguration scheme with sufficient spare capacity, their impact on a reliability and CIC evaluation for a power distribution test system (RBTS) are investigated. The sufficient spare capacity reconfiguration scheme in this study relates to the ability of adjacent feeders to fully supply all the interrupted load points. In other words alternate feeders, close to the feeders suffering an interruption, have enough spare capacity to supply all the interrupted load points.

Therefore all the interrupted load points only suffer a switching time (1 hour), when a fault occurs for components along the main section of each feeder, which improves the SAIDI of the system. It is important to note that a component failure occurring on any lateral section of the feeders will cause the load points on that lateral section to suffer a repair time. For example, if a distribution transformer connected to a load point fails, the customers suffer a repair time irrespective of the reconfiguration scheme and this worsens the SAIDI of the system.

Small variations are seen in the values of SAIFI and SAIDI when comparing the results for each load model with others. These results are further discussed in section 8.2.1. The expected energy not supplied, EENS (MWh/year), and the expected interruption costs, ECOST (Rand/year), vary from one load model to another.

Table 8-2: Results for the reliability and cost indices of the case studies at the reconfiguration scheme with sufficient spare capacity

Case	Load Model	SAIFI (fr/sys.cust)	SAIDI (hr/sys.cust)	EENS (MWh/year)			ECOST (Rand/year) x 10^6		
Base	Average	0.2963	3.4567	66.364			5.707		
1a	Time Varying (Hourly Interval)	0.3069	3.5373	68.297			5.877		
1b	Time Varying (5 min Interval)	0.3065	3.535	59.373			5.061		
2a	5 Steps (y-axis)	0.2971	3.5214	83.940			7.219		
2b	25 Steps (y-axis)	0.2967	3.5247	69.115			5.946		
3a	6 Steps (x-axis)	0.3039	3.5329	69.529			5.997		
3b	24 Steps (x-axis)	0.2958	3.5444	66.473			5.718		
4a	Beta PDF (Hourly Interval)	0.3040	3.44	72.062 (mean)			6.133 (mean)		
				25 % Risk	**20 % Risk**	**15% Risk**	**25 % Risk**	**20 % Risk**	**15% Risk**
				58.12	87.06	129.35	4.312	6.843	10.761
				10 % Risk	**5 % Risk**	**1 % Risk**	**10 % Risk**	**5 % Risk**	**1 % Risk**
				193.05	297.63	466.05	17.027	28.060	47.979
4b	Beta PDF (5 min Intervals)	0.3034	3.4326	63.659 (mean)			5.541 (mean)		
				25 % Risk	**20 % Risk**	**15% Risk**	**25 % Risk**	**20 % Risk**	**15% Risk**
				52.32	78.04	115.09	3.971	6.284	9.820
				10 % Risk	**5 % Risk**	**1 % Risk**	**10 % Risk**	**5 % Risk**	**1 % Risk**
				169.54	254.67	378.55	15.343	24.627	39.608

Time Varying Load Models

The introduction of the time variation at average load at hourly intervals in load modelling slightly increases EENS and ECOST compared to the base case. However a significant decrease in both variables is observed when smaller time intervals (5 min) are used in the load model. Since the load recorded at each 5 min intervals are the actual load of the customers, the results therefore suggest that incorporating time variation with shorter time intervals have an impact on the evaluations. In this particular case of mixed residential and commercial customers, the results observed show a noticeable decrease compared to the base load model. Hence introducing time variation in the load modelling approach is seen to affect the results and indicates that the use of average values is not adequate enough and does not portray the information about the level of reliability of the system and the annual costs of interruptions which can be incurred by the customers.

Step Load Models

The results in cases 2a, b and 3a, b gives an insight into the impact of using probability values in load modelling for reliability and CIC evaluation of the test system (RBTS). Cases 2a and 2b are modelled based on the principle of calculating probability values for pre-selected percentage load levels of the peak demand. The probabilities are calculated by dividing the amount of time each load level occurs in the load duration curve by the total duration. Therefore each probability value represents the ratio of each load level in the interrupted load. Cases 2a and 2b are modelled with a finite number of uniform steps along the y-axis (load level) in the load duration curve. The results in case 2a indicate that using only a few steps (5 steps) produces a large increase in the indices while those of case 2b shows that increasing the number of steps (25 steps) produces a smaller increase in the indices. As discussed previously, increasing the number of steps increases the accuracy of representation, and therefore the large inflation in the values of the indices in case 2a can be attributed to this imprecision.

As discussed earlier, cases 3a and 3b are also modelled using the same principle as cases 2a and 2b, except for the axis of the load duration curve in which the uniform steps are chosen. In this case, the pre-selected parameter is the probability and finite number of uniform steps are chosen along the x-axis (duration). Therefore equal probabilities are assigned to each step and the load levels for each probability are determined. The results obtained for cases 3a and 3b show a lower increase in the indices, when compared to the base case, than cases 2a and 2b respectively. However, increasing the number of steps (case2b) along the x-axis (duration) in this study also produces a lower rise in the indices (when compared to the base case). The difference between cases 2a, b and 3a, b can be attributed to the axis of the load duration curve in which the uniform number of steps is chosen. The step load models incorporate the probability of load levels occurring and are modelled from the load duration curve as percentages of the peak load rather than the average load. The results indicate that the indices are affected when uncertainty is introduced in the load representation.

Time Dependent Beta PDF Load Models

The results based on the last load modelling approach proposed in this study provide an insight on the impact of combining both time variation and uncertainty in the load model. Case 4a is modelled using a time dependent beta PDF load and the beta parameters are calculated for the average individual loads at hourly intervals. This means that the average load over each hour is calculated for each individual customer in the load point and the beta parameters are determined from the load distribution of these customers for each hour. The simulations using beta parameters calculated at hourly intervals show an increase in the indices when compared to the base case. However this increase is found in between the results of case 1a (load modelled with time variation) and case 2a (load modelled with probability), which agrees with the trend in implementing the different factors. The results in Table 8-2 first shows the mean values of the EENS and ECOST distributions, followed by the possible values of EENS and ECOST at various risk levels (or conversely, confidence levels).

The results in case 4b indicate a decrease in the indices when the beta parameters are modelled at 5 min intervals. In the different comparisons involving cases 1a and 1b, 2a and 2b, 3a and 3b, and 4a and 4b; the results suggest that some information is lost when the load values are averaged over time and customers. It is important to note that the mean values of EENS and ECOST obtained for cases 4a and 4b are the results of annual energy not supplied and annual costs of interruptions which are calculated similarly to the other simulations of the other load models (annualised indices). However uncertainty is incorporated in the interrupted load at each service point. The randomly generated individual load at each interrupted service point when an interruption event occurs are summed to obtain the total load interrupted. The distribution of EENS and ECOST can also be obtained from the simulation. It is important to note that the distributions are the annual energy not supplied and annual interruption costs that are obtained after simulating for, n, number of years. The annual indices may be zero or the sum of all energy not supplied or interruption costs due to several component failures in a year. Using these distributions, an estimation of the true values of these annual indices can be made with different levels of confidence (or conversely, levels of risks), instead of using the mean of the distributions.

For example, the values of the indices obtained at 95% confidence level (5% risk level) mean that, there is a 95 % confidence that estimate of the true value of the indices is equal to or less than the value obtained at that confidence level or that there is a 5 % risk that the estimate of the true value exceeds the value obtained at that level.

Therefore, based on the type of modelling approach used, different values for the reliability indices are obtained. This suggests that, when planning for power systems, system planners are less likely to make their decisions efficiently when their assumptions are based solely on the average values of the indices. A more efficient way of planning would be to choose the resulting indices in which information such as time and statistical variations are not lost. Additionally, information such as the risk or the confidence levels can be used to make informed decisions by estimating the true values of the indices. Therefore the annual energy not supplied and the annual cost of interruptions can be obtained with a degree of confidence or conversely a degree of risk which can be used for comprehensive decision-making.

Table 8-3: Comparison of the reliability indices of cases 1 – 4 with the base case (average load) with sufficient spare capacity reconfiguration.

Indices	Time Varying Load (hourly) (Case 1a)	Time Varying Load (5 min) (Case 1b)	Step (y-axis) Load (5 Steps) (Case 2a)	Step (y-axis) Load (25 Steps) (Case 2b)	Step (x-axis) Load (6 Steps) (Case 3a)	Step (x-axis) Load (24 Steps) (Case 3b)	Beta PDF Load (hourly) (Case 4a)	Beta PDF Load (5 min) (Case 4b)
	% difference	% difference	% difference	% difference	% difference	% difference	% difference	% difference
SAIFI	3.58	3.44	0.27	0.13	2.56	-0.17	2.60	2.40
SAIDI	2.33	2.27	1.87	1.97	2.20	2.54	-0.48	-0.70
EENS	2.91	-10.53	26.48	4.15	4.77	0.16	8.59	-4.08
ECOST	2.97	-11.32	26.49	4.18	5.08	0.20	7.46	-2.91

Table 8-3 above illustrates the percentage difference of each load model compared to the base case for the system reliability and cost indices. This comparison provides an insight on the impact that each load model has on system indices as discussed above when different varying factors such as time variation, probability and uncertainty are implemented. The inclusion of one or more of these factors in the load modelling provide an indication of how sensitive the EENS and ECOST indices are to changes in the load representation as shown in Table 8-3.

8.2.1 SAIDI and SAIFI

Figure 8-1 and Figure 8-2 below illustrate SAIDI and SAIFI values for all the load models at the sufficient spare capacity reconfiguration. SAIDI (hr/sys.cust) and SAIFI (fail/sys.cust) values for all load models are relatively consistent and only have very small deviations. SAIDI is consistent for all load models as simulations are performed such that alternate feeders connected by normally open switches are fully capable of supplying the adjacent interrupted load points. Hence, depending on where the failure occurs, instead of being affected by repair durations (5 hours), interrupted customers may only be affected by a switching duration (1 hour).

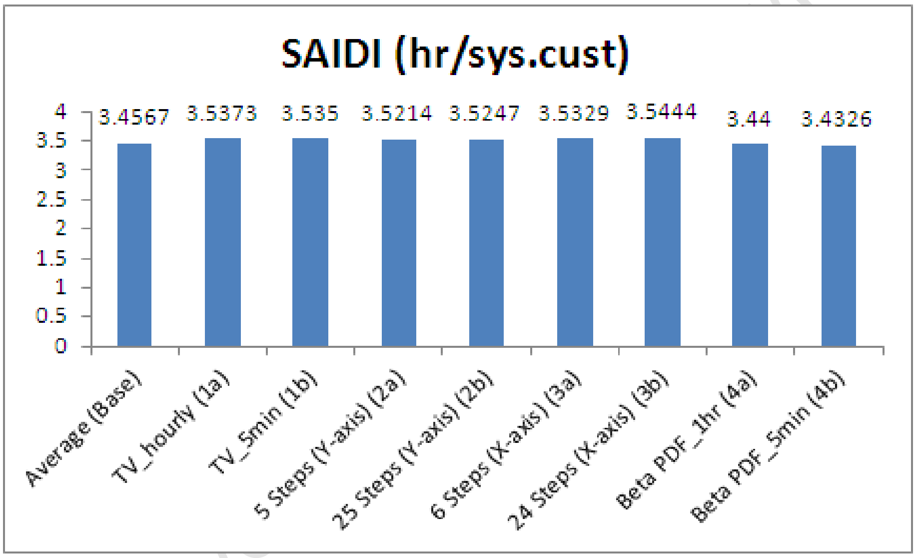


Figure 8-1: SAIDI for the different load models with sufficient spare capacity reconfiguration.

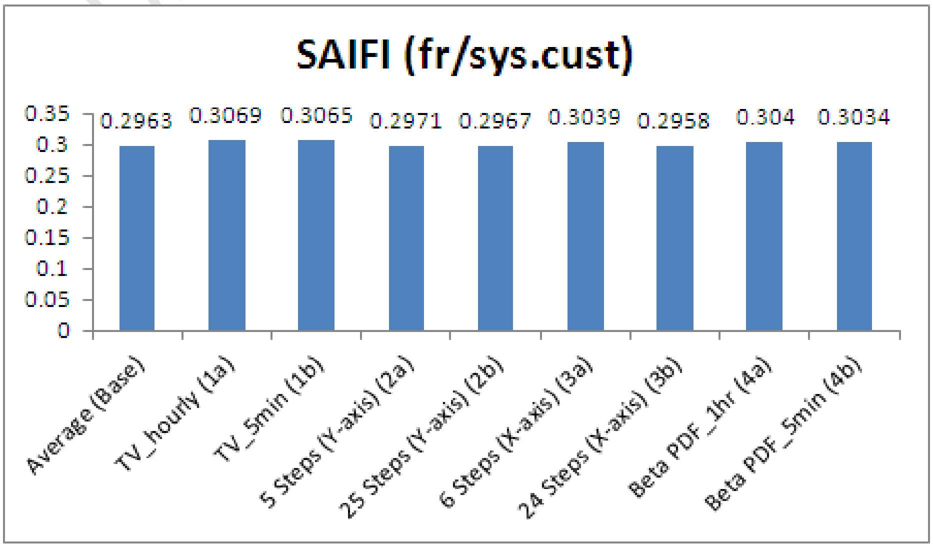


Figure 8-2: SAIFI for the different load models with sufficient spare capacity reconfiguration.

However, SAIDI values will vary if the alternate feeders have a limited spare capacity and cannot supply all the interrupted load points from adjacent feeders. As the interrupted load at a load point is perceived by the way the load is modelled, different load modelling approaches may have an effect on the SAIDI values. Section 8.3 of this chapter provides more insight on the impact of load models on interruption duration indices when using the reconfiguration scheme with limited spare capacity. Furthermore, section 8.4 provides the effect on SAIDI values for different load models, when load growth is taken into consideration with a limited spare capacity reconfiguration (i.e. spare capacity set to the average load of the interrupted feeder).

8.2.2 EENS and ECOST

A comparison of the expected energy not supplied (EENS) and the expected costs of interruption (ECOST) are illustrated in Figure 8-3 and Figure 8-4 respectively between the different load models. The EENS for these load models vary from one another and this can be explained by the way the load in each approach is modelled.

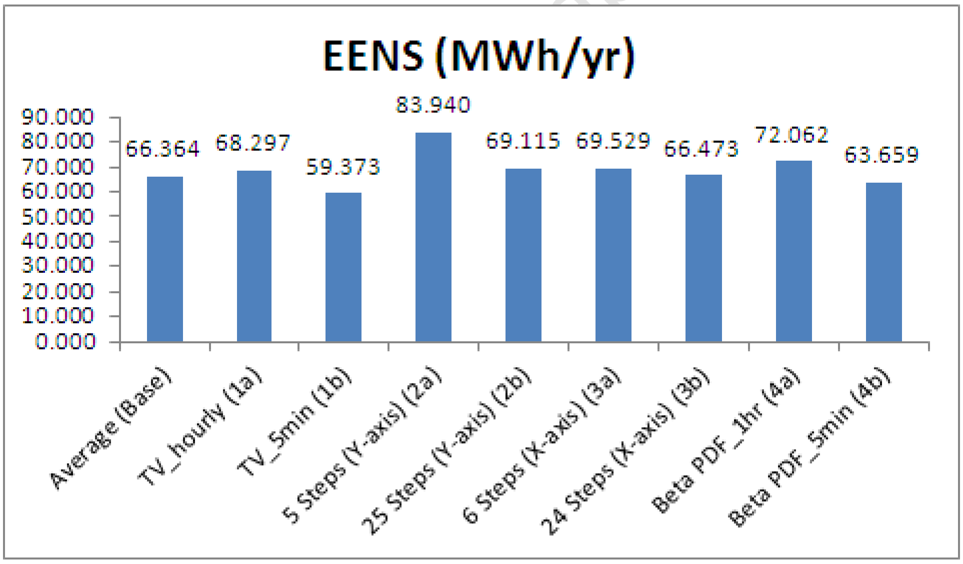


Figure 8-3: EENS for the different load models with sufficient spare capacity reconfiguration.

The time varying load model uses daily load profiles for each load point. The time varying load model is further divided into two. The one that uses the mean load at hourly intervals and the other method is modelled using the actual load (NRS, 1995-2006) recorded at 5 min intervals. A large difference is seen between the two methods, a 13.16 % decrease in EENS is observed when the time interval in the load modelling approach is reduced from 1 hour to 5 min. This shows that while the load at 5 min intervals are the actual load of the customers, averaging the load over hourly intervals overestimates the true value of these indices by a significant amount. This behaviour can also be seen when increasing the number of steps used in load duration curves, for the step (y-axis) and the step (x-axis) load models. Case 3b (step (x-axis) with 24 steps) may be more appropriate to use as it produces results that are closer to case 1b (time varying load at 5 min intervals), which are based on the actual load of the customers when modelled with time variation only. The step load models however indicate that associating a probability to load usage affects the resulting indices.

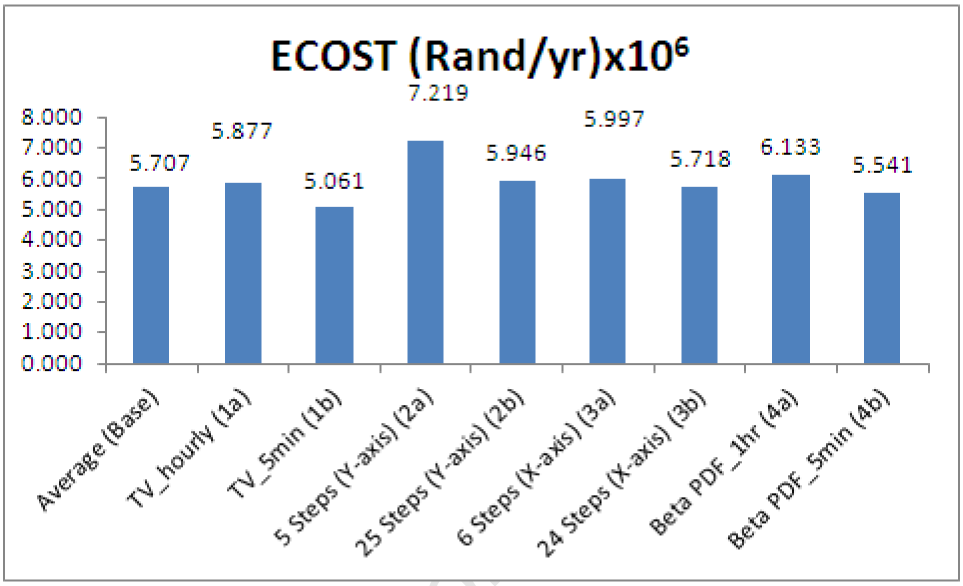


Figure 8-4: ECOST for the different load models with sufficient spare capacity reconfiguration.

A difference can be seen in EENS values when the number of steps are changed, thus shows that increasing the number of steps has an effect on the representation of the load. Jonnavithula, (1997), and Chowdhury & Custer, (2004), have established that increasing the number of steps in the step load model increase the accuracy of representation. Therefore the results obtained in cases 2b and 3b, where the numbers of steps are increased, can be considered more accurate than cases 2a and 3a respectively.

It should be noted that a constant cost model was used throughout the simulations for each load modelling techniques. However it is known from literature that the cost of interruptions also vary with time and therefore using a time varying cost model combined with a time varying load model (chronological) may also have an impact on the ECOST when compared to using a load duration curve (non-chronological) such as in the steps load models.

As both the time variation and the uncertainty in load usage have an impact on the EENS and ECOST results, both parameters are implemented as a time dependent beta PDF load model. Similarly to the time varying load models, the results for the beta PDF load model indicate a significant decrease when the time intervals are reduced from 1 hour to 5 min. But in case 4b (beta PDF at 5 min intervals), the EENS and ECOST values are slightly higher than that of the results in case 1b (time varying at 5 min intervals). This change can be attributed to the uncertainty of the customer loads at different times of the day.

Overall, the load modelling approaches generated indices (EENS and ECOST) with differences of varying degrees when compared to the average load model. When considering the impact that both time variation and the uncertainty in load usage have on the results, the time dependent beta PDF load model may be described as the most accurate of the load models presented in this study. Additionally, the time dependent beta PDF load model provides information such as the skewness of the distributions of EENS and ECOST and the possible values of EENS and ECOST associated with various confidence or risk levels. These additional features are discussed in the next section.

8.2.3 Using Probability Distributions and Percentage Confidence/Risk Levels to Describe Indices (EENS & ECOST)

8.2.3.1 Beta Probability Distributions (EENS & ECOST)

The beta probability distributions of the EENS and ECOST values recorded in the simulations, using the time dependent beta PDF load model at 5 min intervals and a sufficient spare capacity reconfiguration, are represented in Figure 8-5 and Figure 8-6 respectively. The results for the 5 min intervals are used to plot the distributions as it produces the best representation of the actual values of EENS and ECOST compared to the other load modelling approaches as discussed previously.

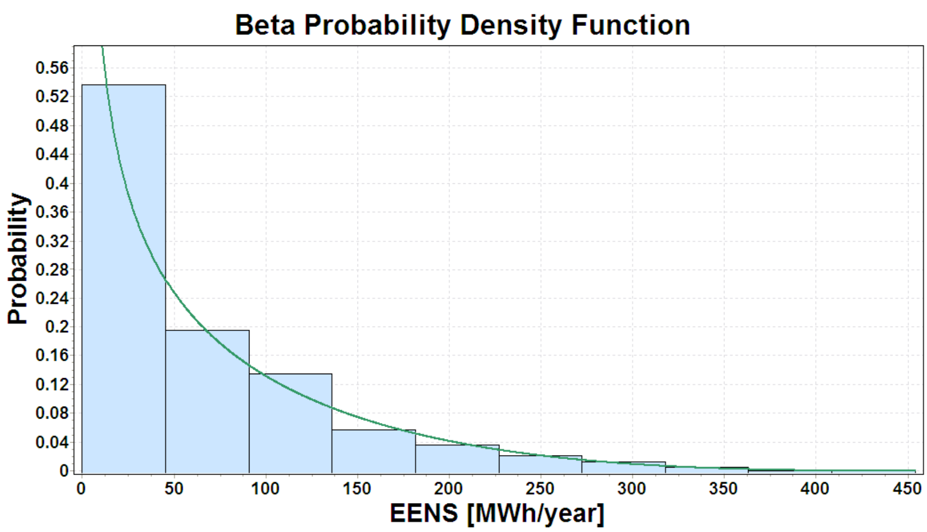


Figure 8-5: Beta probability density function for the annual energy not supplied.

Figure 8-5 above shows that EENS values between 0 and 50 MWh/year have the highest probability of up to about 0.54, followed by values greater than 50 MWh/year with probabilities under 0.2. Although the highest probability of occurrence is in the lower extreme of the distribution, the highest annual energy not supplied with smaller probability of occurrence is in the upper extreme. The two extremes have a large difference in EENS values as they are affected by the number of failures per year and the location of the failures. For example, a component failing along the lateral of a feeder will affect fewer customers than if the failure occurred to a component along the radial line of the feeder. Also the types of customers on the affected feeder have an impact on the results. In this case the majority of the customers are residential while only a few are commercial customers. Therefore, interrupted load of residential customers have a higher probability of occurrence in the distribution, as the system consists of 44 load points of which 35 are residential and 9 are commercial customers.

Figure 8-6 shows that the ECOST values also follow a similar pattern to that of Figure 8-5. Depending on the shape of the beta distributions of EENS and ECOST, which are mostly affected by the types of customers in the system, different information can be extracted and used for the planning and operation of power systems.

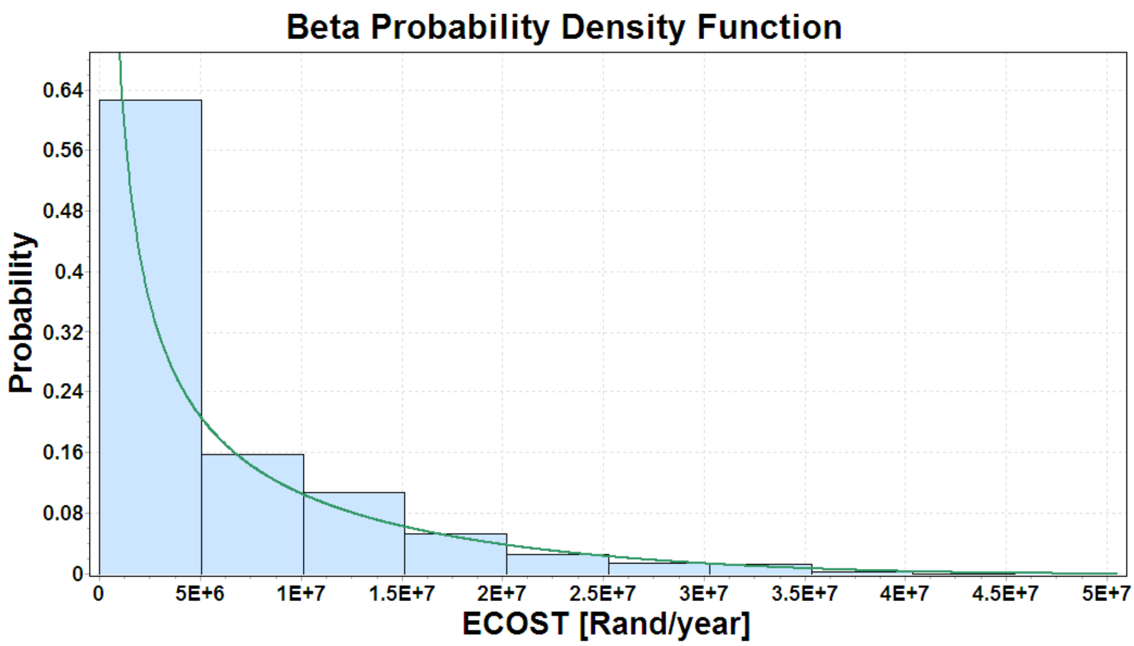


Figure 8-6: Beta probability density function for the annual costs of interruptions.

For example, if the system has mostly commercial and industrial customers with a few residential customers, the beta PDF of the EENS and ECOST can show up as a normal distribution with some negative skewness/skewed to the left (where the left tail is longer, the mass of the distribution is focused on the right on the figure and it has relatively few low values) or positive skewness/skewed to the right (where the right tail is longer, the mass of the distribution is focused on the left of the figure and it has relatively few high values).

This is justified by the load modelling technique used, as the beta PDF is applied to historical load data. If a power distribution system consists of mixed residential and commercial customers, but the overall system's load profile follows that of commercial customers, then the beta parameters calculated from the historical load data would also follow that of the commercial customers. However, in a system consisting of mixed residential and commercial customers and dominated by the former the distributions of the EENS and ECOST indices are positively skewed (mass of distributions are focused to the left of the figures). However as the ratio of commercial customers to residential customers increase, the mass of the distribution shifts towards the left of the figure. The probability distributions provide an idea of the probability that values of EENS and ECOST occur as shown in Figure 8-5 and Figure 8-6 above.

This method of load modelling provides power system planners with a wider range of information to make their decisions on as compared to the other load modelling techniques. This is achieved with the help of the beta PDFs of the EENS and ECOST indices which show how skewed these distributions are and the level of skewness provides information about the shape of their distributions and the probability of their lower and upper limits. Although mean values are useful to represent the whole population of the system, the information about its shape and where the values of EENS and ECOST with the lowest or highest probability of occurrence lies, is lost.

8.2.3.2 Percentage Confidence/Risk Levels (EENS & ECOST)

Figure 8-7 below shows the results of EENS and ECOST at various confidence levels (or conversely risk levels, e.g. at 95 % confidence level carries a 5 % risk) for the beta probability density function load model. While initially the mean values are calculated from the EENS and ECOST distributions and therefore are similar to the approach of other load modelling techniques used in this study, estimates of the true value of these indices can be calculated from the beta PDFs of these indices. Usually the true values of these indices are estimated at 95 % confidence level (i.e. at 5 % risk level), but the estimates for both EENS and ECOST are also calculated for different confidence levels (e.g. 50 %, …, 5 %, 1 %) as shown in Figure 8-7.

For example, at 80 % confidence level (i.e. 20 % risk level), the EENS value is 78.04 MWh/year and the ECOST value is R 6, 840,000/year, which are close to the mean values of the respectively distributions obtained from the simulations. These can be interpreted as having a 80 % confidence (or conversely, 20 % risk) that the value of EENS will be less or equal to 78.04 MWh/year and that the value of ECOST will be less or equal to R 6, 840, 000/year. Other ways to interpret this result is that there is either an 80 % confidence that the EENS and ECOST will not exceed 78.04 MWh/year and R6, 840, 000/year respectively or that EENS and ECOST have a 20 % risk of exceeding 78.04 MWh/year and R6, 840, 000/year respectively. The higher the level of confidence (or the lower the level of risk), the more likely the whole range of EENS and ECOST occurring annually in the system is included in the estimate.

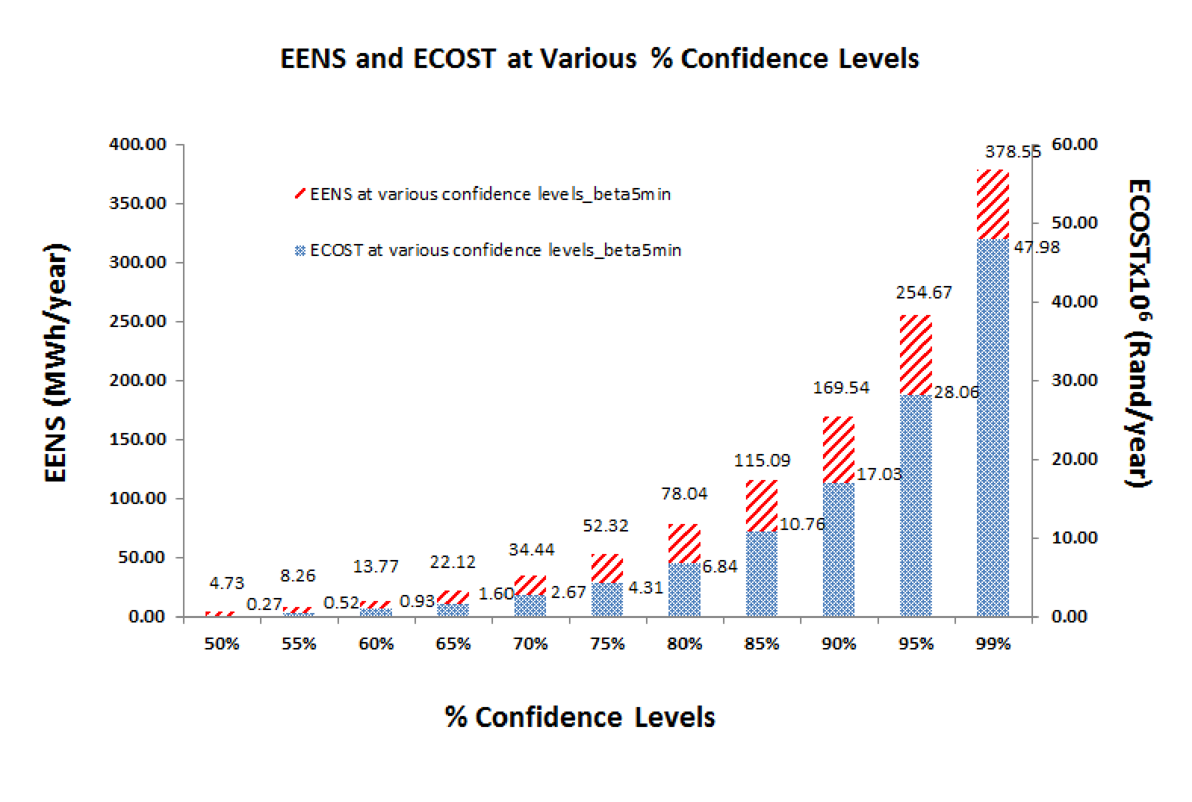


Figure 8-7: EENS at various risk levels for the beta PDF load model at 5 min intervals.

The EENS and ECOST values obtained in Table 8-2 for case 4b (beta PDF load at 5 min intervals) are 63.66 MWh/year and R 5, 540, 000/year respectively. These values when compared to Figure 8-7 fall between 75 % and 80 % confidence levels, which can be considered acceptable odds. While the initial EENS and ECOST results obtained for the beta PDF load models at the 5 min intervals demonstrate that there is a noticeable difference in the mean EENS (-4.08 %) and ECOST (-2.91 %) values when compared to the base case for Bus 3 of the RBTS, the probability distributions of these indices provide an indication on the skewness of the distribution (i.e. the shape of the distribution and more importantly in which area of the distribution does most of the indices lie) and finally the confidence/risk levels indicate whether the values of these indices are an acceptable range of probabilities.

Therefore, probabilistic approaches combined with time varying conditions can be effectively used to model the actual load during an interruption. The step load models presented are also probabilistic in nature; however a load duration curve is used instead of using the actual load interrupted at the time of the interruption. The modelling of load in reliability and customer interruption costs evaluation, therefore, should be chosen based on how detailed the information should be for the use by system planners. Detailed information is required when accurate indices are needed to make reliable planning decisions when financial resources are limited and investments require thorough justifications.

Power system planners face a wide range of uncertainties which cannot be addressed adequately with traditional planning tools and methodologies which are based on a deterministic approach. Moreover, the type of load modelling technique used in reliability and CIC evaluations has an impact on the resulting indices, and therefore adequate planning cannot be efficiently made when the actual load is not represented accurately. To account for these uncertainties and complexities, approaches such as the beta PDF load model can be used instead, as the impact and the risk of contingencies can be quantified adequately.

For example, the calculated indices indicate that the mean value of EENS will be less or equal to 63.66 MWh/year with a confidence level between 75 % and 80 %. Therefore the system planner may decide to use the EENS of 78.04 MWh/year at 80 % confidence and this means that there is a 20 % risk that the EENS may exceed this value. With regards to what reliability indices and confidence to use, there is no standard value as it depends on the system and the risks that the electric utilities are willing to take. However, there is a relatively high risk (20 %) that the actual EENS suffered by the system may not be the mean value (78.04 MWh/year) obtained as explained above. From Figure 8-7, it can be seen that at higher confidence levels, for example at 95 %, the EENS value is much higher at 254.67 MWh/year. Although there is a 95 % confidence that the EENS of 254.67 MWh/year will not be exceeded, when compared to the probability distributions of EENS in Figure 8-5, 254.67 MWh/year has only a very small probability of about 0.02 of occurring. Therefore, for example, power system planners may decide to opt for less expensive designs and use the values at 80 – 85 % confidence levels as reference or choose a more robust design using 90-95% confidence levels.

Therefore it is useful to associate a degree of risk/confidence to reliability indices so that system planners can effectively base their decisions on adequate reliability indices after weighing the risks involved. The usual practice is to use mean value of the indices, however Figure 8-5 and Figure 8-6 show that the distribution of these indices are highly skewed and using the mean value in this particular scenario does not provide an accurate picture of the indices during power outages. Thus the time dependent beta PDF load model can be used for adequate reliability and CIC evaluation of power distribution systems and by incorporating an appropriate risk or confidence in the indices obtained, the financial optimization of power distribution system projects can be more meaningful and useful to power system engineers.

8.3 Case 5: Results for System Reliability and Cost Indices (Reconfiguration Scheme with Limited Spare Capacity)

This section presents the results obtained when the simulations are ran using limited spare capacity reconfiguration (spare capacity limited to the average load of interrupted feeders).

8.3.1 Impact on SAIDI

Table 8-4 and Table 8-5 show the impact on the results of reliability and cost indices, for the sufficient and limited spare capacity reconfigurations, for the load models that are used in this study. The limited spare capacity reconfiguration in this study relates to the ability of alternate feeders to partially supply interrupted loads to adjacent feeders. In other words alternate feeders close to the feeders suffering an interruption have limited spare capacity to supply interrupted load points up to a certain capacity.

In this case the spare capacity available from the alternate feeders is the average load demand of the adjacent feeders. Once this limit is reached, the remaining interrupted load points cannot be supplied by the alternate feeders and suffer a repair time (5 hours) instead of a switching time (1 hour).

At 100 % loading and the remaining spare capacity from alternate feeders set to the average load at each feeder, there is a significant increase in the values of SAIDI as expected when compared to those of the optimal configuration scheme. The analyses by Wang, (1998), which show that alternate supplies have an impact on the reliability of the load points and the system, are used to support the results obtained in Table 8-4 below.

Table 8-4: Comparison of SAIDI results of the case studies when using sufficient and limited spare capacity reconfiguration

Case	Load Model	SAIDI (hr/sys.cust)		
		Sufficient Spare Capacity Reconfiguration	Limited Spare Capacity Reconfiguration	Difference
Base	Average	3.4567	3.6256	4.89 %
1a	Time Varying (Hourly)	3.5373	4.0874	15.55 %
1b	Time Varying (5 min)	3.535	3.7829	7.01 %
2a	5 Steps (Y-Axis)	3.5214	4.4665	26.84 %
2b	25 Steps (Y-Axis)	3.5247	4.4551	26.40 %
3a	6 Steps (X-Axis)	3.5329	4.4796	26.80 %
3b	24 Steps (X-Axis)	3.5444	4.1557	17.25 %
4a	Beta PDF (Hourly)	3.44	3.9935	16.09 %
4b	Beta PDF (5 min)	3.4326	3.7486	9.21 %

Significant changes are observed for cases 2a, b and 3a, b when considering the two reconfiguration schemes. Smaller changes are seen in the case 1a and case 4a when the load is modelled at hourly intervals and the smallest changes are found in case 1b and case 4b when the load is modelled at 5 min intervals.

The results indicate that based on the type of load modelling used, SAIDI will be significantly different from that of the base case. In general, the results show high degrees of poor reliability performance which varies with the type of load modelling approach. This means that using the average load model to represent the interrupted load in a system is clearly not an adequate approximation of the actual interrupted load and therefore incorporating the variation of load with time and its stochastic nature can provide more comprehensive and practical results.

Figure 8-8 below shows the SAIDI values for each load model at 100 % loading and for both the sufficient and limited spare capacity reconfigurations. Cases 2a, b and 3a, b have the largest difference in SAIDI between the two reconfiguration schemes as they are modelled using probabilities that different load levels occur in load duration curves. Cases 1a and 4a are modelled based on hourly load intervals and have a slightly lower increase in SAIDI. Similarly, cases 1b and 4b have the lowest increase in SAIDI as they are modelled at 5 min intervals.

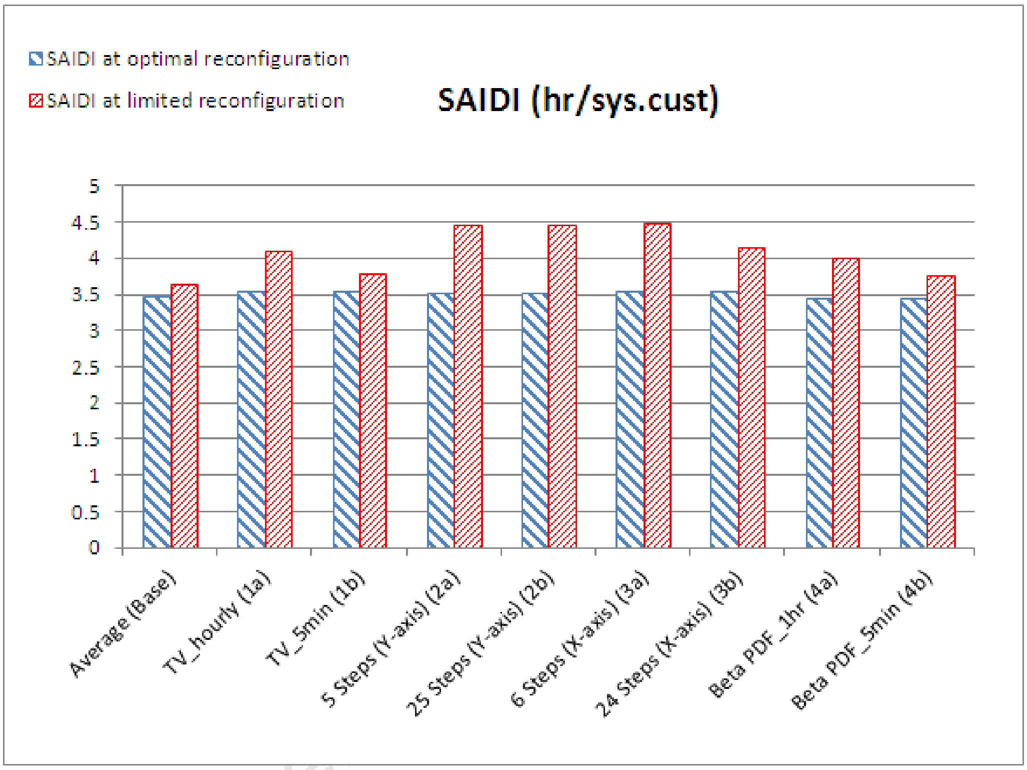


Figure 8-8: SAIDI for the different load models with limited spare capacity reconfiguration.

An increase in SAIDI values means that the reliability (SAIDI) performance of the system decreases. The impact of system load growth on the SAIDI performance using the different load models was also investigated and reported in section 8.4.

8.3.2 Impact on EENS and ECOST

Table 8-5 below shows the results for EENS and ECOST for the different load models using the sufficient and the limited spare capacity reconfigurations.

Table 8-5: Comparison of EENS and ECOST results for the case studies when using sufficient and limited spare capacity reconfigurations

Case	EENS (MWh/year)			ECOST (Rand/year) x 10^6		
	Sufficient Spare Capacity Reconfiguration	Limited Spare Capacity Reconfiguration	% Difference	Sufficient Spare Capacity Reconfiguration	Limited Spare Capacity Reconfiguration	% Difference
Base	66.364	66.392	0.04 %	5.707	5.735	0.49 %
1a	68.297	94.872	38.91 %	5.877	6.987	18.89 %
1b	59.373	69.200	16.55 %	5.061	5.9692	17.94 %
2a	83.940	133.988	59.62 %	7.219	9.2272	27.83 %
2b	69.115	108.988	57.69 %	5.946	7.508	26.27 %
3a	69.529	109.659	57.72 %	5.997	7.5827	26.44 %
3b	66.473	89.276	34.30 %	5.718	6.5883	15.21 %
4a	72.062	109.806	52.38 %	6.133	8.025	30.85 %
4b	63.659	72.981	14.64 %	5.541	6.3155	13.98 %

The results in Table 8-5 show an increase of varying degree in each index between the sufficient and limited spare capacity reconfigurations throughout the load modelling approaches.

Figure 8-9 shows the EENS values for the sufficient and limited spare capacity reconfigurations for the different load modelling approaches. A significant increase can be seen in the time varying load model at hourly intervals, the step load models and the beta PDF load model at hourly intervals. The largest difference is seen in the 5 Steps (y-axis) load model while the smallest difference is found in the time varying and beta PDF load models at 5 min intervals. The difference in the increase in these indices can be attributed to the way the load is modelled as each load modelling approach perceives the load demand at the time of interruption in a different manner and therefore each approach will increase differently.

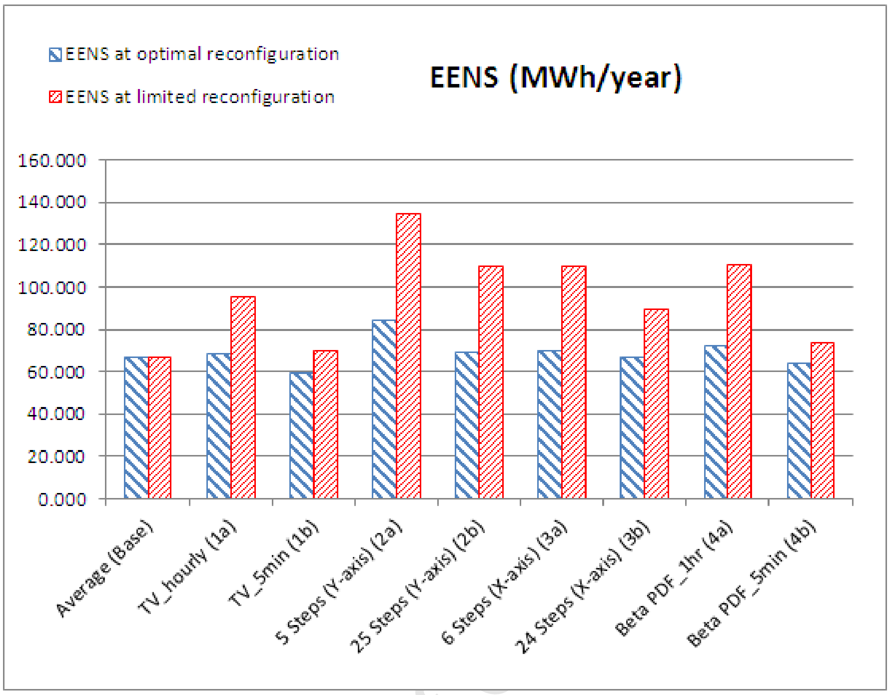


Figure 8-9: EENS for the different load models with the limited spare capacity reconfiguration.

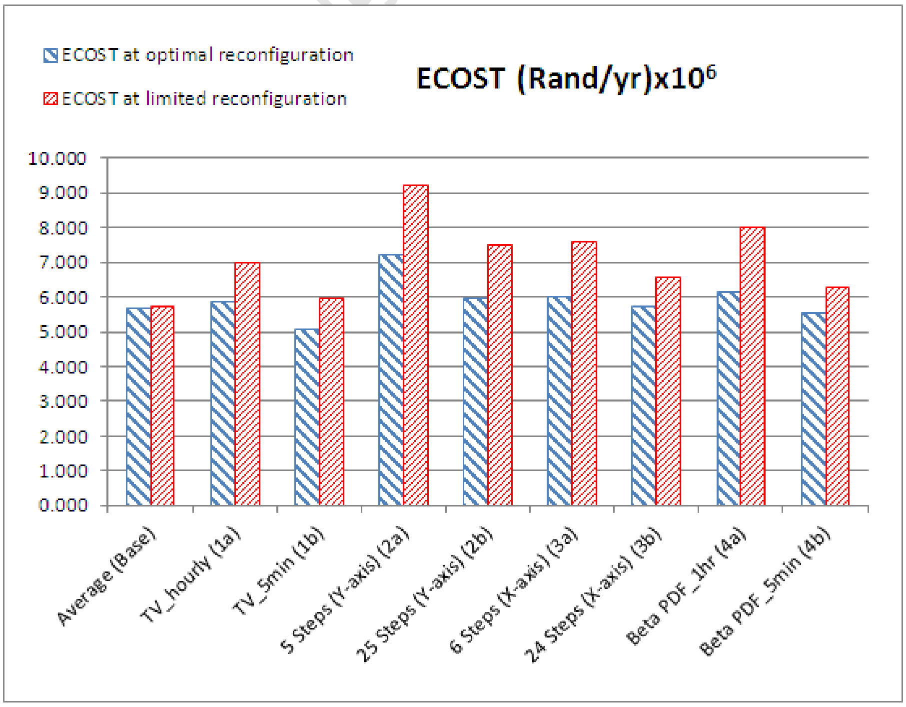


Figure 8-10: ECOST for the different load models with the limited spare capacity reconfiguration.

Figure 8-10 shows a comparison in the difference in ECOST values between the two reconfiguration schemes for each case study. The results follow similar pattern to that of EENS values and indicate that the EENS and ECOST values are sensitive to the load modelling approach used in the simulations when the sufficient spare capacity reconfiguration is used. However the resulting values are significantly more sensitive to the load modelling approach when the limited spare capacity reconfiguration is implemented.

8.4 Effect of System Load Growth Using Different Load Modelling Approaches

This section aims at showing the impact of different load modelling techniques on reliability evaluation of power systems when system loading is considered with the limited spare capacity reconfiguration. The SAIDI performance for each load model is investigated when the system loading is increased using the limited spare capacity reconfiguration. This is performed by increasing the load demand but keeping the alternate feed capacity fixed at the average of the initial year. A fixed capacity from alternate feeders is set by using the average load demand for each load points. Therefore Figure 8-11 shows the SAIDI performance with increasing system loading for the different load modelling approaches.

Average Load Model

The average load model (base case) is constant until 100 % loading and increases sharply up to 125 % system loading, and then remains constant. The sharp increase at 100 % loading occurs as the spare capacity reconfiguration is set as the average load at each load point in the system. As the loading increases, which usually occurs over time, the alternate feeds, which only have limited available extra capacity to provide to interrupted load points, will be unable to supply all the interrupted load points if their load requirements exceed the available spare capacity. Therefore the SAIDI values increase at a certain rate and thus decreasing the reliability performance.

Time Varying Load Models

The time varying load models, case 1a (hourly intervals) and case 1b (5 min intervals) have similar profiles and SAIDIs are constant, then increases smoothly at 60 % loading up to their maximum value at approx. 180 % loading. However the change in SAIDI performance for the time varying load model at 5 min intervals occurs at a slower rate, which suggests that the load representation used in the study has an impact on the rate of increase in SAIDI values when the spare capacity reconfiguration is not sufficient.

Step Load Models

The 5 Steps (y-axis) and the 25 Steps (y-axis) load models have similar profiles but SAIDI increase sharply to their maximum values starting at different system loading. The sharp increase occurs sooner at approx. 60 % system loading for the 5 steps (y-axis) load model while that of the 25 steps (y-axis) occurs at approx. 80 % system loading. This difference indicates that increasing the number of steps in the step (y-axis) load model has an impact on the increase in SAIDI values.

The 6 Steps (x-axis) load model has a similar profile to that of the 25 steps (y-axis) load model, however as the number of steps is increased in the steps (x-axis) load model, the SAIDI profile changes as the rate of increase is now slower. This behaviour indicates that modelling the step load model along the x-axis (duration axis) is different from the one modelled along the y-axis (percentage load level axis).

Time Dependent Beta PDF Load Models

The probabilistic model using a beta probability density function also demonstrates the smoothest rate of increase in SAIDI values as the system loading is increased. Similar to the time varying load models, modelling the load at shorter time intervals (5 min) also slows down the rate of increase in SAIDI values.

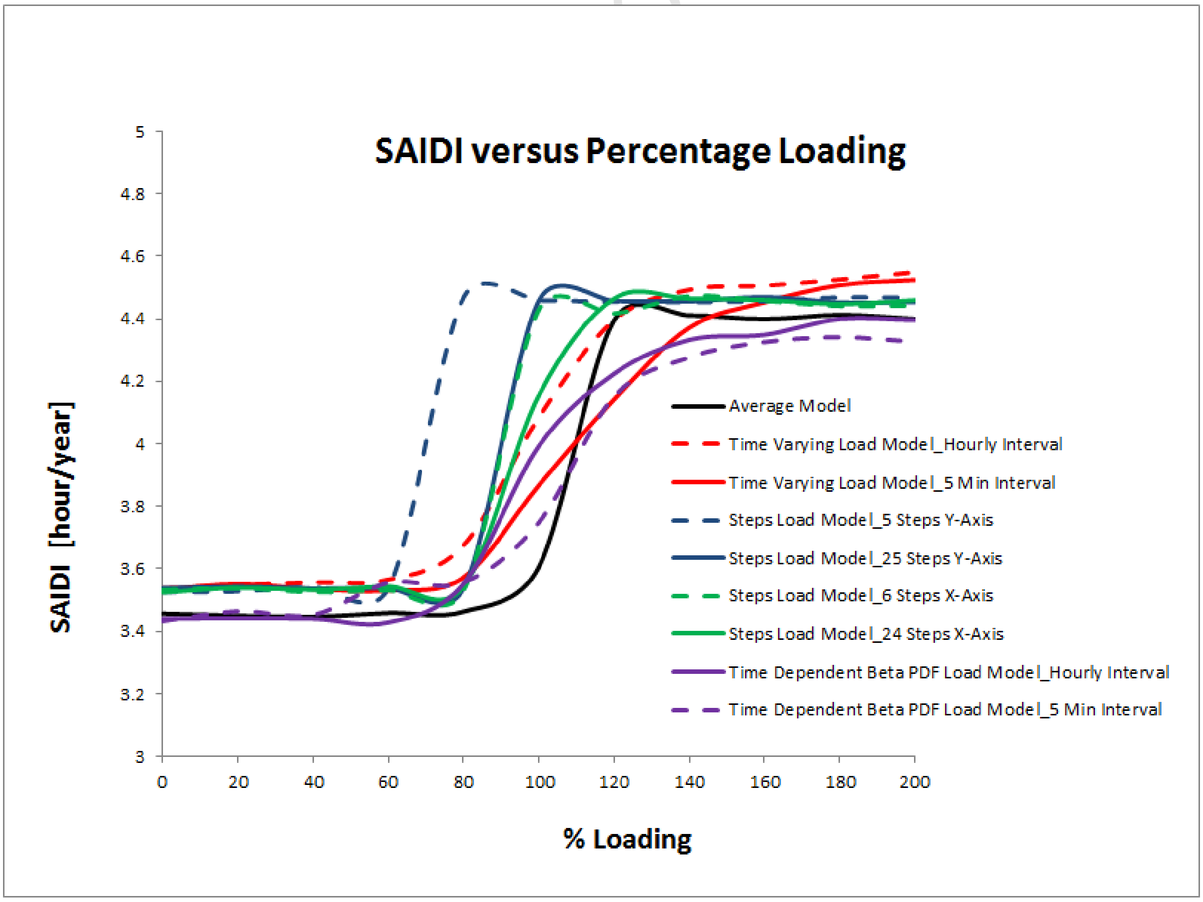


Figure 8-11: SAIDI performance versus Percentage Loading.

As expected, as the system loading increases, SAIDI increases at different rates for the different load modelling techniques, which shows that the load demand is starting to exceed the alternate feed capacities for some feeders. This difference can be attributed to the way the load is modelled in each case. Past 180 % system loading, the SAIDI values in all load models are constant again and have reached their worst performance, as the system load has now exceeded the alternate feed capacities for all feeders.

As discussed in earlier chapters, in the time varying load model, the load is modelled using the average load at hourly intervals in the first case and using 5 min intervals in the second case. Therefore the SAIDI profile is quite different from that of the average load because of the change in load presentation. Another example is found in the beta PDF load model, in which alpha and beta parameters are calculated from the load information for hourly intervals, and the circuit breaker limit used as parameter, C. These parameters, along with the number of customers for each load point in the system, are used to generate random load demand for each individual customer at the load point and the summation accounts for the load interrupted for a particular load point when an interruption occurs. The randomly generated load demands are based on individual customer load use patterns over time. Therefore the beta PDF load model first determines the time of interruption and uses the corresponding beta parameters to randomly generate the individual customer loads, which are used in the calculation of the system reliability indices.

Figure 8-11 shows that the type of load modelling approach used can have an impact on the result of the SAIDI evaluation of a power system. The beta PDF load model modelled at 5 min intervals show the slowest rate of increase in SAIDI values with increasing system load growth over a wider range. The beta PDF load model modelled at 5 min intervals can be considered a better representation of the actual load when an interruption occurs and therefore extends to a better presentation of the SAIDI performance.

Therefore, for a fixed spare capacity, the load interrupted can have an impact on the SAIDI values by extending the outage duration of the interrupted customer by a long duration (repair duration) instead of a switching duration when it exceeds the fixed allowable extra capacity from alternative feeders.

8.5 Simulation Performance

This section focuses on the simulation performance for each load model. It is important to note that the average, time varying and step load models use a number of iterations, which are defined by the time reduction method by using the convergence approach described in APPENDIX E – Simulation Time Reduction Methods.

The simulation results were computed on an Intel® Core 2 Duo, with processing speed of 1.34 GHz. The simulation codes were written in MATLAB 7.10.0 (R2010a). The simulation performance depends also on the specification (processing power) of the computer used as discussed in APPENDIX E – Simulation Time Reduction Methods.

Table 8-6: Simulation Performance for the various case studies

Case	Load Model	Elapsed Time (seconds)	Number of Iterations	Complexity	Variables
Base	**Average**	20.87	134	Very simple	None
1a	**Time Varying (1hr)**	22.99	161	Fairly Simple	Time, Load
1b	**Time Varying (5 min)**	28.53	168	Fairly Simple	Time, Load
2a	**5 Steps (Y-axis)**	84.39	488	Fairly complex	% Load Levels Probability
2b	**25 Steps (Y-axis)**	112.32	499	Fairly complex	% Load Levels Probability
3a	**6 Steps (X-axis)**	59.48	145	Fairly complex	% Load Levels Probability
3b	**24 Steps (X-axis)**	69.08	146	Fairly complex	% Load Levels Probability
4a,b	**Beta PDF (EENS, ECOST);**	8.58	1	Fairly complex	Time & Beta Distribution
4a,b	**Beta PDF (SAIDI, SAIFI)**	822.04	100	Fairly complex	Time & Beta Distribution

The beta PDF load model is only simulated for 1 iteration (or 1 simulation period), as the results are recorded in vectors which are simulated for n = 1000 years (simulation years). The recorded simulated results in the vector are then used to obtain the distributions for EENS and ECOST. SAIFI and SAIDI are simulated separately to obtain an accurate estimate and it takes approximately 822 seconds as shown in Table 8-6 to obtain these values using the convergence method.

When comparing the elapsed time, the load models demonstrate a range of simulation time. Based on the results, the base case, case 1a, b and 4a, b (for EENS and ECOST only) have the fastest simulation time. However the case 4 (SAIDI & SAIFI) requires the most time (approx. 14 min) to simulate, and since all indices are usually considered in a reliability or CIC analysis, the beta PDF model is considered to have the worst simulation time performance. The increase in elapsed time can be attributed to the number of iterations needed to meet the convergence criterion and also to the number of calculations to be computed in the simulation. For example, Case 2a and 2b have longer elapsed time because of the number of iterations required to meet the convergence criterion while cases 4a and b have longer elapsed time per iteration because of the complexity and number of calculations required in the simulation programming. Another observation between cases 2a and 2b and cases 3a and 3b, is that using more steps also increases the simulation time in both cases.

Chapter 9

9 CONCLUSIONS

The research carried out for this dissertation aims at demonstrating the need for using time and statistical variations in load modelling for reliability and CIC evaluations of electric power distribution systems. Therefore, this study investigates the impacts that different types of load models have on such evaluations and additionally, the potential advantages of a time dependent probabilistic load modelling approach are highlighted and compared with other existing load modelling approaches. The outcomes of the study are discussed in this chapter.

9.1 Reliability and Customer Interruption Costs Evaluation

The general aspects involved in carrying out reliability or customer interruption costs (CIC) evaluations have been provided in this study. Depending on the type of study performed, different models are required; such as a reliability model, a cost model, and in both cases, a load model. It has been established that several load modelling methods have been proposed and applied in reliability and CIC assessments in power systems (generation, transmission and distribution).

Among these load models, the average load model is generally used as the base case, to which, subsequent load models that are more intricate, are compared. Other factors such as the time of occurrence and weather can be introduced to improve the representation of the actual load that is interrupted during an outage. Therefore, time varying models have also been discussed in Chapter 4. However, to model the interrupted load as accurately or closest to the actual value, uncertainty has to be incorporated. Therefore, probabilistic methods combined with other factors such as time or weather, have an impact on the results that are obtained from these studies. Two types of steps load models and their variants, which use load duration curves to find the probability values associated with percentage load levels of the peak load, are used in this study. Another load model, using time varying load combined with load variation due to uncertainty portrayed by a beta PDF, is proposed.

The distribution of individual customer load at each load point using alpha and beta parameters incorporates randomness in load modelling and hence introduces statistical variation in the model. Then these calculations are done at hourly and 5 min intervals of daily load profiles separately, which incorporates the time varying nature in the load. In the reliability evaluation, the expected energy not supplied is the most relevant index, which shows the impact of the different load models in the study. On the other hand, the expected interruption cost (ECOST) is relevant to the CIC evaluation.

9.2 Impacts of Load Modelling Techniques in Reliability or CIC Evaluations

If average load values are used when performing reliability and CIC studies, there is a considerable loss of information. Essential information such as load chronology and the stochastic nature of the load are lost in the averaging process. As a result, the evaluations carried out will only provide a rough estimate of the indices.

The impacts of different load models used in reliability and CIC evaluation can be seen in the results obtained for EENS and ECOST in Chapter 8. The results show that several load modelling approaches can provide results different from that of the average load, when simulating with the same reconfiguration scheme using sufficient spare capacity. However a much larger difference in the results is observed when simulating with a reconfiguration scheme using limited spare capacity. The difference varies from one load model to the other. The reconfiguration scheme with limited spare capacity is used in simulation with each load representation approach and the impact on the resulting reliability and cost indices can be observed. Section 8.4 shows the results of increasing the system load growth when the reconfiguration scheme with limited spare capacity is used. From the SAIDI values, it can be clearly observed that the use of different load modelling approaches have an impact on the rate at which the SAIDI performance declines. The time dependent beta PDF load model provides a smooth and slow rate in the decrease in SAIDI over a wider range of system load growth, while the some of the other load models show a steeper increase before reaching their maximum SAIDI.

Table 8-5 shows the comparison of the EENS and ECOST values for the various case studies between the two reconfiguration schemes (with sufficient and with limited spare capacity). There is a significant increase in EENS and ECOST values as expected as shown in Table 8-5 when simulating with the reconfiguration scheme with limited spare capacity. When considering the time dependent beta PDF load model, a range of EENS and ECOST values are available which are associated with respective confidence/risk levels. Also their probability distributions can be obtained, which shows the shapes or skewness of the distributions. The information obtained from the confidence/risk levels can be correlated with the probability distributions of EENS and ECOST to determine the likelihood that the value of EENS and ECOST occur at these levels. As discussed earlier, at 95 % confidence for instance, much higher EENS and ECOST values at 254.67 MWh/year and R28, 060, 000/year are obtained than at 80 % confidence (78.04 MWh/year and R6, 840, 000/year). But if the values of EENS and ECOST at 95 % confidence are used, they cover a much wider range of EENS and ECOST and carry only a 5 % risk that the actual EENS and ECOST recorded in a particular year exceed these values. However in this particular study, using higher EENS and ECOST values also mean that are less likely to occur as seen from the probability distributions of EENS and ECOST in Figure 8-5 and Figure 8-6. Therefore the relationship between the confidence/risk levels and the probability distributions of the EENS and ECOST indices are useful to power system planners as their decisions for power system projects are bound by what risks the electric utilities are willing to take.

The additional information provided by the beta PDF load model makes it very flexible in a decision-making process. The consequence of not using a load model that represents the actual load adequately is usually the loss of information about the load, which can lead to poor or less efficient planning. The loss of information usually occurs as actual load values are averaged and therefore the information lost can be the load variation over time or/and the uncertainty in load, as load usage is stochastic in nature.

9.3 Load Modelling Methods and Simulation Performance

Several load modelling approaches have been presented in this study. Each case study has been subjected to the same conditions except in the modelling of the load, so as to observe the impacts of different load models in the evaluation of reliability and CIC in power systems. As the load is modelled differently in each case, the simulation code for each differs from the others and also affects the simulation time. However, the type of time reduction technique used and also how the results are stored and calculated, have an impact on the simulation time as well. Therefore, the simulation time for each case varied with different load models and other factors such as the computer processing power has a direct effect on the simulation performance.

Apart from the simulation performance, the complexity in the modelling of the load is also an important aspect to be considered. For large systems, the more complex the modelling is the more time will be required in the setup and programming of the simulation. The average load model is a much simpler way to model the load and does not require a large database. The complexity increases as the number of processes increases. For example, the addition of variation of load with time in the time varying load model increases the simulation time by just a few seconds.

The simulations for the step load models are also slower than the average load model due to the introduction of statistical calculations in the load model and the simulation time increases as the number of steps is increased. The increase in the number of processes to be calculated in the simulation is the main reason for the extra simulation time required. In the beta PDF load model, information such as EENS and ECOST calculated for each interruption event and are cumulated in separate vectors. Therefore the fewer the number of processes are simulated, the faster the simulation time. The stored information in vectors can then be used to calculate different values of EENS and ECOST at various risk or confidence levels. Furthermore, beta distributions of both indices can be plotted to provide an idea of the skewness or shape of the distributions. However since SAIDI and SAIFI are calculated in similar way to the other load models, a number of iterations are required to reach an accurate value, and therefore this makes the beta PDF load model much slower to simulate than the other load models.

9.4 Significance in Power System Planning and Operations

Probabilistic methods applied to load modelling, which incorporates uncertainty and time variation, provide a useful tool for power system planners. Also when combining the calculated indices at various risk levels with their distributions, the beta PDF load model provides an array of choices for power system planners to base their decisions on. Moreover, the values of EENS and ECOST associated with risk levels can be used to weigh the amount of investments in reliability improvements in a power system network against the potential liability that customers incur during power outages.

Although the beta probability density function method provides useful additional information as well as flexible outputs on which a variety of choices can be made, historical data is required for this study. But once the load parameters for the distributions of different types of customers have been calculated in a particular country, they can be used to model the statistical variation of load of other customers with similar characteristics. For example, typical design load parameters for domestic consumers are available in the National regulatory Services document (NRS 034-1, 2007) published by the Standards South Africa and can be used to model the load for domestic consumers in South Africa

In the absence of large amount of load data, if load durations curves and peak load are available, the step (y-axis) and step (x-axis) load models can be adequate substitutes. The time varying load models can be very useful when load chronology is required. Although the average load or deterministic method is not very accurate in terms of load representation and does not portray the results adequately, it can still be used as a comparative model and provide an approximate understanding of the system's reliability.

It has been established in Chapter 8 that based on how the load is modelled and what varying factors are included (time, probability or uncertainty), each type of load model has an impact of varying degree on the indices calculated in the results. While there is no guarantee that one load modelling approach provides more accurate results than another, only the beta PDF load model incorporates both time and statistical variation which are known to affect the representation of the actual load. Also the introduction of these factors (separately and combined) in this study confirms that using different load modelling techniques using reliability and CIC evaluations of power distribution systems provide varied results.

Additionally, the time dependent beta PDF load model provides information that can help power system planners optimize the financial investments by making decisions based on justifiable risks and information on the shape of the distributions of the relevant annualised indices. As mentioned earlier, the shape or skewness of the distributions indicate which values in the distribution of the indices have the lowest or highest likelihood of occurring. The mean of the distributions of EENS and ECOST obtained from the beta PDF load models are values that are calculate in a similar way to the other load modelling techniques which are the average annualized indices. These indices may be considered a more accurate estimate of the annualised indices as the time dependent beta PDF load model includes both time variation and uncertainty in the load. However, the system planner may decide to choose values of the indices higher or lower than the mean values obtained based on the risk associated with these values and the distributions. There is no standard level confidence or risk to choose from when reliability and the cost of interruptions are concerned. The decision depends on what level of risk electric utilities are willing to take while considering the financial investments available when planning for reinforcement or improvement of a power system.

Using higher indices (EENS and ECOST) have a lower risk (or high confidence) associated, however one has to weigh the benefits against the costs of using index values that have lower risk associated. In this particular case, as described in Chapter 8 the mean value of EENS and ECOST when using the time dependent beta PDF load model at 5 min intervals has between 75 % and 80 % confidence associated to them. Therefore the EENS value (78.04 MWh/year) and ECOST value at R6, 840, 000 at 80 % confidence may be chosen by the system planner and this means that there is a 20 % risk that the annual energy not supplied may exceed 78.04 MWh/year and that the annual interruption cost may not exceed R6, 840, 000, which is rather significant. However, using index values at only 5 % risk is much higher at EENS of 254.67 MWh/year and ECOST of R28, 060, 000 (95 % confidence) and this will impose much more financial investments. These values can also be compared to the probability distributions of EENS which indicate the likelihood that different values of EENS can occur. Therefore the higher financial investments may not be necessarily justified as the likelihood that the values of EENS and ECOST at 95 % confidence (or 5 % risk) are experienced by the system, when correlated from their respective probability distributions, is only about 0.02.

9.5 Validity of the Hypothesis

A number of load modelling approaches have been investigated in reliability and CIC evaluations. The impacts of the various load modelling techniques used in these evaluations have been demonstrated factoring in sufficient and limited spare capacity reconfigurations. The results have shown that the indices obtained for the different load models are significantly different for each load modelling techniques used in this research. The beta PDF however provides a wider range of reliability and cost values associated with risk levels which provides additional options to power system planners in their decision-making. Also when system load growth is considered, the beta PDF clearly shows a smooth rate of increase over a wider range of percentage loading. A smooth, as opposed to a steeper, increase in SAIDI values indicates that the system responds gradually to the increase in load demand instead of reaching the maximum SAIDI value at a lower percentage system loading. In the beta PDF load model the individual customer load demand, which follows the customer's load profile, at each load point for different times of interruption can be simulated. The inclusion of this uncertainty makes the time dependent beta PDF loads more representative of the actual customer loads interrupted. Therefore the beta PDF model can be fitted to historical load data to adequately represent customer load demands by randomly generating their loads using beta parameters (which represent the shape of the distributions) while incorporating the variation of load with time. This is validated by the results provided in Chapter 8.

9.6 Observations

In the light of this investigation on the impacts of load modelling on reliability and customer interruption costs evaluation, several observations have been made on different aspects of the evaluation.

9.6.1 Types of Customers and System Size

The results obtained from the reliability and CIC evaluation of bus 3 of the RBTS considering residential and commercial customers show that different types of customers and their ratio will have an impact on the skewness of the distributions of the EENS and ECOST indices. Bus 3 of the RBTS consists of a mix of residential and commercial customer distributed over 44 load points with about 121 possible components which can fail and cause an interruption. Therefore the test system used in this study is a suitable system size to investigate the impact of various load modelling techniques on the reliability and cost indices for both the planning and operation stage.

9.6.2 Time Dependency and Uncertainties in Load Modelling

This particular study is based on the stochastic nature of load, and therefore a beta PDF load representation is proposed for reliability evaluation and CIC which incorporates both the uncertainty in load variation and the time dependency of load. The individual customer load demands follow distinct patterns which are represented by the beta parameters calculated from their historical load. These parameters are suitable to predict these individual customer loads randomly, at each load point, for different times of the day. When an interruption occurs at a specific time, the beta parameters calculated for each load point at the time of the interruption are used to simulate the individual loads and total load at each load point is interrupted load. Therefore, the proposed load model considers uncertainty in the load from one individual to another at each load point, which is a good representation of how load demand varies between individual customers with time.

9.6.3 Adequacy of Proposed Load Models

This study on the impact of different load models on reliability and CIC evaluation has brought out several load modelling techniques which vary in accuracy of representation, complexity and performance. The average load model, although very simple and easy to implement in a simulation program, is only suitable in some applications. The average load model can be used as a quick reference or as a comparison with other load models to obtain an idea of what the calculated indices will be on average. The time varying load model can also be used for a similar purpose, where the time of interruption is an important feature required in the evaluation. In the absence of historical load data, depending on what kind of information are available, steps load model can be used, however, they do not show the direct impact of the time dependency of load in the evaluation as load chronology is discarded in favour of probability values. A much more elaborate and adequate model which incorporates both load and time variability is found in the beta PDF load model. It also provides the power system planner with very useful information which can be used to take decisions for different situations or conditions. Such information comes in the form of probability distributions of the resulting indices as well as risk levels associated to them.

9.7 Summary of Answers to Research Questions

The summarized answers to the research questions formulated in Chapter are as follows:

- **What are the existing types of load modelling techniques currently available and which method best portray the stochastic behaviour of actual load?**

Several load modelling approaches have been discussed in Chapter 4. The most common and basic load model used in many studies by default or as their base case is the average load model. Other more elaborate approaches include; the time varying model, the step load probabilistic model, the fuzzy load model, and probabilistic models. Some of these models can be combined to form hybrid load models such as the combined probabilistic and fuzzy load model or probabilistic models considering time variation (or time dependent probability approach). The beta probability density function method has been found to be the best approach to represent the uncertainty in load and its stochastic behaviour. The method consists of beta parameters which can be calculated at different time intervals and then be used to reproduce the load distribution at a particular time of interruption.

- **What additional or useful information can probabilistic load modelling techniques provide for power system planners and power utilities for practical purposes?**

The benefits of using probabilistic load modelling methods for reliability and CIC evaluations are discussed in Chapter 5 (5.1.1). Several characteristics associated with the use of a probabilistic method as described in Chapter 5 include the introduction of uncertainties associated with the quantitative results as well as providing a better representation through the availability of risk or confidence levels and graphical illustrations of the probability distributions of the outputs showing the skewness or shape of the distributions.

- **Can the chosen load modelling approaches be implemented in a simulation program?**

Several load modelling approaches are used for comparison with a proposed beta probability density function load model approach. These methods can be implemented using sequential Monte Carlo Simulation techniques. This simulation method can then be programmed in MATLAB simulation software. The justification for the use of MCS techniques for reliability or CIC evaluations can be found in **APPENDIX D – Monte Carlo Simulation**.

- **Are there any evidence/results showing that the output of reliability or CIC studies are affected by the load modelling approach used? How is the impact of load models on reliability or CIC evaluations assessed?**

Chapter 5 offers an insight on several studies that indicate significant impacts on the results obtained using different load modelling approaches. Generally, conventional load modelling methods such as the average load model is used as the base case as a control for the results obtained for novel or modified load modelling approaches that are presented. Chapter 6 provides a summary of various information and procedures to follow to carry out reliability or CIC evaluations.

- **Does any load modelling approach help in particular power system planners to effectively make their planning decisions?**

As described in Chapter 5, the average load model is one of the conventional methods of modelling the load in reliability or CIC assessments. However, they provide very little to no additional information to the system planner. But this method can be easily and quickly implemented as it is simple to model. Therefore if power system planners are required to provide a fast approximate estimate of the preliminary planning of a power system, the average load model is suitable for this task. A more elaborate approach by using a time varying model will provide a better representation of the actual load of the customers at the time of an interruption. However additional information is needed such as load profiles or historical data. It has been established in Chapter 5 that the uncertainty has to be considered when modelling load for reliability or CIC evaluations. The steps load models provide an adequate option based on load duration curves and probability values associated with percentage intervals of peak loads. Although the uncertainty in load is introduced, this method does not depend directly on the time at which an interruption occurs. A more useful and reliable representation of the actual can be modelled using a beta probability density function, which provides system planners with additional tools to base their planning decisions on. With the introduction of confidence or risk in the comparisons of the resulting indices, the financial optimization can be made from different combinations, thus providing greater meaning and use for power system engineers.

9.8 Final Thoughts and Way Forward

From this study, it can be concluded that the beta PDF model provides an adequate representation of the actual load by incorporating the uncertainty in load and the time variability of load. Furthermore, it provides power system planners with a combination of choices that can be tailored to their expectations. Additional factors can be implemented in the model such as the variability of load with weather (seasonal factors) and the addition of stochastic reliability and cost data instead of using their deterministic models. Being able to put as accurately as needed a value to the customer cost of interruptions, will allow power system planners to meet their requirements and standards with the optimum financial investments. However this can only be achieved by incorporating uncertainty in all aspects of the evaluation. The reliability and CIC evaluations carried out in this dissertation considered the reliability and cost models to be constant. This is not, however, true in practice as reliability and cost of interruptions do not stay constant throughout the year. Further analyses can be carried out by considering variable reliability and cost models combined with a variable load model.

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APPENDIX A

A. APPENDIX A

A.1 Reliability Metrics and Indices (Brown, 2002) (Brown, 2009)

This appendix presents the different types of reliability indices which can be used in a reliability evaluation study.

System Average Interruption Frequency Index:

$$SAIFI = \frac{Total\ Number\ of\ Customer\ Interruptions}{Total\ Number\ of\ Customer\ Served} \quad fr./sys.cust$$

System Average Interruption Duration Index:

$$SAIDI = \frac{\sum Customer\ Interruption\ Durations}{Total\ Number\ of\ Customers\ Served} \quad hr/sys.cust$$

Customer Average Interruption Duration Index:

$$CAIDI = \frac{\sum Customer\ Interruption\ Durations}{Total\ Number\ of\ Customer\ Interruptions} \quad hr/cust.$$

Customer Average Interruption Frequency Index:

$$CAIFI = \frac{Total\ Number\ of\ Customer\ Interruptions}{Customer\ Experiencing\ 1\ or\ more\ Interruptions} \quad fr./cust.$$

Average Service Availability Index:

$$ASAI = \frac{Customer\ Hours\ Service\ Availability}{Customer\ Hours\ Service\ Demand} \quad pu$$

Customer Total Average Interruption Duration Index:

$$CTAIDI = \frac{\sum Customer\ Interruption\ Durations}{Customers\ Experiencing\ 1\ or\ more\ Interruptions} \quad hr/yr$$

Momentary Average Interruption Frequency Index:

$$MAIFI = \frac{Total\ Number\ of\ Customer\ Momentary\ Interruptions}{Total\ Number\ of\ Customers\ Served} \quad /yr$$

Momentary Event Average Interruption Frequency Index:

$$MAIFI_E = \frac{Total\ Number\ of\ Customer\ Momentary\ Events}{Total\ Number\ of\ Customers\ Served} \quad /yr$$

A.2 Reliability Metrics and Indices (Brown, 2002)

Customers Experiencing Multiple Interruptions:

$$CEMI_n = \frac{Customer\ Experiencing\ More\ Than\ n\ interruptions}{Total\ Number\ of\ Customers\ Served} \quad /yr$$

Customers Experiencing Multiple Sustained and Momentary Interruptions:

$$CEMSMI_n = \frac{Customer\ Experiencing\ >\ n\ Combined\ Momentary\ \&\ Sustained\ interruptions}{Total\ Number\ of\ Customers\ Served} \quad /yr$$

A.3 Reliability Metrics and Indices (Brown, 2002)

Average System Interruption Frequency Index:

$$ASIFI = \frac{Connected\ kVA\ Interrupted}{Total\ Connected\ kVA\ Served} \quad /yr$$

Average System Interruption Duration Index:

$$ASIDI = \frac{Connected\ kVA\ Hours\ Interrupted}{Total\ Connected\ kVA\ Served} \quad hr/yr$$

A.4 Reliability Metrics and Indices (Brown, 2002)

Energy Not Supplied:

$$ENS = \ total\ energy\ not\ supplied\ \text{by the system} = \sum L_{a(i)}U_i \quad [kWh/Yr]$$

where $L_{a(i)}$ = the average load connected to load point *i*.

U_i = the annual outage time

Average Energy Not Supplied:

$$AENS = \frac{total\ energy\ not\ supplied}{total\ number\ of\ customers\ served} = \frac{\sum L_{a(i)}U_i}{\sum N_i} \quad [kWh/Yr]$$

where N_i = the number of customers at load point *i.*

Some indices also involving cost assessments include:

Expected Cost of Interruption:

$$ECOST = \frac{Interruption\ cost\ in\ the\ system}{Load\ interrupted\ in\ the\ system} \quad \text{e.g. Rand/kW or Rand/kWh}$$

Interrupted Energy Assessment Rate:

$$IEAR = \frac{ECOST}{ENS} \quad \text{e.g. Rand/Yr}$$

APPENDIX B

B. APPENDIX B

This appendix presents the failure mode and effect analysis (FMEA) of the feeders in Bus 3 of the RBTS. The FMEA of each feeder is represented separately to facilitate their illustration.

B.1 Failure Mode and Effect Analysis of Feeder 1

Table B - 1: Failure Mode and Effect Analysis of Feeder 1

Component Data		Event Type	Protection	Load Points	Load Points
Event no.	Component	Permanent, Temporary	Triggered Unit	Affected by RT/RpT	Affected by SwT
1	L1	P	Switch	LP1	
2	L2	P	Switch	LP2	
3	L3	T	B1		LP1-LP7
4	L4	P	Switch	LP3	
5	L5	P	Switch	LP4	
6	L6	T	B1		LP1-LP7
7	L7	P	Switch	LP5	
8	L8	T	B1		LP1-LP7
9	L9	P	Switch	LP6	
10	L10	T	B1		LP1-LP7
11	L11	P	Switch	LP7	
12	L12	T	B1		LP1-LP7
13	TLP1	P	FT	LP1	
14	TLP2	P	FT	LP2	
15	TLP3	P	FT	LP3	
16	TLP4	P	FT	LP4	
17	TLP5	P	FT	LP5	
18	TLP6	P	FT	LP6	
19	TLP7	P	FT	LP7	

L1 = Line segment 1; TLP1 = Transformer connected to Load Point 1; B1 = Breaker 1; FT = Transformer F

B.2 Failure Mode and Effect Analysis of Feeder 2

Table B - 2: Failure Mode and Effect Analysis of Feeder 2

Component Data		Event Type	Protection	Load Points	Load Points
Event no.	Component	Permanent, Temporary	Triggered Unit	Affected by RT/RpT	Affected by SwT
20	L13	P	Switch	LP8	
21	L14	T	B2		LP8-10
22	L15	P	Switch	LP9	
23	L16	T	B2		LP8-10
24	L17	P	Switch	LP10	
25	L18	T	B2		LP8-10

L1 = Line segment 1; TLP1 = Transformer connected to Load Point 1; B1 = Breaker 1; FT = Transformer F

B.3 Failure Mode and Effect Analysis of Feeder 3

Table B - 3: Failure Mode and Effect Analysis of Feeder 3

Component Data		Event Type	Protection	Load Points	Load Points
Event no.	Component	Permanent, Temporary	Triggered Unit	Affected by RT/RpT	Affected by SwT
26	L19	P	Switch	LP11	
27	L20	P	Switch	LP12	
28	L21	T	B3		LP11-LP17
29	L22	P	Switch	LP13	
30	L23	T	B3		LP11-LP17
31	L24	P	Switch	LP14	
32	L25	P	Switch	LP15	
33	L26	T	B3		LP11-LP17
34	L27	P	Switch	LP16	
35	L28	T	B3		LP11-LP17
36	L29	P	Switch	LP17	
37	L30	T	B3		LP11-LP17
38	TLP11	P	FT	LP11	
39	TLP12	P	FT	LP12	
40	TLP13	P	FT	LP13	
41	TLP14	P	FT	LP14	
42	TLP15	P	FT	LP15	
43	TLP16	P	FT	LP16	
44	TLP17	P	FT	LP17	

L1 = Line segment 1; TLP1 = Transformer connected to Load Point 1; B1 = Breaker 1; FT = Transformer F

B.4 Failure Mode and Effect Analysis of Feeder 4

Table B - 4: Failure Mode and Effect Analysis of Feeder 4

Component Data		Event Type	Protection	Load Points	Load Points
Event no.	Component	Permanent, Temporary	Triggered Unit	Affected by RT/RpT	Affected by SwT
45	L31	P	Switch	LP18	
46	L32	P	Switch	LP19	
47	L33	T	B4		LP18-LP24
48	L34	P	Switch	LP20	
49	L35	T	B4		LP18-LP24
50	L36	P	Switch	LP21	
51	L37	P	Switch	LP22	
52	L38	T	B4		LP18-LP24
53	L39	P	Switch	LP23	
54	L40	T	B4		LP18-LP24
55	L41	P	Switch	LP24	
56	L42	T	B4		LP18-LP24
57	TLP18	P	FT	LP18	
58	TLP19	P	FT	LP19	
59	TLP20	P	FT	LP20	
60	TLP21	P	FT	LP21	
61	TLP22	P	FT	LP22	
62	TLP23	P	FT	LP23	
63	TLP24	P	FT	LP24	

L1 = Line segment 1; TLP1 = Transformer connected to Load Point 1; B1 = Breaker 1; FT = Transformer F

B.5 Failure Mode and Effect Analysis of Feeder 5

Table B - 5: Failure Mode and Effect Analysis of Feeder 5

Component Data		Event Type	Protection	Load Points	Load Points
Event no.	Component	Permanent, Temporary	Triggered Unit	Affected by RT/RpT	Affected by SwT
64	L43	P	B5	LP25	
65	L44	P	B5	LP26	
66	L45	T	Switch		LP25-LP31
67	L46	P	B5	LP27	
68	L47	P	B5	LP28	
69	L48	T	Switch		LP25-LP31
70	L49	P	B5	LP29	
71	L50	T	Switch		LP25-LP31
72	L51	P	B5	LP30	
73	L52	T	Switch		LP25-LP31
74	L53	P	B5	LP31	
75	L54	T	Switch		LP25-LP31
76	TLP25	P	FT	LP25	
77	TLP26	P	FT	LP26	
78	TLP27	P	FT	LP27	
79	TLP28	P	FT	LP28	
80	TLP29	P	FT	LP29	
81	TLP30	P	FT	LP30	
82	TLP31	P	FT	LP31	

L1 = Line segment 1; TLP1 = Transformer connected to Load Point 1; B1 = Breaker 1; FT = Transformer F

B.6 Failure Mode and Effect Analysis of Feeder 6

Table B - 6: Failure Mode and Effect Analysis of Feeder 6

Component Data		Event Type	Protection	Load Points	Load Points
Event no.	Component	Permanent, Temporary	Triggered Unit	Affected by RT/RpT	Affected by SwT
83	L55	P	Switch	LP32	
84	L56	P	Switch	LP33	
85	L57	T	B6		LP32-LP38
86	L58	P	Switch	LP34	
87	L59	T	B6		LP32-LP38
88	L60	P	Switch	LP35	
89	L61	P	Switch	LP36	
90	L62	T	B6		LP32-LP38
91	L63	P	Switch	LP37	
92	L64	P	Switch	LP38	
93	L65	T	B6		LP32-LP38
94	TLP32	P	FT	LP32	
95	TLP33	P	FT	LP33	
96	TLP34	P	FT	LP34	
97	TLP35	P	FT	LP35	
98	TLP36	P	FT	LP36	
99	TLP37	P	FT	LP37	
100	TLP38	P	FT	LP38	

L1 = Line segment 1; TLP1 = Transformer connected to Load Point 1; B1 = Breaker 1; FT = Transformer F

B.7 Failure Mode and Effect Analysis of Feeder 7

Table B - 7: Failure Mode and Effect Analysis of Feeder 7

Component Data		Event Type	Protection	Load Points	Load Points
Event no.	Component	Permanent, Temporary	Triggered Unit	Affected by RT/RpT	Affected by SwT
101	L66	P	Switch	LP39	
102	L67	T	B7		LP39-LP41
103	L68	P	Switch	LP40	
104	L69	T	B7		LP39-LP41
105	L70	P	Switch	LP41	
106	L71	T	B7		LP39-LP41

L1 = Line segment 1; TLP1 = Transformer connected to Load Point 1; B1 = Breaker 1; FT = Transformer F

B.8 Failure Mode and Effect Analysis of Feeder 8

Table B - 8: Failure Mode and Effect Analysis of Feeder 8

Component Data		Event Type	Protection	Load Points	Load Points
Event no.	Component	Permanent, Temporary	Triggered Unit	Affected by RT/RpT	Affected by SwT
107	L72	P	Switch	LP42	
108	L73	T	B8		LP42-LP44
109	L74	P	Switch	LP43	
110	L75	T	B8		LP42-LP44
111	L76	P	Switch	LP44	
112	L77	T	B8		LP42-LP44

L1 = Line segment 1; TLP1 = Transformer connected to Load Point 1; B1 = Breaker 1; FT = Transformer F

APPENDIX C

C. APPENDIX C

Appendix C presents some of the reliability and system data as well as the Costs data used in this study.

C.1 Residential Customer Load Data for Bus 3 of the RBTS

The average load data are available in the spread sheet labelled “Average_Load.xlsx” in the CD provided. The time varying load data at 1hr time intervals and the 5min time intervals are available in the spread sheets labelled “Time_Varying_Load_1hr.xlsx” and “Time_Varying_Load_5min.xlsx” respectively found in the CD provided. The steps load data for the steps (x-axis) and steps (y-axis) load model are available in the spread sheets labelled “Steps(x)_Load.xlsx” and Steps(y)_Load.xlsx” respectively. The beta parameters for the time dependent beta PDF load model at 1hr and at 5min intervals are available in the spread sheets labelled “Beta_Parameters_1hr.xlsx” and “Beta_parameters_5min.xlsx” respectively.

C.2 Residential Customer Damage Function

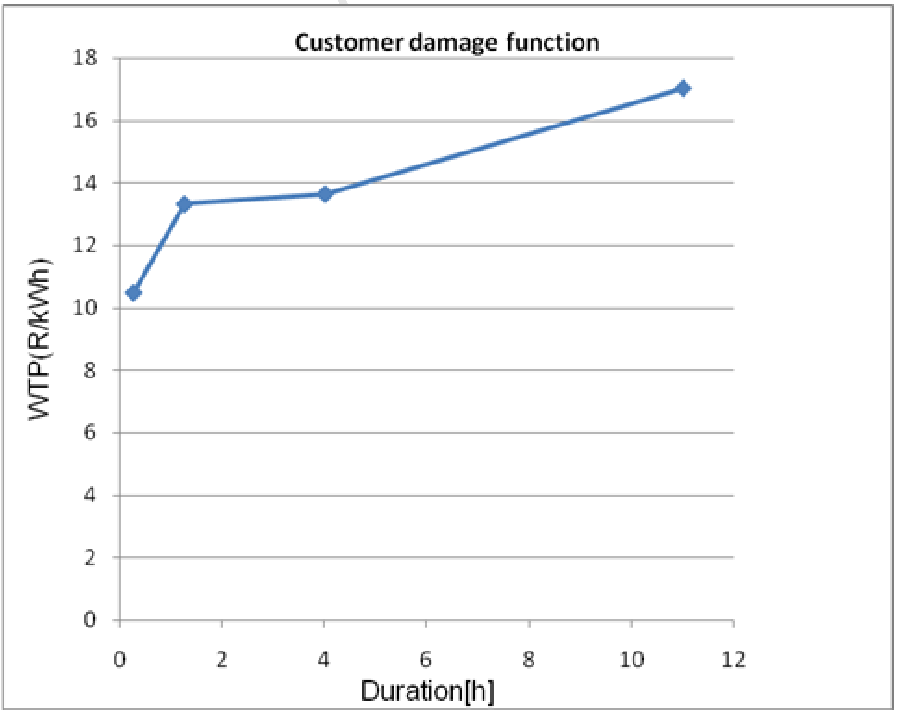

Figure C - 1: Residential Customer Damage Function **(Dzobo, et al., 2009; Herman & Gaunt, 2008)**.

Table C - 1: Data for Residential Customer Damage Function

Duration	Residential Cost kR/MWh
1	12.50
5	14.25
10	16.80
200	113.7

C.3 Commercial Customer Damage Function

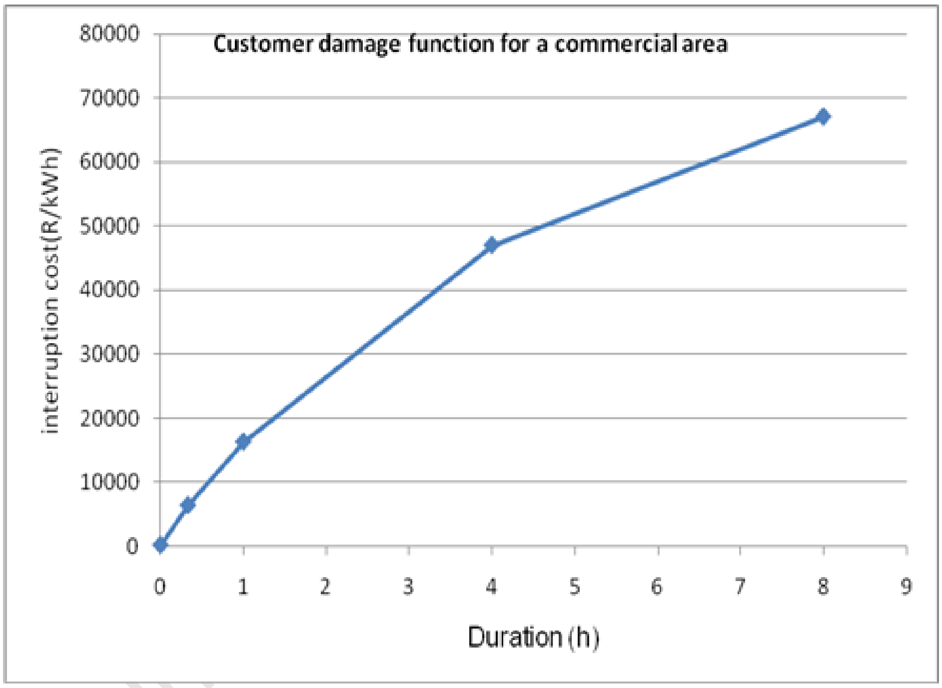

Figure C - 2: Commercial Customer Damage Function **(Dzobo, et al., 2009; Herman & Gaunt, 2008)**.

Table C - 2: Data for Commercial Customer Damage Function

Duration	Commercial Cost kR/MWh
1	16000
5	52000
10	67500
200	656500

C.4 Reliability and System Data

Table C - 3: Reliability and system data

component	λ_P	λ_A	λ_T	λ''	r	r_P	r"	r_C	s	
transformers										
138/33	0.0100	0.0100	0.050	0.5		15	168	0.083	1.0	
33/11	0.0150	0.0150	0.050	1.0		15	120	0.083	1.0	
11/0.415	0.0150	0.0150			200	10			1.0	("line" systen
									3.0	("cable" syste
breakers										
138	0.0058	0.0035	0.050	0.2	8		108	0.083	1.0	
33	0.0020	0.0015	0.020	0.5	4		96	0.083	1.0	
11	0.0060	0.0040	0.060	1.0	4		72	0.083	1.0	
busbars										
33	0.0010	0.0010	0.010	0.5	2		8	0.083	1.0	
11	0.0010	0.0010	0.010	1.0	2		8	0.083	1.0	
lines (single weather state)										
33	0.0460	0.0460	0.060	0.5	8		8	0.083	2.0	
11	0.0650	0.0650			5				1.0	
lines (two weather states)										
33 (normal)	0.0139	0.0139	0.018	0.5	8		8	0.083	2.0	
(adverse)	5.860	5.860	7.60							
cables										
11	0.0400	0.0400			30				3.0	

weather data: average duration of normal weather = 724hr
average duration of adverse weather = 4hr
line failures occuring in adverse weather = 70% of total

33kV line lengths: SP1-SP2 and SP2-SP3 = 10km
SP1-SP3 = 15km

transformer ratings: SP1(Bus4), SP(Bus2) = 16MVA each
SP2 and SP3 (Bus4) = 10MVA each

where: λ_P = permanent (total) failure rate (f/yr) [for lines/cables (f/yr.km)]
λ_A = active failure rate (f/yr) [for lines/cables (f/yr.km)]
λ_T = temporary failure rate (f/yr) [for lines/cables (f/yr.km)]
λ'' = maintenance outage rate (out/yr)
r = repair time (hr)
r_P = replacement time by a spare (hr)
r" = maintenance outage time (hr)
r_C = reclosure time (hr)
s = switching time (hr)

and: single weather state - rates are annual averages
two weather states - rates are per year of appropriate weather condition

Table C - 4: Feeder types and lengths (Billinton & Jonnavithula, 1996)

Feeder Type	Length (km)	Feeder Section Numbers
Bus 3		
1	0.6	1 2 3 7 11 12 15 21 22 29 30 31 36 40 42 43 48 49 50 56 58 61 64 67 70 72 76
2	0.8	4 8 9 13 16 19 20 25 26 32 35 37 41 46 47 51 53 57 60 62 65 68 71 75 77
3	0.9	5 6 10 14 17 18 23 24 27 28 33 34 38 39 44 45 52 54 55 59 63 66 69 73 74

C.5 Customer Data

Table C - 5: Customer Data (Billinton & Jonnavithula, 1996)

Number of Load Points	*Load Points*	*Customer Type*	*Load Level per Load Point, MW*		*Number of Customers*
			Peak	*Average*	
Bus 3					
15	1, 4-7, 20,24, 32, 36	residential	0.8367	0.4684	250
5	11,12, 13,18, 25	residential	0.8500	0.4758	230
4	2, 15, 26, 30	residential	0.7750	0.4339	190
3	39, 40, 44	large users	6.9167	4.3886	1
3	41-43	large users	11.5833	7.3496	1
3	8, 9, 10	small industrial	1.0167	0.8472	1
9	3, 16, 17, 19, 28,29,31, 37, 38	commercial	0.5222	0.2886	15
2	14, 27	office buildings	0.9250	0.5680	1

C.6 Examples of Residential and Commercial Load Profiles

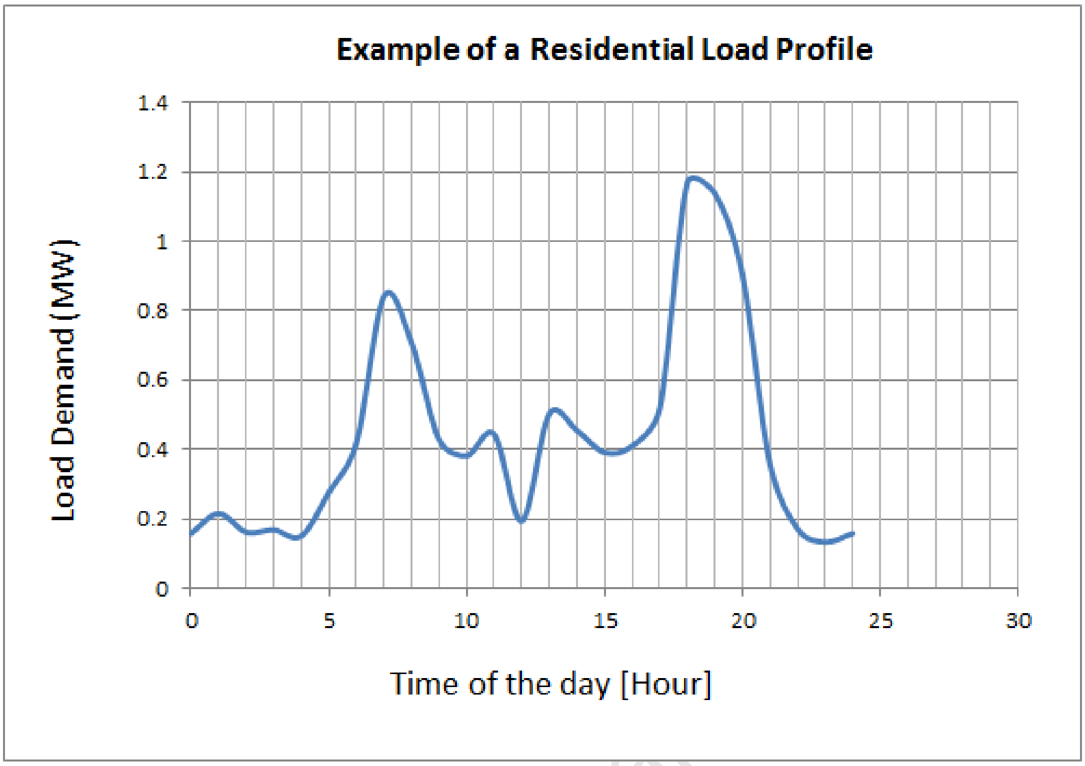

Figure C - 3: Example of a Residential Load Profile.

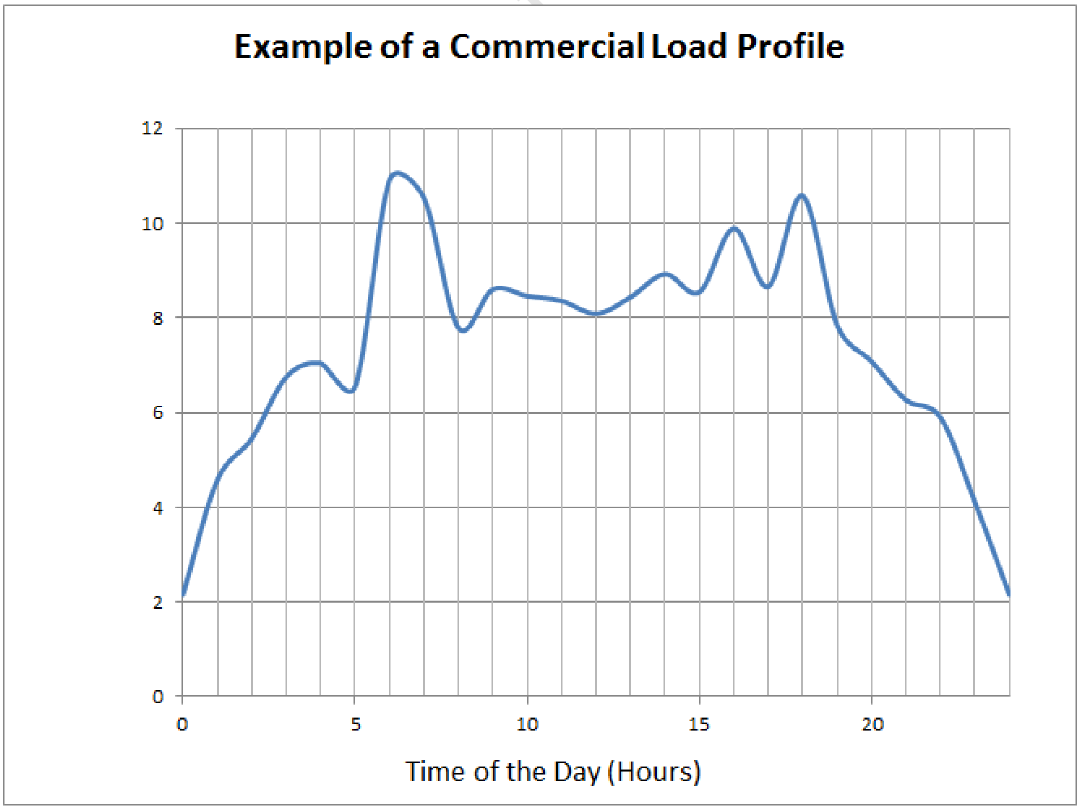

Figure C - 4: Example of a Commercial Load Profile.

C.7 Examples of Residential and Commercial Load Duration Curves

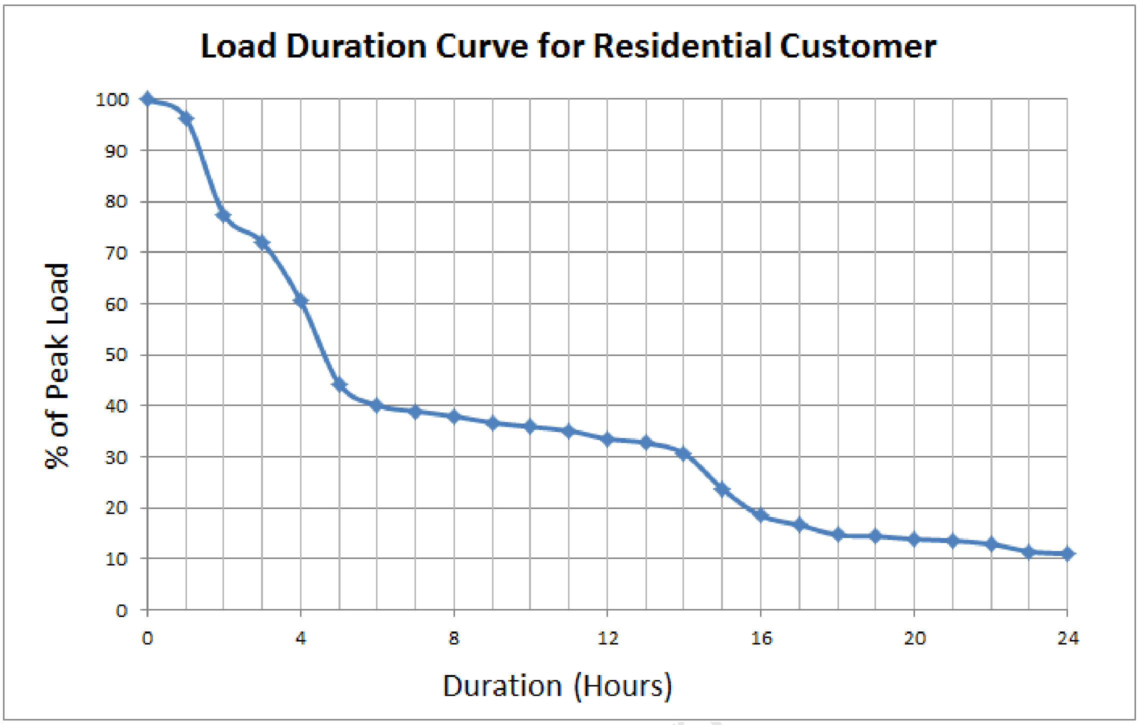

Figure C - 5: Example of a Load Duration Curve for Residential Customers.

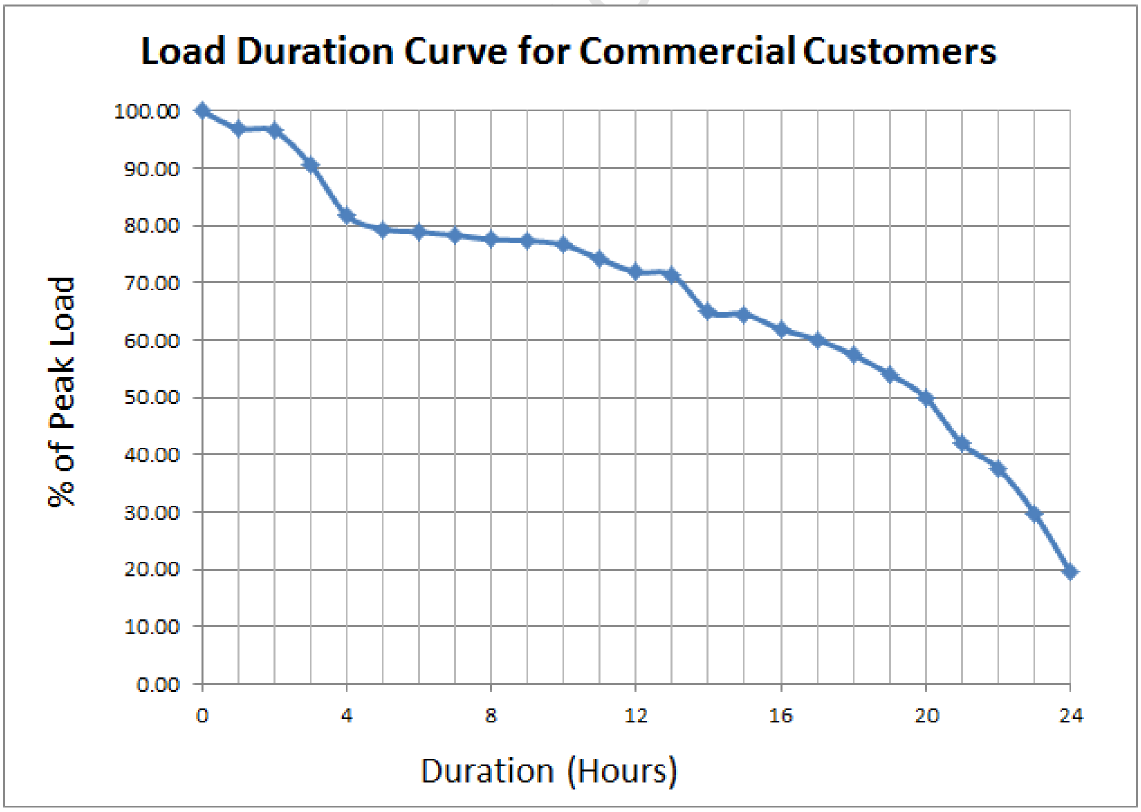

Figure C - 6: Example of a Load Duration Curve for Commercial Customers.

APPENDIX D

D. APPENDIX D – MONTE CARLO SIMULATION

Appendix D provides information on the using of Monte Carlo Simulation techniques in reliability studies of electrical power systems. The evaluation of reliability of power systems can be done using two approaches: state space and chronological representation. In the first technique using state space, the operating states of the system components (elements) can be selected from two distinct methods: analytical enumerations and non-sequential Monte Carlo simulation, in which the states of all components are sampled and a system state is obtained by combining the states of the components.

The second technique showcasing chronological representation samples the operating states of the components sequentially along several time periods, simulating the stochastic operating process of the system (EPRI, 1987; Veliz, et al., 2010). The most common method used for chronological representation is the sequential Monte Carlo simulation (Veliz, et al., 2010). The Monte Carlo method is the general description for stochastic simulation using random numbers (Billinton & Li, 1994). Although useful in solving stochastic problems, the Monte Carlo method can also be used to solve deterministic problems. The applications of Monte Carlo techniques vary from the fields of complex mathematical calculations, stochastic process simulations, medical statistics, engineering system analysis, and also for reliability evaluation.

For example, in a study by Billinton & Wang, (1999), the Monte Carlo simulation approach provides the opportunity to develop an appreciation of the variability associated with the annual indices of a distribution system reliability evaluation. The work in (Billinton & Goel, 1986) present an analytical technique can be used to evaluate the probability distributions associated with basic distribution system reliability indices. Billinton & Wang, (1999), explain that although this technique can be used to determine approximate probability distributions, when the system increases in complexity and the probability distributions of the component failures are widely spread, it is difficult and sometimes not possible to obtain an evaluation of the probability distributions of the reliability indices using the technique by Billinton & Goel, (1986), and large errors may be associated with the results obtained (Billinton & Wang, 1999). The processes in performing Monte Carlo Simulation for reliability evaluation of power system are shown in this chapter.

D.1 Introduction to Monte Carlo Methods

The Monte Carlo Simulation process can follow one of two approaches (Billinton & Allan, 1996):

(a) Non-sequential (Random) - this examines basic intervals of time in the simulated period after choosing these intervals in a random manner.

(b) Sequential – this examines each basic intervals of time in the simulated period in chronological order.

The basic interval of time is selected according to the type of the system under study, as well as the length of the period to be simulated in order to ensure a certain level of confidence in the estimated indices. The choice of a particular simulation approach depends on whether the history of the system plays a role in its behaviour. The random approach can be used if the history has no effect, but the sequential approach is required if the past history affects the present conditions. This is the case in a power system containing hydro-plant in which the past use of energy resources (e.g. water) affects the ability to generate energy in subsequent time intervals (Billinton & Allan, 1996). Sequential Monte Carlo simulation is described as a very flexible method for reliability assessment in (Bordeerath, 2011) since it can sequentially imitate the random nature of system components. According to Billinton & Allan, (1996), it is important to note that irrespective of which approach is used, the predicted indices are only as good as the model derived for the system, the appropriateness of the technique, and the quality of the data used in the models and techniques. The non-sequential MCS approach is also referred as state sampling technique by Billinton & Sankarakrishnan, (1995), in which the states of all components are sampled and a non-chronological system state is obtained. Billinton & Sankarakrishnan, (1995), present two basic techniques used in Monte Carlo applications to power system reliability evaluation, namely, the sequential and non-sequential techniques. In the sequential method, the up and down cycles of all components are simulated and a system operating cycle is obtained by combining all the component cycles. The sequential approach allows chronological-based problems to be solved (Billinton & Sankarakrishnan, 1995). Billinton & Sankarakrishnan, (1995), mention that the sequential technique usually requires a larger investment in computing time and effort compared to the non-sequential technique.

D.2 Non-Sequential Monte Carlo Simulation Techniques

Significant research work has been done in reliability evaluation of power systems using non-sequential Monte Carlo simulation techniques. In the work by Manso & Leite da Silva, (2004), a non-aggregated Markov Model is used in a non-sequential Monte Carlo simulation to calculate frequency and duration indices using a one-step forward state transition process. Billinton & Li, (1991), present a hybrid approach using non-sequential Monte Carlo simulation and an enumeration technique, along with an aggregated load model, in a sensitivity analysis of adequacy indices of different composite systems to the number of steps in the load model. Several other papers have based their studies on non-sequential Monte Carlo simulation (Billinton & Li, 1991; Melo, et al., 1992; Mello, et al., 1994; Mello, et al., 1997).

D.2.1 Non-sequential MCS Methods

Several methodologies based on non-sequential MCS techniques have been implemented in reliability studies and are fully described in (Melo, et al., 1992; Mello, et al., 1994; Sankarakrishnan (Jonnavithula) & Billinton, 1995).

D.2.2 Simulation Procedures

The conceptual algorithm for composite reliability evaluation by non-sequential MCS can be represented simulation procedures and examples of such procedures can be found in (Billinton & Sankarakrishnan, 1995; Veliz, et al., 2010).

D.3 Sequential Monte Carlo Simulation Techniques

This section briefly illustrates the fundamental concepts of sequential Monte Carlo simulations and describes the development of the algorithm using this technique for reliability evaluation.

D.3.1 Basic Concepts of Time Sequential MCS Techniques

The time sequential simulation process can be used to examine and predict real behaviour patterns in simulated time, to obtain the probability distributions of the different reliability load point or system parameters and to estimate the expected or average value of these parameters (Billinton & Wang, 1999). In a time sequential simulation, an artificial (simulated) history that shows the up and down times of the system elements is generated in chronological order using random number generators and the probability distributions of the element failure and restoration parameters (Billinton & Allan, 1996; Billinton & Wang, 1999).

Using the generated component histories, a sequence of operating-repair cycles of the system is obtained using the relationships between the element states and system states (Billinton & Wang, 1999). The system reliability indices and their probability distributions can be obtained from the artificial history of the system. The complete and detailed explanation of using Monte Carlo methods is available in (Billinton & Li, 1994; Billinton & Allan, 1996; Billinton & Wang, 1999)

D.3.2 Application to Reliability Evaluation

The necessary requirement in time sequential simulation is to generate realistic artificial operating/restoration histories of the relevant elements, which depend on the system operating/restoration modes and the reliability parameters (failure rates and outage duration) of the elements (Billinton & Wang, 1999).

Distribution system elements generally include but are not limited to transmission lines, cables, transformers, disconnect switches, fuses, breakers and alternate supplies. For example, line sections and transformers can be represented by the two-state model shown in Figure D-1 where the up state indicating that the element is in operation and the down state implying that the element is out of service due to failure (Billinton & Wang, 1999).

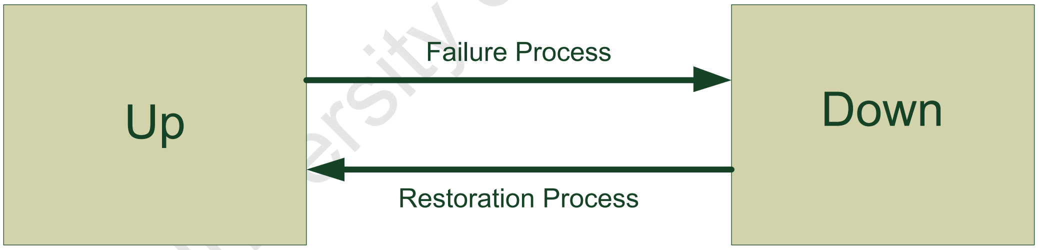

Figure D-1: State space diagram of element (Billinton & Wang, 1999).

TTF (time to failure) or FT (failure time) is used for the time during which the element remains in the up state and the restoration time, TTR (time to repair or time to replace) is the time during which the element is in the down state (Billinton & Wang, 1999). In some cases where switching operations are included, the restoration time also include the switching time, TTS, where the element is also in the down state. Transition form an up state to a down state can be caused by component (element) failure or by the removal of elements for maintenance. Figure D-2 shows a simulated element operating/restoration history.

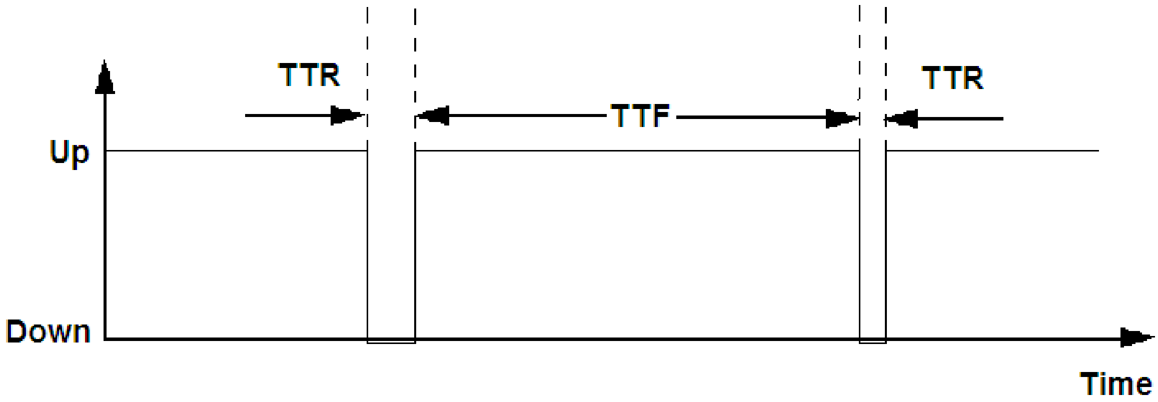

Figure D-2: Element operating/repair history (Billinton & Wang, 1999).

The parameters TTF and TTR are random variables and may differ in probability distributions which are simulated using most often using the exponential, lognormal, gamma, normal and Poisson probability distributions (Billinton & Wang, 1999). Breakers and fuses can be used to automatically isolate failed elements or failed sections from healthy sections and can exist in either functioning or failed states, which can be described in terms of their probabilities. In situations where alternate supplies are available, they can be described by probabilities of availability which can be simulated using a uniform distribution (Billinton & Wang, 1999).

D.3.3 Load Point Failure Analysis

Distribution systems supply electricity to individual customers at different load points. Element (component) failures may affect one or multiple load points. The primary difficulty in the simulation is to determine the load points, which are affected by the failure of an element and to find their operating/restoration histories, which are dependent on the network configuration, the system protection and the maintenance philosophy (Billinton & Wang, 1999). To minimize the difficulty, a structured approach can be devised, in which the distribution system can be broken into general segments. A complex radial distribution system can be divided into the combination of main feeder (a feeder connected to a switching station) and sub-feeders (a sub-feeder is a branch connected to a main feeder or to other sub-feeders). This method is also referred to as failure mode and effect analysis (FMEA), which is an inductive analysis used in different areas such as product development, system engineering/reliability engineering and operations management, for the analysis of potential failures within a system for classification by the severity and likelihood of the failures (IMCA, n.d.). The direct search procedure for determining the failed load points and their operating restoration histories is described in (Billinton & Wang, 1999):

D.3.4 System Reliability Indices

The evaluation of power system reliability can be expressed in terms of load point and system indices. Both the average and the probability distributions of these indices can be computed from the load point operating/restoration histories (Billinton & Wang, 1999). The three basic load point reliability indices often used are the average failure rate λ, the average outage time *r*, and the average annual unavailability or average annual outage time *U* (Billinton & Allan, 1996; Billinton & Wang, 1999). The average values of these three elementary load point indices for load point *j* can be calculated from the load point up-down operating history using the following formulae (Billinton & Wang, 1999):

$$\lambda_j = \frac{N_j}{\sum T_{uj}} \quad \left[\frac{failures}{year}\right] \ldots\ldots\ldots (D.1)$$

$$r_j = \frac{\sum T_{dj}}{N_j} \quad [hours/failure] \ldots\ldots\ldots (D.2)$$

$$U_j = \frac{\sum T_{dj}}{\sum T_{uj} + \sum T_{dj}} \quad [hours/year] \ldots\ldots\ldots (D.3)$$

Where $\sum T_{uj}$ and $\sum T_{dj}$ are the respective summations of all the up times T_u and all the down times T_d and N_j is the number of failures during the total sampled years.

The probability distributions of the load point failure frequency can be found by calculating the period values *k* of this index for each sample year. The number of years *m*(*k*) in which the load point outage frequency equals *k* is counted. The probability distribution *p(k)* of the load point failure frequency can be calculated using (Billinton & Wang, 1999):

$$p(k) = \frac{m(k)}{M} \quad k = 0, 1, 2 \ldots\ldots\ldots (D.4)$$

where M is the total sample years. The probability distribution of the load point unavailability can be found in a similar way. The calculation of the probability distribution of outage duration involves counting the failure number *n(i)* with outage duration between *i-1* and *i.* the probability distribution *p(i)* is (Billinton & Wang, 1999):

$$p(i) = \frac{n(i)}{N} \quad i = 1, 2, 3 \ldots\ldots\ldots (D.5)$$

where N is the total failures in the sampled years.

The system indices and their distributions can be calculated from the basic load point indices as system indices are mainly weighted averages of the individual load point values (Billinton & Wang, 1999).

D.3.5 Simulation Procedures

The time sequential Monte Carlo method can be applied for reliability studies in power systems using the following steps (Billinton & Wang, 1999):

Step (1) Generate a random number for each element in the system and convert it into TTF corresponding to the probability distribution of element parameter.

Step (2) Determine the element with minimum TTF

Step (3) Generate a random number and convert it into the repair time (RT) of the element with minimum TTF according to the probability distribution of the repair time.

Step (4) Generate another random number and convert this number into switching time (ST) according to the probability distribution of the switching time if this action is possible.

Step (5) Perform the FMEA of the system and record the outage duration for each failed load point.

Step (6) Generate a new random number for the failed element and convert it into a new TTF, and return to Step (2) if the simulation time is less than one year. If the simulation time is greater than one year, go to Step (9).

Step (7) Calculate the number and duration of failures for each load point for each year.

Step (8) Calculate the average value of the load point failure rate and failure duration for the sample years.

Step (9) Calculate the system indices and record these indices for each year.

Step (10) Calculate the average values of these system indices

Step (11) Return to Step (2) if the simulation time is less than the specified simulation years, otherwise output the results.

The simulation procedure may differ from the above steps; however the main concept for time to failure, TTF, applies to most if not all cases. Other examples of similar procedures are described in (Billinton & Sankarakrishnan, 1995; Veliz, et al., 2010).

APPENDIX E

E. APPENDIX E – SIMULATION TIME REDUCTION METHODS

When using Monte Carlo methods for reliability evaluation, a number of techniques can be used to reduce the duration of the simulation process. The simulation time varies with different complexity of the simulation program. Using deterministic values in an evaluation will produce faster results than when using stochastic approaches. A general description of deterministic and stochastic models is as follows (McLaughlin, 1999):

A *deterministic* model is one in which every set of variable states is uniquely determined by parameters in the model and by sets of previous states of these variables. Therefore, deterministic models perform the same way for a given set of initial conditions.

Conversely, in a *stochastic* model, randomness is present, and variable states are not described by unique values, but rather by probability distributions.

The implementation of time varying factors can also increase the simulation time. If the evaluation is time-dependent, such as varying on hourly, daily, weekly or yearly basis, simulation time can considerably increase thus reducing the simulation performance.

E.1 Computer Performance and Technology

One obvious way to increase the simulation performance, and therefore reducing the simulation time of the evaluation, is to use more advanced and powerful processors. With time, computers with more core processors, which are also more powerful, are available to the consumer market at competitive prices. More core processors mean faster simulation time, however this still requires some financial investment even if prices are going down. There are other ways to improve the simulation performance using the Monte Carlo methods without having to upgrade one's computer system. Other methods of reducing the simulation time using the Monte Carlo methods are available and are explained below.

E.2 Convergence Approach

When using the Monte Carlo approach for reliability evaluation, a fluctuating convergence process is created as shown in the work by Billinton & Li, (1994). There is no certainty that a few more samples will definitely lead to a smaller error, however the error bound or the confidence range decreases as the number of samples increases (Billinton & Li, 1994).

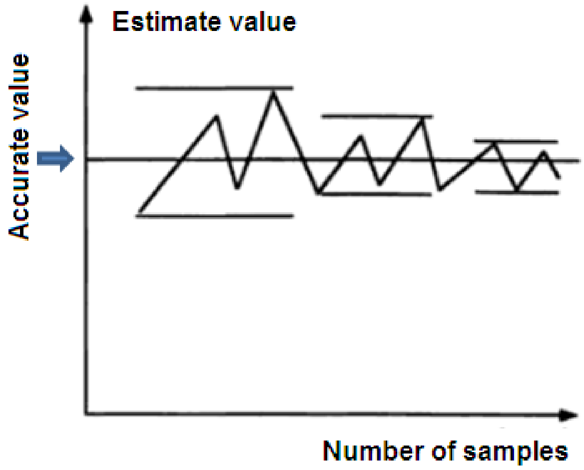

Figure E-1: Convergence in Monte Carlo Simulation (Billinton & Li, 1994).

A fundamental parameter in reliability evaluation is the mathematical expectation of a given reliability index. Let Q denote the unavailability (failure probability) of a system. The variance of the expectation estimate is given by the following equation (Billinton & Li, 1994).

$$V(\bar{Q}) = \frac{1}{N}(\bar{Q} - \bar{Q}^2) \ldots\ldots\ldots (E.1)$$

where N = number of system state samples,

The standard deviation of the estimate can be obtained as follows:

$$\sigma = \sqrt{V(\bar{Q})} = \frac{\sqrt{V(x)}}{\sqrt{N}} \ldots\ldots\ldots (E.2)$$

The above equation indicates that two measures can be used to decrease the standard deviation in a Monte Carlo simulation. Firstly, increasing the number of samples and secondly, decreasing the sample variance. The first method whereby increasing the number of samples is explained in this section. Effectively selecting the correct number of samples in the simulation can be very difficult if the appropriate approach is not used. Variance reduction techniques can be used to improve the effectiveness of Monte Carlo simulation. The variance cannot be decreased to be zero, and therefore it is necessary to use a reasonable and adequately large number of samples (Billinton & Li, 1994).

The coefficient of variation is often used as a convergence criterion in Monte Carlo simulation (Billinton & Li, 1994) and is a normalized measure of dispersion of a probability distribution. It is defined as the ratio of the standard deviation to the mean as shown below.

$$c_v = \frac{\sigma}{\mu} \dots\dots\dots (E.3)$$

In power system reliability evaluation, the convergence speeds vary for different reliability indices. The coefficient of variation of the expected energy not supplied (EENS) index has been found to have the lowest rate of convergence. Therefore this coefficient of variation should be used as the convergence criterion in order to guarantee reasonable accuracy in a multiple-index study (Billinton & Li, 1994).

Equation {6.3) can then be expressed as (Billinton & Li, 1994; Alvehag, 2008):

$$c_v = \frac{\sigma(X)}{\mu(X).\sqrt{N}} \dots\dots\dots (E.4)$$

The reliability index estimated is denoted X in equation (6.4) and X is a vector consisting of the reliability index values for all samples. A maximum tolerance error (ϵ) is also required and when the inequality $c_v < \epsilon$ is satisfied, the simulation is interrupted (Alvehag, 2008). A maximum tolerance error of 3 % or 0.03 is also specified in (Alvehag, 2008) while in (Billinton & Sankarakrishnan, 1995), a maximum tolerance error of 6 % or 0.06 is used. Therefore the tolerance error varies from one another.

E.3 Other Methods

Other methods to reduce the simulation time are described in (Billinton & Li, 1994) (Gentle, 2005) and include variance reduction methods which are categorized as follows:

- Analytical Reduction
- Stratified Sampling and Importance Sampling
- Use of Covariates
- Constrained Sampling
- Dagger Sampling
- Stratification in Higher Dimensions: Latin Hypercube Sampling