UNIVERSITY OF CAPE TOWN
Faculty of Engineering and Built Environment

RISK-BASED INTERRUPTION COST INDEX BASED ON CUSTOMER AND INTERRUPTION PARAMETERS

A Thesis in
Department of Electrical Engineering
by

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Submitted in Fulfillment
of the Requirements
for the Degree of

Doctor of Philosophy

DECLARATION

I hereby declare that this dissertation, *Risk-based interruption cost index based on customer and interruption parameters* is my own work, except for excerpts and summaries whose sources are indicated and acknowledged in the references. I also certify that this work has not been submitted to any other university for any other degree or examination.
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OLIVER DZOBO

DEDICATION

To my Mom and Dad

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I would like to acknowledge the following:

My God, Jehovah, for His wisdom and superb inspirational words.

To my Mom and Dad l say thank you very much for everything,
you are a pillar of strength and your help will echo into eternity.

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I am indebted to my colleagues and friends for providing a stimulating and fun environment.

For there is one God, Jehovah Almighty.
And Jesus Christ my Saviour

Not to us, Oh Jehovah, but to your Name be the glory because of your steadfast love and faithfulness! Psalms 115:1

Oliver Dzobo
Cape Town, 2014

ABSTRACT

Modern competitive electricity markets do not ask for power systems with the highest possible technical perfection, but for systems with the highest possible economic efficiency. Higher economic efficiency can only be achieved when accurate and flexible analysis tools are used. Thus, the modelling of reliability inputs, methodology applied in assessing supply reliability and the interpretation of the reliability outputs should be carefully considered in power system management.

In order to relate investment costs to the resulting levels of supply reliability, it is required that supply reliability be quantified in a monetary way. This can be done by calculating the expected interruption costs. Interruption costs evaluation, however, cannot be done correctly in all cases by methods that are based on the commonly used average values. It is the objective of this thesis to find a new way of calculating interruption costs which would combine the precision of a probabilistic method with the flexibility and correctness of customer and interruption parameters.

A new reliability worth index was found, based on customer and interruption parameters. This new index was called a Risk-based interruption cost (RBIC) index and is described in detail in this thesis. The technique applies a time-based probabilistic modelling approach to network reliability worth parameters. The approach uses probability distribution functions to model customer interruption costs (CICs) while taking into account seasonal, day-of-week and time-of-day influences. In addition, customer specific parameters - economic activity, energy consumption, turnover and power interruption mitigation measures are used to segment electricity customers into customer cluster segments of similar cost profiles. Unlike the conventional deterministic approach, the new technique thus considers variability in CICs. The new model and methods to calculate the new reliability worth index have been implemented in a computer program and the accuracy of the calculation method was tested in various case studies and by comparison with the traditional average process.

This research shows that probability density functions are superior to deterministic average values when modelling reliability worth parameters. Probability distribution functions reflect the variability in reliability worth parameters through their dispersion and skewness. Disregarding the effects of probability distribution of the interruption cost leads to large errors, up to 40% and more, in the calculated expected interruption costs. The actual error in specific reliability worth calculations is hard to estimate. It is however clear that this error cannot be simply ignored.

Furthermore, the risk-based approach applied to the interpretation of risk-based interruption cost (RBIC) index significantly influences the perception on the network's reliability performance. The risk-based approach allows the uncertainty allowed in a network planning or

operation decision to be quantified. Use of the new reliability worth index offer more flexibility in reliability worth assessment and produce more accurate results. It can be used in all areas of power system reliability worth assessment which have always been exclusive domain of the average process.

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LIST OF SYMBOLS

AIC	Average Interruption Cost
CAIFI	Customer Average Interruption Frequency index
CDF	Customer Damage Function
CIC	Customer Interruption Cost
ECOST	Expected interruption cost
hr	hour
kW	Kilowatt
kWh	Kilowatt-hour
kW/h	Kilowatt per hour
LP1	Load point 1
NERSA	National Energy Regulator of South Africa
PDF	Probability distribution function
p.u	per unit
RBIC	Risk-Based Interruption Cost
RBTS	Roy Billinton Test System
RNC	Revenue not collected
R50billion	Fifty billion South African rands
S.A	South Africa
SAIDI	System Average Interruption Duration Index
SAIFI	System Average Interruption Frequency Index
SIC	Standard Industrial Coding System
SIC - Stats SA	Standard Industrial Coding system - Statistics of South Africa
TBP	Time-based probability
TVC	Time-varying cost
UCT	University of Cape Town
U.S	United States
U.S2billion or $2billion	two billion United States dollars
WTA	Willingness to accept
WTP	Willingness to pay
yr	year
α, β, C	Beta parameters
%	Percentage

R/kWh . . . South African Rand per kilowatt-hour
R/kW . . . South African Rand per kilowatt
10kR . . . Ten thousand South African Rands
$/kWh . . . United States dollar per kilowatt-hour
$/kW . . . United States dollar per kilowatt

CHAPTER

ONE

INTRODUCTION TO THE STUDY

1.1 Introduction

Around the world, electrically driven production processes and demand for decent living conditions have placed electricity provision at the centre of sustainable economic growth and social development of a country. The dependence on electricity has increased with increased utilization. Such increasing dependence brings an awareness of the need for a high reliability of power supply, and the inconvenient and losses to electricity customers incurred due to power supply interruptions.

Modern society, because of its pattern of social and working habits, has come to expect that the supply of electricity should be continuously available on demand. However, the critical issue faced by most power utilities today is that the demand for electricity is high and growth in supply is constrained by technical, environmental and most importantly by financial impediments. A completely reliable system is therefore impossible to obtain. The question is: *What levels of power supply reliability can be tolerated to achieve the highest efficiency of satisfying electricity customer needs and expectations?* High levels of power supply reliability can only be reached by high investments and will result in too high costs for electricity customers. Low levels, however, will lead to an unacceptable number of power interruptions. It is evident therefore that the reliability and economic constraints can compete, and this can lead to difficult managerial decisions at both planning and operation levels of power systems.

Significant changes in the form of privatization have taken place in the power industry.

In many European countries, power system owners have been unbundled and, retail and production of electricity are now conducted on a competitive market [Alvehag, 2011]. In some developing countries like South Africa, the electricity regulator has introduced Performance Based Rates (PBR) indices with associated penalties and rewards as they try to balance cost or tariffs against power system reliability [NERSA News, August 2006]. This has shifted the focus of the power industry from the national economic focus to the profit driven focus.

To meet customer needs and expectations for affordable and reliable service while complying with regulatory requirements, with limited budgets, power utilities need to find tools and techniques that can be used to optimally maintain power system network reliability at the least cost. The only way in which all these competing and diverse constraints can be weighted together in an objective and consistent fashion is by use of value based reliability (VBR) evaluation techniques [Chowdhury and Koval, 1999]. The value based reliability evaluation framework assumes that customer needs and expectations can be measured. It aims to link investment decisions to customer needs and expectations in order to establish socio-economically justifiable reliability target levels for power systems. To measure the needs and expectations of electricity customers, the benefits to society of power system reliability need to be translated into monetary terms. The value of financial benefit of power supply reliability to electricity customers can be measured by their customer interruption costs (CIC) - the costs they incur when their activities are interrupted by power interruption.

To asses CIC, customer surveys are commonly used. CIC data derived from customer surveys can only cover a fraction of possible outage events [Sullivan and Keane, 1995]. Commonly, only the CIC for the worst case scenario, that is, a power interruption occurring at the worst time is surveyed for a few hypothetical outage durations [Wacker and Billinton, 1989]. A CIC model that can make predictions of CIC for an arbitrary outage event is then derived from the worst case scenarios. This is used as an input to the value based reliability evaluation framework. The challenge therefore, is to derive a CIC model that can accurately estimate CIC for arbitrary outage events.

1.1.1 Customer interruption cost

CICs are challenging to estimate since they are a function of many different factors [CEER, 2010]. Traditionally, CICs are estimated using the customer damage function model [Billinton and Allan, 1996]. It models the average CIC for each customer type as a function of duration.

However, there are other factors other than duration which affect CIC. CIC changes with the time of occurrence of a power interruption [Billinton and Wangdee, 2005; Alvehag and Söder, 2007]. For example, the CIC for a retail customer is larger when a power interruption occurs during a peak shopping period than when it occurs at a relatively light shopping period. The possible correlation between CICs and time of occurrence of power interruptions have not yet been fully considered in reliability worth assessments of power systems.

The linearisation of CIC with the duration of the interruption does not describe the dispersed nature of CIC that occurs for individual electricity customers as well as for the different durations [Ghajar *et al.*, 1996; Herman and Gaunt, 2008]. It is unrealistic to use average CIC values for the different durations considered, such that the input average CIC values will have the same value 100% of the time. The average CIC values show how the electricity customers are impacted by power interruption on average but it might be interesting to investigate the risk for extreme cases. Therefore, for realistic CIC analyses, variability in CIC cannot be ignored and should be included in the model being used to represent it. Since probability distribution functions allow for variation about the mean, they are a good tool for describing statistical variation (uncertainty) in the CIC estimation.

CICs vary substantially between customers and/or within classes of customers as a result of the very diverse activities these customers carry out [Lawton *et al.*, 2003]. The variation is a function of the degree to which customer applications are dependent upon electricity and to what extent production or other services can be impacted subsequent to a power interruption. In order to obtain more insight into the impact of these factors, it would therefore be necessary to ensure that customer class mix for CIC analyses are very carefully designed, properly executed, and thoroughly analysed according to these customer specifics/characteristics. If electricity customers with similar cost characteristics are clustered together, this would ensure a reduction in the dispersion of the final CIC estimates for each customer cluster segment formed.

The final CIC estimates for each customer cluster segment are used in calculation of quantitative power system reliability worth indicators for support in planning and operation decision processes of power systems. Investments can then be judged by the gain in the indices. Power system management decisions that could affect service delivery are not always based on sound engineering analyses but are often politically and socially driven [Herman and Gaunt, 2010]. To improve communication between all stakeholders involved, it is prudent to express the quantitative reliability indices in monetary terms. Financial decision makers are more likely to understand indices expressed in monetary terms than in engineering terminology. The application of reliability indices in combination with appropriate currency leads to the unification and comparability of different reliability indices. This technique is still a relatively young discipline in reliability worth assessment of power systems.

1.2 Hypothesis

Based on the above discussion, the basic hypothesis that this research addresses is:
A risk-based interruption cost index that incorporates customer and interruption parameters is a more useful tool than the existing deterministic reliability indices to represent cost of interruption and damage on a power system.

To test the validity of this hypothesis, it will be necessary to investigate the following research questions:

1. *What components and structure of reliability worth index provides a reliable, consistent measure of the power system?*
   - *Evaluate the effect that different customer parameters have on CIC estimation*
   - *Evaluate the effect that different interruption parameters have on CIC estimation*
2. *Can probability distributions be used to characterise uncertainty (or risk) in interruption cost assessment of power systems?*
   - *Investigate the use of PDFs in CIC estimation*
3. *How does the approach applied and interpreted make the tool more useful than the alternatives?*
4. *Are the system networks on which the index is developed or tested appropriate to represent the general cases?*
5. *Is the index absolute or comparative?*

The overall objective of this thesis is to derive a risk-based interruption cost index based on customer and interruption parameters.

1.3 Scope

Power system reliability consists of both adequacy and security of supply [Billinton and Allan, 1988]. Adequacy relates to the existence of sufficient facilities within the system to satisfy consumer load demand and system operational constraints. Security relates to the ability of the system to respond to dynamic and transient disturbances arising within the system. Normally, security evaluation requires the analysis of dynamic, transient, or voltage stability in the system. This thesis is going to focus on system adequacy only, which means that power system dynamics and transient disturbances are not considered.

A power system includes the three fundamental functions of generation, transmission (including substation), and distribution [Billinton *et al.*, 1994a]. This thesis is going to focus on both transmission and distribution power system networks.

Risk is a combination of probability and consequences. To perform a risk assessment of a system network three different models are used: customer interruption cost model, a load model and a reliability model. The load model describes the loss of load and energy not supplied due to power interruptions. It can either model the average annual load or the actual time varying load of the system, capturing its time dependence. The customer interruption cost model predicts the consequences or financial costs of a power interruption to the electricity customers, commonly normalized by annual peak load. By combining the customer interruption cost and load models, the interruption cost can be estimated in monetary terms. The reliability model describes the system component failures and their restoration processes during power interruptions. One common simplification of the reliability model is to assume constant failure rates and non-time varying restoration times for components [Alvehag and Söder, 2008a]. However, failure rates and restoration times for most system components are dependent upon time-varying factors such as weather conditions [Edimu *et al.*, 2011]. Severe weather is generally more common during certain seasons making the power interruptions caused by weather time dependent. Thus, when considering a cost-benefit analysis of an investment in increased reliability of the system the time dependent probability of this particular event should be included. In this thesis, the average load model is used and system components are assumed to be fully reliable. The two subjects of load and system components reliability are considered to be beyond the scope of this thesis. Only the customer interruption cost model is considered to derive a risk-based interruption cost index based on customer and interruption parameters.

1.4 Thesis outline

Chapter 2 gives necessary background in power system reliability worth assessment and value based planning approach as applied in power systems. The benefits of accurate estimation of CIC estimates are also discussed.

Chapter 3 provides an overview of methods to assess customer interruption costs and existing cost models. The chapter ends with a discussion of possible modelling improvements that can be done.

Chapter 4 starts with an introduction to the existing different time-dependent CIC models. Validation of different time varying cost (TVC) weighting factors is also performed using proportional test results. The chapter ends with a discussion of the different interruption parameters that affect CIC for different electricity customers.

Chapter 5 provides an overview of the different customer segmentation models used in CIC analyses. A new customer segmentation model is proposed that considers different customer characteristics. Incorporating these customer parameters makes it possible to reduce the dispersion of CIC estimates for different customer cluster segments. Furthermore, the CIC model aims to include mitigation measures implemented by electricity customers

Chapter 6 presents goodness of fit test results of different probability distribution functions when estimating power system reliability worth inputs and outputs. The chapter ends with a discussion of the test result and the best fitting probability distribution function is presented.

Chapter 7 presents the flowchart of the proposed time-based probabilistic CIC model and the advantages of its application. The proposed time-based probabilistic CIC model is applied to two different test systems and results are reported and discussed. A comparison of the proposed time-based probabilistic CIC model and average CIC model is carried out.

Chapter 8 concludes the thesis and areas of recommendations are discussed.

CHAPTER

TWO

POWER SYSTEM RELIABILITY WORTH ASSESSMENT

2.1 Introduction

Designing, planning and operating standards and techniques have been developed over many decades for resource or investment planning and operation of power system networks. This comes as a result of different technical bodies which have compiled statistics and published standards so that the power system reliability can be analysed and its reliability worth quantified [IEEE, 1997].

Traditionally, power system reliability levels have been planned according to subjective engineering standards - deterministic techniques. In a deterministic approach, the reserve margin is normally determined based on the ability to supply the forecast peak load with a specified number of units out of service. For example, many utility power systems have been planned based on the N - 1 criterion (reserve margin or failure contingencies). This means that there must be enough reserve on the system such that no load will lose power if any one line or any one generator fails. Many of these criteria and techniques are still in use today [Allan *et al.*, 1988; Svendsen *et al.*, 2012].

Severe power outage events have happened frequently in recent years. For instance, on August 14, 2003, the massive blackout in the east of North America covered eight states in the United States and two provinces in Canada, bringing about 50 million people into darkness for periods ranging from one to several days [Faranda *et al.*, 2007]. Between November 2007 and March 2008 the South African economy lost an estimated R50 billion due to scheduled power interruptions [NERSA, 2008]. These severe power outages let us realize that the single-contingency criterion (the N-1 principle) that has been used for many years in the power industry may not be sufficient to preserve a reasonable power system reliability level. The techniques are severely limited in their application as they solely depend on the historical data and experience from both the power system planners and operators. They do not recognize and reflect the inherent heterogeneity of customer needs and expectations, when evaluating the validity of power system improvements or setting target reliability levels. Intuitively, it is also commonly recognized that no power utility can financially justify the N-2 or N-3 principle in power system planning and operation.

Recent and emerging advances in communication and control technologies are beginning to make it feasible for the power utility to offer limited menu of price-reliability choices to electricity customers i.e service unbundling [ERGEG, 2009]. This alternative power system model design would offer a range of reliability choice options to better match the spectrum of customer needs and expectations. The electricity customers are grouped into customer cluster segments based on their needs and expectations for service reliability. The utility can then structure a menu of service options based upon a value based reliability evaluation framework of the available load control, investment strategies and pricing strategies of each unbundled option. Decisions on the actual numbers and types of service choices to be offered will depend on the distribution of customer needs and expectations for supply interruptions of different characteristics under each option. The following section will look at value based reliability evaluation as used in power system planning and operation.

2.2 Value Based Reliability Evaluation of Power Systems

The primary objective of value based planning approach is to identify socio-economically efficient investment strategies for power systems. This approach assumes that to achieve socio-economic efficiency in power system reliability planning and operation, the level of power supply reliability to electricity customers must correspond with the customer needs and expectations (- economic value of service that electricity customers require). This means if the cost of power system 8investment required to improve the level of power supply reliability exceeds the economic value of the service improvement the customer experiences, then the investment is unnecessary and should not be made. Otherwise, if the economic value of service to the electricity customer exceeds the cost of power system investment required to produce it, then the improvement is worth the additional cost, and investment should be made. Power system planners and operators must therefore balance the costs the utility will require to develop, operate and maintain the power system against the economic value attached by electricity customers to the service they provide. Investment, operating and maintenance costs are obtained using standard engineering cost estimation procedures [Sullivan *et al.*, 1997]. The economic value attached by electricity customers to the service provided by the power utility is measured by their CICs - the costs they incur when their activities are interrupted. Fig 2.1 illustrates a hypothetical example of how the power system investment cost (network cost for the power utility) and the customer interruption cost are combined to give the total reliability cost for society. From the diagram it can be seen that the cost of reliability is described from two perspectives, the utility cost graph and the CIC graph.

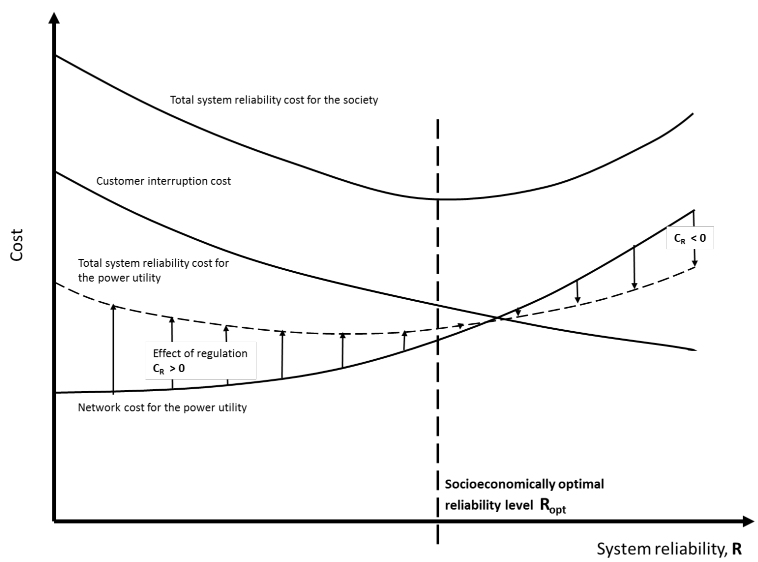

Figure 2.1. Determination of optimum reliability level of a power system

The utility cost graph shows the financial value of power system investments done in order to attain a certain level of reliability. It contains both tangible costs for the reliability enhancement, such as investment costs C_I, maintenance cost C_M, restoration cost C_{Res} and also intangible costs such as loss of goodwill in case of frequent power interruptions.

$$Network\ cost\ for\ the\ power\ utility = C_I + C_M + C_{Res} \quad (2.1)$$

The CIC graph shows the cost incurred by electricity customers due to power interruptions. From the graph it can be noted that for low levels of reliability the CIC are significantly high. It is therefore true that unreliable power systems are very costly to electricity customers whereas very high power system reliability levels are costly to the power utility. When the two costs are combined together it can provide the total system cost and is given by the following equation.

$$Total\ reliability\ cost\ for\ society = C_I + C_M + C_{Res} + cic \quad (2.2)$$

The minimum total system cost is reached when both the cost of reliability enhancement by the power utility and the reliability benefit that these improvements bring to the electricity customers are at minimum. This will indicate the optimal target level of power system reliability (R_{opt}). In the diagram the point is indicated at point **A**. At this point, both the utility and electricity customers' costs will give the least total system cost.

In some cases, regulatory authorities specifies performance standards for system quality indicators and implements rewards and penalties C_R for achieving and failing to achieve these standards, such that the power utility is penalized when it does not fulfil these standards and rewarded when it surpasses the set standards. The total reliability cost for the power utility is therefore affected and is defined as:

$$Total\ reliability\ cost\ for\ the\ power\ utility = C_I + C_M + C_{Res} + C_R \quad (2.3)$$

Thus the total reliability cost for society becomes:

$$Total\ reliability\ cost\ for\ society = C_I + C_M + C_{Res} + C_R + cic \quad (2.4)$$

From the graph, it can be seen that for low system reliability i.e when the power utility does not fulfil the regulator set standards, the total reliability cost for the power utility increases as indicated by the dotted line in figure 2.1. However, for high reliability, the power utility will receive incentive from the regulator and thereby reducing the total reliability cost for the power utility. A profit-maximizing power utility would therefore try to keep the reliability level at a point where its cost is minimized. Optimum reliability is achieved when the additional costs of providing higher reliability by the power utility are equal to the resulting decrease in customer interruption costs. If C_R is designed optimally by the regulator, this would result in the power utility striving for the reliability level R_{opt} that also minimizes the total reliability cost for society - see figure 2.1. Whether the regulator succeeds in setting an optimal C_R or not will therefore clearly depend on the regulator's ability to properly measure the customer interruption cost.

2.3 Need for accurate CIC assessment

The value based reliability evaluation framework is therefore a method used to balance supply and demand side costs. This makes it a recommended technique for all power system planners and operators looking to establish or confirm the socio-economic reliability goals for their company. As good as the concept of value based planning is, it presents a number of practical difficulties to the power system network planner. The most difficult is that different electricity customers have widely varying preferences for prices and service reliability. At one end, are electricity customers who need highly reliable service. These electricity customers are willing to pay a premium to ensure that the power supply reliability is very high because they experience high costs when power interruptions occur. At the other end, are electricity customers with less needs for power supply reliability and a preference of low cost electricity. Many of these electricity customers will tolerate power interruptions in exchange for lower prices. Because of the diversity of needs for power supply reliability by the electricity customers, developing the power system to achieve certain arbitrary reliability target levels may result in investments that are economically inefficient. The use of such arbitrary reliability target levels may cause under-investment in power system facilities needed to serve electricity customers who require high power supply reliability level. This results in electricity customers willing to pay more for high reliable power service. Accordingly, the arbitrary reliability targets may cause system planners to invest in system network facilities that provide greater power supply reliability than electricity customers really require, resulting in unnecessary electricity cost increases. Another problem faced by system planners is that load points of the power system differ dramatically in the types and sizes of electricity customers they serve. All load points do not serve the same customer mix of residential, commercial and industrial customers. Hence the economic value attached to power supply reliability by electricity customers should always be considered in power system reliability planning and must be customer specific. Without understanding and allowing for these differences, the economic efficiency will be less effective and power system reliability planning less sustainable.

Thus, with respect to the value based reliability evaluation framework, being able to estimate accurate CIC is desirable from more than one aspect:

- From a regulatory point of view, accurate CIC estimates are essential in order to tune the incentives schemes. If the regulatory impact of the interruption is based on the socio-economic costs of the interruptions, the power utilities are given incentives to make investments that are socio-economic correct. Consequently, socio-economic correct valuation is only possible with accurate CIC estimates and enables equally correct incentive schemes to be used. Furthermore, it can be used to balance tariffs against power supply reliability level or more so, to come up with associated penalties or rewards charged to the power utilities [Alvehag and Söder, 2008b].

- In the case of a power utility, accurate CIC estimates are used as input to cost-benefit analysis of power system reliability investment projects. If the CIC estimates are under-estimated, there is risk of power system reliability deterioration due to postponed investments and tighter maintenance schemes thus increasing the probability of power interruptions. On the other hand, over-estimated CIC values will result in untimely investment and the subsequent cost to the electricity customers. In addition, it is of great use in cases where the power utility and the electricity customer are negotiating to solve the customer's unique needs at a special price. In this case, it can be used to balance the utility's power supply reliability level and price against the electricity customer's needs.

In both scenarios, the electricity customer is affected. Therefore, determining accurate CIC values is the basis of good and acceptable customer service by the regulator and power utility.

2.4 Discussion

- *How best can an adequate level of power supply reliability worth be obtained from a socio-economic perspective?*

The best method to determine an adequate level of reliability from a socio-economic perspective is by using the value based reliability framework. To perform this analysis, both the cost of an action alternative aimed to enhance reliability and the expected benefits of the action alternative to the electricity customers, must be estimated. The benefit of increasing the reliability level is assumed to be equal to the economic value electricity customers attach to power supply reliability. This economic value cannot be measured directly, but it is assumed to be measured by the cost incurred by electricity customers as a result of power interruptions - CICs. The cost of power interruption is not identical to the value of reliability worth but it is considered as a good representative measure of it [Chowdhury and Koval, 1999]. The value based reliability framework will balance the investment costs by the power utility with the customer interruption cost. The reasonable or acceptable level of supply reliability is the point where the total system cost is minimal. In other words, it is the point where both the power utility and the customer will benefit most when the proposed alternative action is implemented. This will give a benchmark on which the power system planners and operators can base their decision making especially for maintenance and upgrading of the power system network. Thus, with respect to the value based reliability evaluation framework, good planning criteria and maintenance practices can therefore not be employed unless the CICs are fully appreciated by the regulator, utility and electricity customers. It is therefore important that both costs are accurately determined. This thesis is going to focus on accurate assessment of CIC from electricity customers. The following chapter will look at the CIC assessment methods used to collect CIC data from electricity customers.

CHAPTER

THREE

CUSTOMER INTERRUPTION COST ASSESSMENT METHODS

This chapter will look at the different customer interruption cost assessment methods used to collect customer interruption cost data from electricity customers. The different normalisation factors used in customer interruption cost analyses are also discussed.

3.1 Introduction

Customer interruption cost model is an input to the value based reliability framework and is needed to find the socio-economic adequate level of power system reliability. The method used for assessing the customer interruption costs has a direct impact on the accuracy of the CIC model [Alvehag and Söder, 2012]. Various CIC assessment methods, with different number of interruption and customer parameters included, have been proposed. The methods can be conveniently grouped into the following three categories namely; analytical methods, blackout case study and customer survey.

3.2 Analytical methods

The analytical methods analyse the interruption costs from a mainly theoretical economic perspective and are sometimes referred to as proxy or market based methods [Sullivan and Keane, 1995]. These approaches aim to capture the indirect cost faced by electricity customers due to power interruptions. The methods are based on a top-down approach with no direct contact of electricity customers and it is therefore difficult to capture the customers' actual needs and expectations. The value of power system reliability worth is viewed as equal to the economic value of a replacement commodity. For example, one approach used is to assume that the production output of firms, or more correct, the value added, as proportional to the input of electricity. Thus, it is possible in principle to estimate lost input by multiplying the interrupted kWh of electricity with the estimated average value added per kWh. In practise the real costs can exceed the added value of the lost production significantly due to damages to equipment or due to restart costs.

In addition, the methods do not consider most of the interruption and customer parameters [Chowdhury *et al.*, 2004]. They are usually based on annual data, which may not be appropriate for analysing short power interruption with durations of a couple of hours. However, one important advantage with the various analytical methods is that they are straight forward, since they are based on available data.

A. Example:

1. What are the investment cost for your backup solutions (\$)_____________
2. What are the operational costs for these backup solutions in one year (\$)_____________

3.3 Blackout case studies

The blackout case study method implies conducting a case study of a specific power interruption event, often a major blackout. The approach follows blackout events that may take place as a result of major disruption in the power system network such as earthquakes and floods. It is able to capture the direct and indirect costs faced by electricity customers due to a particular blackout [Chowdhury *et al.*, 2004]. Examples of blackout case studies upon which studies have been made are the Canadian Ice storm in 1998 and major storm Gudrun in southern Sweden in 2005 [Alvehag, 2011].

The advantage with this method is that the interruption costs are based on electricity customers' actual experiences and not hypothetical scenario. The main disadvantage of using this method is that it views power interruptions as only limited to a particular blackout. It is therefore difficult to generalize the results since no two blackouts are identical. The time of year when the incident occurs and the duration of the outage are factors that influence the interruption costs.

Blackout case studies are rarely performed for smaller interruptions. In this case a similar approach called Event Chasing is used [Herman and Gaunt, 2008]. The approach investigates interruption costs for electricity customers that have recently experienced a power interruption. A drawback with this method is that it may not be possible to get a representative sample of the entire electricity customer base. Electricity customers that experience low electricity supply reliability will be over represented. Therefore, this method might work best in countries with generally low level of power supply reliability.

In some instances, it is possible to combine blackout case study (also referred to as event chasing [Herman and Gaunt, 2008]) and customer survey methods (*see Section 3.4*). As such, blackout case studies will mainly focus on CIC estimates of a particular interruption event and customer surveys will capture interruption costs from hypothetical interruption scenarios. It is thus because of this difference, that blackout case studies are considered as a separate method from customer survey. However, a customer survey for a particular power interruption event is expected produce the same CIC estimate from the same respondent if a blackout case study in conducted for the same power interruption event. For example, if there is a blackout for 6 hours during the period between 6am - 12am in the morning and an electricity customer is asked to estimate the financial loss due to the blackout. The same CIC estimate should be expected in a customer survey, if the same respondent is asked to estimate a hypothetical power interruption scenario of 6 hours between the same period of 6am -12am. The only difference will be in the structure or approach of the cost questions asked to the responded. For a blackout case study, the respondent is expected to both give the period of time the blackout occurs and the CIC estimate, whereas for the customer survey the questionnaire designer is the one who comes up with the hypothetical power interruption period. The following gives examples of a blackout case study and customer survey CIC estimation question.

A. Blackout case study CIC estimate question example:

Please describe your most recent power interruption you have experienced using the information below:

- ***Outage Date:***__________________________
- ***Duration:***__________________________
- ***Start time:***__________________________

- ***End time:***______________________________
- ***Cost estimate:***______________________________

B. Customer survey CIC estimate question example:

On a **summer weekend morning** a planned load shedding is scheduled to occur and will last **2 hours**. Considering all of the costs you might experience as a result of this outage, please estimate the highest total outage cost that you would experience without considering backup power supply. R_____________________________ **Highest total outage cost (Worst case)**

3.4 Customer Surveys

The customer survey methods focus on the customer valuations of the interruption cost for hypothetical power interruptions or other quality deviation scenarios. It aims at quantifying the interruption costs by asking the electricity customers how the power interruptions affect their activities [Tollefson *et al.*, 1994]. The method is based on the fact that electricity customers are in the best position to assess the effects of power interruption and therefore best able to determine the associated costs [Tollefson *et al.*, 1994; Chowdhury *et al.*, 2004]. The method is therefore based on a bottom-up approach by involving the electricity customers in the evaluation of their interruption cost and thus represents the needs and expectations of electricity customers about their power utility. In the literature, four main customer survey methods have been used to estimate power interruption effects on electricity customers, namely: contingent valuation; indirect costing; contingent ranking and direct costing.

3.4.1 Contingent valuation methods

Contingent valuation method quantifies the customer interruption cost by asking electricity customers to state how much they are willing to pay (WTP) to avoid a power interruption or how much they are willing to accept (WTA) in compensation for a power interruption. Usually the willingness to pay is given as the maximum amount of money a customer is willing to pay to avoid a power interruption scenario, whereas the willingness to accept is given as the minimum amount of money which is required as a compensation to be indifferent to the welfare losses in the given power interruption scenario. Research studies have shown that people are more willing to accept money than they are to spend it, which results in the WTA usually being larger than WTP by a factor of approximately 2 [EPRI, 2000; Sullivan and Keane, 1995]. The question will be: *Which one of these two cost estimate values is the correct value that can be used in the CIC model in order to get the optimum socio-economic supply reliability level required by electricity customers?*. Many of the researchers have suggested that the WTP and WTA can be seen as lower and upper bounds for the interruption cost respectively [Billinton *et al.*, 1991; EPRI, 2000]. This means both results cannot be used to develop an accurate CIC model that can be used as an input to the value based reliability framework.

A. Example: Willingness to pay

Assume that a backup power supply is available that could supply the entire company's electricity needs during a power interruption. The backup supply is purchased only for the time actually in use. How much would your company be willing to pay for such a service to maintain power supply during a power interruption with the following characteristics and thus avoid the cost of the power interruption?

Duration: 2 hours

Season: Summer

Day of week: working day

Time of day: 6 am

Willing to pay for the service $____________

B. Example: Willingness to accept

Suppose the power utility could provide you with a credit on your bill each time your home experience power interruption, whether or not you were home. What would be the least amount that you would consider a fair payment for a 2 hour power interruption at your home?

Option 1: $1

Option 2: $2

Option 3: $5

Option 4: $10

3.4.2 Indirect costing methods

Indirect costing method uses the economic value of substitution principle, where the value of a replacement commodity is equated to the value of power supply reliability [Chowdhury and Koval, 1999; EPRI, 2000]. For example, the value of purchasing a generator is taken as the value of power supply reliability or cost of power interruption. This method addresses the preference of the respondent (electricity customer) rather than the straight monetary value of power interruption. The results from this method can therefore be greatly affected because different electricity customers have different views about power interruptions. The method is very effective when social effects are expected to constitute a significant part of the interruption costs [Chowdhury and Koval, 1999].

A. Example:

1. What are the investment cost for your backup solutions ($)____________
2. What are the operational costs for these backup solutions in one year ($)___________

3.4.3 Contingent ranking methods

Contingent ranking method is when electricity customers are presented with a set of choices or menu program from which they are asked to choose a program or answer [EPRI, 2000]. Each set of choices is connected to a specific power interruption cost and may consist of several different power interruption events. The power interruption events differ by duration and time of occurrence. The method can produce results that are very accurate due to the close duplication of actual customer choice procedures [EPRI, 2000].

The major drawback to this method is that the electricity customers are not given the chance to express their views on interruption cost and yet they are the ones that are affected. The method assumes that the provided choices will cover the preferences of the entire customer base, which may not be the case. The assessed value may thus be misleading since it is related to the approach used in designing the set of choices or menu program. Therefore the results cannot be used in developing general CIC models and can only apply to the customer base surveyed.

3.4.4 Direct costing methods

Direct costing method aims at capturing the monetary value the electricity customers suffer as a result of a power interruption [Chowdhury and Koval, 1999]. Electricity customers are asked to identify the impact of a particular hypothetical power interruption scenario and the associated costs. Sometimes specific power interruption events are also investigated [Herman and Gaunt, 2008]. Examples of costs that can be captured by this method are costs due to spoilage, damaged equipment, lost production, wages paid to idle labour, overtime to make up for lost production or services. Research evidence has shown that this method can produce results that are very consistent when applied to electricity customers with quantifiable interruption costs [Billinton *et al.*, 1991; EPRI, 2000].

A. Example:

On a **summer weekend morning** a planned load shedding is scheduled to occur and will last **2 hours**. Considering all of the costs you might experience as a result of this outage, please estimate the highest total outage cost that you would experience without considering backup power supply. R____________________________ **Highest total outage cost (Worst case)**

3.5 Summary of cost estimation methods

Table 3.1. Overview of different CIC assessment methods

Method	**Advantages**	**Disadvantages**
Direct cost method	• Customers normally are the best to know their own costs. This should in principle lead to good and precise estimates of their monetary costs. The reliability of the estimates derived from this method is increased if the interviewer is involved in the estimation process to avoid calculation errors • Spill-over costs on clients, suppliers etc may also be estimated if such questions are included in the survey (however estimates will be highly uncertain) for estimation	• Only monetary costs are covered. Non-monetary costs could be a considered part of total customer cost, especially for households • Often, a large effort is needed from the respondent to answer a Direct cost survey, as the questions are usually quite demanding. The complexity of the questions might cause the accuracy of the answers to suffer, especially if the study includes many scenarios. • Strategic responses may occur. The questions are only hypothetical; no payment is actually being made. If the respondent knows that the results are to be used in the future regulation of the power sector (for example to set compensation rates), it may lead the respondent to overstate the costs
Contingent valuation method	• Contingent valuation studies focus explicitly on the purpose of the study; to get an estimate of the total costs for different parties, including non-monetary costs. • The questionnaire often includes only one question about worth. Thus, it is less demanding for the respondent than answering to several cost categories.	• The willingness to pay and willingness to accept estimate should be equal, they differ from each other substantially because of loss aversion of the customers (willingness to pay considerably lower than willingness to accept) • In general the costs and the effort for conducting a survey may be high, especially if the survey is implemented through personal interviews • There may be problems with strategic answering since no real payment is made • In general,it maybe cognitively difficult for people to put a monetary value on services they are not accustomed to assess in monetary terms.
Contingent ranking method	• It allows for non-monetary costs to be included • Choosing between alternatives produces less stress among respondents and is considered a more realistic decision situation than expressing willingness to pay directly. It is also probably more difficult for respondents to answer strategically and show protest behaviour • The method leads automatically to the decomposition of preferences into utilities for separate attributes, which is suitable for power interruptions since these have a multi-dimensional character.	• This method needs sophisticated econometric models to estimate the costs. This may be quite laborious and the results may also be difficult to explain. • It might be challenging to set the right value of the price tags in the scenarios • Another possible drawback is that people are not explicitly aware of the valuations they make, and this may reduce the reliability of the results.
Indirect cost methods	• It is normally easy to collect data, since available market data can be used. • Data shows real market behaviour, not hypothetical statements.	• Spill-over are not included. • It is difficult to calculate the actual costs of power interruption since it depends on other factors such as duration, time of occurrence. • Sometimes customers will often try to mitigate the problem by none-market means as well, which maybe difficult to capture in this approach. • Usually the methods are based on annual data, which may not be appropriate for analysing shorter interruptions with durations of a couple of hours.

3.6 Normalization of customer interruption cost data

The CIC estimates from the survey respondents are given as absolute cost for a given power interruption scenario. The collected CIC data need to be transformed into normalized data so that it is usable for different applications in power system management. The purpose of normalization is to be able to calculate the aggregate or average costs of different electricity customers, but otherwise similar cost characteristics.

The normalized cost for a certain respondent and for a given power interruption scenario at reference t can be represented as follows:

$$c_{N,i}(r,t) = \frac{C_i(r,t)}{N_i(r,t)} \quad [Rands/kWh \ or \ kW] \tag{3.1}$$

where

$c_{N,i}(r,t)$ = *Normalized cost for respondent i for an interruption of duration r occurring at time t*

$C_i(r,t)$ = *Monetary value of respondent i (from the survey) for an interruption of duration r occurring at time t*

$N_i(r,t)$ = *Normalization factor for respondent i*

The normalised cost in equation 3.1 can now be used to calculate the average normalized cost $C_{N,j}(r,t)$ for a corresponding customer group j by averaging the individual normalised cost of the total customers n in that customer group. Equation 3.2 describes this calculation.

$$C_{N,j}(r,t) = \frac{1}{n} \sum_{i}^{n} c_{N,i}(r,t) \tag{3.2}$$

The cost for a given interruption is found as the product of the normalized cost data from the corresponding customer group and the customer's normalization factor i.e corresponding to the type of normalization factor used to calculate the normalized cost data. The reference time used in the survey represent the time t in the expression of the normalized cost. This should be taken into account in the application of the cost estimates. An approach for handling the time dependency in interruption costs is proposed in *Chapter 4*.

The choice of normalization factors should be seen in connection with the use of the CIC data and available data in the actual project at that time. Commonly, the CIC estimates from customer surveys are normalized by energy consumption or peak load [CE, 2008; Sullivan and Keane, 1995]. Annual energy consumption is usually available from the electricity customers themselves or can be imputed based on available information about electricity bills or tariffs. Information about peak load or load at reference time are usually not publicly available but can be estimated from load curves. For example, if load curves are available for individual electricity customers, or if general and credible load curves exists such estimation will be possible. The normalization per unserved energy has to rely on good data about the load curves of different electricity customers which is needed to estimate the unserved energy due to the power interruption. Caves *et al.* [1990] argue that it is otherwise impossible to say if a variation in CIC is due to a genuine variation in the value of unserved energy or whether it is due to the approximations and assumptions used to estimate the amount of unserved energy during the given power interruption.

In contrast, Targosz and Manson [2007] argue that normalization for large industry should be done per annual turnover and not electricity consumed. The authors argued that for very large industries the annual turnover has a very much greater effect on CIC estimates than the energy consumption. This is because for large industries energy consumption is a very small fraction compared to the company's annual turnover and therefore its effect may become very insignificant. Most of the studies however prefer to normalize using the energy not supplied for all customer groups, also done in a recent Norwegian study [Kjølle *et al.*, 2008].

In Ghajar and Billinton [2006] different normalizing factors were used for CIC estimates of different power interruption durations. The author argued that for very short power interruption durations (less than one-half hour) the peak load has a much greater effect on the CIC estimates and for longer power interruption durations (greater than one-half hour) the annual energy consumption will significantly influence the CIC estimates. However, in Sullivan and Keane [1995] it is argued that when peak load and annual energy consumption are used, the two normalizing factors do not produce the same results. The use of peak load is believed to produce results that under estimate the resultant CIC estimates and annual energy consumption will result in over estimation of the resultant CIC estimates

In a survey done by Pandey [1998], the monthly energy cost was found to correlate linearly with the CIC estimates that were provided by the survey respondents. Figure 3.1 shows the correlation between the CICs and the monthly energy cost reported by electricity customers. It can be clearly seen from the figure that the value electricity customers place on electricity is directly related to their monthly energy cost.

To validate the use of average monthly energy cost as a normalization factor, Dzobo [2010]; Dzobo *et al.* [2012b], performed a correlation analysis between CIC estimates provided by

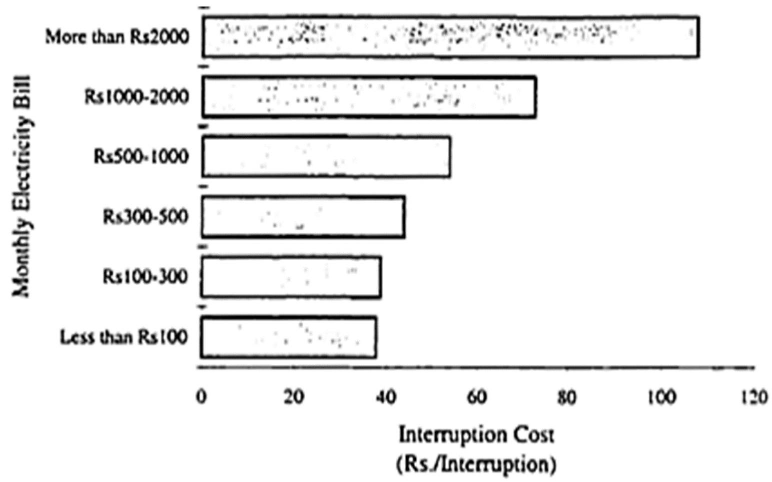

Figure 3.1. Variation of monthly energy bill with interruption cost, [Pandey, 1998]

survey respondents and their respective average monthly energy cost estimates. The customer survey was conducted using in-person interviews with the electricity customers. Figure 3.2 shows a correlation analysis of one of the customer segments that was surveyed in the customer survey. The correlation coefficient is very high and the 90% confidence level is also very narrow. This shows a positive linear correlation between CIC estimates in relation to the average monthly energy cost.

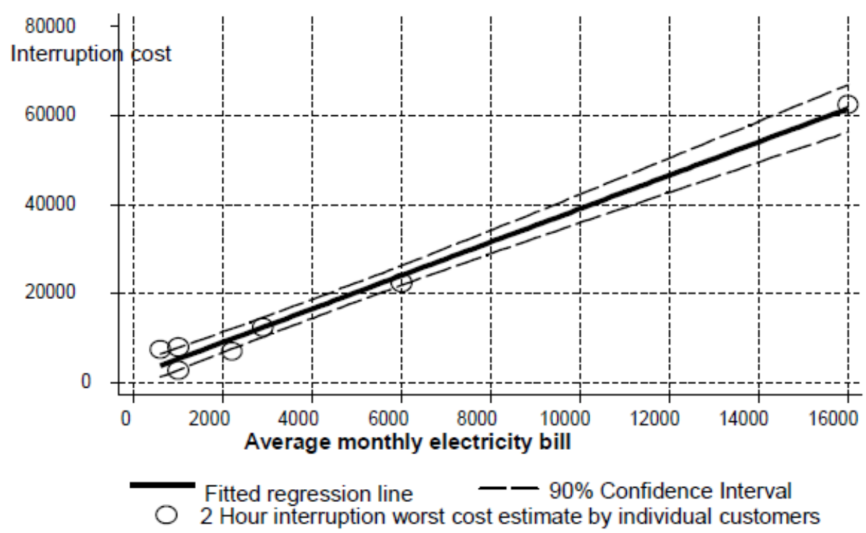

Figure 3.2. Textile/Clothing customer - Correlation between CIC and Average Monthly Electricity cost (including 90-percentile envelope), for a 2-hour outage on a Summer Morning, [Dzobo *et al.*, 2012b]

Similar observations were made from other customer segments and some other results are attached in Appendix A. The correlation between average monthly energy cost and CIC estimates were reported to be between 80% - 99%. The conclusion from the author was that average monthly energy cost can therefore be used as a normalization factor of CIC estimates. The author further used the average monthly energy cost as a normalization factor in [Dzobo, 2010; Dzobo *et al.*, 2011, 2012a] to show its application in reliability worth analyses of power system networks. The advantage of using average monthly energy cost as a normalization factor as noted by the author are that it is easily available from the electricity customers themselves or can be imputed based on available information about electricity consumption or tariffs. The cost estimates, normalized using the average monthly energy cost, are therefore used in this thesis.

Table 3.2. Different normalisation factors based on electricity demand or load

Factor	**Definition**	**Type of data required**
Annual electricity consumption (MW)	The total annual electricity consumed	Total annual electricity consumption monitored as input to the electricity bill
Average load (kW)	Annual electricity consumption / 8760	Total annual electricity consumption monitored as input to the electricity bill
Peak load (kW)	The maximum hourly load in the year	Load data: 8760 hourly loads based on hourly metering or general load curves for estimation
Interrupted load (kW)	The estimated power that would have been supplied at the time of interruption (or voltage disturbance) if the interruption(disturbance) do not occur	Load data: 8760 hourly loads based on hourly metering or general load curves for estimation
Energy not supplied	The estimated energy that would have been supplied if the interruption did not occur	Load data: 8760 hourly loads based on hourly metering or general load curves for estimation
Monthly energy cost	The total amount of money paid by the electricity customer to purchase electricity for the whole month	Total monthly electricity bill monitored as input to the monthly electricity consumption

3.7 Discussion

- *What is the best method to collect CIC data from electricity customers?*

The main difference between CIC assessment methods is whether they are based on stated preferences or revealed preferences. The indirect analytical methods are based on a top-down approach without any communication with the electricity customers and thus, the methods provide CIC estimates on a highly aggregated level. Blackout case studies concentrate on one specific blackout, and do not provide information on how duration, time of occurrence and other factors influence the interruption costs. In customer survey methods, interruption costs for hypothetical interruptions are investigated and the impact of different interruption and customer parameters can be captured. Customer survey is based on bottom-up approach because of the belief that the electricity customers are in the best position to know their own costs of an interruption.

Central in this thesis is the perspective of the electricity customers, and a realistic representation of the consequences of power interruptions that they face. Therefore, the customer survey method is deemed to be the most viable method to provide cost estimates upon which customer interruption cost models can be built. As applied in the context of this research study, the approach is believed to lead to deeper, more meaningful understanding of customer interruption costs which would enable the development of realistic customer interruption cost models. This is also supported by the results from both analytical and blackout case studies, which shows that for interruption cost assessment to be realistic, the cost information should be customer specific [Kaur *et al.*, 2002].

Various costing methods are used in the customer survey method. The contingent ranking costing method provides a set of choices connected to specific power interruption scenarios for electricity customers to choose. However, the set of choices may not be able to cover all the possible preferences of the entire electricity customer base. The indirect costing method assumes that the financial burden the electricity customers are willing to take to mitigate the effects of a power interruption on their activities is equal to their interruption costs. This may not be the case as the interruption cost value reflect only the value put on the replacement good used. The contingent valuation costing method ask electricity customers to state how much they are WTP to avoid a power interruption or WTA in compensation of a power interruption. The two costing methods produce different results and it is therefore not possible to produce a general CIC model for input in the value based reliability evaluation framework. The direct costing method measures the financial losses incurred by electricity customers as a result of a particular hypothetical power interruption scenario. The method produces consistent results for electricity customers with interruption costs that are easily quantifiable in monetary terms.

The results and shortcomings of these empirical research findings therefore informed the design and investigative procedures adopted in this research study. This thesis focuses on the need to use a research design which would allow one to accurately estimate the financial value due to power interruptions to electricity customers, and to develop valid and reliable CIC models that can be used to evaluate effectively in the value based reliability evaluation framework of power systems. The direct costing method was therefore deemed to be the best method to estimate the financial impact of power interruption on electricity customers, as it allows the power interruption impact to be easily converted to monetary value. Direct social effects on electricity customers are not considered in this investigation. The CIC estimates used in this research study are therefore derived from the direct costing method. The following chapter will look at the interruption parameters used in CIC estimation and possible improvements.

3.8 Description of the customer survey used for parameterization

For the parameterization of the customer interruption cost model used in this thesis, the South African customer survey conducted in Cape Town, South Africa in 2009 is used. This survey is presented in [Dzobo *et al.*, 2012b] and is described in detail in this section. The section will explain the selection of population and samples, and subsequently the development of the survey program, organisation and coordination of the treatments, and the measuring instruments used in the survey.

3.8.1 Selection of population and samples

Business customers (industrial and commercial) of Cape Town Municipality were chosen for the investigation. The decision was based on a number of factors:

- Both the commercial and industrial customers account for about 86% of total energy consumption in Cape Town i.e. about 44% commercial and 42% industrial [CCT, 2007].
- Business customers are the worst hit by power interruptions, and their costs are substantial and can be easily changed to monetary value.
- Cape Town was the worst hit town by power interruptions [Eskom-2008, 2008b] and therefore the business customers probably have greater chance of better understanding the costs of power interruptions.
- Cost of power interruptions investigation requires people with the formal reasoning abilities. Because The Cape Town business customers have experienced power interruptions for more than two years they probably have implemented measures to curb the recur-

rence of power interruptions and these need to be investigated so as to help other business customers in other areas or regions.

- Research studies of power interruption costs for Cape Town business customers have been carried out for quite some time at UCT and business customers have expressed enthusiasm in the research program as shown by the high response rate and participation in the research studies.

The Cape Town business customer study population for the investigation was partially taken from the Cape Peninsula 2008/2009 business directory. This decision was based on several reasons:

- The Cape Peninsula 2008/2009 directory uses the SIC system to arrange its customers and therefore an advantage to collect already refined data from this source.
- The directory is widely accepted by government and all business customers as a source of advertising their products and locations.
- All the contact information of the business customers is given.
- The directory is readily available and therefore the business information can be easily accessed.

The industrial and commercial populations were grouped according to the definition given in Statistics South Africa [1993]. An industrial customer was defined as a customer engaging in manufacturing of goods and products. Mostly small scale industries were considered in the survey. These are normally the majority of industries in Cape Town [CCT, 2007]. A commercial customer was defined as any form of business or commercial activities which are not primarily involved in manufacturing. The sector includes government, office buildings, retail shops, financial institutions. Again small scale commercial customers are the majority in Cape Town [CCT, 2007] and therefore they are the ones mostly considered in the survey. The industrial and commercial surveys were conducted concurrently. A business customer with various activities was classified according to the most significant part of that business.

One of the several factors to consider when determining the number of respondents to contact during a survey is the expected response rate. A probability sampling method was used to come up with the potential respondents list. The probability sampling method used in the research study was the systematic sampling method. The method has the advantage of that it is very useful in situations where the population size is not known.

The following steps were taken to come up with the potential respondents list for the research study. The sample was drawn by systematically moving through the sample frame (- provided in the Cape Peninsula 2008/2009 business directory) and selecting every $k_(th)$ element. To introduce randomness in the procedure, the starting point was chosen at random. The k_{th} element was then checked of its area, address and phone number. These potential respondents selected were then contacted by phone. The purpose of the telephone call was to:

- Identify the appropriate respondent within each business firm who is able to answer the power interruption cost questions.
- Contact that person and persuade them to participate.
- Schedule the onsite interview meeting

Respondents who give positive responses were noted. Accordingly, respondents were then visited for interviews with respect to their preferred times indicated. The researcher was responsible for not only selecting the respondents, but also for conducting all the interviews.

3.8.2 The Comprehensive Questionnaire (CQ)

The instrument that was used to measure the explanatory and outcome variables investigated in the survey took the form of a Comprehensive Questionnaire (CQ) (see Appendix A:A2). Because the CQ was to be administered to individual business customers for completion during the face to face interview, it was decided to use items with fixed response options at some stages. The following rationale guided this decision:

- Firstly, with a time constraint of fifteen (15) minutes the closed method would be most economical with respect to ease and speed of answering, and would therefore increase the number of questions which could be asked.
- Secondly, data processing would be less expensive and time-consuming.
- Thirdly, the questions asked, their response options and sequencing are predetermined and the same for all respondent, and this structure helps to increase the chance that each item will have the same meaning for all respondents.

- Fourthly, respondents will not be subject to interviewer bias.
- Finally, fixed format responses are generally considered to be less threatening to respondents and tend to encourage more candid response, particularly on sensitive issues.

The CQ also included open response options at some stages. These types of questions have the advantages that, the respondents can adequately answer the survey questions and statistical analysis of responses can yield extremely interesting information, categories and subcategories.

3.8.2.1 CQ Section A

- **Power Interruption Frequency**

Section A, question 1.1 of the CQ, asked the respondents the number of power interruptions they have experienced in the past 12 months. The objective of the question is to find the reliability level of the power supplier in terms of CAIFI and also to see if there is any difference in the number of power interruptions experienced by each sector considered in the investigation.

- **Satisfaction Level**

Section A, question 1.2 of the CQ, was used to measure the satisfaction level of the respondents regarding the frequency of occurrence of power interruptions. This question is much connected to the previous question (question 1.1) as respondents were supposed to indicate their satisfaction level based on the number of power of interruptions they have given in question 1.1.

The Satisfaction Level scale contained five items relating to respondents' satisfaction with respect to power interruptions they have experienced. A bipolar five point scale (symmetrical) with a neutral point was used. The rationale for the inclusion of the neutral point is that it can be an advantage because some respondents might be truly neutral. If they are not offered the option of a neutral response, some may opt to skip the question or give a less than accurate answer. Two items were positively phrased and two items were negatively phrased. A neutral point was included at the midpoint. The response categories offered are: "Very Satisfied"; "Satisfied"; "Neutral"; "Dissatisfied"; "Very Dissatisfied"

- **Power System Reliability Preference**

Section A, question 1.3 of the CQ, was used to measure the power system reliability preference of the respondents. Acceptable and Unacceptable items are used to measure the power system reliability preference objectively. To encourage honest responses and to discourage blind guessing, an additional response choice was included in the question a "'Do not know", response option was provided.

Because frequency was not the only variable to be measured by the question, duration of power interruption was seen to be a critical determinant. Four test items were used for each variable i.e. frequency and duration; and this make up to sixteen scenarios that needed to be investigated. There was need to keep the question as short as possible so that respondents would not become fatigued and lose interest, factors which sometimes prevent them from completing questionnaires. Multiple survey versions were therefore used to reduce the number of scenarios each respondent will answer. For each duration test item all the four frequency test items were investigated. This results in a total of four survey versions for this question. The duration test items used in the investigation are: "Load shedding lasting few minutes to 1 hour"; Load shedding lasting 1 hour to 2 hours"; Load shedding lasting 2 hours to 4 hours"; Load shedding lasting 4 hours to 8 hours". The four frequency test items are: "Once every week"; "Once a month"; "Once every six months"; "Once a year".

3.8.2.2 CQ Section B

- **Mitigation Measures**

Section B starts with a contingency question type. This arises because of the realization that some respondents might not have the backup power supply and thus the part of the question would be totally inappropriate to them. Therefore to save time, the respondents are guided away from the part of the question to next part where it becomes relevant again.

The type of backup power supply question was taken as a closed question. The rationale for this option was to guide the respondents in the type of answer that was expected from them. To make sure that all possibility answers were covered an " Others: Please specify" option was included in the answer. The question for the characteristics of the backup power supply was then presented as an open question where the respondent had to answer questions about the purpose, size, installation cost, running cost, year of installation and percentage of coverage of plant by the backup power supply.

- **Power Interruption Cost Measurement**

The backup power supply question was combined with the power interruption cost estimate question. In the power interruption cost estimate question the respondents were told not to consider their backup power supply when estimating their power interruption cost.

It is impractical to investigate all the interruption durations and their different times of occurrences. This is because of the number of scenarios respondent are able to answer and the limiting time factor. It is therefore important that the researcher have to choose the number of scenarios that are supposed to be investigated in the customer survey so as to reduce the time needed to answer the survey questionnaire. The problem was simplified by first taking the season as a dichotomous variable i.e. summer and winter. Secondly, the power interruption cost estimation was limited to occur during weekdays and weekend only. Thirdly, time of day was limited to morning, afternoon and evening only. For weekend, only morning was considered for the time of day. The rationale for this decision was that as most of the surveyed samples are small scale business customers, most of the businesses will be closed during the weekend and most only work up to meridian time. The power interruption durations were limited to 1, 2, 4, and 8 hours. This method reduced the number of power interruption scenarios that were asked from respondents to about 32 scenarios.

The method that was used to estimate the power interruption was the percentage reduction technique. In this method the respondents are asked only one power interruption cost estimate for each scenario and the other power interruption cost estimates are derived from this base cost estimate. The 8 hour power interruption cost estimate was taken as the base cost estimate. It was done so because this duration was expected to have the highest total power interruption cost estimate. All the other cost estimates were provided as a percentage to the base cost estimate. For example, respondents are asked to estimate the worst cost power interruption for a summer weekday morning power interruption of 8 hour duration and the other durations i.e. 1, 2, 4 hours are given as percentage to the 8 hour power interruption cost estimate. Again, multiple survey versions were used to reduce that number of scenarios each respondent receives. However, this approach increases the required sample size for the survey proportionately. Only eight power interruption estimates were asked from each respondent. Four survey versions were generated for this question.

- **Ability to Make Up for Lost Production**

Question 2.4 of Section B, was used to measure the ability of the respondent to make up lost production. The response categories that were offered to respondents were, "Not at all", "Partly", "Mostly", and "Not needed". The ability of the respondent to make up for lost production was investigated using four test items of power interruption duration and three test items of time of day. The power interruption duration test items that were considered are: Between few minutes and 1 hour"; "Between 1 hour and 2 hours"; "Between 2 hours and 4 hours"; "Between 4 hours and 8 hours". Morning, afternoon and evening were the three test items for time of day. To investigate all the test items, twelve (12) scenarios were generated. Multiple survey versions were used to reduce the number of scenarios to be investigated on one respondent to four i.e. for each test item of time of day all the power interruption duration test items were investigated. This resulted in three survey versions for this question.

3.8.2.3 CQ Section C

- **Demographic Characteristics**

This section of the CQ comprised three open questions requesting the respondent's size of supply, normal hours of operation and number of employees. In the respondent's size of supply three optional questions asking for the monthly electricity consumption (kWh), monthly maximum peak demand (kVA) and monthly electricity bill (Rand) were provided. These three optional questions were provided because in a pretest survey it was found out that most respondents were not able to provide answers for the monthly electricity consumption and monthly maximum peak demand. The main reason being that some of the respondent were not very technical and were not able to understand what kWh and kVA means. This proved to be so, as most of the respondents managed to provide answers for the monthly electricity bill question.

A categorical question was also included that allowed respondents to indicate the category that best describe their organisation or business. To make sure that no category was missed an option of "Any other: please specify" was provided. This would allow respondents who have their category not listed to specify it on the provided space. In this section the questions were asked in order to assess the range of demographic characteristics of every sample and population used in the investigation.

- **Business Activity Level Scale**

The business activity scale was given on a ten level scale. The values on the business activity level scale are not used in absolute terms but rather to identify how business customers value certain levels of their activities compared to their busiest times. The data generated from the business activity level scale is used to explain the time variation of power interruption cost. A two dimensional measurement matrix was used to measure the variation of business activity level with time of day and day of week. The time intervals considered for the time of day are: 00 - 08a.m; 08a.m - 12pm; 12pm - 2pm; 2pm - 6pm; 6pm - 9pm; 9pm - 12am. The day of week were split into four slots namely: weekdays, Friday, Saturday, and Sunday. The targeted times of the month that were investigated are end of month when employees are paid their monthly salaries, mid-month when some employees are paid their mid-month salaries and also beginning of the month when all customers are expected to buy their requirements for the whole month. The variation of business activity level with month of the year was investigated for all the twelve months of the year.

- **Improvements to Reduce Load Curtailment**

The last question asked respondents to provide options or improvements that can be implemented by the power utility to reduce the impact of load curtailment on their business. The question is an open question where respondents were allowed to express their thinking and expectations about their electricity supplier. A blank space was provided for the answer.

CHAPTER

FOUR

TIME CHARACTERIZATION OF CUSTOMER INTERRUPTION COST

This chapter will address the need for a time varying CIC model. Different examples are given to illustrate how time varying CIC models are developed. A case study is presented and proportion test results are done to validate the use of TVC weighting factors. In addition, the need to develop a time varying CIC model that does not increase the demands on customer survey is discussed.

4.1 Introduction

Even though several CIC models that includes a number of different interruption parameters have been proposed, the most commonly used interruption parameter is the power interruption duration. The reason for its popularity is that the impact of duration on CIC is substantial [CE, 2008; Sullivan and Keane, 1995]. The costs incurred due to power interruptions is presented as a function of power interruption duration. In these cases, the interruption cost versus duration plots are referred to as customer damage function (CDF). The CDF can be determined for a group of electricity customers belonging to particular sector or subdivision of a customer sector. CDF are usually based on CIC data for the worst case scenario as shown in Fig 4.1 [Dzobo *et al.*, 2011].

Two different procedures for calculating the CDFs are: the average process and the aggregating process [Tiedmann, 2004]. In the average process, the CIC data from the survey is first

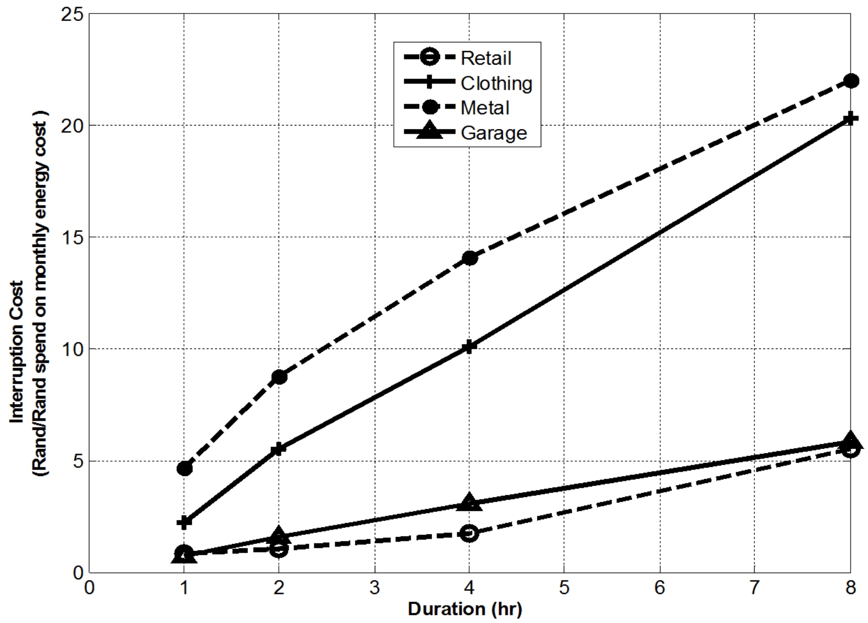

Figure 4.1. Customer damage function models for different customer segments, [Dzobo *et al.*, 2011]

normalized. After normalization, an average value of the normalized cost for each customer sector and surveyed duration is calculated. The second procedure, the aggregating process, first summarizes the CIC data for each customer sector and duration. The result is then normalized by division of the summation of normalizing factors of each sector [CEER, 2010; EPRI, 2000; Sullivan and Keane, 1995]. Research studies have shown that the two procedures do not produce the same results.

When using the CDF, good accuracy of determining CICs depends on surveying a large number of electricity customers and interruption scenarios. CDFs could then be created for every hour of each month. However, because of the limited resources in practice, CIC studies can only be done for a limited number of interruption scenarios and duration. Further, too many interruption scenarios can result in fatigue and boredom of respondents from too many repetitive questions and low response rates. Thus, most CIC studies provide little or no time variant CIC data.

In reality, the CIC usually measures the inconvenience a power interruption causes to the activities of electricity customers. Because activities generally follow a time-dependent pattern and are evaluated differently by electricity customers, the CIC will vary with time of occurrence of power interruption and its associated duration. The main reasons for the variation is that electricity customers performs different activities at different times. For industrial customers, a power interruption during the weekdays is more severe than when the same power interruption occurs during the weekend. This may be as a result of the different number of shifts scheduled for the different weekdays. The same can happen to a commercial customer who maybe involved in fast-food (restaurant) business. A power interruption during the lunch time when people come to buy their food has much greater effect than when the same power interruption occurs at odd hours say when the restaurant has just opened in the early hours of the morning at 6am. Another example is that, the CIC for a retail customer is larger when a failure occurs during a peak shopping period (high activity level) than when an interruption occurs at a relatively light shopping period (low activity level). The season effect can also have a bearing on the magnitude of interruption cost experienced by the electricity customers. This is very much experienced by industrial customer e.g. agricultural customers. If a power interruption occurs during the harvesting time for a wineries farmer, all the wineries may be spoiled by a single power interruption and the same farmer will have to wait for the next season to recover from that financial loss. Table 4.1 shows the variation of business activity for industrial and commercial customers.

Table 4.1. Variation of business activity level with time of year and day of week, day of month and month of year for industrial and commercial population, Dzobo [2010]

Business Activity Level Variation	**Industrial Sector**	**Commercial Sector**
Most Busiest Time of Month	Beginning of Month / Month - End	Month - End
Least Busiest Time of Month	Mid - Month	Mid - Month
Most Busiest Time of Year	July - December/January - March (Summer Season)	October - March (Summer Season)
Least Busiest Time of Year	April June (Winter Season)	April September (Winter Season)
Most Busiest Time of Day and Day of Week	Monday - Saturday (8am - 6pm)	Monday - Saturday (8am - 6pm)
Least Busiest Time of Day and Day of Week Day of Week	Sunday (6pm - 8am)	Sunday (6pm - 8am)

The fact that the maximum CIC during the day, week and season for different electricity customers do not coincide can be valuable to consider in practical applications. For example, it should be possible to use cost/benefit analysis in order to prioritize between electricity customers in case of electricity shortage when load shedding is necessary. By performing the disconnection on a sub-transmission level, the negative consequences of load shedding can be minimized when electricity customers with the largest needs and highest costs can be prioritized. Therefore, in order to prioritize between electricity customers in an efficient way, a time-dependent CIC model is essential. The following section looks at some of the examples of time-dependent CIC models and possible improvements.

4.2 Time-dependent customer interruption cost models

CIC models that take into account the time-dependency of CIC have been published [Alvehag, 2008; Wangdee and Billinton, 2005; Wang and Billinton., 1999; Kjølle *et al.*, 2009]. The time-dependency of CIC is captured in multiplicative CIC models. The multiplicative models are built on CIC data collected from extensive customer surveys that investigate CIC from a number of hypothetical scenarios occurring in different seasons, days of week and time-of-day. The time-dependent CIC models are based on weighting parameters of the time variation phenomenon being investigated. The weighting parameters describe the severity of the CIC at the different time of occurrence of power interruptions. These TVC weighting factors are multiplied with CDF, which is often estimated on the worst case cost.

Wang and Billinton. [1999] developed TVC weighting factors to represent the effects of time of occurrence of power interruptions on CIC estimates. Using the different CICs for different time of occurrence of power interruptions for daily, monthly, and seasonal periods, different weighting factors were developed. The derivation of the TVC weighting factors is defined as in equation 4.1. Equation 4.2 shows the normal CIC estimate weighted by the TVC weighting factor to obtain the time varying CIC estimate.

$$W(t) = \frac{Actual\ interruption\ cost\ at\ hour\ t}{Average\ interruption\ cost} \tag{4.1}$$

$$TVC(t) = W(t) \times AiC \tag{4.2}$$

where:

$$\begin{aligned} W\,(t) &= Time\ varying\ cost\ weight\ factor \\ TVC &= Time\ varying\ cost \\ AIC &= Average\ interruption\ cost. \end{aligned}$$

Although the method may produce very accurate CICs for the different time of occurrence of power interruptions, the model requires a lot of CIC data from the electricity customers in order to populate all the required CIC estimates for the purpose of reliability worth assessment of power systems for shorter periods. Thus, a limitation in its ability to obtain TVC weighting factors for all the different time of occurrence of power interruptions.

The procedure was extended further for application in operational reliability worth assessment of power systems by Wangdee and Billinton [2005], when they characterized a feeder using a time dependent feeder cost priority (FCP) index. The FCP index is divided into two categories, a day time high cost priority index and a night low cost priority index. In determining the curtailment priority of the feeders in a network, feeders are assigned either a low or high FCP index depending on the time an outage occurs. The same CIC is assigned to all faults occurring during the day. Similarly, it is assumed that all faults at night have the same financial impact on electricity customers. However, faults that occur during peak hours of consumer demand usually have a more significant impact than faults recorded outside peak hour intervals. Furthermore, activity patterns vary according to seasonal changes in a given year such that the electricity customers' loss risk posed by power interruptions is sometimes only high for short periods during a given year. The variation of CICs for short periods of time is no longer negligible such that average CIC models are no longer sufficient, particularly for operational reliability worth assessments that relate to different electricity customers.

Another example of a time-dependent CIC model was developed by Alvehag and Söder [2008b]. The authors accomplished this by relating the failure event to the underlying stochastic factors that give rise to the temporal variations in CICs. For residential customers, the CIC estimates were modelled using activity patterns and stochastic factors; weather patterns as defined in equation 4.3.

$$COST(k,t,d) = f_{customer}(k) \times f_{season}(t) \times f_{activity}(t) \times C(d) \tag{4.3}$$

where:

$$\begin{aligned}
f_{customer}(k) &= \textit{Factor for deviation in the number of affected} \\
&\quad\ \textit{household from the reference event} \\
f_{season}(t) &= \textit{Time-varying cost weight factor for seasonal deviation} \\
&\quad\ \textit{from the reference time} \\
f_{activity}(t) &= \textit{Time-varying cost weight factor for deviation} \\
&\quad\ \textit{in activity pattern from the refence time}
\end{aligned}$$

$$C(d) = \text{Normalized reference (worst case) interruption cost for a household due to an outage of duration } d$$

The seasonal factor was modelled through the daily temperature and lighting while, the activity level factor was based on the number of electricity dependent activities at the time of outage. The TVC weighting factors also included the variation in inconvenience that residential consumer experienced at the time of an outage.

For the other sectors i.e commercial, industrial, agricultural and governmental customers, two time-dependent factors were identified; a seasonal and activity level factor. Equation 4.4 shows the multiplicative CIC model that was used.

$$COST^S(t,d) = f^S_{hour}(t) \times f^S_{day}(t) \times f^S_{month}(t) \times C^S(d) \tag{4.4}$$

where:

$$\begin{aligned}
f^S_{hour}(t) &= \textit{Time-varying cost weight factor for hourly deviation from the reference time for sector } S\\
f^S_{day}(t) &= \textit{Time-varying cost weight factor for day of week deviation from the reference time for sector } S\\
f^S_{month}(t) &= \textit{Time-varying cost weight factor for deviation from the refence time for sector } S\\
C^S(d) &= \textit{Normalized reference (worst case) interruption cost for customer sector } S \textit{ due to an outage of duration } d
\end{aligned}$$

The TVC weighting factors were modelled using the activity levels of the electricity customers. The activity levels were however obtained from electricity customer's activity diaries.

A much more flexible time-dependent CIC model was proposed in Herman and Gaunt [2010]. The model proposes a time dependent characterization of CIC so that CIC estimates could be associated with seasonal and time-of-day intervals as shown by the 16 cell - matrix CIC model in Table 4.2. The 16 cell - matrix CIC model in Table 4.2 shows four seasons and four time-of-day intervals. Each cell or time window represents a specific season and time-of-day interval. The authors state that the seasons need not coincide with annual climatic seasons, calendar months or equal duration, but should rather be categorized according to periods in the year when electricity customers' loss risk to power interruptions is high or low. The time-of-day intervals could also be variable dependent on the more likely period of high or low activity levels. The CIC profiles for each time interval are presented as mean μ and standard deviation σ.

Table 4.2. CIC profiles for different time intervals

Period/ Time interval	**Time of day**			
	00-06	**06-12**	**12-18**	**18-24**
Jan-Mar	μ_{11} σ_{11}	μ_{12} σ_{12}	μ_{13} σ_{13}	μ_{14} σ_{14}
Apr-Jun	μ_{21} σ_{21}	μ_{22} σ_{22}	μ_{23} σ_{23}	μ_{24} σ_{24}
Jul-Sept	μ_{31} σ_{31}	μ_{32} σ_{32}	μ_{33} σ_{33}	μ_{34} σ_{34}
Oct-Dec	μ_{41} σ_{41}	μ_{42} σ_{42}	μ_{43} σ_{43}	μ_{44} σ_{44}

Such a CIC model can be consistently applied to both long term and short term reliability worth assessments of power system. For long term, the length of the season in Table 4.2 is increased. Short term studies can consider climatic seasons in a year, a calendar month, week or a couple of hours. However, the model as is, will thus, provide no indication of the effect of day-of-week. In addition, it also requires many different power interruption scenarios to be surveyed in order to populate the whole 16 cell - matrix CIC model. A new method of populating the 16 cell - matrix CIC model was presented in Dzobo *et al.* [2012a]. It was further shown that by using the 16 cell - matrix CIC model, the seasonal and time-of-day dependence of CICs can be captured for any class of electricity customer. The description and validation of the new method of populating the 16 cell - matrix CIC model and some suggested changes are going to be covered in detail in the next sections.

4.3 Estimation of customer interruption cost for the 16 cell - matrix CIC model

Electricity customers in most cases are not worried about how much electricity is not supplied but rather on their interrupted activities. According to Wang and Billinton. [1999], and Alvehag [2011], activity levels of different electricity customers change with time so that CIC estimates are time-dependent. For residential customers the CICs levels follow the daily household pattern while for retail consumers, it is the business activity that determines CIC level such that power interruptions that occur during high activity level correspond to high CICs and vice versa.

The activity level of the electricity customer therefore has a significant bearing on the consequences the electricity customer would face as a result of a power interruption. However, some electricity customers have constant activity level throughout the year e.g. a large continuous processing company. Several other electricity customers have strongly varying activity levels and so experience strongly time-dependent CIC estimates. Although activity levels vary for different lengths of time and having varying severity, they mostly follow a pattern within specific time-of-day or seasons of the year such that the pattern can be attached to the CIC estimates of the electricity customers.

Several studies have been conducted to try and describe how activity levels from electricity customers vary by time-of-day, month and season. The investigation of Swedish customers by Alvehag [2008] showed that different activity levels are performed by electricity customers during different time-of-day as shown in Figure 4.2

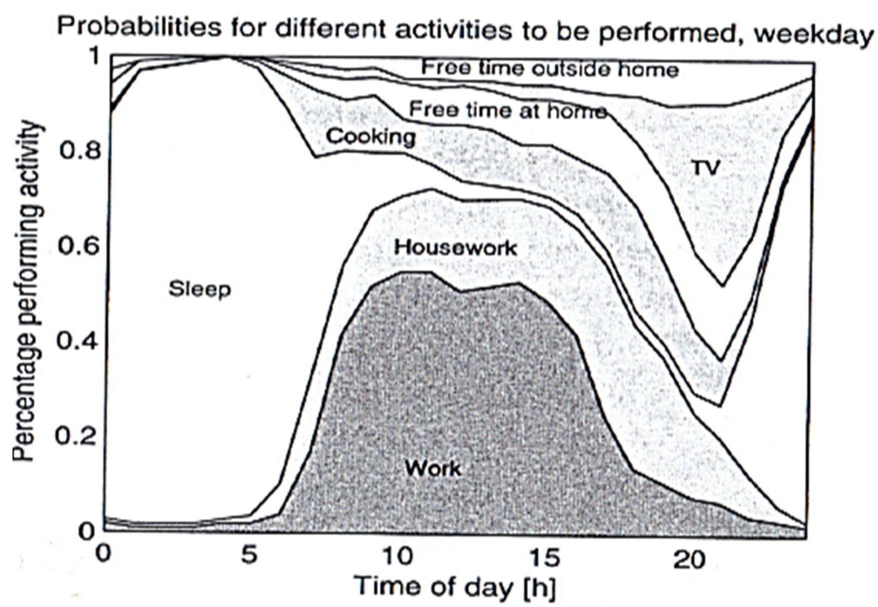

Figure 4.2. Percentage of population performing seven different activities each hour during a weekday. Based on the time-of-use diary data study, [Alvehag, 2008]

Activity level data from South Africa's electricity customers also indicates a high activity level during summer afternoons for both commercial and industrial customers. The activity levels increase in the afternoon when electricity customers are expected to be busy and reach a peak just before the evening times. Dzobo [2010] indicates that peak activity levels for commercial customers during the day occurred at the same time-of-day interval. The author deduced that the peak in activity level between 1200hrs and 1800hrs occurred due to high number of people processing their mid-day meal of the day. Furthermore, the author showed that peak activity levels for industrial and commercial customers occur mainly between November - December and January - March.

Based on activity levels of electricity customers, Alvehag [2008] developed a multiplicative CIC model presented earlier (*see Section 5.2*). The CIC data is grouped into monthly, weekly and hourly periods and different activity levels extracted from customer diaries are used. Using equation 4.4 the sector CIC estimate is time tagged by month, day and hour so that its time dependent cost profile or pattern can be regenerated. The author states that by developing activity levels, a random sampling of effect of time of power interruption occurrence on CIC estimates can be performed while still keeping track of a particular month, day and hour. Different CIC estimates for different time of occurrence of power interruptions from electricity customers are thus not required because the effect of time of occurrence of power interruptions is embedded in the activity levels.

The activity level used to derive the TVC weighting factors is based on the total number of electricity customers performing the same activity at a particular given time. From a planning point of view, the approach provides a better approximation of the overall impact of power interruptions to electricity customers; compared to the use of deterministic average values. However, the activity levels used are not customer specific, but are rather aggregate measure of some sample data. They are based on proportion of number of electricity customers performing a particular activity to the total number of electricity customers. In addition, the analysis periods are quite short and yet the activity levels are based on annual data sets. Applying the models to operation scenarios would thus provide misleading results. The activity levels of electricity customers have a significant influence on reliability worth parameters during such short periods, such that the order of priority between electricity customers changes significantly during the day. Therefore, using reliability worth parameters derived from CIC estimates based on annual estimations may not be sufficient when reliability worth indices for operational purposes are required. As described earlier, specific activity levels are prevalent in distinct periods of time-of-day or year. Central in this thesis is the perspective of the electricity customers, and a realistic description of the consequences of power interruptions that they face. Therefore, the activity levels must be customer specific, as they are in the best position to know their own activity levels.

Dzobo *et al.* [2012a] applied a different approach and developed activity levels on all types of electricity customers. The time-based activity level for each time interval TI is given by electricity customers themselves. Electricity customers are asked to fill their activity levels for the different time intervals in the 16 cell - matrix in Table 4.3. The activity levels were measured on an inconvenience scale. Electricity customers were asked to estimate their activity level on a scale from zero (0) to ten (10), where 0 means no activity taking place or business is closed and 10 means the busiest time.

Table 4.3. Activity level for different time intervals

Period/ Time interval	**Time of day**			
	00-06	**06-12**	**12-18**	**18-24**
Jan-Mar	W_{11}	W_{12}	W_{13}	W_{14}
Apr-Jun	W_{21}	W_{22}	W_{23}	W_{24}
Jul-Sept	W_{31}	W_{32}	W_{33}	W_{34}
Oct-Dec	W_{41}	W_{42}	W_{43}	W_{44}

The average activity levels for the different time intervals are then used as the TVC weighting factors. The time-dependent CIC estimates at a specified time interval were derived using equation 4.5 defined as:

$$TBC_{TI}^{A} = W_{TI}^{A}(t) \times CIC^{A}(d) \tag{4.5}$$

where:

$$\begin{aligned} W_{TI}^{A}(t) &= \textit{Time-varying cost weight factor for a given time interval } TI \\ &\quad \textit{deviation from the reference time for customer cluster segment } A \\ CIC^{A}(d) &= \textit{Normalized reference (worst case) interruption cost for} \\ &\quad \textit{customer sector } A \textit{ due to an outage of duration } d \end{aligned}$$

As noted earlier, the 16 cell - matrix CIC model does not include the effect of day-of-week on CIC. A new TVC weighting factor is proposed. The TVC weighting factor for the day-of-week is derived depending on the ratio of activity levels of weekday and weekend at the respective time intervals, as described in the equation 4.6.

$$W_{TI}^{A}(t, weekday) = \frac{Weekday\ activity\ level\ (t)}{Weekend\ activity\ level\ (t)} \tag{4.6}$$

The reciprocal of the equation is used when the reference CIC estimate is for the weekend day. The TVC weighting factors are derived for each particular customer segment. This is then used as inputs to equation 4.5 to calculate the CIC estimates for the different season, day-of-week and time-of-day.

4.4 Validation of CIC time-varying cost weighting factors: South Africa case study

To validate the use of activity level as TVC weighting factors different proportional tests were done to the customer survey data collected in Dzobo [2010]. The CIC data was collected for different time of occurrence of power interruptions and activity levels based on season, day-of-week and time-of-day were also asked from the electricity customers. The activity level were measured on an inconvenience scale as described earlier. For more information on how the customer survey data was collected and the instruments used to measure it, refer to *Chapter 3: Section 3.8*

4.4.1 Proportion test of CIC estimates and activity levels for different customer segments

Proportional test is used when comparing two groups [Navidi, 2008].

$$\frac{C_1}{C_2} = \frac{A_1}{A_2} \tag{4.7}$$

$where\ C_1\ and\ C_2\ are\ the\ two\ normalized\ CIC\ estimates\ for\ different\ time\ of\ occurre-$
$nce\ of\ power\ interruptions\ and\ A_1\ and\ A_2\ are\ the\ respective\ average\ activity\ levels$

The average normalized cost for a corresponding customer group for the different time of occurrence of power interruptions are obtained using equation 3.1 in *Section 3*. The respective average activity level for the corresponding different times of occurrence of power interruption are obtained using the following formula:

$$A_{j,n}(t) = \frac{1}{n}\sum_{i}^{n} a_i(t) \tag{4.8}$$

where $A_{j,n}(r,t)$ *is the average activity level of a customer group* j *with* n *customers for a particular time* t and $a_i(t)$ is the activity level from respondent i (from the survey) for a particular time t

The proportion of the CIC estimates were compared to the proportion of their respective activity levels using STATA software. The significance differences were noted and the percentage errors were also calculated. The output from STATA software of the statistical significance difference of the two ratios is interpreted in terms of their $p - values$. A small $p - value$ i.e $p - value \leq 0.2$ indicates no statistical significance difference between the two proportions. If there is no statistical significance difference between the percentages then we infer that the activity level percentage can be used to calculate the CIC if one of the CIC estimates is known.

4.4.2 Proportional test results

Tables 4.4 - 4.6 below show some of the proportion test results that were performed for different power interruption scenarios.

Table 4.4. Proportional test results for day of week

Customer segment	**No. of obs.**	**Time of occurrence**	**CIC estimates**	**Activity level**	**p-value @80% c.i**	**Percentage error (+/- %)**
Retail	20	Summer weekday morning	9.68 (9.18)	5.8 (2.26)	0.011	0.4
	6	Summer weekend morning	6.42 (7.53)	3.83 (2.27)		
Hotel and Restaurant	12	Summer weekday morning	3.00 (1.39)	7.13 (2.13)	0.016	0.9
	6	Summer weekend morning	2.62 (1.56)	6.17 (2.33)		

The results show that there is no statistical significance difference when activity level is used to approximate the different CIC estimates of the power interruption scenarios for different day-of-week. The percentage errors for the two presented customer segments are less than 1%.

Table 4.5. Proportional test results for different seasons

Customer segment	**No. of obs.**	**Time of occurrence**	**CIC estimates**	**Activity level**	**p-value @80% c.i**	**Percentage error (+/- %)**
Professional practices	12	Summer weekday morning	9.36 (8.73)	9.01 (1.59)	0.112	9.5
	6	Winter weekday morning	7.24 (5.83)	7.63 (2.01)		
Metal and Engineering	11	Summer weekday morning	4.08 (2.38)	9.07 (0.91)	0.036	2.2
	5	Winter weekday morning	4.05 (3.1)	9.2 (1.10)		
Hotel and Restaurant	12	Summer weekday morning	3.00 (1.39)	7.13 (2.13)	0.035	1.9
	7	Winter weekday morning	1.87 (1.09)	4.36 (2.01)		

Table 4.6. Proportional test results for time of day

Customer segment	**No. of obs.**	**Time of occurrence**	**CIC estimates**	**Activity level**	**p-value @80% c.i**	**Percentage error (+/- %)**
Hotel and Restaurant	12	Summer weekday morning	3.00 (1.39)	7.13 (2.13)	0.083	6.7
	3	Summer weekday afternoon	2.63 (2.30)	6.67 (1.53)		
	12	Summer weekday morning	3.00 (1.39)	7.13 (2.13)	0.200	15.6
	4	Summer weekday evening	1.82 (1.97)	5.00 (5.77)		
	3	Summer weekday afternoon	2.63 (2.30)	6.67 (1.53)	0.082	8.3
	4	Summer weekday evening	1.82 (1.92)	5.00 (5.77)		

The results show that there is no statistical significance difference when activity level is used to approximate the different CIC estimates of the power interruption scenarios for different seasons. The percentage errors for the presented customer segments range from 1% to less than 10%.

Limitation of results: This analysis is performed to get an insight on the relationship between CIC estimates and activity levels. Although the proportion test results re-affirms previous research findings, it should be noted that the relationship between activity levels and respective CIC estimates were derived from a small sample size. The small sample size was as a result of the limited customer survey resources that were available.

4.5 Discussion

- *The need for a time varying CIC model that does not increase the demands on customer survey*

Different authors indicated that CICs are time dependent and predominantly occur in certain seasons and time-of-day during the year. However, most researchers have used several hypothetical outage scenarios occurring at different times in order to capture the time of occurrence effect on CICs in customer surveys. This implies that customers need to be asked to estimate how their CICs vary on a monthly, daily and hourly basis. For most electricity customers this is reasonably a moderate task to do. Furthermore, there is limited amount of effort that survey respondents are prepared to put into filling out customer surveys, a limitation that is particularly relevant in business customers. This has created a new opening for the proposed new approach to estimate the temporal variation of CICs in electricity customers.

In this chapter, an analysis of CIC data was performed to identify the relationship of activity level with CIC estimates using South African CIC data. The percentage error for estimating or calculating the CIC estimates for the different customer cluster segments is below 10 %. For example, the retail customer cluster segment have a percentage error as low as 0.4% when using the activity levels for summer weekday morning and summer weekend morning. For other customer cluster segments the percentage error is large e.g for Hotel and restaurant the percentage error is 15.6 % when using activity level for summer weekday morning and summer weekday evening. The large error may be as a result of most respondents in this category reporting zero costs in the evening because they may have closed business. The issue of operation hours or number of shifts may be considered to segment the customers in order to reduce the large percentage errors. Another reason for the large errors may be because of the small sample size that was used in the analysis.

However, the proportion test results re-affirms previous research findings [Alvehag, 2008] that activity level from an inconvenience scale can be used to estimate CIC estimates for different customer segments of electricity customers. From the analysis it can therefore be recommended that by using the 16 cell - matrix model to measure the activity levels for the different season and time-of-day it is possible to get all the CIC estimates for all the remaining cells of the 16-cell matrix CIC model. The proposed approximation is necessary when compared to the number of survey questions that needs to be included in a questionnaire to populate the 16 cell- matrix CIC model. The following chapter will look at how different customer parameters affect CIC estimation.

CHAPTER

FIVE

CUSTOMER CHARACTERIZATION OF CUSTOMER INTERRUPTION COST

This chapter provides an overview of different customer segmentation models used in CIC analyses. A new customer segmentation model that include mitigation measures implemented by electricity customers is presented and its practical applications is illustrated in a case study. The main objective of the new customer segmentation model is to reduce the dispersion of CIC estimates of different electricity customer cluster segments formed.

5.1 Introduction

Grouping of electricity customers into customer segments of similar characteristics has increasingly continued to be an important concept that enables power utilities to better understand different electricity customer classes [Chicco *et al.*, 2004, 2001]. Determining the different electricity customer classes allow the power utilities to better address the operation of the power system infrastructure and its future enhancement Furthermore,it enables the power utility to design specific market strategies for the various classes of electricity customers in tune with reliability requirements.

The process of grouping customers into different customer segments of similar characteristics is referred to as customer segmentation. In power system reliability worth analyses, customer segmentation or classification has been carried out with the main objective of identifying a suitable set of customer classes with similar CIC profiles. For the customer classes formed, the power utility or regulator can then formulate the reliability worth of the system network or a single load point with different customer mix.

Customer classification for power system reliability worth analysis is typically performed on aggregate CIC data. The classification process may differ from country to country and it also depends on the available information. Table 5.1 shows the most important customer group specific parameters that are commonly considered in a customer survey.

Table 5.1. Common customer characteristics considered in customer surveys

Customer segment	**Customer parameters**
Residential customers	Region (urban/rural and climate) Electricity consumption and bill Number of residents Type of housing Household income Special activities (home business, medical equipment)
Commercial customers and Industrial customers	Sector group (SIC code) Number of employees Turnover Operational hours/ number of shifts Number and types of customers Backup power supply possibilities or insurances Energy consumption, peak load and energy bill Voltage level Location and climate

The region where the electricity customer is located is very important in CIC estimation for two reasons:

- The population density of the region can have an effect on the CIC estimate and should therefore be divided at least into urban and rural.
- The regional climate can explain the electricity needs for heating and cooling (-air conditioning). It can be expected that regions with more extreme climate as strong cold winters or hot summers have higher consequences of power interruptions than regions with moderate climate.

Backup power supply as well as insurances against the consequences of an interruption can reduce the cost estimate directly. It is therefore important to gather information about their presence and other measures to reduce the effects of power interruptions that may have been implemented by the electricity customer. In addition, it should be clarified whether the backup power supply caters for all the electrical needs of the electricity customer or only parts of it. The costs of the backup power supply are usually not included in the CIC estimate since the survey try to give the actual cost picture of power interruptions experienced by the electricity customer.

These customer parameters are used to segment the electricity customers into different customer cluster segments of similar CIC profiles. Generally, three different methods are used for the segmentation of electricity customers as shown in Figure 5.1. These categories are one-dimensional, two-dimensional and multi-dimensional customer segmentation methods.

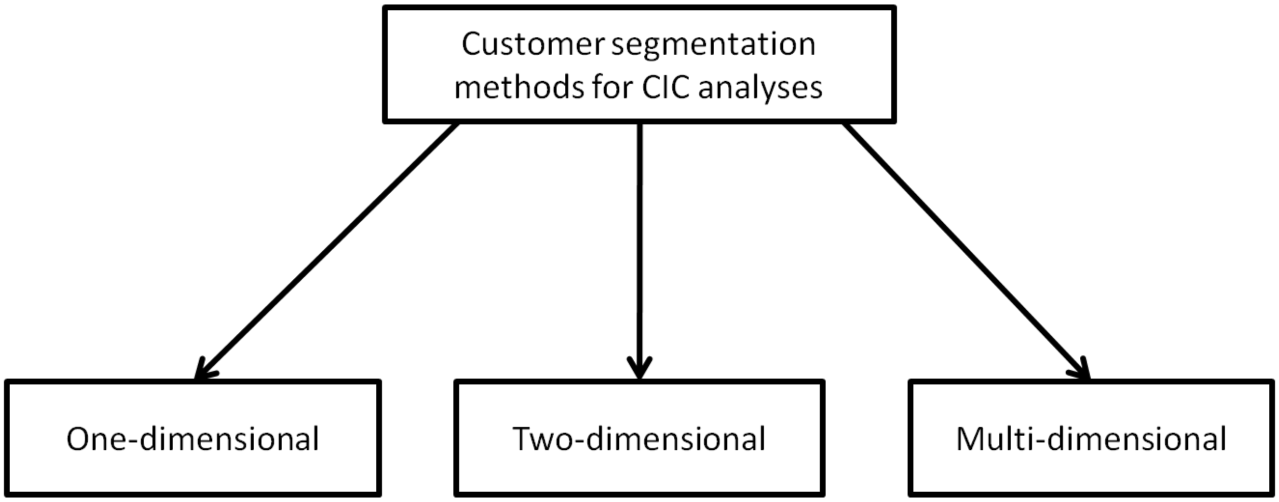

Figure 5.1. The methods used to segment electricity customers for CIC analyses

5.2 One-dimensional customer segmentation

One-dimensional customer segmentation refers to the segmentation of electricity customers using one parameter. The most common one-dimensional customer segmentation is based on activity-type parameters (economic activity). In this case, electricity customer classification follows the rules of segmentation referred to the commercial types of activity, as established for instance by the national institutes of statistics. Usually electricity customers are subdivided into customer segments where electricity customers with similar economic activities are clustered together e.g. using the Standard Industrial Classification (SIC) system [CE, 2008]. For example, customer surveys that provide CIC estimates over a number of customer types within the same customer sector e.g. commercial customers involved in retailing of non-food and food commodities, and financial services [Dzobo *et al.*, 2012b]. The main advantage of this customer segmentation method is that it can estimate CIC for each customer segment of electricity customers up to the last digit level of the SIC system. This may therefore produce very accurate CIC estimates. However, it is not possible to survey all the customer segments because of limitation in the customer survey resources availability.

The solution to this is to cluster electricity customers into different macro-economic categories or sector groups. For example, electricity customers can be divided into five sector groups: residential, commercial, industrial, agricultural and governmental [Sullivan and Keane, 1995; Alvehag, 2011]. In some studies the activity process of the electricity customer is used to cluster the different electricity customers. For example, electricity customers in the industrial sector can be grouped as continuous manufacturing and multi-process industrial customers [CEER, 2010]. Using macro-economic categories, the number of customer segments to be handled together by the classification methods would be greatly reduced and thus limit the customer survey resources requirement. However, there is a great diversity among the CIC profiles of electricity customers belonging to the same type of activity or associated to the same economic activity code. The resultant CIC estimates from such segmentation techniques have therefore shown large variance. As such, customer classifications based on the type of activity and on economic activity codes are not efficient for representing the specific aspects of CIC faced by electricity customers. Many researchers have pointed out that the large variance in the CIC estimates cannot be ignored [Ghajar *et al.*, 1996; Herman and Gaunt, 2008]. Identification of some extra or external features or characteristics can be useful to make a preliminary customer partitioning into customer segments that depict the same CIC profiles.

5.3 Two-dimensional customer segmentation

Two-dimensional customer segmentation refers to the segmentation of electricity customers using two parameters. Commonly, the economic activity-type parameter is combined together with size parameters. The most common examples of size parameters that are combined with economic activity-type parameters are voltage level and turnover. For example, commercial and industrial customers are grouped by their economic size (- turnover) as large, medium and small [Lawton *et al.*, 2003]. The main disadvantage with this technique is that high intensive energy use electricity customers are combined together with low intensive energy use electricity customers. For example, a large retailer company that uses electricity for lighting only (low intensive energy user) is combined with a hotel company which uses electricity for cooking and lighting (relative high intensive energy user).

Industrial customers can also be segmented by their technical connection to the power system network and/or according to the voltage level of the electric equipment that is transmitted from the network to the electricity customer [Sullivan *et al.*, 1997]. The type of connection to the grid (*see Figure 5.2*) is used as a parameter that characterizes the CIC estimates of the electricity customers. However, some electricity customers are connected to particular voltage

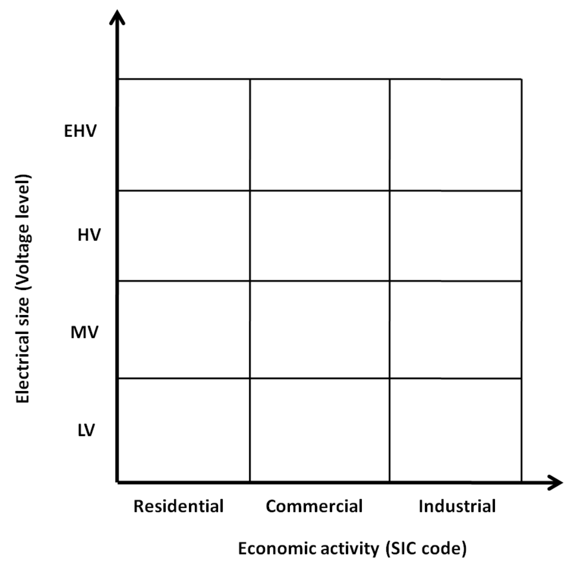

Figure 5.2. An example of a two-dimensional customer segmentation using economic activity and voltage level

level because of the nature of the economic activity involved. For example, a small mining company is connected to a high voltage level because of the production equipment used in the processing of its product. The turnover for the small mining company may be very low compared to a large mining or glass manufacturing company that is connected to the same voltage level. This mismatch of electricity customers to different customer segments may result in high dispersion of the CIC estimates.

5.4 Multi-dimensional customer segmentation

The two problems outlined in Sections 5.2 and 5.3, large dispersion of CIC estimates and large number of customer segments usually has been tackled independently. However, from a power system management point of view, the two problems should be solved simultaneously. Given a set of parameters, it is possible to simultaneously produce accurate CIC estimates and at the same time minimize the number of customer segments on the overall electricity customer base. In an attempt to address these issues, a flexible multi-dimensional customer segmentation model was proposed in Dzobo *et al.* [2013]. A variance-dependent characterization of CIC profiles was used so that CIC estimates are associated with the economic activity, economic value and electricity consumption of the electricity customers. The proposed multi-dimensional customer segmentation model consists of three main steps as shown in Figure 5.3.

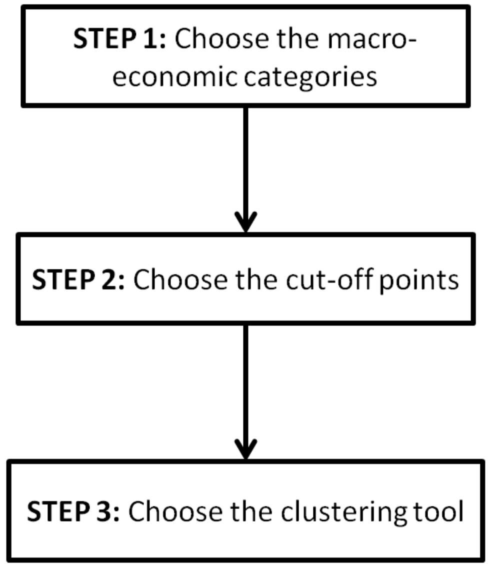

Figure 5.3. Main steps of the multi-dimensional customer segmentation model

The following sections look in detail at all the stages used to derive the final CIC estimates for each customer segment formed using the multi-dimensional customer segmentation.

5.4.1 STEP 1: Choosing the macro-economic categories

The first step corresponds to a one-dimensional customer segmentation model where the whole set of electricity customers is segmented into macro-economic categories defined using the economic-activity parameter. When using economic-activity parameter, electricity customers with similar economic activities are clustered together. It is advisable that the economic activity of the electricity customers is defined by standard institutions, commonly the SIC system is used. The macro-categories are formed at one digit level of the SIC system. The digit level at which the SIC system is considered is important in order to reduce the number of macro-categories formed and thus limiting the number of final customer segments.

5.4.2 STEP 2: Choosing the cut-off points

In the second step, the electricity customers are further segmented into customer segments based on two size parameters. For the size parameters there are cut-off points that divide the customers into segments. The cut-off points must be well defined and readily available at each load point of the network so that the output data is applicable for power system operation and planning purposes. It is therefore always advisable to use standardised values that are well defined by institutions or the power utility. In addition, the size parameters must also be chosen on the basis of their influence to CIC estimates. Figure 5.4 represents the general

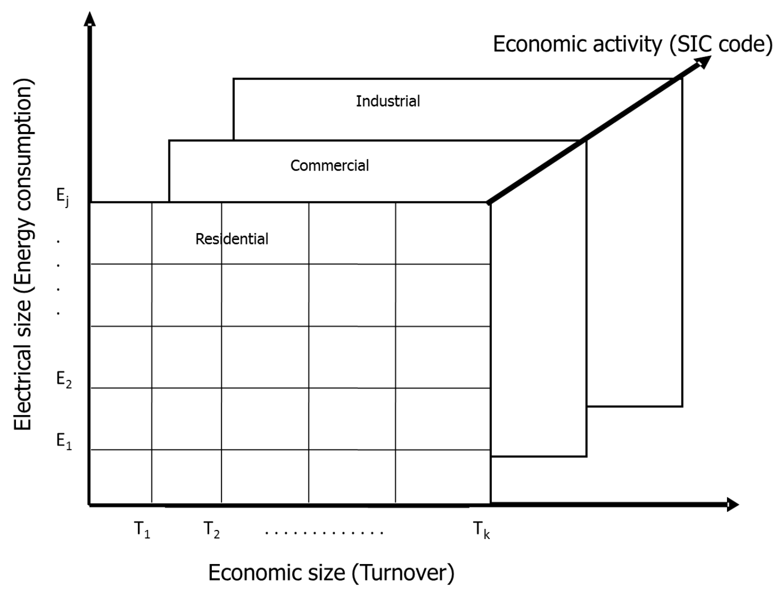

Figure 5.4. Customer value map for electricity customers, [Dzobo *et al.*, 2013]

customer value map for different electricity customer categories namely, residential, commercial and industrial. The electrical size and economic size measured in electricity consumption and turnover, respectively are used as the two size parameters.

The CIC estimates from the survey respondents are distributed into each of the cells or interval. Each interval window takes into account the CIC estimates of all electricity customers within a given sector that are within the given cluster range. The intervals for both energy consumption and turnover need not to coincide with the annual energy consumption or turnover of particular electricity customers, but should rather be categorized according to standardized intervals given by the power utility and/or by the national institute of statistics. The cut-off points E_1 to E_j and T_1 to T_k are used as a starting point for the clustering technique and are shown in Figure 5.4. Step 3 looks in detail at the clustering technique used in the CIC analysis.

5.4.3 STEP 3: Clustering tools

Many clustering methods have been developed, each of which uses a different induction principle. Fraley and Raftery [1998] suggest dividing the clustering methods into two main groups: hierarchical and partitioning methods as shown in Figure 5.5.

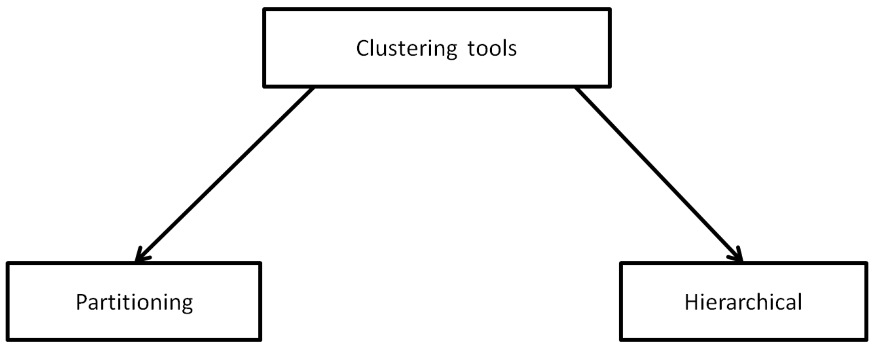

Figure 5.5. Main categories of clustering tools

The clustering tools are generally chosen dependent on the main objective of the analysis [Chicco *et al.*, 2004]. One disadvantage the partitioning methods have in the context of the objectives of this thesis is that it relocates instances by moving them from one cluster to another, starting from an initial partitioning and it requires that the number of clusters be preset by the data analyst. The hierarchical methods have the advantage of that they never reverse what was done before and therefore the cluster segments formed as a result of the cut-off points are never changed. Furthermore, the hierarchical methods produce not one partition, but multiple nested partitions, which allow different users to choose different partitions, according to the desired similarity level. The hierarchical methods was therefore used as the clustering tool in this thesis.

A. Hierarchical cluster analysis

Since clustering is the grouping of similar customers, some sort of measure that can determine whether two objects are similar or dissimilar is required. The hierarchical clustering methods could be further divided according to the manner that the similarity measure is calculated as shown in Figure 5.6 [Fraley and Raftery, 1998] .

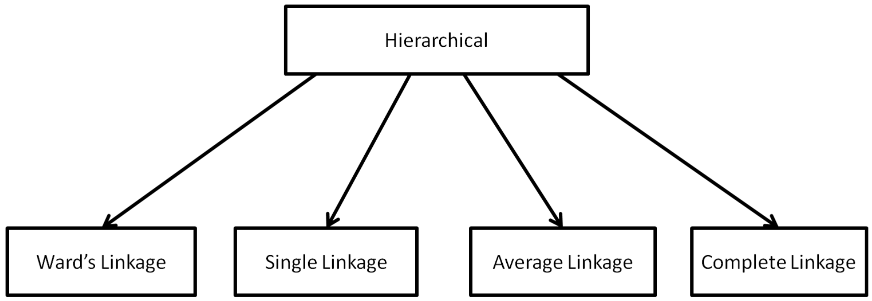

Figure 5.6. Hierarchical clustering techniques

- **Single-link clustering** - The method considers the distance between two clusters to be equal to the shortest distance from any member of one cluster to any member of the other cluster. If the data consist of similarities, the similarity between a pair of clusters is considered to be equal to the greatest similarity from any member of one cluster to any member of the other cluster [Anderberg, 1973]. The disadvantage of the single-link clustering is that few points that form a bridge between two clusters cause the single-link clustering to unify these two clusters into one.

- **Complete-link clustering** - The method considers the distance between two clusters to be equal to the longest distance from any member of one cluster to any member of the other cluster [Chicco *et al.*, 2004].

- **Average-link clustering** - The method considers the distance between two clusters to be equal to the average distance from any member of one cluster to any member of the other cluster [Chicco *et al.*, 2004].

- **Ward's Linkage** - Also known as minimum variance method. The aim in Wards linkage method is to merge clusters such that the dispersion of the final data within a merged cluster is minimised [Ward, 1963]. To do this, each customer begins as its own cluster. Clusters are merged if the merger results in the reduction of the dispersion of final data within the merger formed. The difference between each customer within a cluster and that average similarity is calculated and squared. The sum of the squared deviations is used as a measure of error within a cluster. This means that at each merging stage of clusters the average similarity of the cluster is measured. A cluster is selected to merge another cluster if it is the cluster whose inclusion in the merged cluster produces the least increase in the error.

Central in this thesis is to reduce the dispersion of the final CIC estimates within each customer segment formed and also to reduce the number of customer segments formed. The Ward's linkage method was therefore used to achieve the two objectives. The Ward's Linkage clustering technique uses the Sum of Squared Error (SSE) as the dissimilarity measure and is defined in the following section.

A.1 Dissimilarity measures

Sum of Squared Error (SSE) is the simplest and most widely used criterion measure for clustering and is used to measure the compactness of the clusters. The advantage it has is that it does not use any external information beside the data itself. It is calculated as:

$$SSE = \sum_{k=1}^{K} \sum_{\forall x_i \in C_k} \| x_i - \mu_k \|^2 \tag{5.1}$$

where C_k is the set of instances in cluster k, μ_k is the vector mean of cluster k The components of μ_k are calculated as:

$$\mu_{k,j} = \frac{1}{N_k} \sum_{\forall x_i \in C_k} x_{i,j} \tag{5.2}$$

where $N_k = \mid C_k \mid$ is the number of instance belonging to cluster k

Clustering methods that minimize the SSE criterion are often called minimum variance partitions, since by simple algebraic manipulation the SSE criterion may be written as:

$$SSE = \frac{1}{2} \sum_{k=1}^{K} N_k \bar{S}_k \tag{5.3}$$

where:

$$\bar{S}_k = \frac{1}{N_k^2} \sum_{x_i, x_j \forall C_k} \| x_i - x_j \|^2 \tag{5.4}$$

$(C_k = cluster\ k)$

A.2 Dendrogram

The result of the hierarchical methods is a dendrogram, representing the nested grouping of objects and similarity levels at which groupings change. The dendrogram graphically present the information concerning which customer segments are grouped together at various levels of dissimilarity.

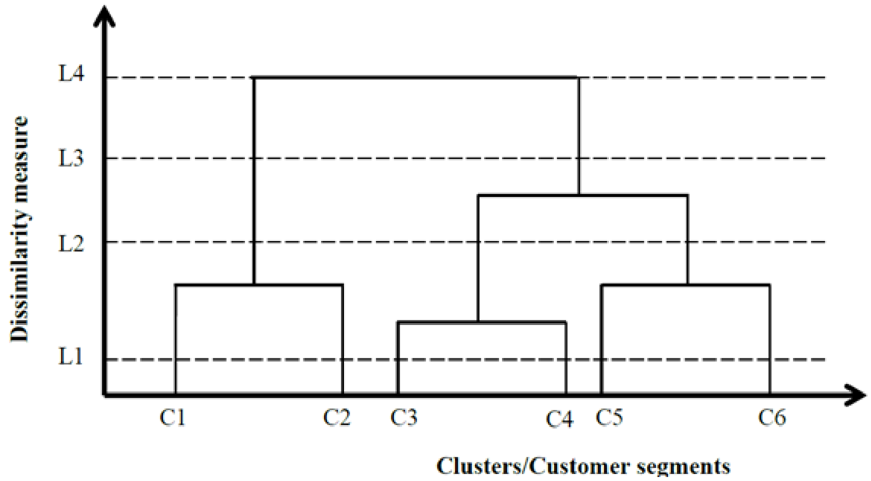

Figure 5.7. Example of dendrogram

Figure 5.7 shows an example of a dendrogram where C1 - C6 represents the clusters/ customer segments and L1 - L4 represents the dissimilarity measure. At the bottom of the dendrogram, each customer segment is considered its own cluster. Vertical lines extend up for each customer segment, and at various dissimilarity measure values, these lines are connected to the lines from other customer segments with a horizontal line. The customer segments continue to combine until, at the top of the dendrogram L4, all customer segments are grouped together. The height of the vertical lines and the range of the dissimilarity measure axis give visual clues about the strength of the clustering. There is no criterion to choose the cut-off dissimilarity measure value at which the final customer segments are formed. It is left to the discretion of the analyst to choose the right cut-off dissimilarity measure level.

5.4.4 Customer segmentation including power interruption mitigation measures

Power interruptions impose losses on electricity customers' activities [Lawton *et al.*, 2003; CEER, 2010]. However, some activities are more vulnerable to power interruptions than others, so that a power interruption of given duration may cause large losses in certain parts of the activities while other activities may be left virtually unscathed. For example, expensive raw materials may be wasted as result of power interruption in a business that refrigerate perishables like fish or vegetables, while business involved in packaging ceramic materials may only suffer minor inconvenience. If power interruptions impose costs on electricity customers' activities, electricity customers have an incentive to take mitigation measure to protect those activities that are particularly vulnerable in order to mitigate the losses that are incurred when electricity is not supplied. Investing in backup power supply is expensive and may not be economically viable if it is not well planned. Therefore, the electricity customers' problem is to decide and choose the optimal degree of backup that minimizes the sunk costs incurred in procuring generation capacity as well as the damage that would result from power interruption.

The benefit of having a backup power supply consists of the continued production and the reduction or prevention of other costs, such as damage to equipment, loss of reputation due to inability to meet customers' demands, etc, that would have resulted from power interruption. The optimal level of scale of this backup would mostly depend on the level of vulnerability, the capital and operating cost of backup generator, and the expected outage time. The mitigated and unmitigated losses are dependent on the backup size. In other words, the greater the backup capacity, the higher will be the mitigated loss, and the smaller will be the unmitigated loss in the event of an outage. However, the mitigation measure itself has a certain capital and operating cost. The total CIC estimate will thus reflect both the operating cost plus the expected unmitigated costs when a backup power supply is installed. Sometimes in order to get the actual CIC estimate the customer incurs as a result of a power interruption it is advaisable to exclude the backup power supply in the survey question [Dzobo, 2010].

The impact of mitigation measures implemented by electricity customers for power interruptions has not yet been explored very much [LaCommare and Eto, 2004]. A research by Sullivan *et al.* [1997] provided evidence that the presence of backup power supply equipment reduces CICs. It should however, be clarified whether the backup power supply can sustain all the electricity needs of the electricity customer or just part of it. The costs of the backup power supply are not included in the CIC estimate since the surveys try to give the actual impact of power interruptions on the electricity customers including the installed backup power supply. In some instances where all electricity customers connected to a certain feeder invest in backup power supply because of poor power supply reliability, there is risk that the total cost incurred by all the electricity customers at the feeder may be higher than the cost for the power utility to improve the power supply reliability of the feeder. This however, depends on the action alternatives that are available to improve the reliability of the feeder. The power utility can only invest to improve the reliability of the feeder if the risk reduction cost is greater than the capital expenditure of improving the feeder reliability (*further discussed in Chapter 7*).

In a research by LaCommare and Eto [2004] a bottom-up approach for estimating economic cost of power interruptions and power quality events was proposed. The framework relies on a simple mathematical expression that includes a vulnerability factor of electricity customers to power interruptions as in equation 5.5. The vulnerability factor was used as a multiplication factor and was taken as a fraction between 1 and 0.

$$\textit{Cost of power interruption and power quality} = \sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{k=1}^{p} N_{i,j}F_{i,j,k}C_{i,j,k}V_{i,j,k} \tag{5.5}$$

where:

$N_{i,j}$ = *Number of electricity customers in customer class i for region j household from the reference event*

$F_{i,j,k}$ = *Frequency of reliability events of type k experienced annually by customer class i in region j*

$C_{i,j,k}$ = *Cost of reliability event type k per customer in customer class i for region j*

$V_{i,j,k}$ = *Vulnerability of customer to reliability event type k in customer class i for region j (a fraction between 0 and 1)*

In Dzobo [2010], a pilot customer survey that was carried out showed that electricity customers who have backup power supply installed at their premises reported higher CICs than those who do not have. Figure 5.8 shows the CDF for industrial customers for those who have backup power supply and those who do not have. The conclusion that was made by the author was that the underlying functional heterogeneity in the risk exposure to power interruption implies that business may be ranked in terms of its vulnerability to power interruptions. This research finding is paramount to take into consideration when estimating CICs so as to capture the effect of mitigation measures implemented by electricity customers on CICs.

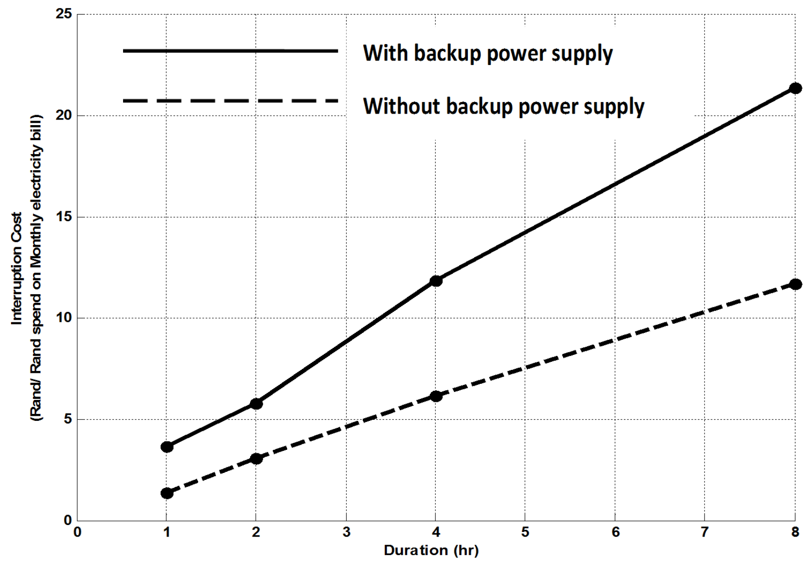

Figure 5.8. Summer morning cost estimate: CDF for industrial respondents with/without backup power supply, [Dzobo, 2010]

The multi-dimensional segmentation model proposed in Dzobo *et al.* [2013] is extended using a case study in this thesis to include mitigation measures implemented by electricity customers and a beta PDF is used to model the CIC estimates. The ownership of backup power supply is included in estimation of CICs by separating the electricity customers with backup power supply and those who do not have.

5.5 Case studies

The analysis in the case study consists of three main steps shown in Figure 5.9. The three main parts A to C are described in this section. In part A the input data are presented. Here two customer surveys from South Africa and Sweden were used [Dzobo *et al.*, 2013]. In this thesis only the South African case study is presented. However, some Swedish case study results from Dzobo *et al.* [2013] are also added. In part B the customer segmentation models tested are described. In Figure 5.9, S1-1D is one-dimensional customer segmentation model using economic activity, S2 - 2D (consumption) is two-dimensional customer segmentation model using economic activity and energy consumption, S3 - 2D (turnover) is two-dimensional customer segmentation model using economic activity and turnover, S4 - multi-D is multi-dimensional customer segmentation model using economic activity, turnover and energy consumption, S5 - multi-D is multi-dimensional customer segmentation model using economic activity, turnover,

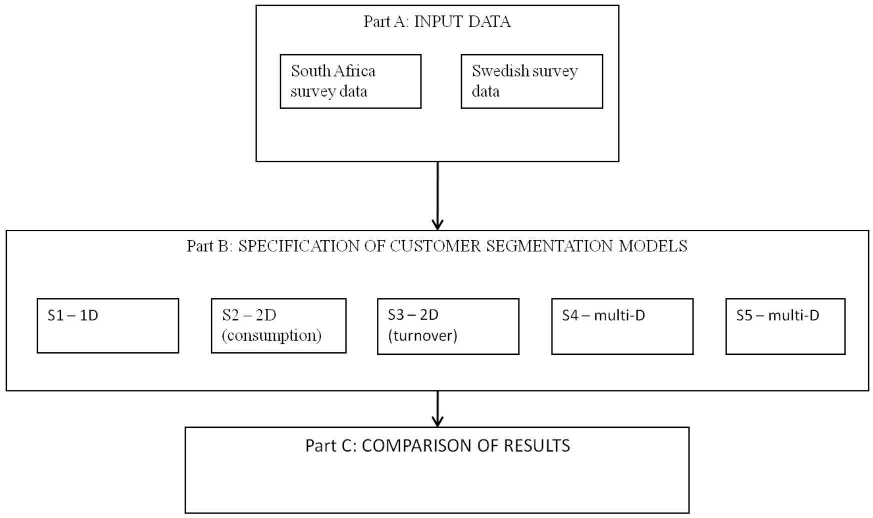

Figure 5.9. Flowchart of the main steps for the case study analysis

energy consumption and ownership of backup power supply. In the last part - part C - the coefficient of variation is introduced as it is used as a measure to see how good the segmentation models decrease the dispersion of the final CIC estimates. The following sections describe the three steps in detail.

Acknowledgement: *The author would like to thank Karin Alvehag at KTH Electrical Engineering - Royal Institute of Technology, Sweden, for sharing the raw material from the Swedish customer interruption cost survey that was used to perform the Swedish case study presented in Dzobo et al. [2013]. Some of the results are presented in this chapter.*

A. INPUT DATA

The CIC data for the South African case study is taken from a customer survey that was done for both industrial and commercial customers in Cape Town, South Africa by Dzobo [2010]. The details of how the survey was conducted is covered in the previous chapter *(-Chapter 3: Section 3.8)*. In the customer survey, the worst case cost data were estimated for different hypothetical time of occurrences of power interruptions. The Swedish survey was carried out for the worst case cost at the worst possible timing. The customer survey detail is covered in Carlsson and Martinsson [Elforsk (2006]. To be able to calculate the average CIC estimates for each customer segment the surveyed CIC estimates from the survey respondents are normalized. Normalization process is done so that each individual CIC estimate from the survey respondents within a particular customer segment can be used collectively to calculate the cumulative CIC of the respective customer segment (*see Section 3.6: equation 3.1 and*

3.2). To normalize the CIC data the annual peak load was used as normalization factor in both case studies. The peak load data was obtained from electricity customers themselves. The electricity customers were asked to give their maximum monthly load in the year of study based on their monthly metering indicated on their electricity bill accounts. For the South African case study, the ownership of backup power supply by electricity customers is taken as binary value. A one (1) means the presence of a backup power supply and a zero (0) means the electricity customer does not own a backup power supply. The SIC system [Statistics South Africa, 1993; EU, 2002] is used to segment between industrial and commercial customers. Table 5.2 below shows the total number of electricity customers who responded in each of the macro-economic categories considered in the case studies.

Table 5.2. Number of survey respondents

Customer Segment	Total number of respondents	
	South Africa	Sweden
Industrial	91	752
Commercial	184	430

B. SPECIFICATION OF CUSTOMER SEGMENTATION MODEL

One-dimensional customer segmentation model: The model is segmented using economic activity only. The customer segmentation is done at one digit level of the SIC system, resulting in two segments: industrial and commercial.

Two-dimensional customer segmentation model: In this model two examples for each case study were performed. The first example used the economic activity and turnover, and the second example used economic activity and energy consumption to segment customers.

- Range of cut-off points: In this thesis, the standardised ranges of annual electricity consumption and annual turnover, were defined on the basis of EUROSTAT [EU, 2002, 2007] which presents a guideline to identify the relation between the consumption ranges and electricity prices. Table 5.3 shows the EU energy consumption ranges and annual turnover ranges used to derive the final customer segments presented in this thesis. 1 Euro $\approx$ 10 South African Rands.

In the two case studies only two macro-economic categories were investigated namely, industrial and commercial sector. The customer segments formed as a result of the cut-off points are used in the CIC analyses.

Table 5.3. Annual turnover and energy consumption ranges for electricity customers

Range	Annual turnover (MEuro)	Total energy consumption (MWh)
1	0 -2	0 -20
2	2 - 10	20 - 500
3	10 - 50	500 - 2000
4	50 - 150	2000 - 20 000
5	150 - 250	20 000 - 70 000
6	250 - 500	70 000 - 150 000
7	>500	>150 000

Multi-dimensional customer segmentation model: In this model two examples were performed. The first example used three parameters economic activity, turnover and energy consumption, and the second example used economic activity, turnover, energy consumption and ownership of backup power supply. The second example was only performed to the South African case study because the electricity customers were asked to reveal their ownership of backup power supply at their premises during the customer survey. For the Swedish CIC data the ownership of backup was not provided in the CIC data used in this analysis.

- The stages that were carried out to perform the first example are as follows:

  Stage 1: The whole set of customers is segmented into macro-economic categories defined using the economic activity parameter - SIC system at one digit level. Only two macro-economic categories were investigated namely, industrial and commercial sector.

  Stage 2: A two-dimensional analysis is performed using the two size parameters - turnover and energy consumption. The objective of the two-way dimensional analysis is to filter and identify electricity customers that represent similar characteristics from an economic value and energy use point of view. The same cut-off points as applied in the two-dimensional customer segmentation model are used.

  Stage 3: The Hierarchical Clustering (Ward's Linkage) process is then applied to the customer segments formed in Stage 2.

- The stages carried out for the second example are as follows:

  Stage 1: The whole set of customers is segmented into macro-economic categories defined using the economic activity parameter SIC system at one digit level. Only two macro-economic categories were investigated namely, industrial and commercial sector.

Stage 2: In each of the macro-economic categories formed the electricity customers are separated by whether they own backup power supply or not. Two groups of electricity customers are formed for each macro-economic category.

Stage 3: A two-dimensional analysis is performed using the two size parameters - turnover and energy consumption. The objective of the two-way dimensional analysis is to filter and identify electricity customers that represent similar characteristics from an economic value and energy use point of view. The same cut-off points as applied in the two-dimensional customer segmentation model are used.

Stage 4: The Hierarchical Clustering (Ward's Linkage) process is then applied to the customer segments formed in Stage 3.

C. COMPARISON OF RESULTS

For each customer segment formed the mean and standard deviation of the CIC estimates are calculated to determine the dispersion of the CIC estimates. The coefficient of variation (CV) is used to measure the dispersion of CIC estimates for all the customer segments formed. For CIC estimates of duration d, with mean μ and standard deviation σ, the CV is defined as:

$$CV = \frac{\sigma}{\mu} \times 100\% \tag{5.6}$$

For each customer segment an average CV for all the durations is calculated to determine the customer segmentation model that has the best or lowest CV

5.5.1 Results

This section presents the effect of customer segmentation models on industrial and commercial customers CIC estimates.

A. South African case study

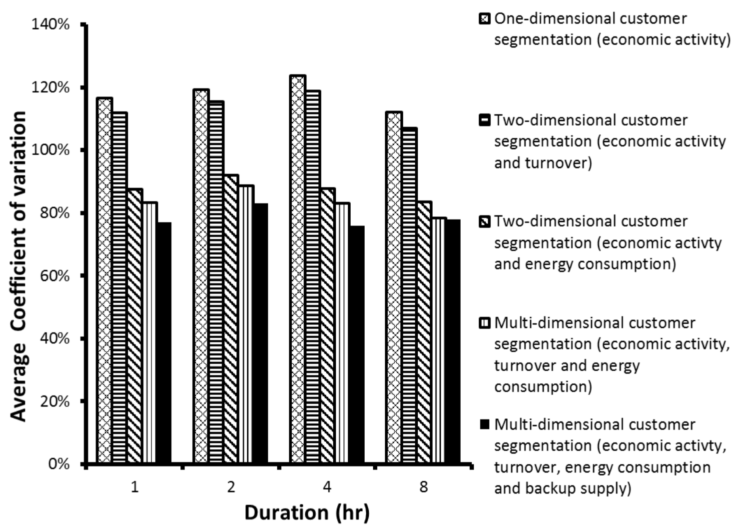

Figure 5.10. Effect of customer segmentation models on CIC estimates of commercial customers for a winter weekday morning power interruption

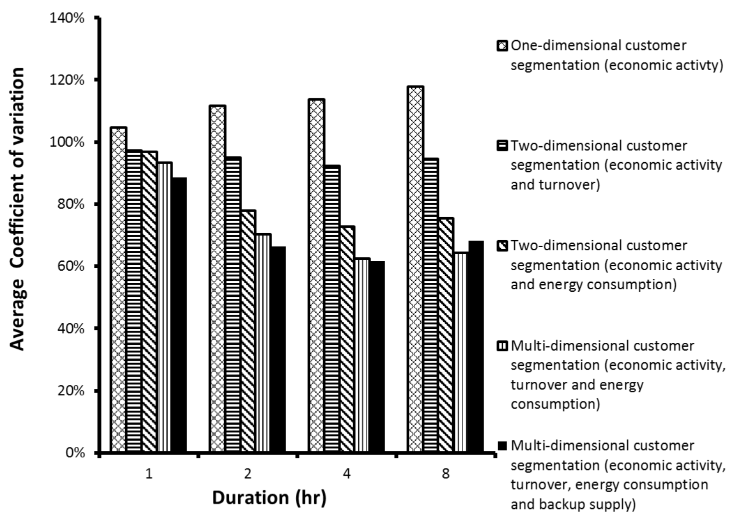

Figure 5.11. Effect of customer segmentation models on CIC estimates of commercial customers for a summer weekday morning power interruption

Figures 5.10 - 5.11 show the effect of customer segmentation on CIC estimates for commercial customers. Two different power interruption scenarios are considered in the analysis.

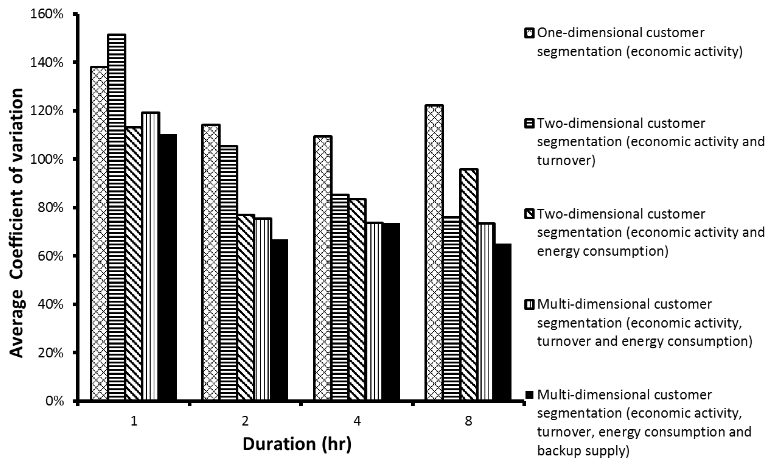

Figure 5.12. Effect of customer segmentation models on CIC estimates of industrial customers for a summer weekday morning power interruption

B. Swedish case study

The following graphs are some of the results obtained from the Swedish case study

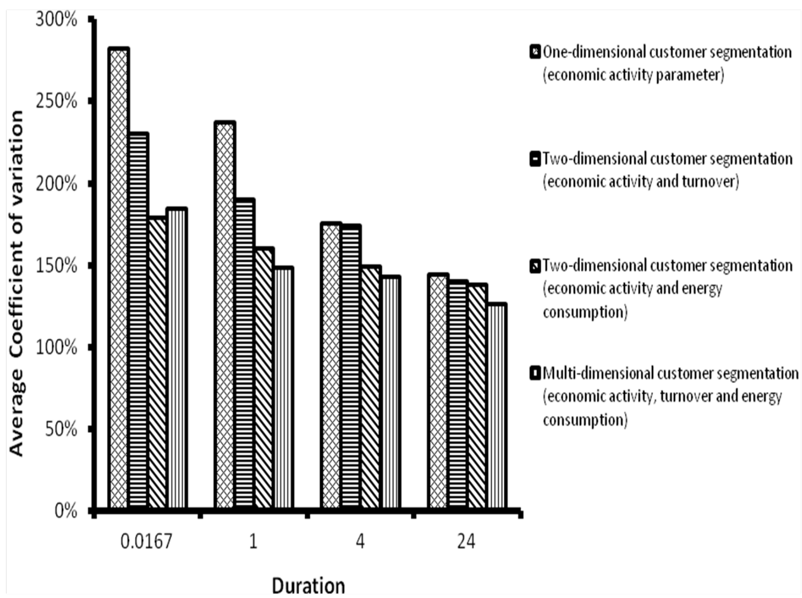

Figure 5.13. Effect of customer segmentation on Industrial customers, Dzobo *et al.* [2013]

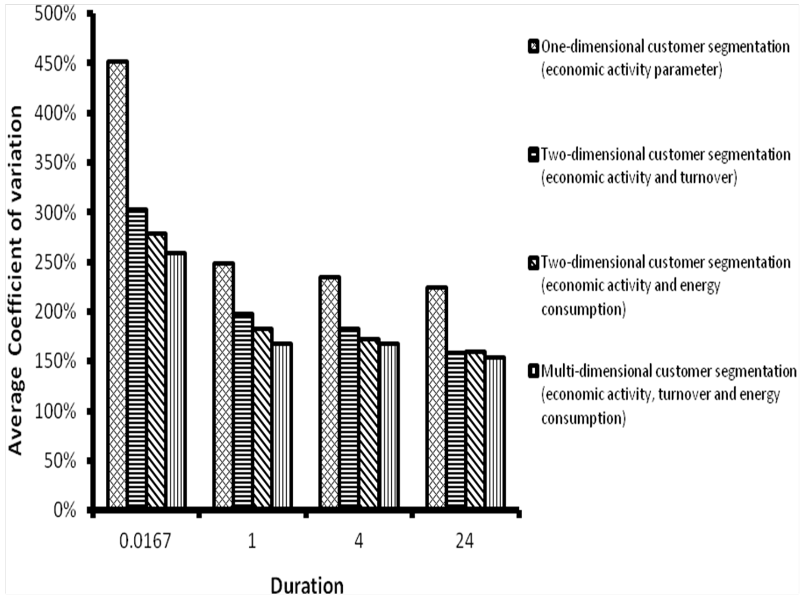

Figure 5.14. Effect of customer segmentation on commercial customers, Dzobo *et al.* [2013]

5.6 Discussion

- *What is the best way of segmenting electricity customers?*

When electricity customers were grouped together using economic activity parameter only - one-dimensional customer segmentation model, the CIC results showed large dispersion in the CIC estimates. The large standard deviations of the CIC estimates from both case studies clearly show that it is difficult if not impossible to find typical accurate CIC estimates from such customer segmentation models. The large dispersion of the CIC estimates can be easily explained from the customer value map in Figure 5.4. The figure shows that perhaps the large dispersion of the CIC estimates is a result of merging electricity customers of the same macro-economic category with completely different cost characteristics. For example, when merging electricity customers with high annual turnover and those with low annual turnover together.

The proposed multi-dimensional customer segmentation model showed CIC estimates with generally low variation when compared to the other customer segmentation methods used in the analysis. It therefore implies that the proposed segmentation method clusters electricity customers into customer cluster segments with almost similar cost profiles. In order to validate this claim, customer survey data obtained from a different source i.e Swedish customer survey data, was used. The results obtained from applying the different customer segmentation models to the customer survey data are similar. The proposed segmentation methods again showed low variation of CIC estimates than the other three segmentation methods used in the analysis. Thus, the multi-dimensional customer segmentation model can be regarded as the best way of segmenting electricity customers into customer cluster segment of almost similar cost profiles.

However, the proposed method was only applied to two types of customers, industrial and commercial customers. Residential customers differ in many ways to these two type of customers but in other ways quite similar. Interruption costs for residential customers have also shown large variations for identical power interruptions [Herman and Gaunt, 2008], implying that different households have very different costs for the same outage. Power interruptions cause mainly non-monetary costs for residential customers in the form of inconvenience. For example, a person present in the building might not be able to continue with their planned activities as watching television or listening to radio. However, direct cost are also experienced such as loss of food in freezer/refrigerator, damaged equipments. etc. When collecting the interruption costs many parameters can be considered (*see Section 5.2: Table 5.1*). Using these parameters to segment the residential customers, it may be possible to reduce the dispersion of their CIC estimates. There was no residential customer interruption cost data available to test the applicability of the proposed customer segmentation model.

After analysing the CIC estimates using the proposed customer segmentation model, it is possible to come up with CDF for the different customer cluster segments formed. Figure 5.15 shows the CDF generated from using CIC estimates from electricity customers that are segmented using one parameter only i.e in this case the economic activity (SIC code). The CIC estimates were normalised using monthly energy cost and therefore the units for the costs are given in p.u i.e Rand/Rand spend on monthly energy cost. Equation 3.1 was used to calculate the average normalized cost and this gives the values of the CDF marked with different symbols in Fig 5.15. To estimate the CIC for any duration, linear interpolation is used between these values. Since the CIC data is only obtained for a worst case scenario, the CDF shows how the worst case cost varies with interruption duration.

To come up with CDF for the multi-dimensional customer segmentation model, the same process as applied to the one dimensional customer segmentation model is used. 5.16 shows the CDF generated from the calculation.

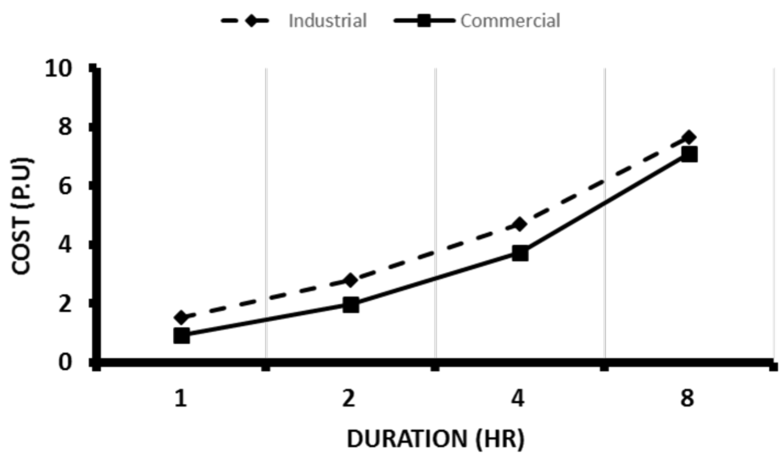

Figure 5.15. CDF generated from one-dimensional customer segmentation model

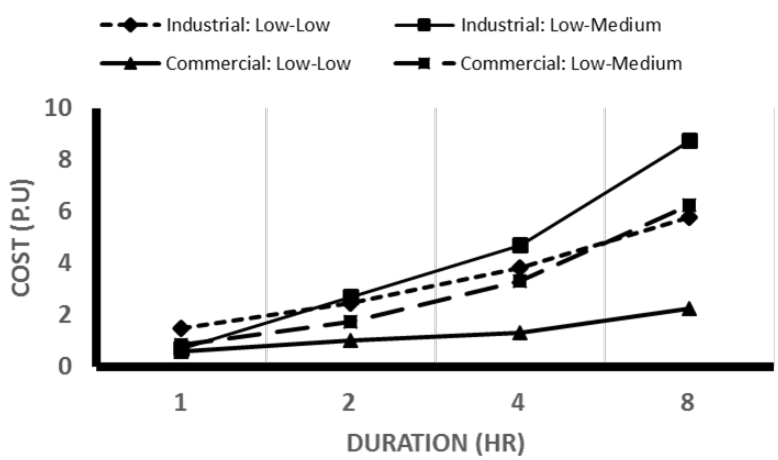

Figure 5.16. CDF generated from multi-dimensional customer segmentation model

Unlike the conventional approach - CDF model, that only considers average values to represent CIC estimates, the matrix cluster modelling approach proposed by the authors include the standard deviation to account for variability within the different cluster segments. The standard deviation however only describes the degree of dispersion about the mean value. CIC profiles are influenced by many factors such that fitted probability distributions could exhibit any shape. The model, as is, would thus provide no indication to the shape or level of skewness of a parameter's underlying distribution. The estimation of CIC estimates with different distribution shapes is extended so that more realistic CIC data distributions can be achieved and is discussed further in chapter 6.

CHAPTER

SIX

PROBABILISTIC CUSTOMER INTERRUPTION COST ESTIMATION

This chapter will address the need to describe reliability worth inputs and outputs beyond the conventional use of average values. The goodness of fit tests are performed for different probability distribution functions (PDFs) and the best fitting PDF is presented.

6.1 Introduction

The current trend in the reliability worth assessment of power system is towards the introduction of reliability inputs and outputs into risk management calculation programs able to assist the regulator and power utility in undertaking decisions concerning system planning and operation. Since the activity of both power utility and electricity customers is profit-oriented, it is important for the power utility to include the uncertainty related to the reliability inputs and outputs into the risk management analysis tools. Finding a more accurate way to compute the CICs including uncertainty is therefore a key challenge for research in reliability worth assessment of power systems.

Most literature on reliability worth assessment considers the period when power interruptions occur as constant so that the CIC estimates are represented as single deterministic values, usually average. This is the criterion commonly followed when reliability worth models are developed for planning purposes. An average year is used such that the average CIC values computed based on worst case scenarios are assumed to be constant 100 % of the time. Previous researchers agree that while this suffices for an overview of the cost incurred by electricity customers, the use of single average values to represent CIC estimates for the entire period of analysis does not describe the dispersed nature of CIC that occurs for individual electricity customers as well as for the different durations and time of occurrence of power interruptions. Thus, in most cases average CIC values provide unrealistic and misleading results.

For realistic analyses, variability in CIC cannot be ignored and should be included in the model being used to represent it. Since PDFs allow for variation about the mean, they are a good tool for describing statistical variation (uncertainty) in the CIC modelling, from which the significance of including statistical variation in CIC modelling becomes clear. Expressing the CIC model in this way would also allow CIC estimates to be determined with a level of confidence or conversely a risk level.

Several PDFs have been identified for use in CIC analyses. Some include the Normal, Log-normal, Weibull and Beta PDFs [Alvehag, 2008; Billinton and Wang, 1999]. However, relatively little work has been published on estimating CICs derived from PDF. [Alvehag, 2008] used PDFs to stress how quantifying the probability distribution of CIC estimates is important to assessment of reliability worth performance of system networks. The author used the customers' activity level data of a particular time window and CIC parameter statistics (mean and standard deviation) were derived for different time of occurrence of power interruption. The data in each cell or time interval was then analysed further so that reliability worth statistics can be derived for each network/load point or the cumulative effective of all customer mix at the same time window. A conclusion that was drawn from the analysis was that using average CIC estimates can significantly underestimate the annual interruption cost account.

Similarly, Dzobo *et al.* [2011] investigated the use of probability distribution functions in reliability worth analysis including time variation in CICs. Instead of using average values, CICs were represented as PDFs. The results showed that average values ignored time variations in CICs and severely underestimated the effect of extreme (high and low) CIC values. In Herman and Gaunt [2010] a 16 cell- matrix CIC model was proposed. Unlike the conventional approach that only uses average values to represent CIC estimates, the modelling approach included the mean and standard deviation to account for variability of CIC within different time intervals. The standard deviation however only describes the degree of dispersion about the mean value. CIC estimates vary so that fitted probability distributions could exhibit any shape. The model, as is, would thus provide no indication to the shape or the skewness of a parameter's underlying distribution. This model is extended further so that more realistic

CIC estimate profiles can be achieved. This section will investigate and validate the suitability of the Beta PDF, over the commonly used PDFs, for use in the PDF-based 16 cell - matrix CIC model.

6.2 Choice of probability density function

Billinton *et al.* [1994b] investigated the use of different PDFs in distribution network reliability worth analysis. The CIC estimates were described by exponential, log-normal, normal and gamma distributions. A key observation from the analysis was that the CIC data exhibited various skewness for different durations of power interruptions. From the analysis it was noted that some PDFs like the exponential and Gaussian exhibit specific shapes and therefore were only applicable to a specific set of data, while others like the gamma and Weibull fitted to a wide range of data sets because they are very versatile in the shape they can exhibit using their shape parameters. The Beta PDF was not considered in the analysis. The authors further removed extreme values - bottom and top 5% CIC values of the CIC data set. There is still no consensus between researchers on how these extreme values can be modelled in CIC analyses. Alvehag [2008] used the normal distribution to model the CICs for the different power interruption durations. One of the disadvantages that the author noted was that the normal distribution cannot be modelled with data containing zero values. The author then had to separate the zero values and model them by calculating the probability of occurrence of zero values. All the other data was fitted to a normal distribution.

Two key limitations of the PDFs presented, with regard to representing CIC data, were identified:

- CIC data exhibit different distribution profiles for different duration and time of occurrence of power interruption.
- Some of the PDFs used are limited in their shape and their applicability to model certain data sets e.g normal distribution cannot model data containing zero values.

The use of different PDFs to model CIC estimates for different durations and time of occurrence of power interruptions can be very cumbersome and can make the analysis of reliability worth assessment of power system very difficult. Because certain PDFs like Weibull, Beta etc have the ability to fit to right or left skewed data through the use of their shape parameters, it should be possible to use one best fitting PDF type to model CIC estimates for all the durations and time of occurrence of power interruptions as examined by Cross *et al.* [2006]. This chapter will investigate the use of different PDFs to model CIC estimates for different durations and time of occurrence of power interruption. The best fitting PDF is presented as the standard PDF that can be used to model all the CIC estimates for different durations and time of occurrence of power interruptions..

The Beta probability density function describes the distribution of a random variable that lies within the interval (0, 1). The shape of the Beta PDF is described by alpha α, beta β and a scaling value C. The shape parameters can be computed using equations 6.1 and 6.2 from the mean μ, standard deviation δ and scaling factor C of measured or computed data.

$$\alpha = \mu\left[\frac{C\mu - \mu^2 - \delta^2}{C\delta^2}\right] \tag{6.1}$$

$$\beta = \frac{(C-\mu)(C\mu - \mu^2 - \delta^2)}{C\delta^2} \tag{6.2}$$

$$f(x) = \frac{x^{\alpha-1}(1-x)^{\beta-1}}{B(\alpha\beta)} \tag{6.3}$$

for:

$$0 \leq x \leq 1, \alpha > 0 \ and \ \beta > 0$$

where:

$$B(\alpha\beta) = \int_0^1 A^{\alpha-1}(1-A)^{\beta-1}du \tag{6.4}$$

The Beta PDF is very versatile in the shapes it can exhibit. Similarly to the gamma and Weibull distributions, it can be used to represent left or right skewed data. This is first accomplished by varying the values of its two shape parameters, α and β. Figure 6.1 illustrates some shapes of the Beta PDF. Both symmetrical and asymmetrical shapes are displayed.

Given the Beta shape parameters and scaling factor of a CIC estimate distribution, the

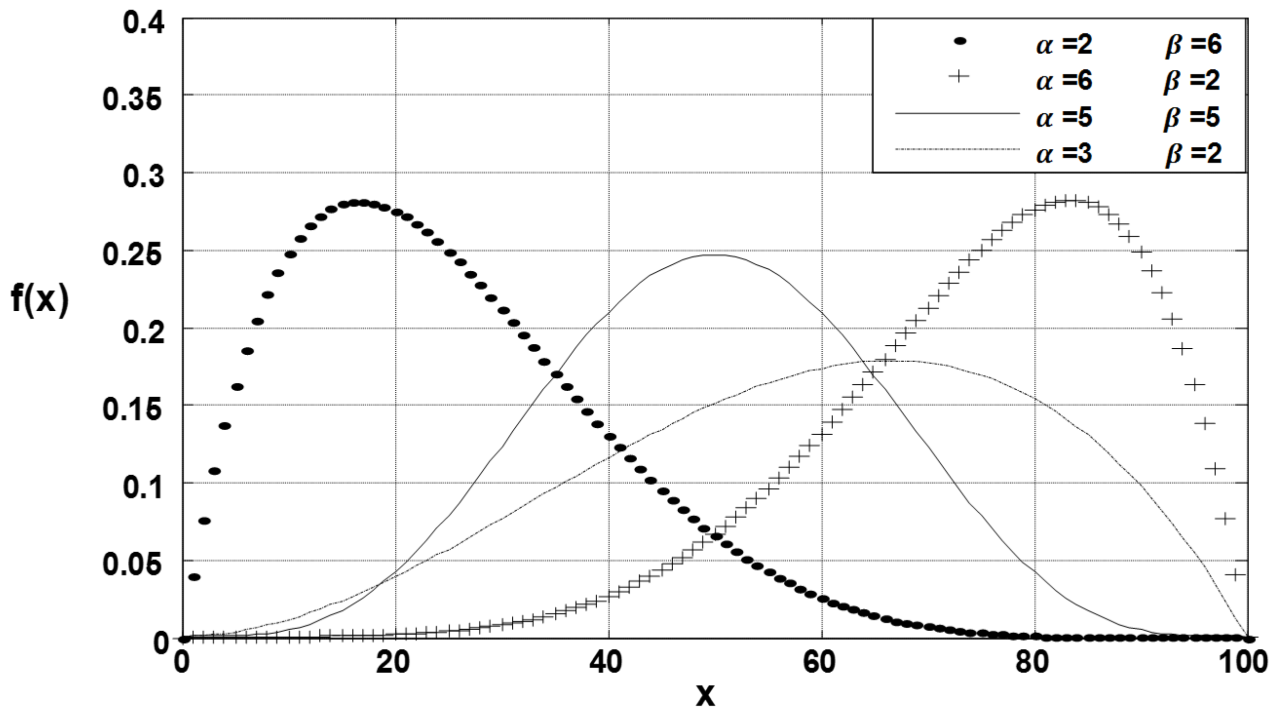

Figure 6.1. Different shapes shown by Beta PDF for different shape parameters, α and β

Beta PDF based CIC profile is generated in the MATLAB software package using equation 6.3. Unlike other PDFs, the range of the Beta PDF can be scaled to a finite range. For example, most reliability worth analyses in operation and planning studies, are most likely concerned with the average and the extreme (high or low) CIC estimates from a fixed possible power interruption event. These can be predicted based on the CIC estimates provided by the electricity customers during customer surveys. For such extreme CIC estimates (high or low), emphasis is on the tails of the distributions. The tails are thus extended by adopting a scaling factor based on extreme value theorem or boundness theorem. The scaling factors of Beta PDFs must be equal to or greater than the maximum value recorded in the data set being described. This is to ensure that the tails of the distribution are well covered and all CIC values are included in the distribution.

To investigate the best fitting PDF to model CIC estimates, a comparative analysis similar to that presented by Cross *et al.* [2006] was carried out. Similarly, the K-S test is used for analysing the goodness of fit of the different probability distributions. Table 6.1 shows some typical probability distributions commonly used to describe CIC estimates.

Table 6.1. Different types of PDFs used for CIC analysis

Parameter	Probability distribution
CIC	Gamma, Exponential, Weibull, Normal, Log-normal, Rayleigh, Log-logistic, Beta

6.3 Case study

CIC data were obtained from a customer survey carried out in Dzobo [2010]. Numerous CIC estimates for different time of occurrence and durations were modelled and then fitted with a Beta PDF. The results presented in this thesis were chosen to best illustrate the versatility and efficacy of the Beta PDF. The codes for the different customer segments are provided in Appendix B.

6.3.1 Objective

The objective of this case study is to investigate the versatility of different PDFs in CIC estimation and to come up with a standard PDF that best fit CIC profiles for different durations and time of occurrence of power interruptions.

6.3.2 Goodness of fit tests of probability distribution functions to customer interruption costs

Figure 6.2 shows a Beta PDF fitted to an exponentially distributed CIC data set using Easyfit software.

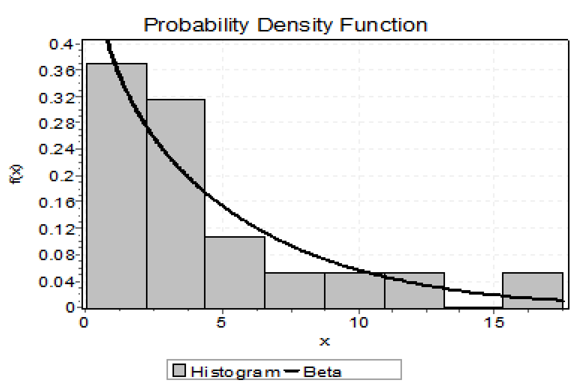

Figure 6.2. Beta probability distribution fitted to histogram of CIC data for an 8 hour power interruption: Retail customer segment. 42 CIC estimate samples were used.

Table 6.2. Beta PDF ranking for Figure 6.2

K–S test	Exponential	Weibull	Gamma	Normal	Lognormal	Beta
p-value	0.12698	0.2163	0.13611	0.24103	0.22078	0.14146
Rank	1	4	2	6	5	3

Table 6.2 presents the results of the K-S goodness of fit tests. As expected the exponential PDF is ranked higher than the Beta PDF. It is however important to note that test statistics of the exponential and Beta PDFs, from the K-S tests are very close. The difference in the test statistics may have been as a result of the differences in the respective tail regions. The CIC PDFs have the same range and almost overlap which indicated that the Beta PDF could be used in place of the exponential to represent the CIC data set. Similar observations were made from other CIC estimates of different time of occurrences and duration.

Figures 6.3 - 6.9 show Beta PDF fitted to some of the customer segments formed as a results of multi-dimensional customer segmentation model proposed in Chapter 5. With finitely ranged CIC inputs, the Beta PDF was generally ranked as the best fit of the CIC data of the selected data set. The results also showed a high ranking attached to the Beta PDF for different power interruption durations and customer segments.

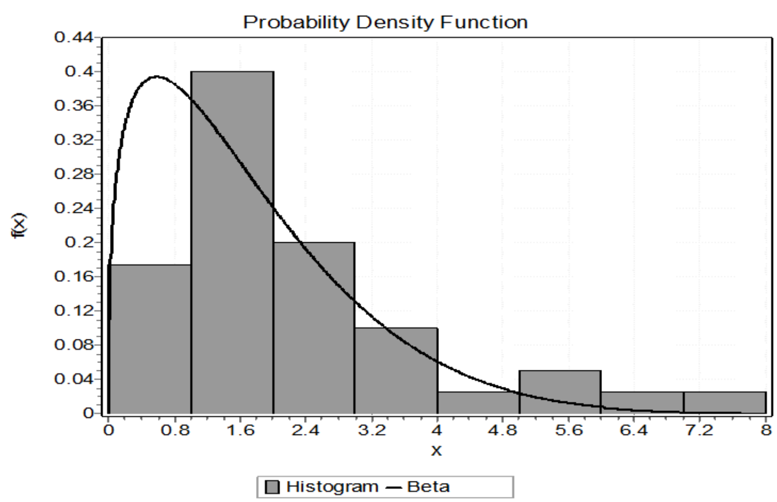

Figure 6.3. Beta probability distribution fitted to histogram of CIC data for a 2 hour summer weekday morning power interruption - Commercial: low-high. The CIC estimates were normalised using average monthly energy cost. 15 CIC estimate samples were used.

Table 6.3. Beta PDF ranking for Figure 6.3

K–S test	Exponential	Weibull	Gamma	Normal	Log-normal	Rayleigh	Log-logistic	Beta
p-value	0.24978	0.34008	0.37592	0.25164	0.38798	0.45231	0.36709	0.2168
Rank	2	4	6	3	7	8	5	1

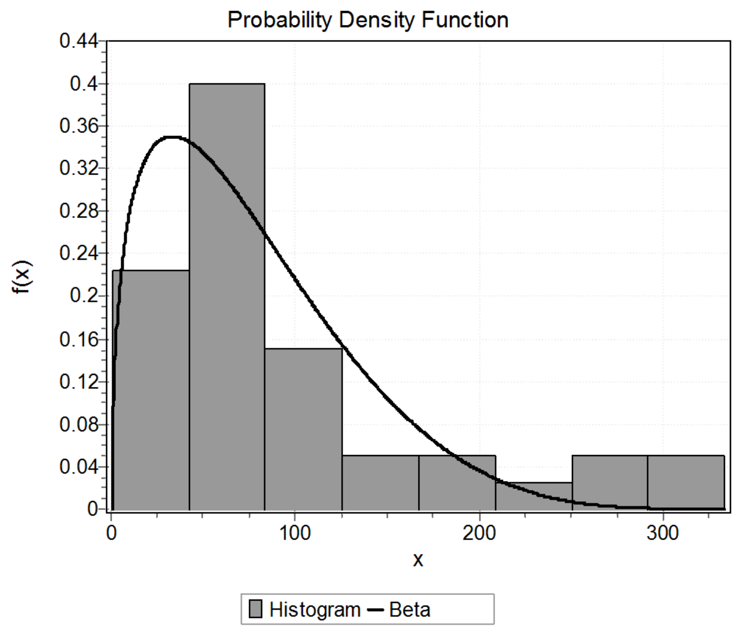

Figure 6.4. Beta probability distribution fitted to histogram of CIC data for a 4 hour summer weekday morning power interruption: Commercial: low-high. The CIC estimates were normalised using peak load. 40 CIC estimate samples were used.

Table 6.4. Beta PDF ranking for Figure 6.4

K–S test	**Exponential**	**Weibull**	**Gamma**	**Normal**	**Log-normal**	**Rayleigh**	**Log-logistic**	**Beta**
p-value	0.15927	0.14082	0.11555	0.22141	0.16707	0.25042	0.18797	0.13993
Rank	4	3	1	7	5	8	6	2

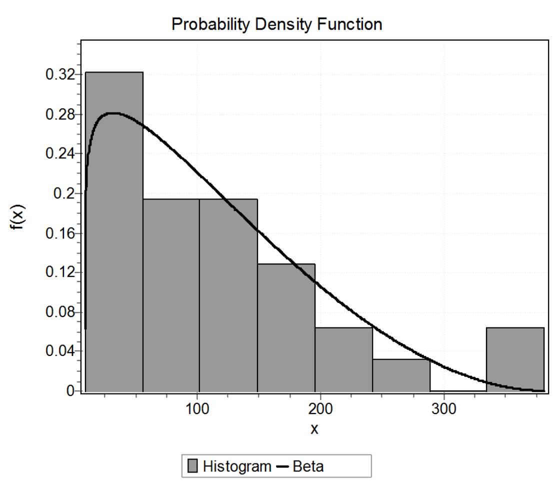

Figure 6.5. Beta probability distribution fitted to histogram of CIC data for an 8 hour power interruption: Winter weekday morning: Commercial: low-high. The CIC estimates were normalised using peak load. 31 CIC estimate samples were used.

Table 6.5. Beta PDF ranking for Figure 6.5

K–S test	Exponential	Weibull	Gamma	Normal	Log-normal	Rayleigh	Log-logistic	Beta
p-value	0.15942	0.11238	0.09566	0.16412	0.14854	0.18844	0.17066	0.0794
Rank	5	3	2	5	4	8	7	1

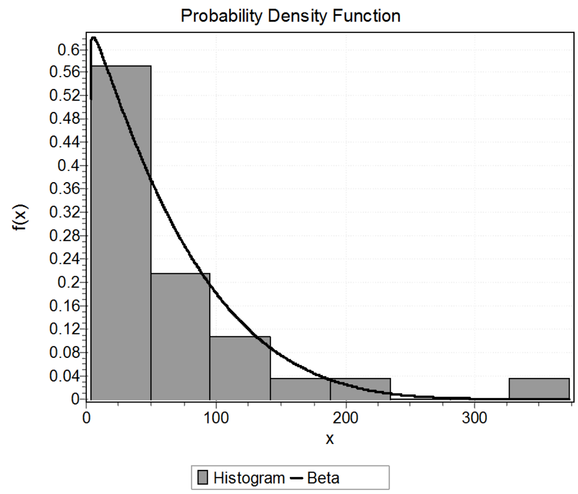

Figure 6.6. Beta probability distribution fitted to histogram of CIC data for a 2 hour power interruption: Summer weekday morning: Industrial: low-high. The CIC estimates were normalised using peak load. 8 CIC estimate samples were used.

Table 6.6. Beta PDF ranking for Figure 6.6

K–S test	Exponential	Weibull	Gamma	Normal	Log-normal	Rayleigh	Log-logistic	Beta
p-value	0.14702	0.12553	0.19476	0.2009	0.10089	0.28248	0.11818	0.10272
Rank	5	4	6	7	1	8	3	2

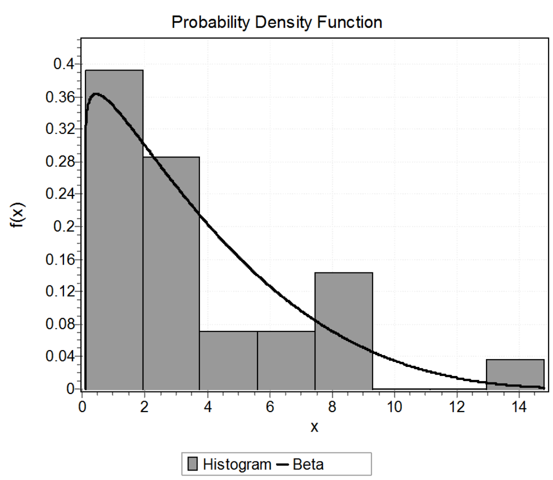

Figure 6.7. Beta probability distribution fitted to histogram of CIC data for an 8 hour power interruption: Summer weekday morning: Industrial: low-high. The CIC estimates were normalised using average monthly energy cost. 28 CIC estimate samples were used.

Table 6.7. Beta PDF ranking for Figure 6.7

K–S test	Exponential	Weibull	Gamma	Normal	Log-normal	Rayleigh	Log-logistic	Beta
p-value	0.15831	0.14416	0.11114	0.20122	0.12426	0.23726	0.15816	0.10314
Rank	6	4	2	7	3	8	5	1

6.4 Goodness of fit tests of probability distribution functions to reliability worth outputs

Wangdee and Billinton [2005] state that reliability indices vary from year to year and should therefore be regarded as random variables that are dependent on the system topology and, operating philosophy and conditions. The level of skewness of the distribution of a reliability index is important when interpreting the index [Billinton and Allan, 1996]. For example, the likelihood of occurrence of extreme (high or low) CIC estimates can be investigated using the tails of its distribution. Dzobo *et al.* [2011] performed a comparison of the Beta PDF against the use of average reliability worth inputs and outputs. Figure 6.8 shows the reliability worth index at one of the load points. The conclusion was that the use of average values does not take into account the spread of the reliability worth index and it underestimates extreme (high or low) values of the CIC estimates.

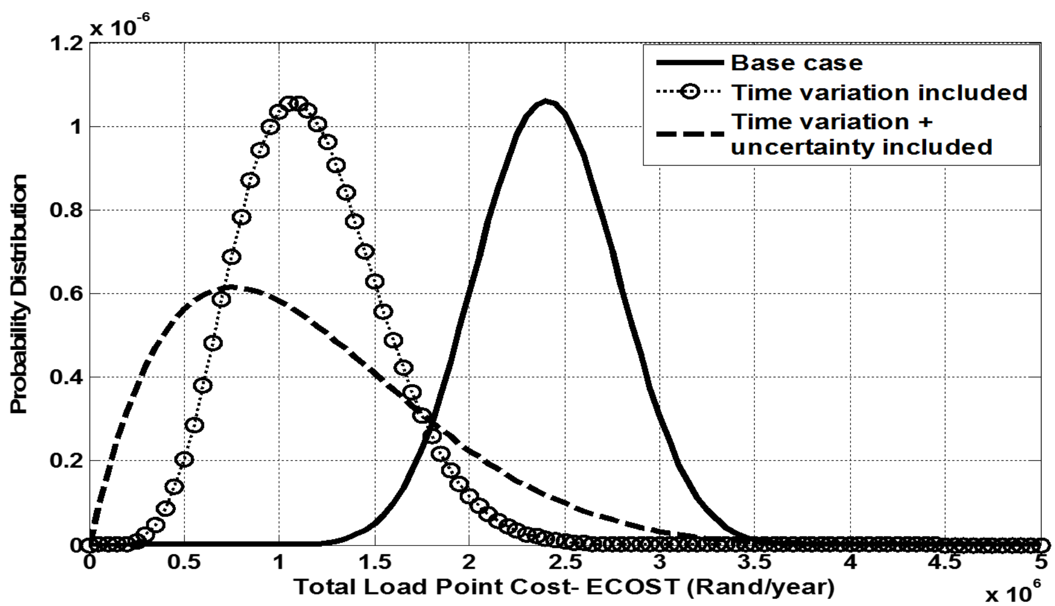

Figure 6.8. ECOST value for Load point 1,[Dzobo *et al.*, 2011]

The goodness of fit of the Beta PDF for the reliability worth index data sets is computed in Cross *et al.* [2006]. Figures 6.9 and 6.10 show histograms developed by the authors from the reliability indices computed for a load point. The Beta, gamma, log-normal and Weibull PDFs were fitted. The results of the goodness of fit tests are presented in Tables 6.8 and 6.9 respectively.

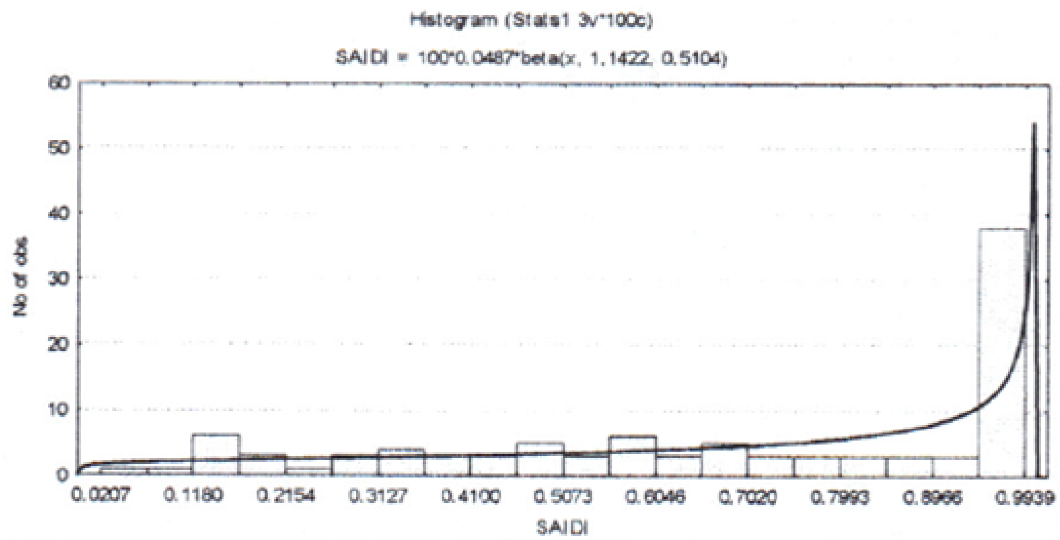

Figure 6.9. SAIDI histogram and beta fit, [Cross *et al.*, 2006]

Table 6.8. Beta PDF ranking for Figure 6.9

K–S test	Exponential	Weibull	Gamma	Normal	Lognormal	Beta
p-value	0.241782	0.196063	0.188467	0.191840	0.220562	**0.154954**
Rank	6	4	2	3	5	**1**

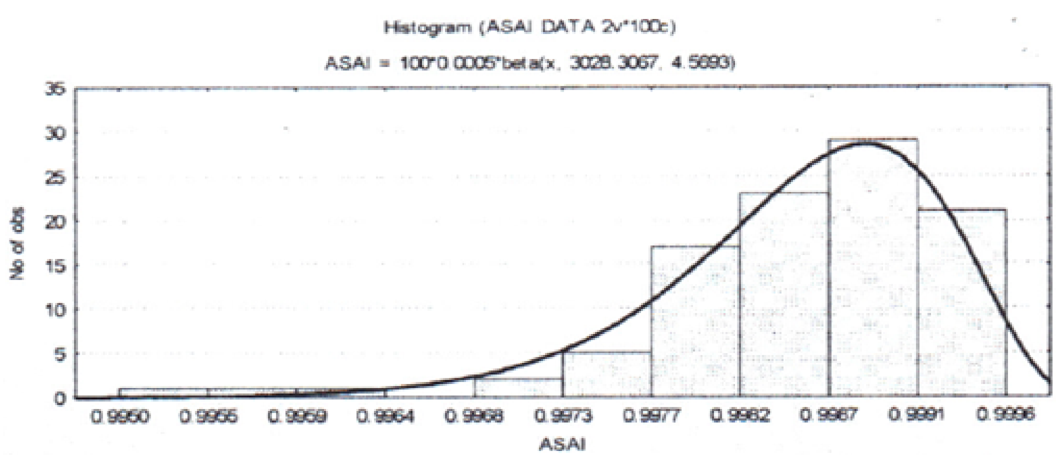

Figure 6.10. ASAI histogram and beta fit, [Cross *et al.*, 2006]

Table 6.9. Beta PDF ranking for Figure 6.10

K–S test	**Exponential**	**Weibull**	**Gamma**	**Normal**	**Lognormal**	**Beta**
p-value	0.630837	0.055751	No result	0.094715	0.094842	**0.071655**
Rank	5	1		3	4	**2**

6.5 Discussion

- *What is the best probability distribution function that can be used to characterise uncertainty (or risk) in interruption cost assessment?*

This chapter identified the need to describe reliability worth inputs and outputs, beyond the conventional use of average values. For both reliability worth inputs and outputs, the Beta PDF is consistently able to exhibit the basic shape of the given histogram. This is significant because it indicates that the Beta PDF is able to illustrate the reliability risk or confidence associated with reliability inputs and outputs. This statistical information is shape-dependent and is often omitted by other PDF types that are fitted to data sets.

The goodness of fit test results of the K-S tests indicate that the Beta PDF is often not always the best-fitting PDF, but is a generally good fitting PDF for all CIC data sets. Because the Beta PDF lies within a finite range, it is able to describe realistic and practical reliability worth inputs and outputs. All of the information about statistical characteristics (moments) and the shape of the Beta PDF is contained in three parameters. This feature allows the Beta PDF to be mathematically flexible and manageable. From the results it is clearly illustrated that the Beta PDF has the ability to take on an assortment of shapes, and it is simple to derive its statistical parameters. It is therefore possible to use the Beta PDF as a standard PDF to model CIC estimates for all different durations and time intervals. This has the advantage of that only one PDF is used as a standard PDF model for all the CIC estimates for the different customer segments, durations and time of occurrence of power interruptions. This will greatly reduce the time required to model all the CIC estimates. However, the analysis described in this chapter was carried out on customer survey data based on one location in South Africa. For different locations and other countries, the results may be different. However, no customer survey data was available to substantiate this. This points to the need for a power utility to conduct customer surveys in different location of the country in order to fully understand the best PDF to use for CIC estimation.

The use of Beta PDF for both reliability inputs and outputs would create a possibility of integrated reliability worth studies. If all of the reliability inputs and outputs of a power system network can be modelled using the Beta PDF, a direct link between reliability worth inputs and outputs by means of mathematical algorithms which use information captured by the model's parameters can be created. The following chapter summarizes the mathematical algorithm used to derive the direct link between reliability worth inputs and outputs from information captured by the model parameters presented in the previous chapters.

CHAPTER

SEVEN

RISK-BASED INTERRUPTION COST INDEX: CASE STUDIES

This chapter provides a methodology to determine the Risk-based Interruption Cost index at a bus having a variety of customer mixes. The index is derived using time-based probabilistic reliability input parameters and is calculated at different risk levels. A comparison of the RBIC index and average ECOST is carried out in a case study.

7.1 Introduction

Generally, there are two major problems that arise if interruption statistics are used for investment justification or for estimating the relative importance of the various parts of the system. The first problem is the fact that the costs of increased reliability, which is in monetary units, cannot be directly compared with a non-monetary reliability performance index like SAIFI or SAIDI. The non-monetary reliability indices can be used to establish minimum system requirements or to rank different design alternatives, but they cannot be related to the investment costs. The second problem is that the interruption statistics express the supply reliability from the system's point of view i.e. they express the system performance within the context of the system alone. The supplied electricity customers are only regarded as far as their electrical effects on the system. Electricity customers with identical electrical behaviour are treated equally. It is therefore difficult, if not impossible, to account for the effects of specific customer importance or interruption damage functions in the calculated interruption statistics. In other words, if the power consumption, and frequency and mean duration of the power interruptions are identical for a hospital, for instance, and a shopping mall, then their calculated interruption statistics will also be identical. It will not be possible to bias the non-monetary reliability performance indices for the difference in importance of these two loads, even when that importance is known to be completely different.

Furthermore, power system management decisions that could affect service delivery are not always based on sound engineering analyses but are often politically or socially driven. To improve communication between all stakeholders involved, it is prudent to express the quantitative reliability indices in monetary terms. Financial decision makers are more likely to understand indices expressed in monetary terms than in engineering terminology. For investment justification or for comparing different design alternatives on a monetary basis a more detailed risk-based interruption cost index (RBIC) based on the interruption and customer parameters derived in previous chapters is proposed in this thesis.

The general steps required for developing the Risk-based Interruption Cost index is shown in Figure 7.1.

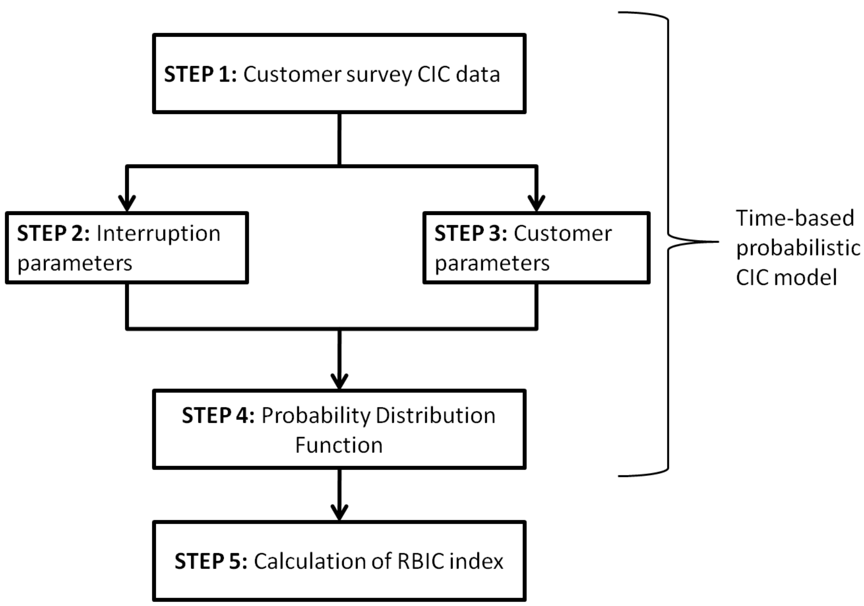

Figure 7.1. General steps of data requirement for derivation of Risk based Interruption Cost index

7.2 Proposed time-based probabilistic (TBP) CIC model

The model applied when using the time-based probabilistic CIC model is an extension of the 16-cell matrix CIC model presented in section 6.2. The model previously used the mean and standard deviation to represent reliability worth input parameters. A scaling factor is introduced to describe the reliability worth inputs. Also, the range of the parameter data set in each cell has its scaling factor, dependent on the maximum CIC estimate in a given time window. Using equations 6.1 and 6.2, Beta PDF parameters are then computed, for each time window such that probabilistic time-dependent CIC models are derived.

- **STEP 1: Customer survey CIC data -** Collect CIC data from electricity customers dependent on the customer and interruption parameters discussed earlier.

- **STEP 2: Interruption parameters -** Distribute the CIC data into the 16 cells of the matrix depending on duration and time of occurrence of power interruption (*see Table 4.2*).

- **STEP 3: Customer parameters -** A matrix is developed for each customer class depending on the economic activity, economic size, energy consumption and ownership of backup power supply. The final customer cluster segments are derived using hierarchical (Ward's linkage) clustering technique as described earlier in chapter 5. The size of the matrix depends on the available CIC data.

- **STEP 4: Probability distribution function -** Compute the statistical parameters, mean, standard deviation and maximum value, for each cell's CIC data or sub-data sets. Calculate the shape parameter for the Beta PDF of each cell CIC data set or sub-data set. The shape parameters is an indication of the skewness of the distribution that describes the parameter. A Beta PDF is derived with respect to a single CIC data set (sub-data sets). The Beta PDF describing a given CIC data set is scaled using the maximum value of each respective CIC data set. The developed new time-based probabilistic CIC model is used to input reliability worth parameter PDFs with different levels of dispersion and skewness in reliability worth analyses of power systems.

7.2.1 Advantages of the proposed time-based probabilistic CIC model

The advantages of adopting the proposed time-based probabilistic CIC model are numerous:

- It is possible to reduce the number of customer survey questions to be asked in a customer survey by using underlying factors that cause variation of CIC estimates i.e activity level. The activity levels of electricity customers must be customer specific.

- The model can help identify which time of occurrence provide the largest irritation factor for electricity customers or times which electricity customers find inappropriate or difficult to comply with. The activity level measurement reveals where the electricity customers would incur the highest CIC, and also where reduction in power supply reliability can be applied to greatest effect.

- The use of the Beta PDF not only allows for different reliability worth inputs at different risk levels to be used as inputs but also allows for a direct link between the reliability worth inputs and outputs.

- Clustering of different electricity customers of similar cost characteristics greatly reduces the dispersion of the final CIC estimates and therefore allows for accurate estimation of reliability worth indices. Furthermore, the clustering of different electricity customers reduces the number of final customer cluster segments formed for CIC analyses.

- It allows one to analyse CIC data for different purposes. A matrix can be built with regard to a specific customer segment, the whole network, a specific duration, load point or geographical region. One can also move from one type of analysis, for a given matrix to another. This is achieved by aggregating CIC data sets and/or sub CIC data sets. Aggregated results can be regarded as the composite of the contributing CIC data or sub-data sets.

- It also allows the derivation of Risk-based Interruption Cost index in monetary terms which has the advantage of being easily understandable and comparable with other indices.

7.3 Calculation of RBIC index

Figure 7.2 presents the flowchart describing the main stages for evaluating the Risk-based Interruption Cost index.

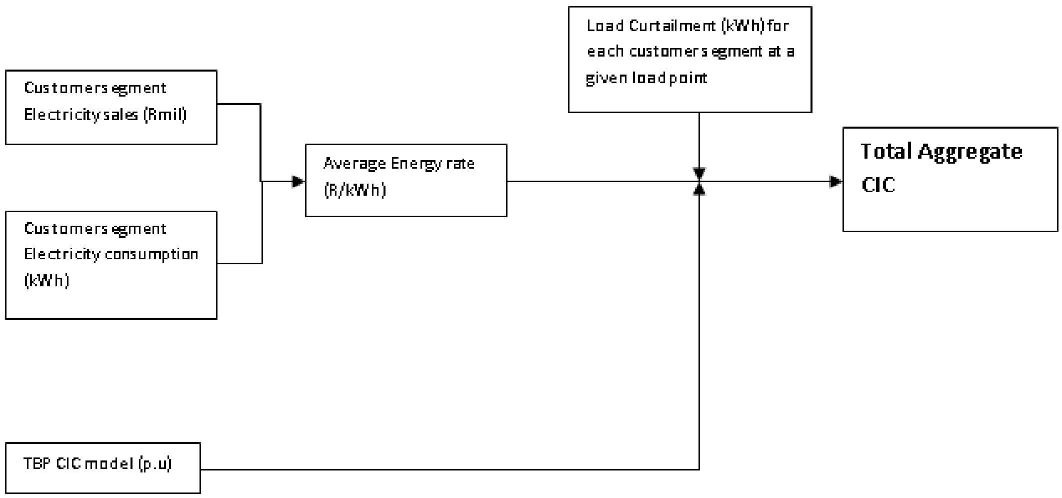

Figure 7.2. Flowchart for derivation of Risk-based Interruption Cost index

The flowchart is simplified in the following steps:

Step 1: Identify the failed component that constitutes a load point outage event: For each failure event, caused by a failed component, the affected load points and time of occurrence of the failure event have to be identified and type of outage time (switching time, restoration time, repair time or replacement time) for each load point must be determined. Some loads will be affected only by switching time for a certain failure event while others will be un-supplied during the whole replacement or repair time. The load points that are affected and type of outage time for a load point will depend on the protection system, network configuration and maintenance philosophy.

Step 2: Calculate the load curtailed for each customer cluster segment: For each affected load point, the outage duration, time of occurrence of failure event and load curtailed are recorded. If there is a customer mix at the affected load point then calculate the load curtailed for each customer cluster segment. The Load curtailed for each customer cluster segment is given by:

$$Load\ curtailed\ =\ Percentage\ of\ load\ composition_{\mathbf{A}}\ x\ Total\ load\ curtailed \tag{7.1}$$

*where **A** is the customer cluster segment.*

Step 3: Calculate the average monthly revenue not collected (RNC) by the power utility due to the load curtailment for each customer cluster segment:

This step is used to calculate how much the load curtailment costs the power utility. The RNC is calculated using the average monthly energy rate (ER) or corresponding electricity rates for each customer cluster segment. The average monthly energy rates are sometimes estimated from the average monthly energy bill of the electricity customers and their corresponding average monthly energy consumption. The formula used to derive the average monthly energy rate is given by:

$$ER = \frac{Average\ monthly\ bill}{Average\ monthly\ energy\ consumption} \tag{7.2}$$

The RNC is then given by:

$$RNC_{av} = Load\ curtailed_{\mathbf{A}}\ x\ ER_{\mathbf{A}} \tag{7.3}$$

*where **A** is the customer cluster segment and ER is the energy rate*

Step 4: Calculate the total financial loss for each customer cluster segment:

In this stage the financial loss distribution (F) at each load point is calculated using the TBP CIC model for each customer cluster segment. The financial loss distribution (F(x)) is given by:

$$F_A(x) \quad = \quad RNC_A\ x\ f(x)_A \tag{7.4}$$

where f(x) is the beta probability distribution profiles of the CIC data sets described by its shape parameters α, β and C.

$$f(x)_{\boldsymbol{A}} \quad = \quad C_A.\ beta\ (\alpha_A, \beta_A) \tag{7.5}$$

and RNC is the revenue not collected due to the load curtailment and A is the customer cluster segment.

Step 5: Calculate the total aggregate RBIC index value for the load point:

The total aggregate RBIC index is derived by simple addition of the financial loss distribution for each customer cluster segment at a given load point. The total aggregate RBIC index at a load point is given by:

$$Total\ RBIC\ index(k, l) \;=\; \sum_{A} F_A(x, \mathbf{risk\ level}) \tag{7.6}$$

*where Total RBIC index(k, l) is the total financial impact a failure event (l) due to component (k) have on electricity customers and $F_A(x, \boldsymbol{risk\ level})$ is the total financial impact a failure event (l) due to system component (k) at a load point have on customer cluster segment A given at a **risk level** from the financial loss distribution*

The proposed TBP CIC model is validated by comparing its performance with that of the conventional CDF approach in reliability worth assessment of different power system networks in the next sections.

7.4 Description of the case study test system

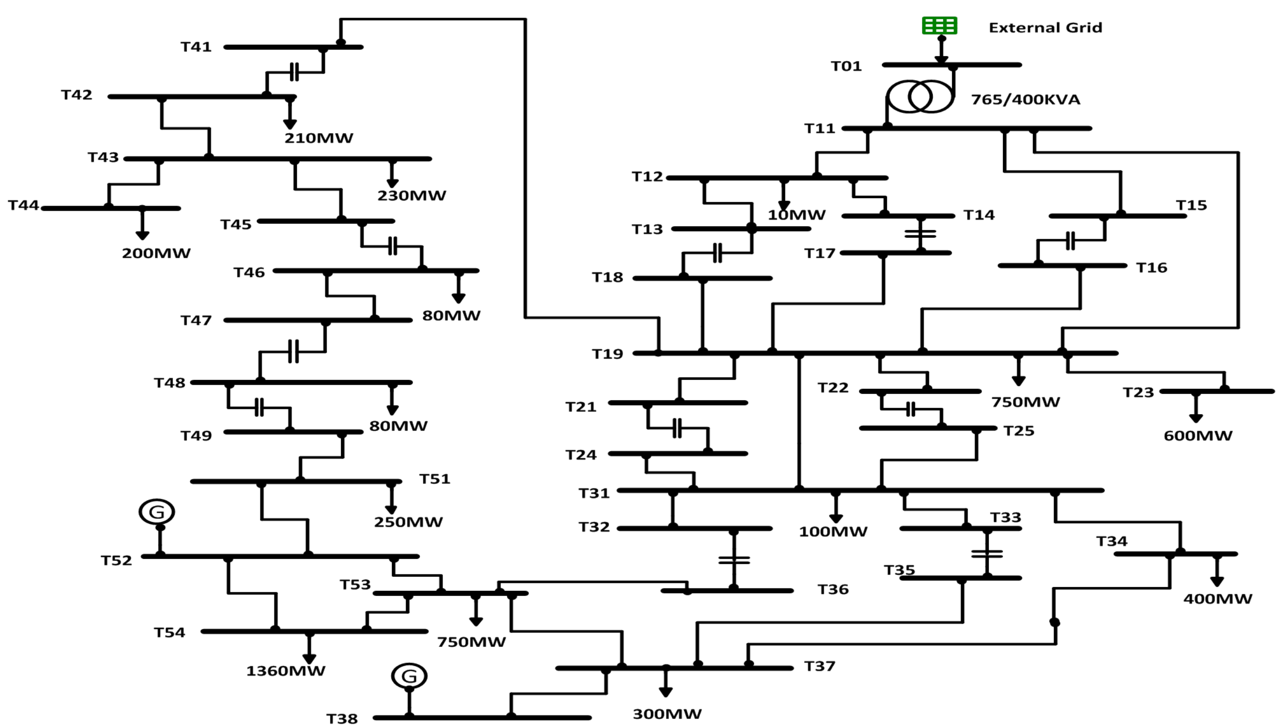

Figure 7.3. South Africa pseudo-network

A single line diagram of the test system is displayed in Figure 7.3. Some parameters describing the size of the test system are given in Table 7.1. It is similar to a portion of the real South African transmission network - Western Cape Province. The test system network have been developed in a project within a research group at University of Cape Town, in order to provide consistent set of data which enables reliability and customer interruption cost assessment. To ensure the similarity of the test system to South African networks in terms of load, component and customer data as well as network topology, the main power utility Eskom South Africa was an integral part of the development process. The test system network was taken as a good representative of actual South African system network, and thus suitable for further research on reliability and regulation polices. For example, the effect of time-dependent on power system reliability assessment can be studied by using the developed test system [Edimu *et al.*, 2011]. This network covers the area where the CIC data was collected. The network is composed of 36 buses with a total load of 6.3 GW. The maximum generating capacity is 2.2 GW with make-up in-feed (slack-bus) from Terminal 01 (shown in Figure 7.3). The base voltage and power for the network is 400 kV and 100 MW respectively. The loads indicated at each load point are the peak load values.

The test system is a radially operated transmission network, in which all loads can be fed from two sides. This system is a pseudo network described in Edimu *et al.* [2011]. This system is chosen here because of its size and complexity. The evaluation method presented in section 7.3 is used to show how the RBIC index is derived at a load point with different customer mix. The peak load demands for the load points are indicated at each load point in the system network and the load composition at each load point is given in Table 7.1.

Table 7.1. Load composition at different load points

Sector	**Cluster Segment**	**Load composition (%)**			
		T42	**T43**	**T44**	**T46**
Industrial	**Low-Low**	0.30	-	0.45	0.40
	Low-Medium	0.10	0.50	-	0.60
Commercial	**Low-Low**	0.60	0.20	0.20	-
	Low-Medium	-	0.30	0.35	-

The average CIC estimates for the different customer cluster segments are given in Table 7.2. The average CIC estimates are normalised using the average monthly energy cost and are therefore expressed in per-unit.

Table 7.3 shows the Beta PDF fitted CIC estimates for the different customer segments given in Table 7.2

Table 7.2. Average CIC estimates (p.u) for different customer segments: Summer weekday morning

Sector	Cluster Segment	Number of respondents	Duration (hr)			
			1	2	4	8
Industrial	Low-Low	28	1.47	2.48	3.83	5.79
	Low-Medium	8	0.7	2.7	4.7	8.71
Commercial	Low-Low	15	0.6	1.01	1.32	2.25
	Low-Medium	40	0.84	1.75	3.29	6.26

Table 7.3. Beta PDF CIC profiles for different customer segments (α, β, C): Summer weekday morning

Sector	Cluster Segment	Duration (hr)			
		1	2	4	8
Industrial	Low-Low	0.75, 5.99, 9	1.09, 7.46, 16	1.06, 4.18, 18	1.27, 3.90, 21
	Low-Medium	5.60, 3.10, 2	0.37, 0.44, 4	0.38, 0.77, 8	0.35, 0.72, 16
Commercial	Low-Low	0.20, 0.32, 2	0.21, 0.35, 2	0.28, 0.44, 2	0.40, 0.61, 4
	Low-Medium	1.43, 8.95, 6	1.91, 10.69, 10	1.20, 4.54, 14	1.45, 6.11, 28

7.5 Case 1: Calculation of RBIC index at different load points with different customer mix

Objective: To investigate the effect of using time-based probabilistic CIC values as compared with average CIC values. The time-based probabilistic CIC values produces averaged values, but also confidence limits. Different confidence levels are used and are compared with average expected interruption cost (ECOST) values. The calculations utilised all the five steps outlined in section 7.3

Step 1: Identify the load point outage event

Assume a total load loss for two hours at all load points during the period of October - December (Summer) at 7:00pm - Weekday. The load demands on each load point before the emergency occurred are assumed as follows: **T42: 210MW, T43: 230MW, T44: 200MW, T46: 80MW.** For simplicity, the load demands and emergency scenario is assumed to be the same for all the time of occurrence of power interruptions considered in the analysis.

Step 2: Calculate the load curtailed for each customer segment

Load curtailed is given by:

$$Load\ curtailed\ =\ Percentage\ of\ load\ composition_{\mathbf{A}}\ x\ Total\ load\ curtailed \qquad (7.7)$$

*where **A** is the customer cluster segment.*

For example for Industrial: **Low-Low** connected at load point **T41**, the load curtailed is given by:

$$\begin{aligned} Load\ curtailed &= 0.30\ x\ 210\ MW \\ &= \mathbf{63\ \ MW} \end{aligned}$$

The load curtailed for each customer cluster segment is shown in Table 7.4.

Table 7.4. Load curtailed at different load point for each customer cluster segment

Sector	Cluster Segment	Load curtailed (MW)			
		T42	T43	T44	T46
Industrial	Low-Low	63	-	90	32
	Low-Medium	21	115	-	48
Commercial	Low-Low	126	46	40	-
	Low-Medium	-	69	70	-

Step 3: Calculate average monthly revenue not collected by the power utility due to the load curtailed

This step is used to calculate how much the load curtailment costs the power utility. In Dzobo [2010] this was referred to as the Revenue Not Collected (RNC). This term is also used in this thesis. The RNC is calculated using the average monthly energy rate (ER) or corresponding electricity rates for each customer cluster segment. The average monthly energy rates is sometimes estimated from the average monthly energy bill of the electricity customers and their corresponding average monthly energy consumption. The formula used to derive the average monthly energy rate is given by:

$$ER = \frac{Average\ monthly\ bill}{Average\ monthly\ energy\ consumption} \tag{7.8}$$

However, in this thesis the average monthly energy rate values are taken from the electricity rates found in reference Eskom-2008 [2008a] and are shown in Table 7.5.

Table 7.5. Average monthly energy rate for different electricity customer cluster segments

Sector	Cluster Segment	Average monthly energy rate (R/kW)
Industrial	Low-Low	0.2537
	Low-Medium	0.2237
Commercial	Low-Low	0.2505
	Low-Medium	0.2237

The RNC is given by:

$$RNC_{av} \quad = \quad Load\ curtailed_{\mathbf{A}}\ x\ ER_{\mathbf{A}} \tag{7.9}$$

where $\boldsymbol{A}$ *is the customer cluster segment and ER is the energy rate*

For example for Commercial: **Low-Medium** connected at load point **T43**, the RNC value is calculated as:

$$\begin{aligned} RNC_{av} &= 69\ MW\ x\ 0.2237\ R/kW \\ &= \mathbf{15.44\ kR} \end{aligned}$$

The RNC values for the different load points are presented in Table 7.6

Table 7.6. RNC values for each customer cluster segments at different load points

Sector	Cluster Segment	RNC values (kR)			
		T42	T43	T44	T46
Industrial	**Low-Low**	15.98	-	22.83	8.12
	Low-Medium	4.70	25.73	-	10.74
Commercial	**Low-Low**	31.56	11.52	10.02	-
	Low-Medium	-	15.44	15.66	-

Step 4: Calculate the total CIC of each customer cluster segment at different load points

The CIC estimates given in Table 7.2 are used to calculate the total AIC for each customer cluster segment. The time-based probabilistic CIC estimates are taken from Table 7.3. The time interval considered is the time at which the load curtailment took place i.e. October - December: 06am - 12pm: Weekday. The total AIC for each customer cluster segment is calculated as follows:

$$Interruption\ Cost_{\mathbf{A}} = CIC(d)_{\mathbf{A}}\ x\ RNC_{\mathbf{A}} \tag{7.10}$$

where CIC (d) is the cost of interruption for a power interruption of duration d, RNC is the revenue not collected for customer cluster segment $\boldsymbol{A}$.

For example the total Average Interruption Cost (AIC) for Industrial: **Low-Medium** connected at load point **T46** is given by:

$$\begin{aligned} AIC &= 10.74\ x\ 2.7 \\ &= \mathbf{28.99\ kR} \end{aligned}$$

The total AIC for each customer cluster segment is presented in Table 7.7.

Table 7.7. Total aggreagte AIC for each customer cluster segment connected at different load points

Sector	Cluster Segment	AIC (kR)			
		T42	**T43**	**T44**	**T46**
Industrial	**Low-Low**	39.64	–	56.63	20.13
	Low-Medium	12.68	69.46	-	28.99
Commercial	**Low-Low**	31.88	11.64	10.12	-
	Low-Medium	-	27.01	27.40	-
Total Aggregate Cost		**84.20**	**108.11**	**94.15**	**49.13**

Using the TBP CIC model the financial loss probability distribution for each customer cluster segment is derived by using equation 7.4:

$$F_A(x) \quad = \quad RNC_A \ x \ f(x)_A \tag{7.11}$$

where f(x) is the probability distribution of CIC described by the beta parameters and RNC is the revenue not collected due to the load curtailment and A is the customer cluster segment.

From the equation, it can be clearly seen that RNC values are used as weighting factor of *f(x)*. Therefore it is possible to multiply the maximum value C of the beta parameters to get the $F_A(x)$ profile for each customer cluster segment A. The shape parameters (α, β) of the beta distribution does not change. Replacing $f_A(x)$ the financial loss distribution $F_A(x)$ for different customer cluster segments is calculated as illustrated below.

$$F_A(x) \quad = \quad RNC_{\mathbf{A}} \ x \ C_A \ beta \ (\alpha_A, \beta_A) \tag{7.12}$$

For example the financial loss distribution F(x) for Commercial: **Low-Medium** connected at load point **T44** is given by:

$$\begin{aligned} F(x) &= 15.66 \ x \ 10 \ x \ beta \ (1.91 \ , \ 10.69) \\ &= \mathbf{156.60 \ x \ beta \ (1.91 \ , \ 10.69)} \end{aligned}$$

Since *F(x)* is expressed as a probability distribution, singular values can be extracted from such distribution based on levels of confidence or conversely, level of risk. Therefore, from the financial loss distribution of each customer cluster segment, the RBIC index for each cluster segment can be determined at different risk levels. For example, if we consider Commercial: **Low-Medium** connected at load point **T44** with a financial loss distribution as calculated above i.e. *F(x)* = **156.60 x beta (1.91 , 10.69)**. The RBIC index value at 5% risk level is obtained by extracting or taking a singular value at 95% confidence level or 5 % risk level of the probability distribution. In this case the **RBIC index value @ 5% risk level = 53.04kR**.

Using the RNC values presented in Table 7.6, the RBIC index beta parameters are derived and presented in Table 7.8.

Table 7.8. RBIC index beta parameters for each customer cluster segment at different load points

Sector	Cluster Segment	RBIC index values			
		T42	T43	T44	T46
Industrial	Low-Low	0.75, 5.99, **255.73**	-	1.06, 4.18, **365.33**	1.27, 3.90, **129.89**
	Low-Medium	5.60, 3.10, **18.791**	0.37, 0.44, **102.90**	-	0.35, 0.72, **42.95**
Commercial	Low-Low	0.20, 0.32, **63.126**	0.21, 0.35, **23.04**	0.28, 0.44, **20.04**	-
	Low-Medium	-	1.91, 10.69, **154.35**	1.20, 4.54, **156.60**	-

Step 5: Calculate the total aggregate RBIC index value for each load point.

The total aggregate AIC or average ECOST is derived by simple addition from the total AIC of each customer cluster segment at a given load point. The results of the total aggregate AIC are included in Table 7.7. For the time-based probabilistic CIC values the financial losses distribution of each customer cluster segment is calculated at any risk level of interest to the power system operator or planner. The system operator or planner may wish to know the extreme financial loss for each load point and may suggest taking a 5%, 10%, 20% and 50% risk levels to see how the electricity customers are affected at each load point. The total aggregate RBIC index values for each load point are derived at the different risk levels and compare to the AIC values in Figures 7.4 - 7.7

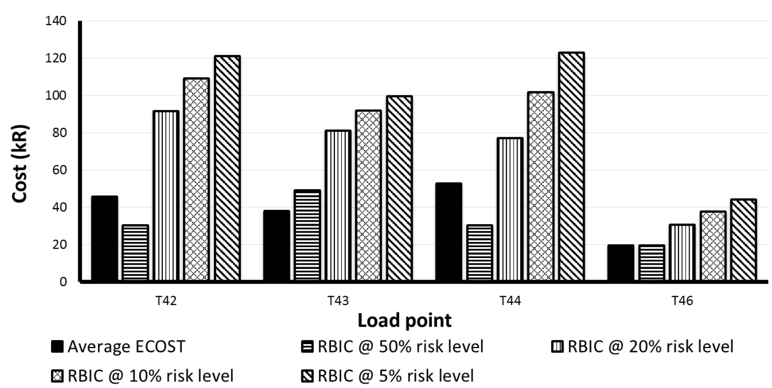

Figure 7.4. Comparison of average ECOST and RBIC at different risk levels for a 1 hour power interruption

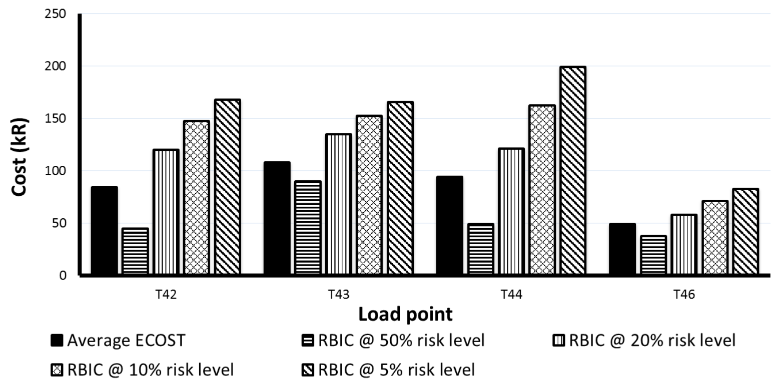

Figure 7.5. Comparison of average ECOST and RBIC at different risk levels for a 2 hour power interruption

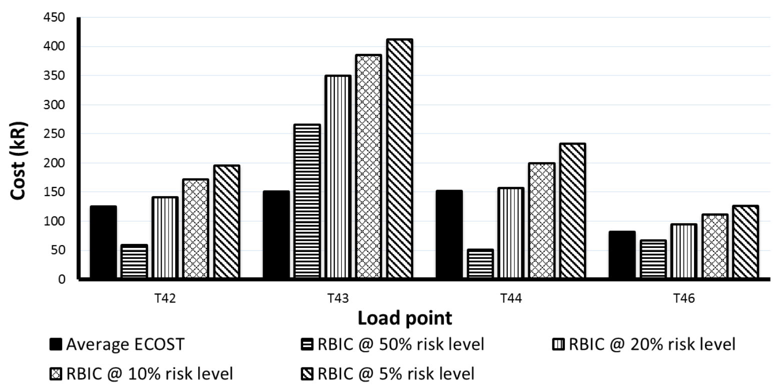

Figure 7.6. Comparison of average ECOST and RBIC at different risk levels for a 4 hour power interruption

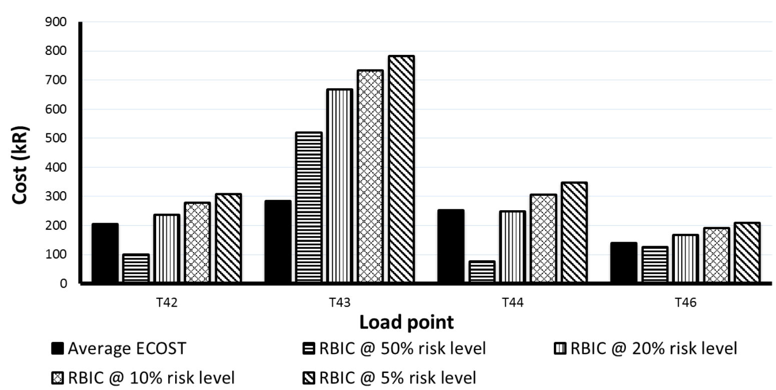

Figure 7.7. Comparison of average ECOST and RBIC at different risk levels for a 8 hour power interruption

The difference between the reliability worth output index values derived using average CIC values and time-based probabilistic CIC values is well over 40 % for all load points at 5% risk level. These differences are calculated as relative to the average value results and thus can be interpreted as a relative error of the AIC results. This difference is remarkable, it gives a different impression about the system network regarding its reliability worth.

7.5.1 Discussion of results

Power system planners and utility owners usually have to determine the level of network reinforcement and the cost attached to each action alternative. Realistic and accurate reliability worth analyses are critical to such decision making. The reliability cost and worth analyses are used to determine where in a power system network the reliability worth exceeds cost of electric supply (- reliability cost).

From Figs. 7.4 - 7.7, it is clear that the application of uncertainty to the reliability worth input (CIC) has a significant effect on the RBIC index. The fact that continuous PDFs were applied when describing reliability worth input (CIC) should therefore be noted. Average values have limited application when time dependent variability is considered. Using average CIC values means power system planners and utilities assume the CIC value to have the same value 100% of the time. In many cases, this is not good enough, such as for implementation of efficient energy delivery techniques. For effectiveness of these techniques, PDFs provide more information. This might include comparing low risk (high confidence) index values with the high risk (low confidence) index values to justify network reinforcements. For example, from Figure 7.7, the RBIC index results indicate a 50.5% increase in RBIC index value if one decides to use 5% risk values over 50% risk values. The increase in the risk cost can then be compared to the cost of implementing a switchgear upgrade. Therefore, the final decision on whether to implement the upgrade or not, will be based on index values that, as observed from the results, have risk levels attached.

For optimization, the cost-effective ratio index is defined as:

$$R = \frac{\Delta Risk\ cost(k,l)}{CE(k,l)} \tag{7.13}$$

where R is the cost-effective ratio index, $\Delta Risk\ cost(k,l)$*is the risk reduction cost for maintaining or investing in a component (k) to reduce the impact of failure (l) and CE(k,l) is the capital expenditure by the power utility on component (k) to reduce the impact of failure (l)*

The prioritization algorithm is as follows:

a. Obtain R for each action alternative

b. Rank all action alternatives by R

c. For maintenance or investment action alternatives on the same component, select the action alternative with the highest ranking and eliminate all others from the list.

d. Otherwise, elect action alternatives from the top of the ranking list until the cost limit is reached i.e reliability target is reached.

This translated the justification into a rate of return analysis balancing capital expenditure against reducing the impact of failures on electricity customers, presenting a financial case that power utility management is familiar with. For $\Delta Risk\ cost(k,l) > CE(k,l)$ the reduction of impact of failure on electricity customers is great and therefore investment should be done. Conversely, for $\Delta Risk\ cost(k,l) < CE(k,l)$, the power utility will suffer loss and may cause unnecessary increase in electricity cost, thus investments should be deferred. The optimum level is reached when $\Delta Risk\ cost(k,l) = CE(k,l)$.

7.6 Case 2: Effect of customer segmentation on reliability indices

Objective: To investigate the effect of customer segmentation on calculation of reliability worth index. The same power interruption scenario and system network as in Case 1 is used. The difference in this case is that CIC estimates from one-dimensional customer segmentation model are used. The results are compared with the RBIC index results in Case 1.

A. Method

The CIC estimates from one-dimensional customer segmentation models used in this case study are shown in Table 7.9. The total number of industrial and commercial customers presented in the table are 42 industrial and 58 commercial customers. The same customers were segmented using the proposed multidimensional customer segmentation model; and from the segmentation process the final customer cluster segments formed are presented in Table 7.2. The number of industrial and commercial customer after the multi-dimensional customer segmentation model reduced. This is as a result of some customers not within the ranges or cut-off points specified i.e their turnover or energy consumption were too high. As a result 6 industrial and 3 commercial customers were excluded in the analysis using the multi-dimensional customer segmentation model.

Table 7.9. Average CIC estimates for different customer segments: Summer weekday morning

Sector	Number of respondents	Duration (hr)			
		1	2	4	8
Industrial	42	1.53	2.82	4.7	7.68
Commercial	58	0.93	1.97	3.72	7.12

Steps 1 - 5 as described in Case 1 are used in the analysis and the ECOST at each load point is calculated and the results are presented below.

B. Results

The graphs below show the results of RBIC index and average ECOST for different load points investigated in this case study.

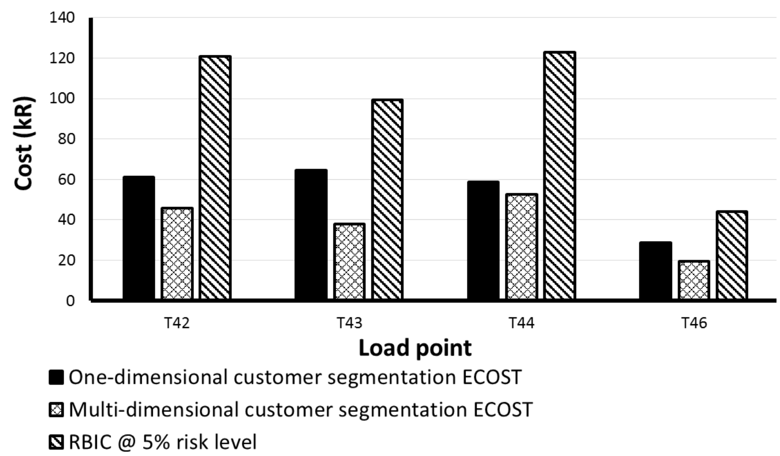

Figure 7.8. Effect of customer segmentation on RBIC for a 1 hour power interruption

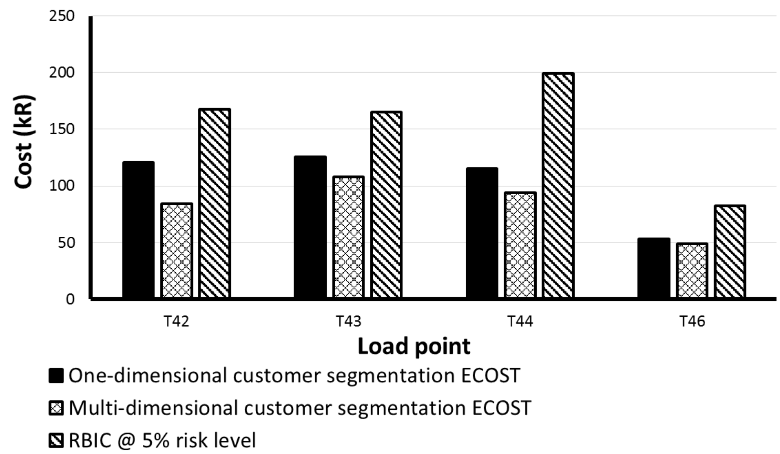

Figure 7.9. Effect of customer segmentation on RBIC for a 2 hour power interruption

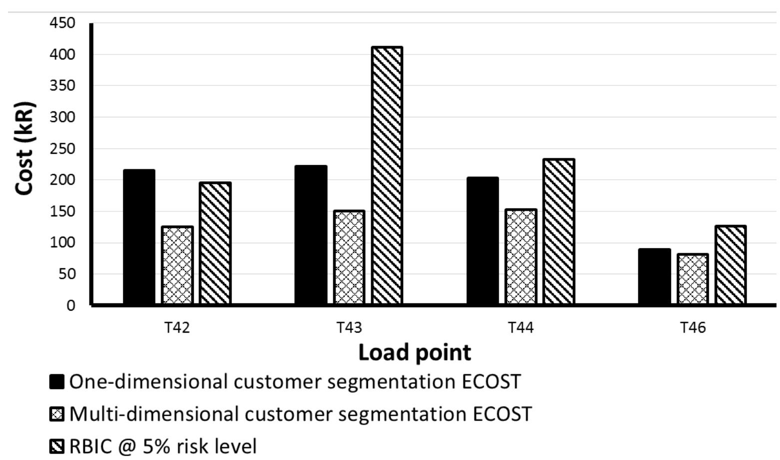

Figure 7.10. Effect of customer segmentation on RBIC for a 4 hour power interruption

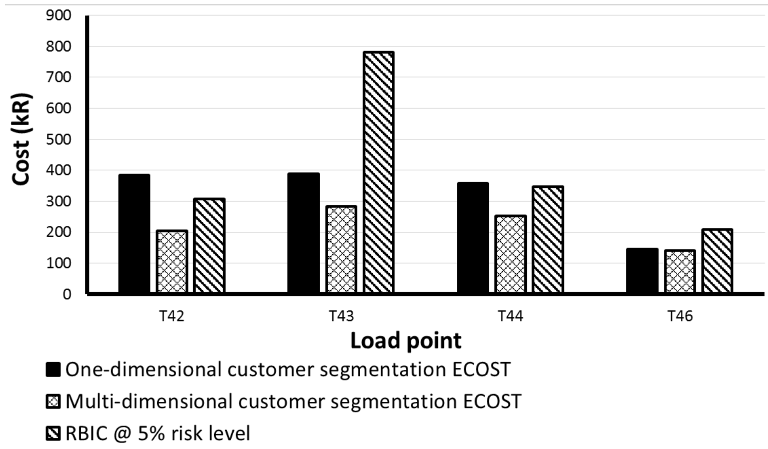

Figure 7.11. Effect of customer segmentation on RBIC for a 8 hour power interruption

7.6.1 Discussion of results

The results generally show that the RBIC index at 5 % risk level have a significantly higher value than the average ECOST from one-dimensional customer segmentation model. However, at some load points e.g load point T42 for a 4 hour or 8 hour power interruption the ECOST values are lower. This maybe as a result of the skewness of the TBP CIC model for the customer cluster segments connected at the load point. This can be computed by analyzing the tails of TBP CIC model. For example, the ECOST value of load point T42 for a 4 hour power interruption implies that low CIC estimate values are more likely compared to high CIC estimate values. Comparing with ECOST value of T43, the likelihood of very low CIC estimate values is significantly lower. However, it should be noted that while the values of ECOST varied in this analysis, load point connection of customers with different characteristics e.g. ownership of backup power supply, may lead to different ECOST distributions. The level of change is dependent on the system being analyzed and the variability applied.

The results also show that the ECOST values for one-dimensional customer segmentation model are generally higher than that of multi-dimensional customer segmentation model for all the scenarios analysed in this case study. Therefore, one-dimensional customer segmentation model can be said to overestimate ECOST values when compared to multi-dimensional customer segmentation model.

7.7 Case 3: Effect of time-dependency on reliability indices: Load shedding scheme

Load shedding occurring under emergency conditions can have significant monetary impacts on electricity customers. Minimizing the CICs associated with a load curtailment event is therefore an important factor in maintaining customer satisfaction. System operators are required to make a load shedding decision based on system security concerns when an unscheduled outage occurs in a composite system. The load demands to be curtailed at the individual load buses are supplied to the distribution system operators at the given buses. The operators, therefore, have to take load shedding actions on the distribution feeders at the bus based on their load curtailment policies and strategies. The number of feeders curtailed (load shedding set) to meet the deficiency is dependent on the emergency situation.

Many load shedding techniques have been developed to optimize the required load curtailment without violating the system security constraints. Most of these techniques are focussed on minimizing load curtailment and increasing the speed of the load shedding process. The available techniques are not generally concerned with CICs in a given load shedding situation. Some work that has incorporated load shedding with CICs is presented in Billinton and Satish [1996]; Wang and Billinton [2000]; Wangdee and Billinton [2005]. These applications however, do not consider the time at which the load curtailment occurred and also the dispersed nature of CIC. This example focusses on incorporating these factors in a load shedding strategy, which identifies and determines the priority of the distribution feeders on a given bus during an emergency. The basic objective in the example is to minimize the CICs, and to determine the number of feeders that should be curtailed in a given emergency situation with respect to time of occurrence. The RBTS Bus 2 is used as the study system and a specific emergency situation is assumed. It was important that the proposed RBIC index be tested on a proven algorithm and system network for its application on designing load shedding schemes. The emergency scenario is assumed to be the same as the one given in Wangdee and Billinton [2005] with some adjustment to suit the objective of the analysis.

Step 1: Load shedding scenario

Emergency situations occur in summer (October - December) during a weekday at different time-of-day. The load demands on each load point before the emergency occurred are as follows: F1: 5.10MW, F2: 3.50MW, F3: 4.27MW, F4: 4.80MW. For simplicity, the load

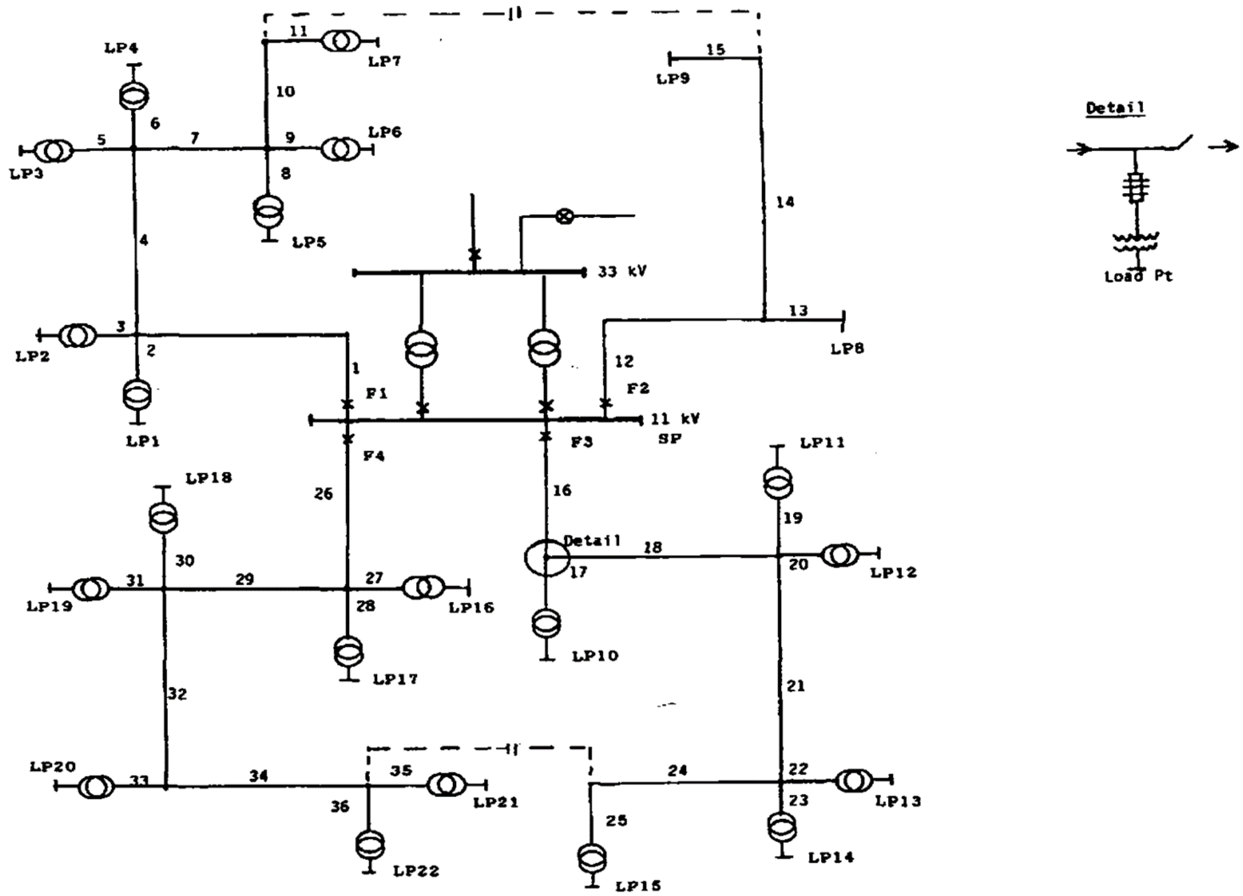

Figure 7.12. A single line diagram of the RBTS Bus 2 system network

demands and emergency scenario is assumed to be the same for all the time of occurrence of power interruptions considered in the analysis.

The load distribution for the different electricity customers connected at each load point is shown in Table 7.10.

Table 7.10. Load composition at different load points

Sector	Cluster Segment	Load composition (%)			
		F1	**F2**	**F3**	**F4**
Industrial	**Low-Low**	0.20	-	0.40	0.60
	Low-Medium	0.50	0.20	-	0.40
Commercial	**Low-Low**	0.30	0.20	0.10	-
	Low-Medium	-	0.60	0.50	-

The deficiency in this emergency is 8MW and the expected power interruption duration is 2 hours. Only one load shedding strategy was considered in all the emergency situations: Single outage: 2 hours (no feeder rotation)

Step 2: Determine the number of load shedding sets

The number of load shedding sets = $2^n - 1$, where n, the number of feeders in the bus. The number of load shedding sets for this example = $2^4 - 1 = 15$ sets. The load shedding sets and their expected load curtailments are shown in Table 7.11

Table 7.11. Load shedding sets at RBTS Bus 2 for the specific emergency

No.	Load shedding set	Expected load curtailed (MW)
1	F2	3.50
2	F3	4.27
3	F4	4.80
4	F1	5.10
5	F2 + F3	7.77
6	F2 + F4	8.30
7	F2 + F1	8.60
8	F3 + F4	9.07
9	F3 + F1	9.37
10	F4 + F1	9.90
11	F2 + F3 + F4	12.57
12	F2 + F3 + F1	12.87
13	F2 + F4 + F1	13.40
14	F3 + F4 + F1	14.17
15	F2 + F3 + F4 + F1	17.67

The capacity deficiency under the specific emergency is 8MW, and therefore, the sets from No.6 to No.15 are candidates. Load curtailments for Sets No.11 - 15 exceed the deficiency. Load shedding actions using these sets, therefore, will lead to over-shedding in this case. Sets No.6 - 10 are therefore considered further in this situation.

Step 3: Determining the CIC beta parameters for the respective time of occurrence of power interruption

CIC estimates from multi-dimensional customer segmentation model are used *(see Table 7.3)*. The CIC estimates are given for a summer weekday morning power interruption. To estimate the CIC estimates for a power interruption that occurs for the other time of occurrences, TVC weighting factors derived from activity levels are used. Equation 4.5 is used to determine the respective time-varying CIC estimates. The TVC weighting factors are given in Table 7.12 and some additional TVC weighting factors for the other customer segments are given in Appendix B.

Table 7.12. Time varying cost weighting factors for industrial:low-medium

Period/ Time interval	Time of day			
	00-06	06-12	12-18	18-24
Jan-Mar	3.4	8.2	9.3	4.7
Apr-Jun	3.1	7.6	8.5	4.0
Jul-Sept	3.0	7.7	8.7	4.0
Oct-Dec	3.6	8.8	10	5.1

For example - Industrial: **low-medium:** The CIC estimates for time interval 12:00 am - 18:00 pm are calculated as follows -

$$
\begin{aligned}
CIC(t2) &= \frac{W(t2)}{W(t1)}\ x\ CIC(d,t1) \\
W(t1) &= 8.8 \\
W(t2) &= 10 \\
CIC(t2) &= \frac{10}{8.8}\ x\ 4 \\
&= 5.68
\end{aligned}
\tag{7.14}
$$

Thus: Industrial **low-high:** $CIC(t2) = 5.68\ x\ beta(0.37, 0.44)$
In a similar manner, the CIC beta parameters for the other cluster segments are presented below.
Industrial **Low-Low:** $CIC = \frac{10}{8.7}\ x\ 16 = 18.39\ x\ beta(1.09, 7.46)$
Commercial **Low-Low:** $CIC = \frac{10}{7}\ x\ 2 = 2.86\ x\ beta(0.21, 0.35)$
Commercial **Low-Medium:** $CIC = \frac{10}{7.5}\ x\ 10 = 13.33\ x\ beta(1.91, 10.69)$

Step 4: Results - Single outage 2 hours (no load point rotation)

Consider each set from Set No.6 to 10 using the TBP CIC data from *Step 3*, the RBIC index values at 5 % risk level for the different load shedding set at the given time interval are derived as .

Set No.6 (F2 + F4): $Total\ RBIC = RBIC_{2,2h} + RBIC_{4,2h}$
$Total\ RBIC = 5.2510 + 5.9070 = 11.1580\ kR$
In a similar manner:
Set No. 7: $Total\ RBIC = 9.7735\ kR$
Set No. 8: $Total\ RBIC = 13.3730\ kR$
Set No. 9: $Total\ RBIC = 11.9886\ kR$
Set No. 10: $Total\ RBIC = 10.4295\ kR$

It can be seen from the above that Set No.7 has the lowest RBIC index. This indicates that load shedding set No.7 containing F1 and F2 provides the minimum financial loss in this case, and is the optimum load shedding set under the load shedding strategy for the respective time of occurrence. The tables below show the RBIC index results at different risk levels for different time of occurrence investigated in this case study.

Table 7.13. Effect of time of occurrence on RBIC index at 5% risk level

Load shedding scenario	Time of day			
	00-06	**06-12**	**12-18**	**18-24**
F2 + F4	**1.1071**	11.1580	13.6037	7.3347
F2 + F1	1.2316	**9.7735**	12.2230	7.5021
F3 + F4	1.1465	13.3730	16.1243	7.7319
F3 + F1	1.2709	11.9886	14.7436	7.8992
F4 + F1	1.9965	10.4295	**12.1398**	**3.8294**

Table 7.14. Effect of time of occurrence on RBIC index at 10% risk level

Load shedding scenario	Time of day			
	00-06	**06-12**	**12-18**	**18-24**
F2 + F4	**1.0340**	10.2168	12.5110	7.0513
F2 + F1	1.1816	9.3239	11.6918	7.3111
F3 + F4	1.0649	12.0029	14.5388	7.3763
F3 + F1	1.2125	11.1100	13.7195	7.6361
F4 + F1	1.9098	**9.2753**	**10.8116**	**3.5667**

Table 7.15. Effect of time of occurrence on RBIC index at 20% risk level

Load shedding scenario	Time of day			
	00-06	**06-12**	**12-18**	**18-24**
F2 + F4	**0.9042**	8.6491	10.6315	6.2213
F2 + F1	1.0604	8.2012	10.3016	6.5303
F3 + F4	0.9261	9.9618	12.1166	6.4631
F3 + F1	1.0822	9.5139	11.7867	6.7721
F4 + F1	1.7122	**7.6944**	**8.9779**	**3.1060**

Table 7.16. Effect of time of occurrence on RBIC index at 50% risk level

Load shedding scenario	Time of day			
	00-06	**06-12**	**12-18**	**18-24**
F2 + F4	0.8240	5.2320	6.1733	2.5677
F2 + F1	**0.4664**	**2.6826**	**3.2980**	**1.8747**
F3 + F4	0.8343	5.8436	6.8631	2.6655
F3 + F1	0.4767	3.2942	3.9878	1.9725
F4 + F1	1.1985	5.5929	6.4326	2.1040

The results obtained using this strategy show that RBIC index values at risk levels 5 % and 10 % have the same effect for all time of occurrence of power interruptions. However, if the risk level is increased to 20 % or 50 % the effect of load shedding changes. It is therefore worthwhile to note that the risk level attached to the RBIC index provide different perception on the supply reliability of the power system. For each risk level examined, it can be seen that the priority of load changes at each time of occurrence of power interruption.

The load point that needs to be curtailed to minimize the financial loss to electricity customers can be determined under a specific emergency situation. The use of the generalised RBIC index values is illustrated in this simple example. Distribution system operators can utilize the RBIC index values to create practical load shedding schemes.

In a practical situation for example, distribution system operators can use the RBIC index data to identify the load shedding set and the load shedding duration in order to minimize the customer interruption costs due to the emergency. A time varying load with the same time intervals can be used to calculate the RBIC index for the different time intervals in advance and scheduled load shedding rotation can be prepared. Calculating the RBIC index in advance is done in order to check the best or least cost lost shedding feeder or set. The load shedding scheme using the RBIC index becomes more flexible if the load bus has many feeders. This gives the distribution system operators a wide range of load shedding strategies to consider i.e a rotating strategy to reduce long outage duration resulting from a severe loss-of-generation to many short outage events with different load shedding sets giving the least total financial impact on electricity customers.

It is also possible for distribution system operators to carry out this analysis at the time when load shedding is necessary using the actual load data for the expected load curtailment as proposed by [Svendsen *et al.*, 2012]. In online operation the risk level of the system is calculated say every 5 minute and evaluated if the risk level of the system is out of boundary or accepted level for the coming hours. Actual load data for the expected load curtailment is used to calculate the RBIC index of the affected load points during the particular period. The least cost load shedding strategy can then be prepared based on the RBIC index of the load points affected.

7.8 Discussion

The results showed that the perception on reliability vary depending on the input parameter models and the risk level attached to the computed RBIC index. A planner or operator is thus able to quantify the uncertainty in the index values selected. Further, it was shown that it is important to know the variation in the CIC and this can be done using the RBIC index. The RBIC index considers the risk level at which the CIC estimates are measured from the CIC profile. For example the CIC estimates can be estimated at 5% risk level and used to calculate the aggregate CIC cost at a load point. The resultant CIC estimate is the RBIC index for that load point. A distribution of the RBIC index will provide the financial loss distribution of the effect of a particular power interruption to electricity customers for that load point. The RBIC index can then be interpreted as the financial loss distribution to electricity customers with an attached risk level exposed to the customers from the probability of the load being shed.

The TBP CIC model allows the probability distributions of CIC data in each time interval to be derived. Analysing the skewness provides more information that relates to most likely financial impact of power interruptions at a given time of occurrence. The distribution system operator can consider a wide variety of load shedding strategies i.e. a rotating strategy, to reduce a long outage duration to many short outage events with different load shedding sets.

CHAPTER

EIGHT

CONCLUSIONS AND RECOMMENDATIONS

In this final chapter, a review of the research questions and the main conclusions drawn are discussed. Ideas for future work are also presented.

8.1 Hypothesis validation

This thesis was based on a hypothesis which states that: *A risk-based interruption cost index based on customer and interruption parameters is a more useful tool than the existing deterministic reliability indices to represent cost of interruption and damage on a composite power system.*

The answers to the research questions aimed at validating the hypothesis are summarized below.

Q.1 ***What components and structure of reliability worth index provides a reliable, consistent measure of the composite power system?***

Power system management decisions that could affect service delivery are not always based on sound engineering analyses but are often politically and socially driven [Herman and Gaunt, 2010]. To improve communication between all stakeholders involved, it is prudent to express the quantitative reliability indices in monetary terms. Financial decision makers are more likely to understand indices expressed in monetary terms than in engineering terminology. The application of reliability indices in combination with appropriate currency leads to the unification and comparability of different reliability indices.

Commonly, input parameters for derivation of reliability worth indices are considered as average values. However, it is necessary to consider the uncertainty of the input parameters such as dispersed nature of CIC. As shown in this thesis, this can be done by bringing probabilistic analyses techniques into the planning and operation practice to capture the impacts of the uncertainty in the input parameters. Incorporating probabilistic input parameters, enhances the accuracy of system planning and operation studies and assures appropriate decision making in planning and operation of power systems.

The model approach, applied to CIC models, illustrates a large and complex problem of dynamic interrelations between many parameters that affect the impact of power interruptions. From the research findings it can be assumed that both customer characteristics and interruption parameters affect the CIC. Customer parameters include economic activity, energy consumption level, ownership of backup systems and the economic size. Interruption parameters include duration and time of occurrence (time-of-day, day-of-week and season of year).

Customer parameters:

From the case studies investigated, results showed that different customer segments are affected differently by the same power interruption. The fact that different customer segments are affected differently by the same power interruption can be used effectively for accurate assessment of CIC. Electricity customers can be clustered into various customer cluster segments of similar CIC characteristics in order to reduce the dispersion of the final CIC estimates and at the same time reduce the number of customer cluster segments to be surveyed. Where the classification does not reflect interruption cost drivers - customer parameters, there is risk associated with mismatching of CIC estimates and changes in decisions made for planning and operation of power systems.

Interruption parameters:

Commonly CICs are modelled as a function of power interruption duration. However, this research study has shown that the time of occurrence of power interruptions also has a great effect on CICs. The results from the CIC analysis showed that to describe CICs as realistically as possible it is therefore important to take time of occurrence into consideration in addition to power interruption duration. The fact that the maximum CIC during the day, week and season for different customer sectors do not coincide is valuable to consider in practical applications. By performing the disconnection of electricity customers at system feeder level for the given case study, the negative consequences of load shedding was minimized when electricity customers with the largest needs and highest costs were prioritized. Therefore, in order to prioritize between electricity customers in an efficient way, a time-varying CIC model is essential.

Q.2 ***Can probability distributions be used to characterise uncertainty (or risk) in interruption cost assessment of composite power systems?***

This research identified the need to describe reliability worth inputs/outputs, beyond the conventional use of average values. The research showed that realistic reliability worth inputs/outputs could be derived with PDFs. Expressing the reliability worth inputs/outputs in this way allowed it to be determined with a level of confidence or conversely a risk level. The statistical information from the PDFs of the reliability worth inputs/outputs are shown to be shape-dependent.

For both reliability worth inputs/outputs, the Beta PDF was consistently able to exhibit the basic shape of the given histogram. This is significant because it indicates that the Beta PDF is able to illustrate the reliability risk or confidence associated with reliability inputs/outputs.

Q.3 ***How does the approach applied and interpreted make the tool more useful than the alternatives?***

The model was developed so that Beta PDF models could be developed for reliability worth inputs/outputs profiles in each time window. The Beta PDFs aided decision making by providing a range of values with different level of risk or confidence level attached. Therefore, the proposed approach enables decision making process to be passed with more information on the extreme (high or low) values of the reliability worth indices.

The use of PDFs, in the planning and operation analyses, improved the representation of reliability worth inputs/outputs so that realistic impression of the network's reliability worth was achieved. The results showed that the perception on reliability worth of power systems that the computed RBIC index provide, varies depending on the input

CIC model and the risk level attached to the index values. The actual range of the derived index and its skewness were incorporated in the PDF profile. A planner or operator is thus able to quantify the uncertainty in the index values selected.

Q.4 ***Are the system networks on which the index is developed or tested appropriate to represent the general cases?***

South Africa is a developing country with a large diverse of electricity customers. Moreover, the diverse climate exposes the power grid to a range of power interruptions. Real CIC data from different electricity customers was available for use in the analyses considered. The South Africa power grid thus makes an interesting and suitable case study. The test system contain the data needed for reliability worth assessment. However, it should be noted that while the results obtained in this thesis only apply to the system network considered, load point connection of customers with different characteristics e.g. ownership of backup power supply, may lead to different results. The level of change is dependent on the system being analyzed and the variability applied.

Q.5 ***Is the index absolute or comparative?***

The reliability worth index derived in this thesis is comparative since it is expressed in monetary value. This concept of expressing a reliability index in terms of currency is a relatively new technique and it is possible to add the calculated reliability index at different levels of analyses.

8.1.1 Assessing the validity of the hypothesis

The research questions were answered completely. This research study has demonstrated that customer surveys provide significant insight to the economic value placed by electricity customers to the power supply reliability. It has further proved the validity of the hypothesis through the statistical analysis done, by showing that time-based Beta PDF that describe reliability worth inputs/outputs, can be used for effective network planning and operations. By use of case studies it was shown that the inclusion of time dependencies greatly improves the accuracy of CIC models. Furthermore the case studies done in this thesis showed that the time-based probabilistic CIC profiles can be applied usefully in management of the power system network by revealing the worst affected load points and providing a range of reliability worth output values with different level of risk or confidence level attached. This is an important aspect in planning and operation of power systems because it gives provision for system load prioritisation depending on the economic value placed by electricity customers to the power supply reliability level provided.

The main contributions during the course of this research include:

- **Development of a multi-dimensional customer segmentation model including power interruption mitigation measures**

  A variance-dependent characterization of CIC profiles was used so that CIC estimates are associated with the economic activity, economic value and electricity consumption of the electricity customers. Furthermore, mitigation measures implemented by electricity customers to reduce the impact of power interruption was included in the analysis. The intervals for both energy consumption and turnover need not to coincide with the annual energy consumption or turnover of particular electricity customers, but are rather categorized according to standardized intervals given by the power utility and/or by the national institute of statistics.

  Each interval window takes into account the CIC estimates of all electricity customers within a given sector that are within the given cluster range. The CIC data in each cell can thus be analysed further so that CIC parameter statistics can be derived for each customer sector or a cumulative of all the customer sectors that fall within the cluster segment. The final cut-off values for the customer cluster segments were obtained using hierarchical clustering technique (Wards linkage). This enables a reduction in the dispersion of the final CIC estimates within customer cluster segments formed. Such a matrix clustering technique can be consistently applied for power system reliability worth assessment.

  The algorithm presented in this thesis is able to provide a highly detailed separation of the clusters, isolating electricity customers with uncommon behaviour and creating large groups of electricity customer with similar CIC profiles. These properties make the algorithm particularly suitable for a customer segmentation oriented towards grouping electricity customers into small number of customer classes for CIC formulation purposes. The most relevant aspects for the power suppliers are related to the possible reduction of the data set size and the determination of the best number of clusters possible. An indicative number of customer classes not higher than 15-20 could fit the supplier's needs [Fraley and Raftery, 1998].

- **Development of a mathematical algorithm to estimate time-varying CIC estimates**

  Electricity customers in most cases are not worried about how much electricity is not supplied but rather in their interrupted activities. The activity level of the electricity customers therefore has a significant bearing on the consequences the electricity customers would face. The activity level varies with time and hence the consequences of a power interruption will depend on the time of occurrence of the power interruption.

  To formulate time varying CIC estimates, information on how the CICs vary on a monthly, weekly and daily basis is needed. This information is usually collected by extensive customer surveys where electricity customers are asked to state their cost for many different outage scenarios. Instead of collecting this information in extensive customer surveys, the proposed model uses activity level data from electricity customers themselves to capture the time variations in the CIC. The derived TVC weighting factors describe the severity of the CIC at the different time of occurrence of power interruptions. In this way, fewer demands are placed on the customer surveys.

- **Development of a time-based probabilistic CIC model**:

  The time-based probabilistic CIC model accounts for seasonal, day-of-week, time-of-day dependent changes in reliability worth inputs/outputs. The proposed model also incorporates a multi-dimensional customer segmentation model in order to reduce dispersion of CIC estimates and at the same time reduce the number of customer segments to be surveyed. The proposed TBP CIC model is based on risk measurement of reliability inputs/outputs, which gives the benefit that it can be used not only to describe the current risk situation, but also the uncertainties that the future brings. The Beta PDF is used to derive the reliability worth inputs/output parameter values with different levels of dispersion and skewness.

- **Development of a mathematical algorithm between reliability worth inputs and outputs using one PDF**

  A mathematical algorithm to calculate the relationship between reliability worth inputs and outputs using one PDF has been developed. The derived reliability output parameter values are presented at different levels of risk or confidence levels. The Beta PDF has proved to be the most suitable PDF to represent the input/output parameter values for the proposed TBP CIC model. This is beacause of its versatility and ability to consistently able to exhibit the basic shape of the given histogram of the reliability worth input/output parameters.

8.2 Conclusions

The developed TBP CIC model have been shown in case studies to be applicable in reliability worth indices calculation. The main conclusions drawn from the case studies are summarized below.

1. **Time-varying cost weighting factors based on underlying factors need less extensive customer surveys and can be updated easily over time**

   The impact of the timing of power interruption is relatively well covered in surveys. In the surveys, time variations have been found to show different patterns for different customer sectors. Thus, using the time of occurrence when calculating CICs has gained popularity.

   Most researchers have used several hypothetical outage scenarios occurring at different times in order to capture the time of occurrence effect on CICs in customer surveys. This implies that customers need to be asked to estimate how their CICs vary on a monthly, daily and hourly basis. For most electricity customers this is reasonably a moderate task to do. Furthermore, there is limited amount of effort that survey respondents are prepared to put into filling out customer surveys, a limitation that is particularly relevant in business customers. This has created a new opening for the proposed new approach to estimate the temporal variations of CICs in electricity customers.

   The new approach of using underlying factors for estimating time variations in electricity customer interruption costs agrees well with time-varying cost weighting factors derived from CIC estimates of different hypothetical power interruption scenarios. The benefit of using underlying factors is that customer surveys may be less extensive. Shorter surveys probably have a positive effect on the reply rate. The proposed approach uses activity patterns to describe time-of-day, day-of-week and seasonal variations in electricity customer interruption costs. The activity factors are taken directly from the electricity customers and therefore customer specific.

2. **The customer interruption cost estimates for the different time of occurrence of power interruptions have different profiles**

Due to the variability in the CIC estimates provided by survey respondents, the profiles of CIC estimates for different time intervals and/or durations can be left/right skewed. The research showed that the Beta PDF can be used in place of other commonly applied PDFs to represent the different CIC profiles exhibited for the different time intervals. The main advantages of Beta PDF is that it can be scaled to a finite range and at the same time produce right or left skewed profiles. It was thus the most suitable PDF for the research presented.

3. **Time correlations in reliability worth inputs/outputs are important for accurate system load prioritisation**

   A case study was presented when time dependencies were considered, compared to if they were ignored. The results emphasize the fact that time dependencies in inputs/outputs are important for an accurate system load prioritisation.

4. **A risk based model shows benefits or drawbacks of a project that cannot be discovered by the average value**

   When making investment decisions, it may be interesting for decision-makers not only to estimate the average, but also to consider the profile of the reliability worth indices and to know the extreme (high or low) values in the decision-making process. The results showed that this can be achieved with the help of risk tools using the probability distribution function so that the reliability worth indices are measured at different risk levels. Results in the case studies indicate that TBP CIC models are needed to describe these benefits or drawbacks accurately.

5. **The use of one probability distribution function enables the development of a mathematical link between reliability worth inputs and outputs**

   The use of one probability distribution function has enables the development of a mathematical algorithm to directly link between the reliability worth inputs and outputs. The beta distribution because of its versatility was found to be the most suitable PDF to represent the profiles of the reliability worth inputs and outputs. This makes the model simple to implement and use in calculation of reliability worth inputs/outputs.

6. **The significance of using PDFs in reliability worth analyses**

The case studies presented in this thesis show that PDFs are very significant to practical reliability worth analyses. A different perception on the network's reliability was achieved when reliability worth inputs/outputs were represented using PDFs. The PDFs provided a range of values with different level of risk or confidence level attached. Planners and operators would thus be able to quantify the risk induced in their decision making when a given level of reliability is selected. The form of risk based decision making proposed in this thesis has not been used before.

7. **Offer more flexibility in the use of customer damage functions**

   The base case of the proposed model is the customer damage function. However, it extends it to give more realistic values when estimating the CIC of electricity customers. A 16-cell matrix CIC model that describes different season, time-of-day and day-of-week dependence of CIC was considered. The model was developed so that Beta PDF profiles could be developed for CIC estimates in each time window. The time intervals are not fixed but rather variable, dependent on the more likely period of high or low activity levels. This makes the proposed model much more flexible.

8. **Do not effectively increase the computational demand**

   To make the proposed method applicable in industry, the simulation times need to be short. The derived mathematical algorithm is a probabilistic analytical method which does not require simulations. This makes the method easy and reduces the computational time required to obtain the reliability worth outputs.

8.3 Implications

Network Loading: To capture the effects induced in the reliability worth indices due to variability in component parameters, the average loads that could occur in each time window were used in the analysis. In reality, the loading at different load points is quite variable. Since network loading are also seasonal, time-of-day and day-of-week dependent, the matrix model presented can also be applied.

Extensive customer surveys: More research is needed on customer interruption costs when a large geographical area is considered. Most customer surveys typically consider short durations and only affect a local geographic area. For these interruptions, it is common to estimate the total costs of the outage by adding up the costs for individual customers. However, for widespread outages, simply adding up the costs of the individual customers may lead to an underestimation of the total customer interruption costs. One reason for the underestimation is that intangible costs due to lack of public services, for example, are ignored.

Duration of power interruptions: Customer interruption costs for short interruptions, with duration of less than three minutes, have been shown to be large. Voltage disturbances, such as voltage dips, also result in costs for electricity customers. Therefore, to adequately estimate the total reliability worth of a power system network, short interruptions and voltage disturbances should be considered.

APPENDIX

A

ADDITIONAL RESULTS

A.1 Correlation between CIC and average monthly energy cost

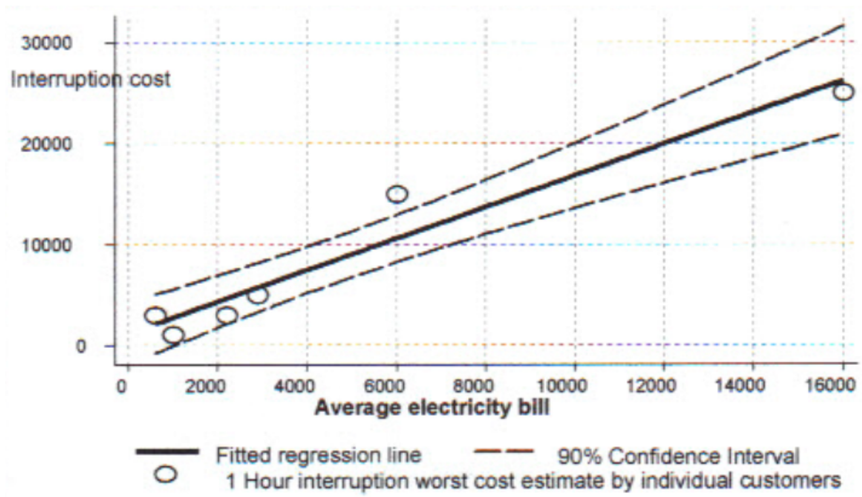

Figure A.1. Correlation between CIC and Average monthly energy cost (including the 90 - percentile envelope) for a one hour outage on a Summer weekday morning

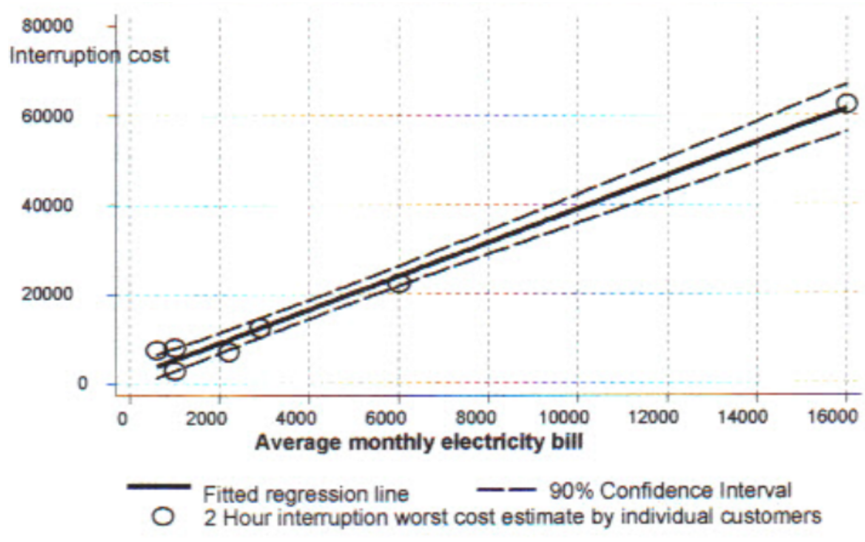

Figure A.2. Correlation between CIC and Average monthly energy cost (including the 90 - percentile envelope) for a two hour outage on a Summer morning

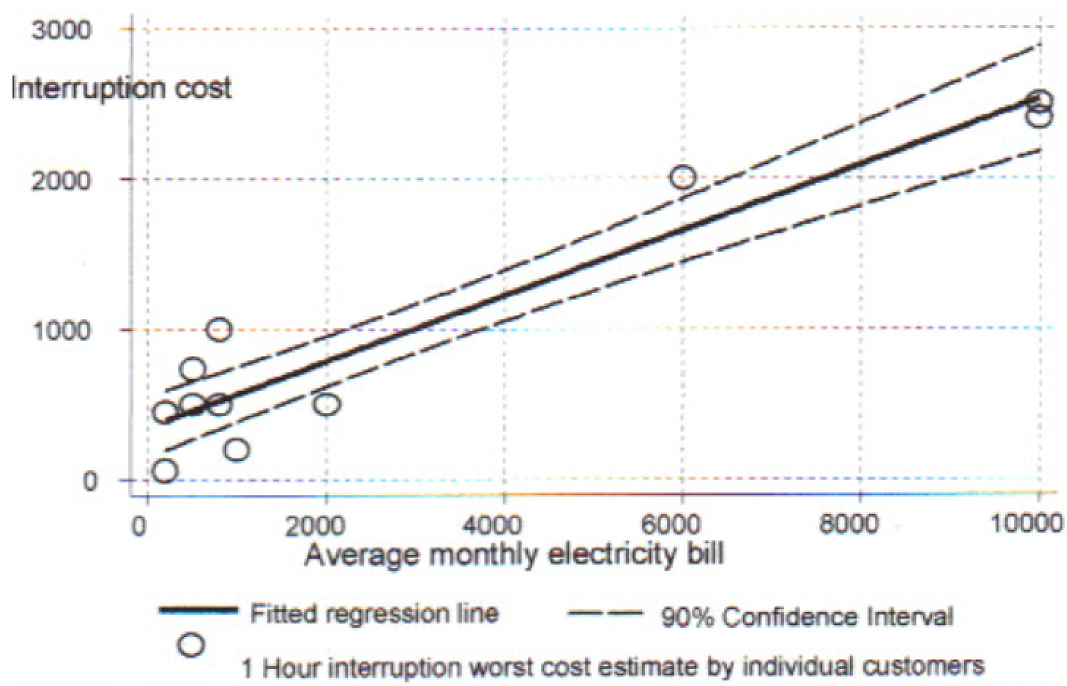

Figure A.3. Correlation between CIC and Average monthly energy cost (including the 90 - percentile envelope) for a one hour outage on a Summer weekday morning

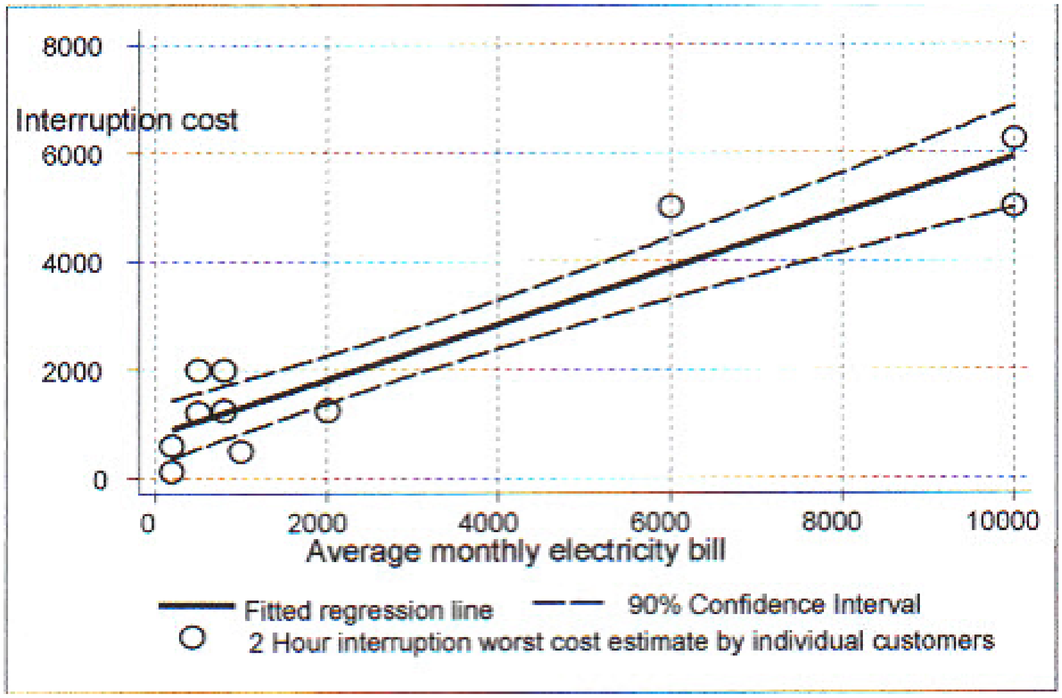

Figure A.4. Correlation between CIC and Average monthly energy cost (including the 90 - percentile envelope) for a two hour outage on a Summer weekday morning

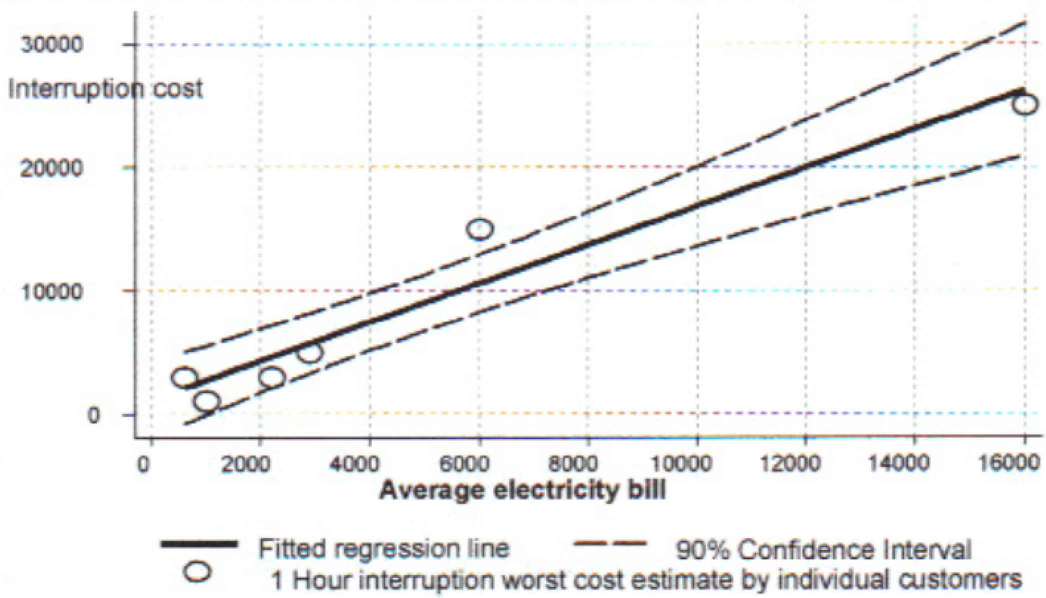

Figure A.5. Industrial customer without backup power supply: Correlation between CIC and Average monthly energy cost (including the 90 - percentile envelope) for a four hour outage on a Summer morning

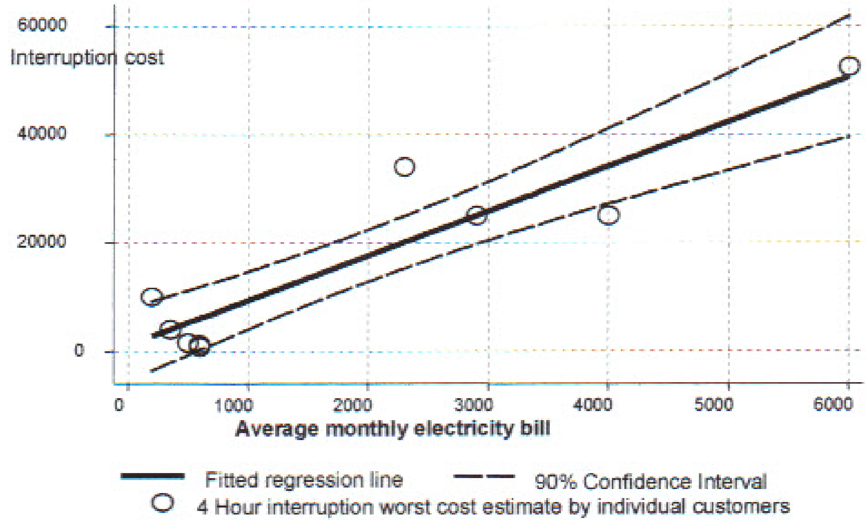

Figure A.6. Industrial customer with backup power supply: Correlation between CIC and Average monthly energy cost (including the 90 - percentile envelope) for a four hour outage on a Summer morning

A.2 Customer Survey Questionnaire

THE RISK OF LOAD SHEDDING REMAINS HIGH!!!

A few months ago, about 16% of Eskom installed capacity was not available due to planned maintenance, unplanned outages, and load losses. This compelled Eskom to introduce emergency load shedding during peak periods when demand increases.

Today, the power system still remains vulnerable to unplanned events, increasing the probability of recurrence of power interruptions and load shedding. It is predicted that the risk of load shedding will continue for the next 5 to 8 years until new base load coal-fired power stations are built.

This survey is designed to collect outage cost information for COMMERCIAL and INDUSTRIAL customers

By answering the questions on the following pages, you can help to devise more cost effective electricity supply programs for the future.

SURVEY RESPONSES WILL BE STRICTLY CONFIDENTIAL

THANK YOU FOR YOUR PARTICIPATION!!

There are no right or wrong answers. We simply want the best response you can provide.

2009

CUSTOMER SURVEY:

WHAT IS THE EFFECT OF PLANNED LOAD SHEDDING ON COMMERCIAL AND INDUSTRIAL CUSTOMERS IN CAPE TOWN-SOUTH AFRICA?

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SECTION A 8 copies

1.2. 1.1. How many times has your organisation experienced power outage in the last **12 months?** _______________

1.3. How satisfied are you with the number of outages your organisation has experienced in the last 12 month

1.4. If each of the following occurred, would you think you were getting acceptable or unacceptable service from the service provider? (Tick one box for each outage scenario)

		Acceptable	Unacceptable	Do not know
Load shedding lasting **4 hours to 8 hours**	Once a week			
	Once a month			
	Once every 6 months			
	Once a year			

SECTION B

2. Outage Cost Measurement

2.1: a. Does your organisation have some form of backup electrical power equipment?

I. No (SKIP TO QUESTION 2.2)

II. Yes (if **yes** please fill the table below)

	UPS (Uninterruptible Power Supply)	Standby Generator	Others :Specify ________________
Size (KW/KVA)			
Installation cost (Rands)			
Running cost (Rand/hour)			
Percentage of coverage of plant (%)			
Purpose			

b. When was your backup power supply installed? Date/ Year: __________________________

2.2. Case 1: On a **summer weekend morning** a planned load shedding is scheduled to occur and will last **8 hours.**

Considering all of the costs you might experience as a result of this outage, please estimate the **highest total outage cost** that you would experience **without considering backup power supply.**

R____________________________ Highest total outage cost (Worst case)

2.3. With reference to **Case 1,** what is the **percentage** of the **highest total outage cost,** if the planned load shedding will now last:

i. (1) **four** hours: ______% ii. (2) **two** hours: ______% iii. (4) **one** hour: _______%

2.4. **Case 2:** On a **winter weekday afternoon** a planned load shedding is scheduled to occur and will last **2 hours.**

Considering all of the costs you might experience as a result of this outage, please estimate the costs for the highest cost case that you would experience **without considering backup power supply.**

R____________________________

Highest total outage cost (Worst case)

2.4. With reference to **Case 1,** what is the **percentage** of the **highest total outage cost,** if the planned load shedding will now last:

i. (1) **four** hours: ______% ii. (2) **two** hours: ______% iii. (4) **one** hour: _______%

2.5. Suppose that the outage is identical to **Case 2** *except that* the outage duration is as given in the table below. Indicate your ability to make up lost production after the power supply has been restored. **(please tick one for each outage duration)**

		Ability to make up lost production			
		Not at all	Partly	Mostly	Not needed
Outage Duration	Less than 1 hour				
	Between 1 – 2 hours				
	Between 2 – 4 hours				
	Between 4 – 8 hours				

2.6. Assume that you have a backup power supply that runs for **2 hours** and covers 10**0%** of your organisation plant, how much **total outage cost** would you incur as a result of **8 hour load shedding in a morning winter:** **R____________________________**

Highest total outage cost (Worst case)

SECTION C

3. About Your Organisation

3.1. Size of supply

___________________kWh/month ___________________kW

Average Monthly Energy Consumption Maximum Peak Demand

OR What is the average cost of energy/month **R_______________**

3.2. What are your normal hours of operation? [ ]

3.3. How many employees are employed by your organisation at this facility? [ ]

3.4. Which of the following categories best describes your organisation? (please tick one)

	Bakeries, Food processing		Metal and Engineering industries
	Chemical industries		Foundries, smelting, glass, ceramic industries
	Retail shops, food and non-food		Agriculture, livestock
	Professional practices (medical, legal, finance consulting)		Service stations, garages, auto workshops
	Commercial and government offices		Warehousing, distribution, transport
	Clothing, textile, furniture, and other industries		Hotel and restaurants
	Any other- please specify:		

3.5. **ACTIVITY LEVEL:**

For the following questions: **3.5.1, 3. 5.2 and 3.5.3** use a scale of **0 (zero) to 10 (ten)** to indicate how you would rate the activity levels of your business for the different times indicated.

NB: 10 (ten) would indicate most busiest time

3.5.1. Variation of the level of business activity with time of day and day of week.

		Time of Day					
		00- 08	08 – 12	12 – 14	14 – 18	18 – 21	21 – 24
D ay of Week	Weekday						
	Friday						
	Saturday						
	Sunday						

3.5.2. Relative variation of level of business activity with the time in a month.

Time of Month		
Beginning of Month	Mid-Month	End of Month

3.5.3. Variation of the level of business activity with the month of the year.

Month of Year											
Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec

3.6. What improvements do you think your electricity supplier could implement to reduce the impact of load curtailment on your business

THANK YOU FOR YOUR PARTICIPATION

Please return this survey in the enclosed envelope to:

University of Cape Town
Department of Electrical Engineering
Private Bag 7701
Rondebosch OR E-mail: oliver.dzobo@uct.uct.ac.za

A.3 Final CIC estimates for different customer segmentation models

Table A.1. Average normalized CIC estimates (Euro/kWh): South Africa case study

Turnover (MEuro/year)	Energy consumption (MWh/year)	Number of respondents	Duration (hr) - mean (standard deviation)			
			1	2	4	8
Industrial	Summer weekday morning	33	4.37 (6.12)	8.05 (8.82)	13.45 (14.14)	21.93 (25.57)
Commercial	Summer weekday morning	47	2.67 (2.79)	5.62 (6.27)	10.61 (12.06)	20.33 (23.95)
	Winter weekday morning	37	1.93 (2.24)	3.87 (4.62)	7.19 (8.90)	13.75 (5.42)

Table A.2. Average normalised CIC estimates (Euro/kWh) of industrial customers considering different size parameters: South Africa case study

Size parameter		Time of occurence	Number of respondents	Duration (hr) - mean (standard deviation)			
				1	2	4	8
Energy consumption (MWh/year)	0 - 500	Summer weekday morning	30	4.61 (6.36)	8.08 (9.23)	13.45 (14.71)	21.64 (26.46)
	500 - 2 000	Summer weekday morning	13	2.00 (1.76)	7.72 (3.05)	13.44 (7.76)	24.88 (17.19)
Turnover (MEuro/year)	2 - 50	Summer weekday morning	31	3.99 (6.03)	7.14 (7.52)	11.19 (9.54)	17.36 (13.19)

Table A.3. Average normalized CIC estimates (Euro/kWh)of commercial customers considering different size parameters: South Africa case study

Size parameters		Time of occurence	Number of respondents	Duration (hr) - mean (standard deviation)			
				1	2	4	8
Energy consumption (MWh/year)	0 - 20	Summer weekday morning	10	1.71 (1.54)	2.89 (1.33)	3.80 (1.35)	6.43 (2.41)
	20 - 500	Summer weekday morning	42	2.79 (2.90)	5.96 (6.55)	11.40 (12.53)	21.92 (24.88)
	20 - 500	Winter weekday morning	34	2.05 (2.30)	4.11 (4.74)	7.68 (9.12)	14.71 (15.73)
Turnover (MEuro/year)	0 - 10	Summer weekday morning	45	2.33 (2.27)	4.73 (4.50)	8.81 (8.13)	16.69 (15.78)
	0 - 10	Winter weekday morning	34	1.58 (1.39)	3.12 (2.87)	5.64 (4.95)	11.08 (9.24)

Table A.4. Average normalized CIC estimates (Euro/kWh) for commercial customers: South Africa case study

Turnover (MEuro/year)	Energy consumption (MWh/year)	Time of occurence	Number of respondents	Duration (hr) - mean (standard deviation)			
				1	2	4	8
0 - 10	0 - 20	Summer weekday morning	15	1.71 (1.54)	2.89 (1.33)	3.80 (1.35)	6.43 (2.41)
0 - 10	20 - 500	Summer weekday morning	40	2.42 (2.35)	4.97 (4.70)	9.41 (8.43)	17.89 (16.34)
0 - 10	20 - 500	Winter weekday morning	31	1.70 (1.41)	3.31 (2.94)	6.03 (5.01)	11.87 (9.30)

Table A.5. Average normalized CIC estimates (Euro/kWh) for industrial customers: South Africa case study

Turnover (MEuro/year)	Energy consumption (MWh/year)	Time of occurence	Number of respondents	Duration (hr) - mean (standard deviation)			
				1	2	4	8
2 - 50	0 - 500	Summer weekday morning	28	4.10 (6.30)	7.08 (7.88)	10.95 (9.80)	16.55 (12.83)
2 - 50	500 - 2 000	Summer weekday morning	8	2.00 (1.76)	7.72 (3.05)	13.44 (7.76)	24.88 (17.19)

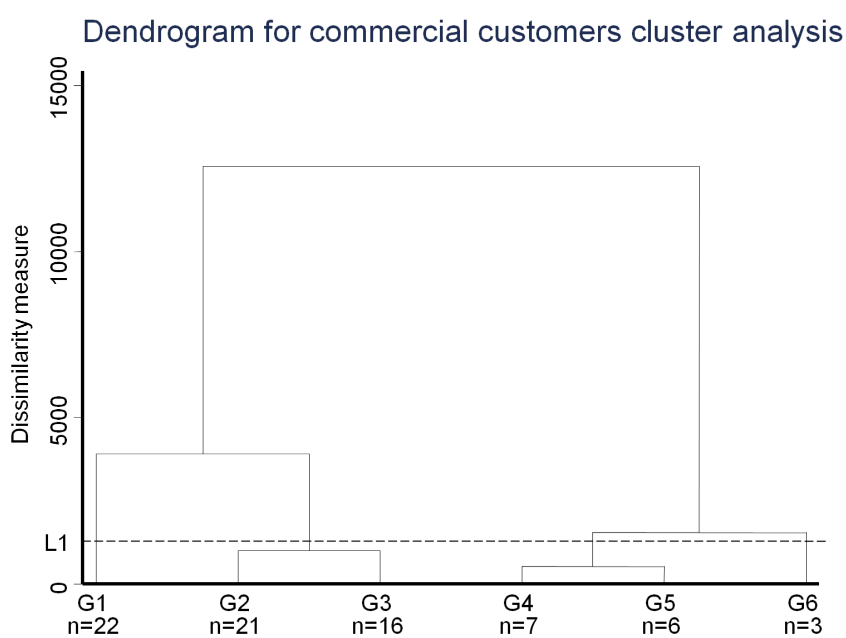

Figure A.7. Effect of customer segmentation models on CIC estimates of commercial customers for a winter weekday morning power interruption, [Dzobo *et al.*, 2013]

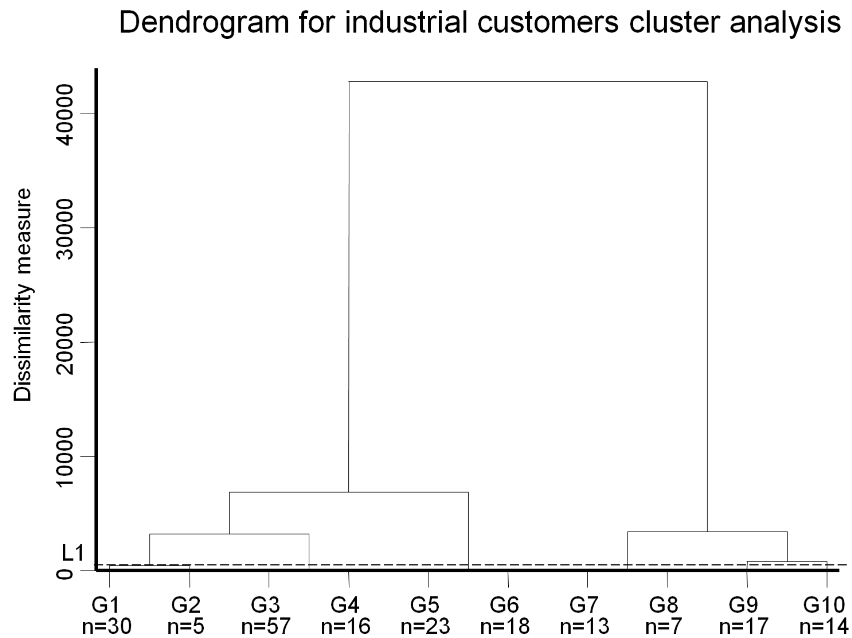

Figure A.8. Effect of customer segmentation models on CIC estimates of commercial customers for a winter weekday morning power interruption, [Dzobo *et al.*, 2013]

APPENDIX

B

ADDITIONAL RESULTS

B.1 Codes for different electricity customer segments

Table B.1. Codes for different customer segments

Sector	Cluster Segment	Range	
		Turnover (Rmillion/year)	Energy consumption (MWh/year)
Industrial	Low-Low	0 - 50	0 - 500
	Low-Medium	0 - 50	500 - 2 000
Commercial	Low-Low	0 - 10	0 - 20
	Low-Medium	0 - 10	20 - 500

B.2 Activity levels for different customer segments

Table B.2. Time varying cost weighting factors for industrial:low-low

Period/ Time interval	Time of day			
	00-06	06-12	12-18	18-24
Jan-Mar	0.4	7.4	8.5	1.5
Apr-Jun	0.2	6.7	7.7	1.2
Jul-Sept	0.3	7.4	8.4	1.3
Oct-Dec	0.3	8.7	10	1.6

Table B.3. Time varying cost weighting factors for commercial:low-low

Period/ Time interval	Time of day			
	00-06	06-12	12-18	18-24
Jan-Mar	0.3	6.0	8.6	3.1
Apr-Jun	0.3	5.3	7.5	2.5
Jul-Sept	0.3	5.5	7.8	2.6
Oct-Dec	0.3	7.0	10	3.4

Table B.4. Time varying cost weighting factors for commercial:low-medium

Period/ Time interval	Time of day			
	00-06	06-12	12-18	18-24
Jan-Mar	0.1	7.3	9.5	8.1
Apr-Jun	0.0	6.0	7.5	6.5
Jul-Sept	0.1	5.7	7.4	6.3
Oct-Dec	0.1	7.5	10	8.3

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