



**RELIABILITY COST AND WORTH ASSESSMENT OF INDUSTRIAL AND
COMMERCIAL ELECTRICITY CONSUMERS IN CAPE TOWN**

BY

OLIVER DZOBO

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Supervisors: Prof. C T Gaunt

Dr. R Herman

DECLARATION

I hereby declare that this dissertation, *Reliability Cost and Worth Assessment of Industrial and Commercial Electricity Consumers in Cape Town* 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.

OLIVER DZOBO

DATE

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For there is one God, Jehovah Almighty

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

ABSTRACT

A good understanding of the financial value that electricity customers place on power supply reliability and the underlying factors that give rise to higher and lower values is an essential tool in the designing, planning and operating standards of power system networks. This research study is a first step toward addressing the current absence of consistent data needed to support better estimates of the economic value of power supply reliability. The economic value of power supply reliability is usually measured through power interruption costs faced by electricity customers. Examples of power interruption costs are retail losses for commercial customers and production losses for industrial customers. The aim of this research study was to develop Customer Interruption Cost (CIC) models for both commercial and industrial customers. The CIC models describe the consequences or financial costs faced by business (industrial and commercial) customers due to power interruptions. To investigate this, a customer survey conducted throughout Cape Town using in-person interviews with approximately 275 sample business customers is presented. The customer survey included power interruption cost estimation questions based on the direct costing method. The results of these questions together with the others included in the questionnaire were analysed using statistical methods.

The results obtained show that customer interruption cost for business customers varies with duration and time of occurrence of power interruptions. The variation was shown to be dependent on the customer class or segment. Additionally, business customers of the same segment were affected differently by the same power interruption. Their power interruption costs were associated with the level of their energy bill. Although limited by constraints in the data used, the analysis presented in this thesis indicated that an interruption in power supply can result in considerable costs to end-users in both industrial and commercial sectors. Interruption costs appear to be higher in the industrial sector than in the commercial sector. Furthermore it has been revealed that while business customers may attempt to save their revenue loss by using different mitigation actions like the use of backup power supplies, this strategy may not result in cost savings. The bulk of the costs come in the form of acquisition, maintenance and operation of very expensive backup power equipment. It was also found that business customers who own backup power supplies experience power interruption costs significantly higher than those who do not.

The new set of CIC models developed in this research study was used in reliability cost/worth assessment of two test distribution system networks. Results from the reliability cost/worth assessments showed that customer interruption cost estimates can be applied usefully in planning and management of power system networks by revealing the worst affected load points. The simulation results show that taking time dependencies into account is very important because extreme (high or low) values of power interruption costs are taken into account. The research study advocates for institutional transformations that can enhance the public sector delivery of electricity and the review of energy policies for business customers with great reliability requirement.

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ABBREVIATIONS

ANOVA	Analysis of Variance
CAIFI	Customer Average Interruption Frequency Index
CCDF	Composite Customer Damage Function
CCT	City of Cape Town
CDF	Customer Damage Function
CIC	Customer Interruption Cost
CQ	Comprehensive Questionnaire
CUE	Cost of unserved energy
DBSA	Development Bank of Southern Africa
df	Degree of freedom
DSM	Demand Side Management
ECOST	Expected interruption cost
EENS	Expected energy not supplied/served
ERNC	Expected revenue not collected
GDP	Gross Domestic Product
GWh	Gigawatt-hour
hr	hour
IEAR	Interruption energy assessment rate
km	Kilometre
kV	Kilovolt
kVA	Kilovolt-ampere
kVA-hr	kilovolt-ampere - hour
kW	Kilowatt
kWh	Kilowatt-hour
kW/h	Kilowatt per hour
LOLE	Loss of Load Expectation
LP1	Load point 1
MW	Megawatt
NERSA	National Energy Regulator of South Africa
NIRP	National Integrated Resources Plan
OLS	Ordinary Least Square
r	average outage duration
R ²	Coefficient of determination
RBTS	Roy Billinton Test System
RNC	Revenue not collected
RT	Repair time
RcT	Re-closing time
R _p T	Replacement time
R/kVA	South African rand per kilovolt-ampere
R/kVA-hr	South African rand per kilovolt ampere per hour
R53billion	Fifty three billion South African rands
S.A	South Africa
SAIDI	System Average Interruption Duration Index
SAIFI	System Average Interruption Frequency Index

SCDF	Sector Customer Damage Function
SIC	Standard Industrial Coding System
SIC – Stats SA	Standard Industrial Coding system – Statistics of South Africa
SwT	Switching time
TST	Total specified time/period of simulation
TTF	Time to failure
TTR	Time to repair
TTS	Time to switch
U	Unavailability or annual outage duration
UCT	University of Cape Town
UPS	Uninterruptible Power Supply
U.S	United States
U.S2billion or \$2billion	two billion United States dollars
WTP	Willingness to pay
WTA	Willingness to accept
yr	year
λ	average failure rate
$\beta_1, \beta_2, \beta_3$	binary coefficients
%	Percentage
\$/kWh	United States dollar per kilowatt-hour
\$/kW	United States dollar per kilowatt

CHAPTER 1

INTRODUCTION TO THE STUDY

1.1 BASIC POWER SYSTEM RELIABILITY WORTH EVALUATION

1.1.1 Background

The primary function of a power system is to provide sufficient electricity supply of good quality to satisfy its customers' needs and expectations. These customers expect to receive the electricity at the lowest possible total cost.

In four years 2004/2008, Eskom - South Africa has spent over R53 billion on the construction and resuscitation of their power system and had an estimated spending of R46 billion for the 2008/9 financial year [Eskom 2008b]. It has also embarked on a very large infrastructure expansion programme which has a board-approved budget of R343 billion (excluding inflation) up to 2013 and is expected to grow to more than a trillion rand by 2026 [Eskom 2008b]. This massive infrastructure expansion programme is intended to adequately respond to the challenge of electricity availability and reliability. Such investment and commitment is made only where substantial benefits are anticipated, which leads to two obvious questions: What benefits will be derived and what is the adequate level of supply reliability that would give the least cost of electricity to the electricity customers?

Traditionally, power system planning was basically straightforward, plant construction was relatively easy, repair or replacement times were relatively short, and costs were relatively stable [Billinton and Allan 1988:5]. The situation today has drastically changed. Inflation and huge increases in oil prices have created a rapid increase in consumer tariffs and fluctuating growth patterns. This has greatly impacted on the economic and social well being of many nations. This is illustrated by the recent statement by Manuel, Governor of the DBSA:

"..... Also worth noting are the power shortages that have affected more than 30 African countries, including South Africa, causing energy insecurity and constraining our growth path. This has been a sobering reminder of the importance of basic services such as electricity, which millions of people still live without every day. It has also made the enormous task of eradicating poverty and inequality more challenging" [DBSA 2008:5]

The power supply industry is being monitored very closely by different stakeholder groups and individuals. Governments, licensing bodies, consumer advocates and even private citizens are expressing their concerns in ways which did not exist a decade ago:

"...Representatives of civil society, organised labour, business and government, worked together and agreed on a common submission to NERSA. It was agreed at the summit that the new price proposals must be done in a manner that protects the poor and ensures that they still have access to affordable electricity..." [Eskom 2008b:11]

Environmental considerations created by public concern have been added to the construction difficulties, and safety and reliability problems. Conservation has become a major issue and renewable energy sources have and are being considered for replacing some of the energy generated by fossil-fired stations.

"...Renewable Energy (RE) options are being explored. The plan currently has 100MW of Wind Energy and a Solar Power plant of 100MW is also under consideration." [NERSA 2008a:9]

Deregulation of the power industry in many countries has also shifted the focus of the power industry from the national economic focus to the profit driven focus. Power utilities in many countries started to seek new optimum solutions for power system planning. In addition regulators have started to introduce performance based rates with associated penalties and rewards as they try to balance cost or tariffs against reliability:

"...It is important to formulate the performance indicators that will be used as a basis to measure the successes and failures of the utilities. In order to establish technical performance of utilities we have in the basket load based indices or customer based indices as one of the key indicators which can be used for monitoring purposes"[NERSA 2006:6]

In the same report quoted above it was further pointed out that, "With the incentive scheme developed for Eskom Distribution, NERSA opted for a customer based index called the System Average Interruption Duration Index (SAIDI) as a start." [NERSA 2006:6]

Aging of the power system network which by nature requires much longer time for repair and /or replacement has also been added to the problem of power system reliability planning. This is illustrated by the statement from Eskom [2008b]:

"The average age of plant in the transmission network is 31 years. The oldest substations and lines are 52 years old. This calls for a high level of network plant and equipment maintenance and also refurbishment and replacement of plant that has reached the end of its useful life"

The widely varying preferences of electricity customers for prices and service reliability have also aggravated the complexity of power system reliability planning. At one end, are electricity customers who need high power supply reliability level. These electricity customers are willing to pay a premium or fee to ensure that their power supply reliability level is very high, because they experience huge losses when their power supply is interrupted. At the other end, are electricity customers with less demand for reliable power service and greater preference for low cost electricity. Many of these electricity customers will tolerate power outages in exchange for lower prices.

The power system planning has therefore become very complex. This is substantiated by the statements from the policy makers and suppliers:

"...Achieving the vision requires in-depth planning and implementation in a complex environment characterised by economic growth, greater demand for electricity and the increased need for significant infrastructure expansion, as well as competition for scarce materials (coal and equipment), funding, skills and supplier inputs. Challenges are compounded by the rising cost of primary energy and new components, restructuring of the electricity distribution industry, the need to continually improve our environmental performance and the growing involvement of stakeholder groups." [Eskom 2008b:2]

It is with this background that the present power system reliability planning techniques and concepts are being developed, utilised and scrutinised. These problems have always been widely recognised by power system managers, designers, planners and operators, as they seek optimum level of supply reliability that would give the least cost of electricity to the electricity customers.

1.1.2 Customer Interruption Cost

Power system reliability consists of both adequacy and security of supply [Billinton and Allan 1988:2]. Power system adequacy relates to the ability of the power system network to satisfy the consumer load demand. These include the facilities necessary to generate

sufficient energy and the associated transmission and distribution facilities required to transport the energy to the load points. For example generators, transmission lines and control systems within the power system network. On the other hand, power system security looks at the ability of the power system respond to any disturbances arising within the power system network such as loss of major generation and transmission facilities. Power system security is beyond the scope of this research study.

Reliability has technical and financial aspects. Technical assessment is quite well developed, but the financial assessment of reliability is still not yet well accepted although a prodigious number of research papers has been published [Billinton and Allan 1983, Kaur 2002]. The financial assessment of power supply reliability is a complex task to conduct directly [Ghajar et al 1996]. The complexity comes from the fact that there are many intangibles involved in the process which are not always convertible to their financial values, for example, loss of life and crime. The financial losses incurred by electricity customers due to unreliability of power supply are often referred to as **Customer Interruption Cost (CIC)**. It is believed that quantifying the financial losses incurred by electricity customers as a result of power interruptions is a reasonable representative measure of the benefit of power supply reliability (reliability worth) [Ghajar et al 1996].

Reliability worth evaluation studies are regularly performed at generation, transmission and distribution levels [Billinton and Allan 1988]. Complete power system reliability worth evaluation studies are usually very difficult to perform, because of the scale of the problem [Billinton and Allan 1988]. The reliability worth assessment of distribution systems is often performed only in the distribution functional zone. This is done despite that failures in generation and transmission will affect distribution supply reliability. The main reason for this simplification is that 80 percent of the customer power interruptions occur within the distribution systems [Billinton and Allan 1988]¹. Therefore the reliability worth indices will not change much if the power interruptions in the generation and transmission are included in the analysis [Billinton and Allan 1988].

¹ Customer power interruptions caused by generation and transmission system failures are normally only about 20 percent of the total load point power interruptions.

In the context of South Africa, the shortage of electricity is as a result of shortage of generation supply capacity [NERSA 2008a]. Load shedding is therefore taken as a last resort to prevent a collapse of the national electricity supply system. The load shedding programme is implemented at distribution level. Therefore most of the power interruptions that affect the electricity customers occur within the distribution systems. Thus, this research study will investigate the cost of power interruptions in a power system at distribution level.

1.1.3 Brief Overview of Load Shedding in South Africa

Currently, Eskom - South Africa (SA) is facing a critical shortage of electricity in its power grid. The reserve margin is critically low and is estimated at below 8% [Eskom 2008b]. High rates of unplanned and planned maintenance [UBS 2008, NERSA 2008a] forced the supply authorities (Eskom and the municipalities) to regularly implement load shedding in order to reduce the risk of total blackouts. The average duration of Eskom load shedding for the period of November 2007 and April 2008 was 2 to 2.5 hours each day [Eskom 2008a]. The load shedding programme was done through a rotational basis between all customers. There is high expectation that the conditions will persist for the next 5 to 6 years. This is pointed out in the report by NERSA [2008a: 1] in their report; "*National response to South Africa's electricity shortage*". It states that:

".....The risk of load shedding will remain high until at least 2013 if we do not take immediate actions to ameliorate the situation, especially during the times of high levels of planned maintenance. Specific and immediate interventions are needed to minimise the risk of load shedding until the new peaking plant and base-load electricity generating capacity being built comes online."

Moreover, the National Integrated Resource Plan (NIPR) of NERSA has shown that low reserves margins of 7 – 14 % will remain for the period of 2007 to 2011. The loss of load hours for these years is estimated at about 700 hours per annum, a magnitude well above the targeted reliability level of 2.4 hours per annum [NERSA 2008b]. Thus, a well timed power interruption cost investigation of longer outage duration for electricity customers could be efficacious in helping the electricity suppliers and regulators to understand the

balance between the investment made and the benefit derived from it; hence the particular importance of this type of research study.

Load shedding is not only confined to South Africa. As reported by Faranda et al [2007], blackouts are becoming more frequent in industrial countries because of network deficiencies and continuous load growth. Demand side management (DSM) and load shedding have been used to provide reliable power system operation under normal and emergency conditions. DSM is specifically devoted to the installation of energy efficient and load shifting technologies to alter the load profile of the power utility. Load shedding is a methodology used worldwide to prevent power system degradation to blackout.

The following steps were done in carrying out the load shedding programme as taken from an article in Eskom [2008b] subtitled "*Securing continuity of Supply*":

"What is load shedding?

When there is insufficient power station capacity to supply the demand (load) from all the customers, the electricity system could become unstable, possibly resulting in a national blackout.

To increase supply, Eskom runs its power stations at maximum available capacity. In addition to the coal and nuclear plant, hydro and gas turbine stations are used at peak times when demand is high.

To reduce demand, Eskom will first call on customer contracts that allow for supply to be reduced or interrupted for specific periods and durations. If this is not enough, Eskom is forced to cut supply to all other customers. This could be done through either scheduled or emergency load shedding.

During scheduled load shedding, parts of the network are switched off according to a predetermined schedule, with the impact spread equitably over the customer base. Load shedding is predictable and allows for customers to plan accordingly, as opposed to blackouts that are not.

In exceptional circumstances, such as many unplanned outages at power stations, additional emergency load shedding could be required. Control centres will then shed load using emergency switching in order to protect the network. This will be less predictable and all customers may be affected at any time. "

In the Eskom 2008 annual report some of the proposed demand reduction options given when demand exceeds supply were load shedding, power rationing, and demand side management.

1.2 HYPOTHESIS AND RESEARCH QUESTIONS

The evaluation of power interruption costs of electricity customers requires a good understanding of the nature of customer impacts resulting from power interruptions. Many of the electricity customers rely on the constant supply of electricity for their activities. When power supply to their activities is disrupted, the electricity customers may incur huge power interruption costs. The power interruption costs can be classified as direct and indirect costs [Chowdhury and Koval 1999]. Direct costs are further classified as economic and social costs. These costs are as a result of the cessation of power supply to the electricity customer. Direct economic costs include costs due to lost production, product spoilage and damage to plant equipment. The direct social costs include transport unavailable, risk of injury or health, uncomfortable building temperature, loss of leisure time. Indirect costs are associated with the losses incurred subsequently as a consequence of power interruption. This include economic, social and relational effects such as changes in business plans and schedules, looting, rioting, legal and insurance costs, changes in business patterns.

From the two statements issued in the report by the NERSA [2008b] which states that:

"...The economic impact of load shedding events is not readily available. However for generation capacity planning purposes the cost of not supplying electricity is deemed to be R75 per kWh. This implies that the load shedding in the period (1 November 2007 to 31 January 2008) cost the South African economy approximately R50billion" NERSA [2008b:8].

The power shortage requirement that was lost because of load shedding during this period was given as 67GWh.

".....Despite the fact that most of the financial implications of load shedding on industries and the economy as a whole cannot be accurately quantified at this stage the cost of unserved energy (CUE) is estimated at about R50billion. Reduced economic activity will have a negative impact on output levels and ultimately on GDP" [NERSA 2008b:36]

The question that arises from the two statements above is: By how much did load shedding affect the electricity customers? It therefore becomes imperative to close the gap of finding the financial implications of load shedding on electricity customers of South Africa for the benefit of the electricity customers, power utilities and the regulator. Moreover, it is equally important to confirm whether the financial losses faced by electricity customers due to load shedding are equal to the cost of unserved energy (CUE).

If load reduction in the form of load shedding is not implemented in a power system network when the demand exceeds supply, it can sometimes result in widespread blackouts. An example was given in Faranda et al [2007] which occurred in the western North American grid. The loss of the Keeler-Allston 500kV line and the Ross-Lexington 230kV line in Oregon resulted in excess load, which resulted in the tripping of the generators, causing 500MW oscillations. This led to the islanding and blackouts in 11 US states and two Canadian provinces. It was estimated to cost from U.S \$1.5 to U.S \$2 billion including all aspects of the interconnected infrastructures and even the environment. Among several studies that followed, some researchers have shown that a dropping/ shedding of about 0.4% of the total network load for 30 minutes would have prevented the cascading effects of this blackout. This shows the paramount importance of load shedding in the power system network. The problem is how to implement it so that the electricity customers would suffer the least cost of power interruptions. This statement is substantiated by the statement from Eskom – S.A 2008 in its response to NERSA. It states that:

".....The solution is not to defer outages but rather creating the space to do outages and to choose the right outages to ensure that plant performance improves and enable plant to run at appropriate load factors for the primary energy supply chains taking into account design limitations" [NERSA 2008b:43].

This statement means power interruptions are inevitable and therefore the only solution to reduce its impact on electricity customers is to choose the right outages. The right outages means power interruptions done at the right time and this can only be achieved by understanding the electricity customer requirements and their activity levels at the respective times. Therefore, assessing power interruption costs of electricity customers

would help understand the complex relationship of customer and interruption attributes to power interruption costs.

Specifically, there is need to use predictor variables which would allow one to develop valid and reliable interruption cost models that can be used to accurately estimate the customer interruption costs. Research studies have found that generally the average power interruption cost increases as the energy consumption and demand increases. Sullivan et al [1997], in their survey conducted among commercial and industrial customers, cited customer energy use as the most important predictor variable of customer interruption cost. Both energy consumption and demand are used to normalise the customer interruption cost [Chapel 1999, EPRI 2000]. This approach is used to offset the impact of small number of respondents who report large or small interruption costs. Research findings have shown that the two approaches produce different results. Tiedmann [2004] used several regression models in order to try and find the effect of the interruption variables on the CIC. He recommended that further research is needed to better understand the drivers of power interruption costs, particularly for individual business customer segments. Hence, in the context of this study, it is necessary to explore the significant effect of some of the interruption variables on power interruption cost. The question is: Which parameters best characterises the CIC?

1.2.1 Customer Categories

From the research findings, electricity customers are usually sub-grouped into three main categories namely; residential, commercial and industrial [EPRI 2000, Lawton et al 2003]. Commercial and industrial customers present special problems in all applications of utility investment and operations planning [Chowdhury and Koval 1999]. The level of their energy use and increasing dependence of their production process equipment on electricity has continuously increased their expectations regarding power system supply reliability provided by their power utilities. The revenue losses they incur as a result of power interruptions problems are usually very high [Sullivan et al 1997]. For example, research findings by Sullivan et al [1997] shows that although residential customers are numerous within most utility power system networks, the range of their power interruption costs are relatively small. Residential customer interruption costs for a 1-hour outage occurring on a summer

afternoon at 3 p.m. were found to be between U.S\$0 and U.S\$64, with mean of U.S\$5.39. Contrast this with the power interruption costs for industrial customers in the same survey, the power interruption costs ranged from U.S\$0 to over U.S\$1000 000, with an average of about U.S\$9400.

Additionally, industrial and commercial customers have engineering and legal resources to effectively challenge the utility's provided power system reliability levels before the power utility management, regulators, and courts. For this reason, it is very important to address their electricity requirements when evaluating power system network design and operating alternatives that affect their service. Therefore commercial and industrial customers are perceived as a particularly important group to focus on, concerning power interruption costs.

In some studies the business customers are usually further segmented in terms of their SIC codes [Lawton et al 2003]. This technique identifies the primary business of each respondent company. However, research findings have indicated that there is a discrepancy in the use of this technique. For example, a retail company that gets the bulk of its business between 9a.m and 5p.m; and another that does 80% of its business in the evenings will react differently to a power interruption that occurs in the afternoon. In this case indication of the regular business hours and business activity levels for the different times or normal working hours of the company would add some clarity. Another problem is that large business customers are grouped together with smaller business customers. In a study where SIC classification was not applied, Tiedmann [2004] concluded that grouping business segments into more homogeneous groups would allow for more accurate CIC models. The author recommended that further research would be needed to understand how power interruptions affect individual business sector. It is for this reason that in this research study several segments of the business sector are going to be investigated. By focusing on only the business customers the CIC of these segments could be determined with larger sample sizes. This would allow for a better comparison between business segments from which recommendations could be made regarding the use of CIC functions in power system reliability planning.

1.2.2 Mitigation measures

The time taken by a business customer to recover from or adjust to power interruptions is very important as this can reduce their revenue losses. The effectiveness of the corrective

and preventive measures taken to mitigate the losses is dependent on the good understanding of the damages that occur and the losses accrued due to the power interruptions. The measures should be developed on the basis of the type of facility, process, and the level of uncertainty associated with the occurrence of the power interruptions.

Preventive measures include the operational and technological measures applied in order to reduce the recurrence or impact of the power interruption. These measures can be done either by the utility or customer e.g. backup power supply. Corrective measures include overtime and sending employees back home during the power interruption period. It is therefore imperative to use a research design which would allow one to test for the interaction effects between some of the mitigation measures and the total power interruption costs.

1.2.3 Customer interruption cost variation

A common feature with all the interruption cost assessment techniques is the need to determine a CIC model that closely represents the different parameters of customer interruption cost [Billinton and Allan 1988, Tiedmann 2004]. A comprehensive CIC model is required so as to identify the most significant factors that could contribute to the customer interruption cost. The conventional method is to consider mean (average) or aggregated values of the cost for a given duration. An important question arising from this approach is: how well will the aggregated or average cost values represent the entire customer response?

Studies carried out at University of Saskatchewan have shown large variations in the costs and in some cases the standard deviation is more than three times the mean value [Ghajar et al 1996]. Recently, at the University of Cape Town, Herman and Gaunt [2008] carried out a survey on both residential and commercial customers. They also noted the large variations of the results and pointed out that there is a need to use the outlier values correctly. A probabilistic approach that uses the distribution of the results instead of a single mean value was recommended by them. It is for this reason that this thesis will examine probabilistic methods to try and model the cost of power interruptions to business customers and see how the results differ from the conventional methods. This begs a question: Which probability distribution function best represent the CIC?

At present time no single model exists which satisfactorily explains or predicts the wide variety of impacts or effects that are linked to power interruption of electricity customers. Most reliability planning researchers agree that the effects of power interruption are complex and multifaceted. Accordingly, most suggest that power utilities or power system planners, have found it very important but difficult to apply power interruption costs in the design of any power system network.

Based on the above discussion, this research tests the following hypothesis:

The distributed nature of the Customer Interruption Cost of business customers can be shown as a function of duration and other interruption variables such as frequency, time of occurrence (day of week, time of day, season, year), and depending on the customer class or segment and this can be applied usefully in planning and management of power system networks.

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

1. How best can one determine the cost of interruptions?
2. Which parameters best characterises the CIC?
3. What is the best way of segmenting business customers?
4. How well can the average or aggregated values from the customer damage functions represent the entire customer response?
5. Which probability distribution function is most useful in representing CIC?
 - I. Is there a difference between the results obtained and those derived when using conventional methods?
 - II. How applicable is the approach and what are the implications of using the approach?

A substantial quantity of data had to be collected, sorted and interpreted to answer the questions. South Africa is different from other regions of the world in many respects, but in other ways quite similar. Despite defining the study region as Cape Town, some of the concepts and evidence considered – and the conclusions – may not be restricted to South

Africa alone, as the investigation also draws on international literature about power interruption costs.

1.3 SCOPE OF THE STUDY

This thesis only covers power system reliability regarding power system adequacy, which means that power system dynamics and transient disturbances are not considered. Additionally, customer interruption costs due to power quality problems, such as voltage dips, are beyond the scope of this thesis.

1.4 THESIS OUTLINE

Chapter 2 provides the relevant theories, principles and concepts underpinning power system reliability planning, and customer interruption cost assessment, together with previous research findings which informed and guided:

- a. The design of the customer survey programme.
- b. The choice of appropriate variables whose measurement could be used to develop effective CIC models for the different business segments.
- c. The choice of independent variables whose measurement might lead to explanations of any outcome differences between business segments.

Chapter 3 presents a detailed description of the investigative procedures employed in the research design, as well as the actual implementation of the investigation. Investigative procedures include a description and discussion of the selection of population, study population and samples; measures; and organisation and co-ordination of treatments. The actual implementation of the survey programme provides details pertaining to questionnaire administration, coding of data, and data capture, verification and transformation.

Chapter 4 sets out the findings and presents a detailed account of the statistical tests performed on the qualitative and quantitative data generated by the Comprehensive Questionnaires. In addition, the findings related to the new set of customer interruption cost models developed for both commercial and industrial customer segments are also presented.

Chapter 5 contains a number of model simulations. The proposed time-varying customer interruption cost models for the different segments are combined together with the reliability and load models to investigate the effect of including time-varying customer interruption costs when assessing reliability worth. A time sequential Monte Carlo technique is applied to two test distribution system networks and results are reported and discussed. A cost benefit analysis of adding disconnectors / isolators at designated points of the power system network is performed for one of the test distribution system networks. The analysis is carried out by using average values of the load point indices.

Chapter 6 is devoted to an evaluation and interpretation of the data analysis findings, the formulation of conclusions, a discussion of the weaknesses and limitations of the study, and the implications of the findings for further research.

1.5 MAIN CONTRIBUTIONS

The main contributions of the thesis are the following:

- New CIC models for the different business segments investigated in this thesis. The CIC models are time-varying, builds on the underlying factors that cause the power interruption costs.
- The proposed CIC models are combined with reliability and load models and the impact of time dependencies on load point indices such as expected customer interruption cost is investigated.
- A case study of a network with and without isolators using a cost benefit approach is investigated.
- Investigation of a beta probability distribution to describe the customer interruption cost.

CHAPTER 2

THEORETICAL FRAMEWORKS AND PREVIOUS RESEARCH FINDINGS

Chapter 1 presented an introduction to the investigation by stating the nature, relevance and importance of the problem; the research questions and hypothesis. This chapter seeks to identify the relevant theories, principles, concepts and research findings in power system reliability planning and interruption cost assessment to answer the research questions posed in chapter 1 and find the gaps that exists. Because multifaceted approaches have been employed by many previous researchers, the research evidence cited in this chapter, in support of or refuting a particular opinion, is likely to be referred to more than once. This strategy has the potential of fragmenting a particular piece of research.

2.1 POWER SYSTEM RELIABILITY WORTH PLANNING APPROACH

2.1.1 Background

Power system reliability evaluation is often used by many researchers and power system planners to quantify the overall reliability of a power system network to perform its anticipated purpose. It has generated a prodigious quantity of published research.

Designing, planning and operating standards and techniques have been developed over many decades in an attempt to resolve the conflict between the economic and reliability constraints. Traditionally, power system reliability levels have been planned according to subjective engineering standards – deterministic techniques (loss of load expectation (LOLE), reserve margin or failure contingencies). Many of these criteria and techniques are still in use today [Billinton and Allan 1988, Chowdhury et al 2004]. For example, many utility power systems have been planned based on the N – 1 criterion (reserve margin or failure contingencies), which 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. These methods rely on the historical data and experience from both the power system planners and operators. While

such criteria have sustained the electricity industry well in the past, there is an important weakness in their use. They do not take into account the probabilistic or stochastic economic value customers assign to reliability when evaluating the validity of power system improvements or setting target reliability levels.

The need for probabilistic evaluation of customer demands has been acknowledged many decades ago and it may be questioned why such techniques have not been extensively used in the past. The main reasons pointed out by Billinton and Allan [1988] were lack of data, limitations of computational resources, lack of realistic techniques, aversion to the use of probabilistic techniques and misunderstanding of the significance and meaning of probabilistic criteria and indices. None of these reasons are valid today as computing facilities are now greatly improved, evaluation techniques are highly developed and most engineers have a working understanding of probabilistic techniques. However, as pointed out by LaCommare and Eto [2004], the lack of collection of updated information on customers' reliability experiences and on the cost of power interruptions to individual customers is still an impediment to the application of this technique.

Modern society, because of the increasing dependence of their activities on electricity, has come to expect that the supply should always be available on demand. This is not feasible due to the random system failures which generally are beyond the control of power system engineers and, in some cases, because of load shedding. The probability of electricity customers being disconnected, however, can be reduced by increased investment in the power system. It is evident therefore that the economic and reliability constraints can conflict, and this can lead to difficult managerial decisions at both the planning and operating phases of the power system. The only way in which all these competing and diverse uncertainties can be weighted together in an objective and consistent fashion is by use of quantitative reliability evaluation techniques.

In order to balance the economics of reliability, utility planners have to link power system investment decisions to customer needs. Value based planning approach is one such method that is designed to balance the level of investment in power system with customers' preferences [Chowdhury and Koval 1999]. This approach assumes that customer preferences for power supply reliability can be measured [Sullivan and Keane 1995] and that these

preferences should be used to establish economically rational reliability targets for power systems. Planning utility investments in power supply reliability according to the value based planning approach requires information from both the utility and the electricity customer. This means the power system planners must 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 power interruption costs – the costs they incur when their activities are interrupted [Chowdhury et al 2001]. The challenge is to accurately estimate the customer interruption cost. It is therefore necessary to look at value based planning approach as used in power system planning.

2.1.2 Value Based Planning Approach

The primary objective of value based planning approach is to identify economically efficient investment strategies for power systems [Sullivan and Keane 1995]. This approach assumes that to achieve economic efficiency in power system reliability planning, the level of power supply reliability to electricity customers must correspond with the economic value of service that electricity customers require. This means if the cost of power system investment 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.

Fig 2.1 below, illustrates a hypothetical example of how the power system investment cost (utility cost) and the customer interruption cost are combined to give the total system cost. From the diagram it can be seen that the cost of reliability is described from two perspectives, the utility cost graph and the customer interruption cost graph. The utility cost graph shows the financial value of investments done in order to attain a certain level of reliability. It contains both tangible costs for the reliability enhancement, such as investment costs, and also intangible costs such as loss of goodwill in case of frequent power

interruptions. Additionally, regulation authorities impose both penalties at low reliability levels and incentives at high reliability levels which also affect the cost. The graph shows that there is an increase in the utility cost as the power system reliability level improves or increases.

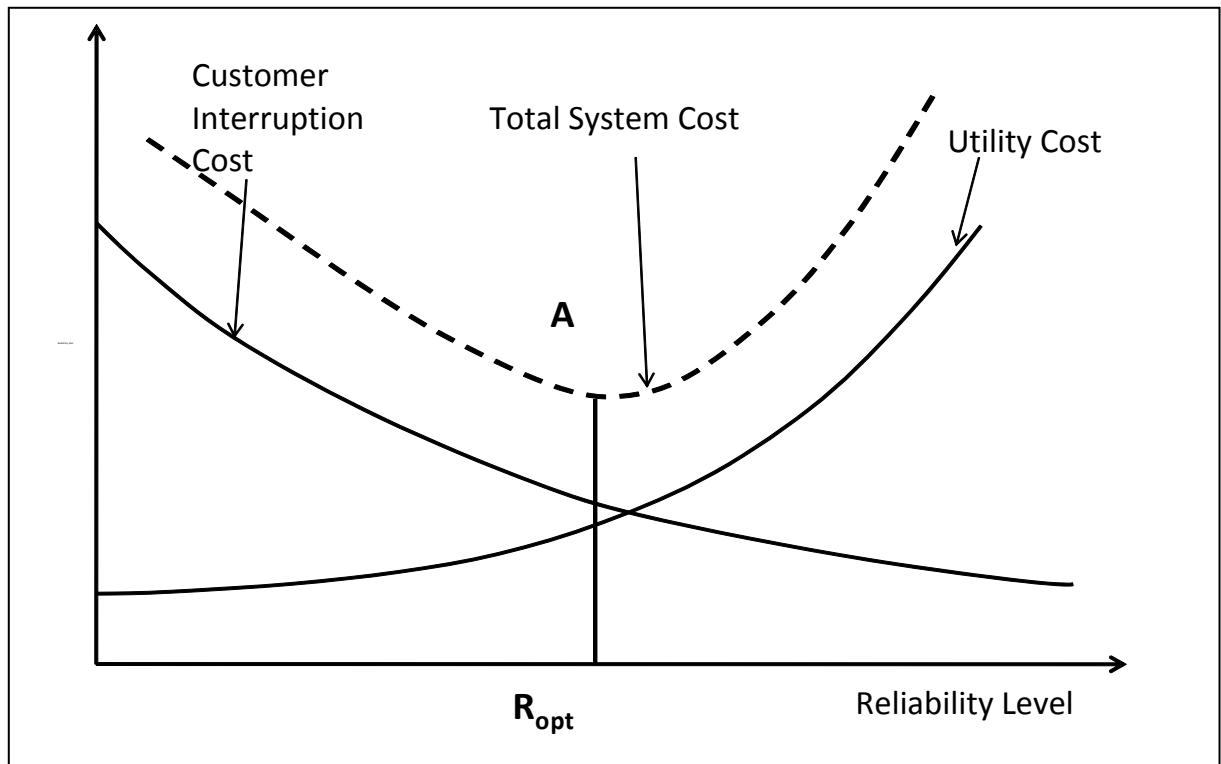


Fig 2.1: Determination of optimum reliability level of a power system [Billinton and Allan 1994 p14]

The customer interruption cost 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 customer interruption cost are very significant. 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. 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 cost.

This concept is quite valid [Billinton and Allan 1988, EPRI 2000]. As good as the concept of value based planning is, it presents a number of practical difficulties to the power system distribution planner. The most difficult is that different electricity customers have widely varying preferences for prices and service reliability. Therefore, developing the power system to achieve certain arbitrary reliability target levels may result in investments that provide greater power supply reliability levels than the electricity customers really require. Conversely, 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. 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.

Despite this and other difficulties, value based planning is a method used to balance supply and demand side costs. This alone makes it a recommended technique for all power system planners looking to establish or confirm the reliability goals for their company. 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 the case of the regulator, 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. Thus with respect to the value based planning approach, accurate estimation of customer interruption cost could help the utility planners to make good planning decisions and be able to grade their projects according to their usefulness or importance to the power system and electricity customers. It is therefore important to give some thought to discuss the parameters that affect CIC, methodologies of assessing CIC and techniques of modelling CIC and the data needs.

2.2 CUSTOMER INTERRUPTION COST

2.2.1 Parameters of Interruption

2.2.1.1 Duration

Research evidence indicates that duration is the most common variable investigated that affects power interruption costs. Perhaps, the main reason for its popularity is that its impact on customer interruption cost is substantial [Alvehag 2008]. Different durations have been surveyed by many researchers and resulted in different correlations between customer interruption cost and duration. Previous studies have shown that customer interruption costs do not vary linearly with duration, but there is an increase as the duration increases [Tiedmann 2004]. Further evidence supporting this finding come from a survey conducted among commercial customers by Jordaan [2006]. In general, the customer interruption cost that electricity customers experience as a result of a power interruption rise instantaneously from zero to some positive value in the first instant their power supply is interrupted. After this instantaneous loss, the customer interruption cost increases over time with the duration of the power interruption. Thus, the longer the power interruption, the higher the total customer interruption cost [Lawton et al 2003]. However, further research by Tiedmann [2004] showed that customer interruption costs appear to rise to a point at which it becomes a maximum. From this point in time, the customer interruption cost is limited to that value which also decreases as the electricity customer changes its operations to minimise the cost of the power interruption i.e. rescheduling of labour, employees being send back home, etc.

The most commonly used outage scenarios involved power interruptions of one and four hour durations at different time of occurrence [Lawton et al 2003]. From the previous chapter it has been pointed out that the duration of the load shedding program in South Africa averaged 2 to 2.5 hours each day. The main focus of this research study was on load shedding, and therefore the hypothetical power interruption durations that were considered in this thesis are from the consultation of load shedding schedules that were posted by the power utility or respective municipality to the electricity customers.

2.2.1.2 Power Interruption Frequency

As power interruption frequency increases above past levels, electricity customers usually become highly adapted to the experienced level of power supply reliability as they make

adjustment to their operations e.g. installation of backup power supply. Details of how power interruption frequency affects customer interruption cost are scarce in the literature. For a while and expected again in the future, South Africa is having shortage of electricity in its power grid and thus the power supply reliability levels are very low due to load shedding being implemented. It is therefore relevant to explore power interruption frequency, as it could be a variable which differentially explains any outcome differences between other research results.

2.2.1.3 Time of occurrence

Customer interruption costs are usually investigated for a number of hypothetical power interruption scenarios occurring at different seasons, month, day of week and hours of day [Sullivan et al 1997]. Research evidence indicates that time variations show different patterns of power interruption cost for different customer sectors. For example, Tiedmann [2004] in a customer survey conducted among business customers, states that the hour of the day show no consistent pattern with the power interruption costs. Nooij et al [2007] (*cited by Alvehag [2008]*), in a recent study in the Netherlands, substantiated this statement by providing evidence that the order of priority² among customer sectors drastically changes depending on time of day and day of week. Seasonal differences in customer interruption costs among electricity customers are said to be highly associated with their electricity consumption [Lawton et al 2003]. Further research by Tiedmann [2004] found that most of the summer months are the worst months for business customers. This was also reported in Jordaan [2006] for commercial customers, where it was believed that these are the highest spending months as customers prepare for the holidays, for example Christmas holiday in December.

The fact that the worst customer interruption costs for different business customers do not coincide with the different time of day, day of week, month and season can be worthwhile to investigate in practical applications. It is for this reason that in this thesis several hypothetical power interruptions at different times of occurrence are going to be investigated. In doing this, customer interruption cost for business customers could be determined for the different times.

² As measured by the power interruption cost incurred by each customer sector.

2.2.2 Parameters of Customer

2.2.2.1 Business Activity Level

Recent research findings indicate that electricity customers are more interested in the costs associated with their activities that are interrupted during a power interruption [Alvehag 2008]. Business activity level data is still very scarce in the literature covered.

Business activity levels in surveys are usually stated on an activity level scale. A customer survey conducted among commercial customers at UCT by Jordaan [2006], confirmed that business activity level data can give the same results for the worst time of occurrence of a power interruption. It is believed to be true because electricity customers gauge their power interruption cost by their activity levels i.e. the period of time when business activity level is highest is stated as the worst time of occurrence of a power interruption. The business activity levels were investigated for different time of day, week and month. Sometimes business activity levels are used to derive activity factors which can be used in multiplicative CIC models [Alvehag 2008]. The results from these CIC models produce results that are very accurate [Wang and Billinton 1999, Billinton and Wangdee 2005, Alvehag 2008]. It is therefore important to consider the business activity level of the business customers in this thesis so as to investigate these findings.

2.2.2.2 Size of Supply

Research studies have found that generally power interruption cost increases as the energy consumption and demand increases. In a survey conducted among commercial and industrial customers by Sullivan et al [1997], customer energy use was cited as the most important predictor variable of customer interruption cost. Both energy consumption and demand are used to normalise the customer interruption cost. This approach is used to offset the impact of the small number of respondents who report large or small interruption costs. The two normalising techniques produce results that are different [Lawton et al 2003].

2.2.2.3 Organisation Categories

Significant differences in customer interruption cost can be as a result of how electricity customers are defined [LaCommare and Eto 2004]. Research evidence show that the SIC is the most widely used method of classifying electricity customers into homogeneous groups. This technique identifies the primary business of each respondent company. However,

research findings have indicated there is a discrepancy in the use of this technique. For example, a large business customer is grouped together with smaller business customers. This may affect the interruption cost data as the cost estimate for the large business customer maybe regarded as an outlier. The measurement of business size such as number of employees and energy consumption of the company may help to clarify the disparity. Another problem is that different firms have different business activity levels at different times. This means they will react differently to a power interruption that occurs at a certain given time. In this case, an indication of the regular business or normal working hours of the company would add some clarity.

2.2.3 Cost Reduction Methods

2.2.3.1 Backup Power Supply

The financial losses and perceived risk of power supply interruption has led many electricity customers to invest in a wide variety of mitigation measures. Backup or standby generators are probably the most well known electricity customer investments. Various other energy storage technologies, such as batteries and fly wheels are also used.

The impact of backup power supply has not yet been explored very much [Lawton et al 2003]. Throughout the literature, it has become evident that the implications and meaning of having a backup power supply is not consistently captured in surveys. For example, in the survey questionnaire for small / medium commercial and industrial customers provided in Sullivan and Keane [1995], respondents were asked at one point whether they have a backup power supply and then only later answered the power interruption cost questions. This introduces two problems in the final power interruption cost estimate: (1) the precise kind of backup power supply equipment is not necessary clarified, for example: was it just for lighting or was it for full operation?; (2) the presence of the backup power supply equipment and the power interruption cost questions were separated, so it is not known if the respondents were taking the backup power supply capability or costs into consideration. A research by Sullivan et al [1997] provided evidence that the presence of backup power supply equipment reduces customer interruption cost. It is therefore important to take the above mentioned problems into consideration when designing a questionnaire so as to capture the effect of backup power supply on customer interruption cost.

2.3 CUSTOMER INTERRUPTION COST ASSESSMENT METHODS

Interruption cost assessment for non-residential (business) customers has been examined in several papers, but the literature is not as extensive as that dealing with residential customers [Tiedmann 2004, Kaur et al 2002]. This research study is focussed on non-residential customers. Those findings related to residential customers will therefore be mentioned only where similar research had not yet been conducted among non-residential customers. Throughout the literature, it has become evident that there are three basic methods that are used to assess customer interruption costs, namely: analytical methods; blackout case study; and customer survey methods [EPRI 2000].

The analytical methods aim to capture the indirect cost faced by electricity customers due to power interruptions. These approaches are sometimes referred to as proxy or market based methods, for example cost of backup power supply, electricity rates [Sullivan and Keane 1995]. In these methods the value of power system reliability worth is viewed as equal to the economic value of a replacement commodity. These methods are based on a top-down approach and no direct contact with the electricity customers is considered. In addition it does not consider most of the interruption and customer variables [Chowdhury et al 2004].

On the other hand, the black-out case studies aim at specific power interruption events. 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]. The main disadvantage of using this method is that it views power interruptions as only limited to particular blackouts. It is therefore difficult to generalise the results since no two black-outs are identical and relatively small number of black-outs can be surveyed for a representative population of customers.

Finally, the customer survey methods aim at quantifying the interruption costs by asking the electricity customers how the power interruptions affect their activities [Tellefson et al 1994]. These methods are 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 [Tellefson 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

power interruption cost and thus represents expectations of electricity customers about their power utility.

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 investigation, 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].

The customer survey method incorporates a fundamental tenet that a realistic CIC model can be obtained by only involving individual electricity customers or groups of electricity customers to quantify their power interruption costs associated with their activities interrupted during a power interruption.

2.3.1 Customer Survey Methodology

As in the literature on residential customers, four main customer survey methods have been used to estimate non-residential customer power interruption effects: direct costing; contingent valuation; indirect costing; and contingent ranking.

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. The method aims to capture the valuation of inconvenience caused by the power interruption [EPRI 2000] rather than the straight monetary value. 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 [Sullivan and Keane 1995, EPRI 2000]. 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 supply reliability 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 for planning purposes as applied in the value based planning approach.

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. For example, some electricity customers may prefer to buy standby backup power supplies. For electricity customers who do not buy backup generators, the method will provide an overestimate of power interruption cost [Chapel 1999]. Therefore the value assessed may not be worth; rather it will be related to other aspects of the approach. The method is very effective when social effects are expected to constitute a significant part of the power interruption costs [Chowdhury and Koval 1999].

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 power 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 not be worth; rather it is related to the approach used in designing the set of choices or menu program. Therefore the results cannot be compared to others and can only apply to the customer base surveyed. The results from this method cannot be used in developing general CIC models.

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 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 power interruption costs [Billinton et al 1991, Goel 1998, Chowdhury and Koval 1999, EPRI 2000].

The results and shortcomings of these empirical research findings therefore informed the design and investigative procedures adopted in this research study. Specifically, there was a need to use a research design which would allow one to accurately estimate the financial value due to power interruptions, and to develop valid and reliable CIC models that can be used to evaluate effectively in the value based planning approach. The direct costing method was therefore deemed to be the best method to estimate the power interruption costs for non-residential customers, as these customers are expected to suffer from power interruption impacts that can be easily converted to monetary value³. Direct social effects on the non-residential customers are not considered in this investigation.

2.4 ESTIMATION OF TOTAL CUSTOMER INTERRUPTION COST

Research evidence has shown that the total power interruption cost estimated in customer surveys is most commonly the total cost for the worst time of occurrence of a power interruption. Sullivan et al [1997] in their customer survey conducted among industrial and commercial customers, in addition to asking about the total power interruption cost, asked respondents to provide a detailed estimate of component costs, including lost production/sales, damage to equipment, cost of operating a backup supply, and other cost associated with the power interruption. The approach of asking a detailed estimate of component costs may produce very accurate results if on-site interviews are used to gather the information [Sullivan and Keane 1995, Sullivan et al 1997]. However, the interviews are very long and would take 3 to 4 hours to complete one onsite interview and coming up with the power interruption cost estimates [Sullivan et al 1997]. This will therefore mean an

³ The direct economic costs are expected to constitute a significant part of the power interruption costs.

increase in the number of survey researchers needed to cover a large sample which in turn increases the survey costs. Intuitively, it is very rare to see a busy business person who would want to spare 3 to 4 hours answering a questionnaire, and this may result in very low response rate [Sullivan and Keane 1995].

Sometimes the total power interruption cost can be estimated using the percentage reduction technique [Koskols et al 1998, Jordaan 2006]. In this technique one of the power interruption cost estimate is used as the base cost estimate. Further cost estimates provided by the respondent are referenced in terms of their percentage to the base cost estimate. It has been noted by Jordaan [2006] that because business customers do not freely divulge their power interruption cost information maybe as a result of the privacy of their financial accounts, it would be easier to use the percentage reduction technique when investigating their power interruption costs. Hence, in the context of this investigation, the percentage reduction technique was chosen as the best method of collecting the power interruption cost estimates from business customers.

2.5 CUSTOMER INTERRUPTION COST MODELS

The customer interruption cost data obtained from the customer survey methods described in the previous sections is used to formulate CIC models. The purpose of the CIC models is to make estimations of customer interruption costs for an arbitrary power interruption event, which is needed for a relevant value based planning analysis.

Many different CIC models have been developed in the past and some are still in use today. Early CIC models assign a cost to the unserved energy (\$/kWh) [EPRI 2000]. For example, recently in S.A the cost of unserved energy was estimated at R75/kWh [NERSA 2008b]. Sometimes, the disconnected load cost (\$/kW) is used together with the cost of unserved energy [EPRI 2000]. However, research findings have indicated that there is often a discrepancy in using these two techniques as the CIC models do not take into account customer and power interruption attributes, such as duration, time of occurrence.

More recent research has shown that the power interruption cost to electricity customers are to a large extent determined by the power interruption duration [EPRI 2000, Tiedmann 2004]. The conventional method used to model power interruption costs faced by electricity

customers is the Customer Damage Function (CDF). The approach models the power interruption cost for each customer sector as a function of duration [Billinton and Allan 1994]. There are two different methods used to calculate the CDF. These are average process and the aggregating process [Midenge and Vargas 2007]. In the average process, the customer interruption costs from the survey are normalised⁴. This is done to transform the customer interruption cost data to usable cost parameters for planning purposes. Additionally, it also helps when comparing power interruption costs of electricity customers with similar cost characteristics but different customer characteristics [Sullivan and Keane 1995, Midenge and Vargas 2007]. After normalisation, an average value of the customers' normalised costs is calculated to obtain the CDFs for each sector. On the other hand, the aggregating process involves pooling all the power interruption costs of the electricity customers belonging to each sector and then normalising it by dividing with the sum of the normalising factors for each sector [Ghajar et al 1996]. The CDF obtained is the Sector Customer Damage Function (SCDF). Research evidence has shown that these two procedures do not produce the same results [Ghajar et al 1996, EPRI 2000]. The SCDFs are weighted to obtain the Composite Customer Damage Function (CCDF) which describes the total power interruption cost for a mixture of customer sectors in a particular region [Billinton et al 1994]. The CCDF obtained is therefore system dependent since it is determined by the specific customer mixture in the power system.

A number of multiplicative CIC models are also used to describe the power interruption costs faced by electricity customers. For example, a detailed multiplicative cost model approach was used by Billinton and Wangdee [2003]. The multiplicative models were built on cost data obtained from customer surveys that investigate the power interruption cost for a number of hypothetical scenarios occurring in different seasons, days of the week, hour of the day. To incorporate the time-varying nature of the CIC model, three time-varying cost weight factors were developed based on the outage cost data. The three weight factors were used to describe the monthly, daily and hourly variations of power interruption cost. The time-varying cost weight factors were multiplied with the SCDF. This means, if a power

⁴ Normalisation can be done using any of the customer attributes e.g. number of employees, energy consumption, e.t.c

interruption occurs at the reference time⁵, the three time-varying factors equal one and for other time of occurrences they take values less than one with respect to the reference time. The time-varying cost models of this kind are usually used together with time-varying load models [Wang and Billinton 1999, Billinton and Wangdee 2003]. These models are said to give reasonably accurate cost estimates.

2.6 DISPERSED NATURE OF INTERRUPTION COST

The power interruption cost data for surveyed duration gathered from customer surveys, have been shown to have a large variation within each customer sector. Its distribution has also shown to be very much skewed [Ghajar et al 1996]. Billinton and Wang [1999] found that using the average of the skewed power interruption cost distribution in the CIC model can lead to underestimation of the power interruption cost. Different models have therefore been developed in an attempt to capture this dispersed nature of power interruption costs. Instead of modelling the variation of power interruption cost data within the customer sector, sometimes predictor variables from interruption and customer characteristics are used to describe the dispersion of the power interruption cost data using linear regression analysis [Sullivan et al 1997, Tiedmann 2004]. In Lawton et al [2003] a Tobit model, an econometric model based on multivariate analysis, was used to model the power interruption cost to depend on power interruption duration, frequency, time of day, season, and various customer characteristics such as income. The research study was based on a database consisting of 24 customer surveys conducted over fifteen years in the U.S.A. A drawback with the Tobit models is that they require a lot of customer data. In many cases this data might not be easily available.

Another model is the Logit model which is used when customer interruption costs are derived from a chosen set of experiments e.g. contingent ranking method. Different attributes such as duration, time of day, household income are included in the analysis and it is possible to see how much more accurately the CIC model reflects the behaviour in the power interruption cost data [Alvehag 2008]. The CIC model gives an insight in what attributes of interruption and customer characteristics are good explanatory variables for

⁵ Usually taken as the worst time of occurrence of a power interruption.

customer interruption costs. This model has not yet been very much explored in power system reliability planning.

2.6.1 The Need for a Beta Distribution

The large variation that exists in customer interruption costs within each customer sector has given many researchers difficulties in modelling customer interruption cost. It is possible that a power interruption mainly affects the electricity customers with the highest costs, since these electricity customers experience costs that are many times higher than the average for the sector. In some studies, for example, it is recommended that all costs that are more than three times the mean value should be regarded as outliers [Ghajar et al 1996, Herman and Gaunt 2008]. The error in estimation of customer interruption cost therefore become far worse than predicted if a CIC model that only considers average values for each customer sector is used. In order not to underestimate the risk of high customer interruption costs, an alternative would be to incorporate this variation within each customer sector using a probability distribution.

Different probability distributions have been used to model the variation of power interruption cost data within each customer sector e.g. normal, lognormal, gamma, weibull etc. A survey conducted by Ghajar et al [1996] on residential customers revealed that power interruption cost estimate for studied durations and non-studied durations cannot be estimated using the same distribution. In their research study the normal distribution was used to approximate interruption cost for the studied durations and for the non-studied durations regression analysis was used to predict the distribution parameters using the values of the studied duration. Therefore, some of these probability distributions cannot model the different distributions shown by power interruption cost data for different durations. The reasons are that they are limited in their shapes and/or do not have a finite range.

In reliability modelling, power interruption cost modelling in particular, the shape of a describing function is significant because it tells users far more about statistical features of the function than a single parameter like mean, without the standard deviation. Cross et al [2006] investigated the usefulness of the beta distribution to model parameters in power system reliability analysis. It was concluded that beta probability distribution can be used to

model data which reflect high dispersion as well as skewness. The beta distribution can show different shapes and has a finite range. The beta distribution was therefore chosen as the most befitting probability distribution because it is versatile and therefore can be used to model power interruption cost for different durations at once.

2.7 DATA COLLECTION METHODOLOGY

A number of different methods are used to collect power interruption cost data from the sample of respondents. Each method has advantages and disadvantages depending on the circumstances, and some methods are better in many ways than others. The method of data collection depends on the data needed by the researcher. This data is also dependent on the problem that needs to be solved and the type of respondents targeted by the researcher. The resources available to the researcher for the research project are also of great importance when choosing a data collection method. Based on the above mentioned constraints a method therefore has to be selected by the researcher. A summary of the few most commonly used data collection methods⁶ as covered by Sullivan and Keane [1995] are described below:

- **Postal Survey:** Questionnaires are mailed to respondents who have to read the instructions and answer the questions. The respondents are responsible for returning the survey packets by fax or mail.
- **Telephone Survey:** The respondents are phoned by the interviewer who ask the questions and record the answers.
- **Face to Face Survey:** Well trained interviewers visit the respondent, ask the questions and record the answers.

⁶ For more detail see Chapter 5, "Survey Designs" in *Outage Cost Estimation Guidebook*, M.J. Sullivan and D. M. Keane, EPRI TR-106082, Project 2878-04, Final Report, December 1995, San Francisco, California

A summary of the advantages and disadvantages of the data collection methods is outlined in the table given below.

Table 2.1: Data collection methods [Sullivan and Keane 1995]

Method	Advantages	Disadvantages
Postal Survey	<ul style="list-style-type: none"> • It is relatively cheap and easy • Respondents can complete the questionnaire at a convenient time. • Respondents can check personal records if necessary. 	<ul style="list-style-type: none"> • Low response rate are very common. • The conditions under which the questionnaire is completed cannot be controlled - the respondent can give the questionnaire to someone else to complete.
Telephone Survey	<ul style="list-style-type: none"> • The survey can be done relatively quickly. • Respondents can be reached across long distances. • The response rate is usually very high. • The interviewer can assist with issues that are not clear to the respondent. • Respondents need to be literate 	<ul style="list-style-type: none"> • The cost is relatively high • The questionnaire cannot be too long • Only people with telephones can be reached. • The interviewer may influence response (interviewer bias)
Face to Face Survey	<ul style="list-style-type: none"> • This method has the highest response rate • Long questionnaires can be used. • The interviewer can assist with issues that are not clear to the respondent. • Respondents need not to be literate 	<ul style="list-style-type: none"> • The cost is usually very high • Interviewers should be well trained • Interviewer bias is a great risk • It is time consuming

A critical requirement to successfully survey business customers is to identify and survey the correct person at the target business. Onsite interview of business customers typically takes a lot of time to come up with the power interruption cost estimates and it is also difficult to schedule interviews with the respondents. Since the likelihood of scheduling interviews with the right respondent decreases with business size [Sullivan and Keane 1995], non-response of this magnitude can result in serious bias of the power interruption cost estimation.

The disadvantages pointed out above were of much consideration in the implementation of this investigation. To address the shortcomings mentioned above, a mixed mode surveying approach combining telephone and face to face or onsite interview technique has been developed. The telephone screening interview is designed to identify the appropriate person at the targeted business to answer the survey questions (usually a business or plant

manager), explain the study to them, elicit their participation in the survey concerning the power interruption cost their firm experiences during power interruptions and schedule the onsite interview. Power interruption cost survey questions are to some extent difficult to formulate and cannot really be answered by respondents during a telephone interview unless the respondent has been given enough time to look at the questions that will be asked. For this reason, the onsite interview technique was chosen as the primary data collection method.

The above discussion has provided answers to the following research questions:

1. What is the basic power system reliability planning approach that can be used to balance the economic and reliability constraints?

From the above discussion it appears that value based planning approach is the most appropriate approach to consider customers in the reliability planning of power system networks. The value based planning approach will balance the investment costs by the power utility with the customer interruption cost. This will give a benchmark on which the power system planners can base their decision making especially for maintenance and upgrading of the power system network.

I. What benefits can be derived from power system investment and how can they be measured?

The benefits derived from power system investments are the increased availability and reliability of the system. 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 economic cost electricity customers suffer as a result of power interruptions. The cost of power interruption is not identical to the value of reliability worth but it is considered as a good representative of it.

II. How is or might the cost of interruption be incorporated in reliability planning and decision making?

Cost of interruption is incorporated in reliability planning and decision making through the value based planning approach. By balancing the utility investment costs and customer interruption costs, the power system planner can decide whether the proposed project can benefit the customers and improve the power system reliability.

III. What is a reasonable or acceptable level of supply reliability?

The reasonable or acceptable level of supply reliability is the point where the total system cost is minimum. In other words the power utility and the customer will benefit most when the proposed project is done.

2. Which definition of customer interruption cost is the most useful?

Customer interruption cost is defined as the worth of reliability of a power system network. This is the benefit that is derived by the customers from the continuous supply of electricity by the power utility.

3. Which parameters best characterises the CIC?

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 characteristics affect the CIC. Customer characteristics include customer segment, size of power supply, number of employees, normal working hours and the business activity level. Interruption characteristics include duration, time of occurrence (season, day of week, time of the month, and month of year) and frequency.

The effects of power interruption on business customers will probably be different for every country and power utility supplier, because of the unique combination of the many cost parameters having an influence. The effects on the business customers in South Africa still need to be assessed by considering the particular circumstances.

4. What is the best way of segmenting business customers?

The best way of segmenting the business customers is using the SIC system. The SIC system is generally accepted by business customers and government.

5. What are the mitigation measures taken by customers to reduce the effect of power interruptions?

Backup power supply is one of the methods used by electricity customers to reduce the impact of power interruption on their activities. The proposed inclusion of the backup power supplies in the calculation of the customer interruption costs appears to be useful, but still needs further investigation to assess its completeness and applicability.

6. How best can one determine the cost of interruptions?

The best method used to determine the cost of interruption is the customer survey upon which an interruption cost model can be built. It has the advantage of involving the electricity customers, and therefore they are able to better understand and quantify how their activities are affected. It is based on the fact that the customers are in the best position to estimate the cost they face when their activities are interrupted.

The results and shortcomings of the empirical research findings has also found that within the customer survey method the best method that can be used to accurately quantify the cost of interruption from business customers and develop a valid and reliable interruption cost model is the direct cost estimation method. This is based on the fact that a substantial amount of the interruption cost faced by the business customers can be easily changed into monetary value.

7. What is the best method to collect interruption cost data from electricity customers?

Data collection method for cost interruption generally depends on a range of factors including the type of problem to be solved and the hypothesis to be tested. It also depends on the cost involved and time frame of the project. The methods can be interlinked to produce a more useful method that can be used to solve the problem investigated.

From the research findings the onsite interview method is found to be the most appropriate method used to collect interruption cost data from the business customers. The onsite interview method needs to be changed a bit if high response rate of respondents is to be achieved.

8. How well can the average or aggregated values from the customer damage functions represent the entire customer response?

The research literature shows some conformity when dealing with the average or aggregated values from the customer damage functions. These values are used as base case estimates of the cost of interruption for a particular duration.

The average or aggregated values from the customer damage functions cannot be said to wholly represent the entire customer base or response since it does not take into account the variation customer interruption costs. It assumes a uniform distribution of interruption costs from the customers. Therefore, their representation of the entire customer response for a given duration appears to be useful but still needs further investigation to assess its applicability.

One question does not appear to have been adequately answered by this review:

9. Which probability distribution function is most useful in representing CIC?

The probabilistic distribution functions used to model customer interruption cost do not appear to provide useful answers for CIC model development. Very little information has been found of how the beta distribution function has been applied in the field of modelling CIC.

2.8 SUMMARY

This chapter has provided answers to some of the questions that were posed in chapter 1. It has also provided an outline of the comprehensive framework for assessing the power interruption cost and the research findings which underpinned the development of the interruption cost models for non-residential customers. The possible explanatory variables which are used to evaluate the impact of power interruptions on non-residential customers

were discussed. Furthermore, the results and shortcomings of previous interruption assessment studies were also revealed.

The next chapter will provide a detailed description of the investigative procedures and actual implementation of the investigation. The framework used to investigate some of the questions that were not answered in the discussion of chapter 2 and the actual implementation of the research study will be explored.

CHAPTER 3

INVESTIGATIVE PROCEDURES AND IMPLEMENTATION OF THE INVESTIGATION

The previous chapter reviewed the theoretical framework underpinning power system reliability planning, and presented where necessary, the previous research findings in power system reliability planning, and customer interruption cost assessment. This guided both the possible explanatory variables used in the analysis of the power interruption cost and the development of the CIC model for business customers. This chapter describes the investigative procedures employed in the investigation, as well as the actual implementation of the study. The selection of the population and samples for the investigation is reported. Subsequently, the survey design chosen to empirically evaluate the impact of power interruption is described together with the fixed/explanatory and dependent variables chosen for the study. The administration of the Comprehensive Questionnaire (CQ) is then reported.

3.1 SELECTION OF POPULATION AND SAMPLES

3.1.1 Selection of Population

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

1. The business customers are located in the vicinity of University of Cape Town (UCT). As the research design require a large sample, time disruption and cost of transportation could be kept to a minimum.
2. 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, ONLINE].
3. Business customers are the worst hit by power interruptions, and their costs are substantial and can be easily changed to monetary value.

4. Cape Town was the worst hit town by power interruptions [Eskom 2008a] and has been going on for more than two years and therefore the business customers probably have greater chance of better understanding the costs of power interruptions.
5. Cost of power interruptions investigation requires people with the formal reasoning abilities. Because it has gone for more than two years these business customers have probably implemented measures to curb the recurrence of power interruptions and these need to be investigated so as to help other business customers in other areas or regions.
6. 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.

3.1.2 Selection of Samples and Survey Procedure

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:

1. 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.
2. The directory is widely accepted by government and all business customers as a source of advertising their products and locations.
3. All the contact information of the business customers is given.
4. 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 SIC – StatsSA [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, ONLINE]. 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, ONLINE] 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. Previous customer surveys that were done at UCT on electricity customers were examined. It was noted in Jordaan [2006] that the use of a sampling method where an interviewer had to go into an area to look for respondents and make appointments has a lot of disadvantages. A major drawback in the method is that, the interviewer had to use some form of convenience sampling and would therefore introduce sampling bias. It was therefore decided in this thesis to try and minimise the sampling bias by considering a probability sampling method to come up with the potential respondents list. The probability sampling method employed in this research study is the systematic sampling method. The method has the advantage of that it is very useful in situations where the population size is not known [Miller and Kobayashi 2009: ONLINE].

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 are then contacted by phone. The purpose of the telephone call was to:

1. Identify the appropriate respondent within each business firm who is able to answer the power interruption cost questions.
2. Contact that person and persuade them to participate.
3. 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. After completing all the interviews of the day, the researcher if possible would move around the area to look for

other possible respondents. The researcher can either schedule interviews or if respondents are willing to answer the survey questions, onsite interviews are done on spot. This was done to increase the number of respondents and also to reduce the cost of transport as in other instances only two or three interviews were scheduled in an area per day. The telephone call interviews were therefore very important in identifying areas in which the researcher can go and look for potential respondents. The researcher was responsible for not only selecting the respondents, but also for conducting all the interviews.

3.1.3 Ethical consideration

UCT has a requirement for researchers to consider ethics when involving respondents in a research study. In general, the research must be planned so that respondents do not suffer physical harm, discomfort, embarrassment or loss of privacy. Permission was therefore sought from UCT through the Faculty Ethics Committee to undertake the research study in the chosen respondents. Informed consent was sought from the respondents i.e. permission was obtained from each respondent after the nature of the research study was fully explained (see Appendix B1). An effort was also made to establish and maintain good rapport with the respondents. Respondents were informed that their participation was voluntary. The identity of the participants is not revealed in the reporting and analysis of the results of the survey.

3.2 MEASURING INSTRUMENTS

3.2.1 The Comprehensive Questionnaire (CQ)

The instrument used to measure the explanatory and outcome variables investigated in this study took the form of a Comprehensive Questionnaire (CQ) (see Appendix A1). 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.

3.3 ASSEMBLY OF CQ INSTRUMENT

3.3.1 Sequencing of Measures and Items

Within the CQ, the measures were ordered from least sensitive to most sensitive and proceeding from one aspect to the next in a logical fashion. The section on power interruption frequency and the acceptability of power system reliability level was placed at the beginning of the CQ. The reason being to secure respondent's interest and co-operation before the more delicate and sensitive questions are posed to them. The demographic characteristics questions were placed at the end of the questionnaire in accordance with Sullivan and Keane [1995] suggestion that placing it at the beginning may give the appearance of a routine form which might de-motivate or alienate respondents and prevent them from proceeding further. At the end of the CQ a blank space was left for respondents to comment on the improvement they would think their power utility can implement to reduce the impact of load curtailment. This was to allow respondents an opportunity to unload some of their thoughts onto paper after having responded to somewhat sensitive questions in the previous sections.

3.4 FORMAT OF CQ

The title page included a heading and a short introduction designed to be non-threatening, serious, neutral and firm to encourage the full, honest and careful participation of the business customers. Where considered appropriate, a section was introduced with a short statement concerning its content and purpose in order to put respondents in the favorable frame of mind for answering the questions. Clear instructions on how to complete each

question were provided and further explanation on how to answer the questions were also provided by the interviewer. All instructions were placed in bold letters.

3.4.1 CQ Section A

3.1.1.1 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 to its electricity customers and also to see if there is any difference in the number of power interruptions experienced by each sector considered in this investigation.

3.1.1.2 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.

a) Description of Satisfaction Level scale

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.

a) Selection of Objectives Response Items

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.

b) Number of Test Items

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 might prevent them from completing the questionnaire. 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".

3.4.2 CQ SECTION B

3.1.1.3 Mitigation Measures

Section B starts with a contingency question type. This arises because of the realisation 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.

3.1.1.4 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.

3.1.1.5 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.

3.4.3 CQ Section C

3.1.1.6 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. It was then thought that respondents will be able to give their average monthly electricity bill [Jordaan 2006], since most of the business managers only deals with expenditure of their monthly electricity especially when presenting their budgets and revenue income to the company. 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.

3.1.1.7 Business Activity Level Scale

The business activity scale was adopted from Jordaan [2006] and it 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 rationale to combine Monday, Tuesday, Wednesday and Thursday as weekdays come from the research evidence provided by Jordaan [2006] which found that these days have almost constant business activity levels. It was further found that Friday and Saturday have the highest business activity levels and Sunday the lowest.

In Jordaan [2006] the variation of business activity level was investigated with day of the month. 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. Therefore the time of the month considered in this thesis were: "beginning of month", "mid-month", and "end of month". The variation of business activity level with month of the year was not changed i.e all the twelve months of the year were included in the investigation.

3.1.1.8 Improvements to Reduce Load Curtailment

The last question asks 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.

3.5 CODING OF CQ

Each respondent's response to items in the CQ was coded by the author in the following manner:

- Responses to items in Section A, B and C were coded in such a way that if the respondent respond to the first option offered, it was coded 1, if the second response option offered was checked it was coded 2 , and so on (Appendix B2)
- Where no response was given to a particular item the response was coded as 0

3.6 DATA CAPTURE AND VERIFICATION

The coded CQs were arranged into two sets according to their groups i.e. commercial and industrial groups. Within each group's data set, the CQs were arranged in numerical order or given identification codes corresponding to individual respondents. Data capture and verification was done in Excel. The coded data was captured, verified and stored in the form of text file in the computer.

3.7 DATA TRANSFORMATION

Scoring of items in CQ measures

The scoring of items in the CQ was performed by writing a program into the STATA package using the item scoring memoranda shown in Appendix B2: Tables B2.1 – B2.8

3.8 SUMMARY

Chapter 3 explained the selection of population, study population and samples. Subsequently the development of the survey program, organisation and coordination of the treatments, and the measuring instruments has been described. Finally, the implementation of the investigation, coding of the CQ, data capture and verification, and data transformation

details has been explained. Chapter 4 will describe the analysis of data generated by measures in the CQ and the results of these data analyses.

CHAPTER 4

DATA ANALYSIS AND RESULTS

Chapter 3 explained the research design, procedures and organisation of the investigation. It also elucidated the implementation of the survey program, administration of the Comprehensive Questionnaire, data collection and verification, and scoring and data transformation of all quantitative measures contained in the CQ. The present chapter provides details of the statistical analysis of the quantitative and qualitative data generated by the CQ. In addition, the findings relating to the regression models derived from the generated data are presented.

4.1 COMPARISON OF COMMERCIAL AND INDUSTRIAL POPULATIONS

4.1.1 Preface

This section presents the population characteristic results obtained from the data generated by the CQ in the customer survey that was conducted.

4.1.2 Survey Response

The respondents were provided with a list of standard company descriptions and asked to select one that best described their company. Table 4.1 and 4.2 provides details regarding the populations and samples to whom the CQ was administered during the investigation. The full descriptions of the business segments considered in this thesis are given in Appendix B2 (Table B2.6). This information is presented to illustrate the extent and limitation of the survey. It also indicates the composition of the business customers surveyed in the investigation.

Table 4.1: Industrial Survey Response

Business Segments	Number of respondents
Clothing	33
Metals	28
Garages	26
Warehousing	4
TOTAL	91

Table 4.2: Commercial Survey Response

Business Sectors	Number of respondents
Retail	117
Professional	26
Office	2
Hotel	39
TOTAL	184

From the above presented statistics it is evident that it was difficult to obtain interviews in the industrial sector. The main reason for this is that all the major established industrial companies have strict policies prohibiting employees and managers from disclosing any company information without authority from their directors. In this way this research study faced a major bureaucratic obstacle. Interviews were however obtained from smaller, newly established industries. In a few unprecedented cases managers of large industrial firms did provide power interruption cost estimates. Thus, the larger industrial customers are not unrepresented in this research study. Difficulties were experienced when trying to schedule interviews for the warehousing segment customers. These customers are somewhat busy all the time and it was very difficult to make contact with the managers. Only four responses were obtained from this group of customers. It was therefore considered important to remove this category from the analysis of power interruption cost.

In the commercial sector, retail and hotel segment interviews were done with a large variety of businesses. The hotel segment includes family restaurants, fast food establishments, coffee shops, small boutique hotels, and large exclusive hotels. The retail segment has the majority of the respondents. This is because of the easy access to these types of respondents especially in shopping malls. Interviews for these segments were easy to schedule as most the interviews were conducted with the owners of the company and they were more willing to give the information. However, for big establishments similar problems to those experienced in the industrial sector were also experienced. In some cases respondents for these segments found it very difficult to estimate power interruptions cost for the different times and durations provided, as this would require them to estimate how their customers would react and how many customers would leave their service for another. Again the office segment was dropped from the analysis of power interruption costs because of the small

number of respondents. Interviews for this segment was very difficult to schedule as most of the respondents were not willing to answer the questionnaire because of fear of responsibility.

The ability of the respondents in the survey to gauge their power interruption costs varied greatly. In the opinion of this author those establishments where the owner was interviewed, were better equipped to estimate possible power interruption costs. Professional segment respondents were often in a better position to judge their power interruption costs.

4.1.3 Population and Sample Characteristics

Data from the CQ completed by each respondent were used to obtain the population characteristics of both industrial and commercial respondents on the fixed/explanatory variables (assumed to be constant within the respondents over the duration of the investigation). The fixed/explanatory variables considered are demographic characteristics, power interruption frequency per year, satisfaction level, business activity level, ability to make up lost production and power system reliability preference.

The objective of the statistical analysis was to examine whether commercial and industrial populations can be regarded as a homogeneous group or not, regarding the fixed/explanatory variables investigated in the survey. The procedure employed in this thesis is to examine the characteristics of both commercial and industrial populations and to determine whether or not they are significantly different. If they are significantly different we reject the hypothesis that the two groups are homogeneous and if they are not significantly different we say that the characteristics or variables do not contradict the hypothesis. These tests are used to detect group difference using frequency (count) data. In this regard, the Chi-square test of independence was deemed as the appropriate test method for the analysis. All the predictor variables i.e. demographic characteristics, power interruption frequency per year and observed frequencies from the other predictor variables: satisfaction level, ability to make up lost production and reliability preference were used to perform chi-square tests to determine equivalence of industrial and commercial populations. The findings are

interpreted in terms of their *p-values*⁷ or ratings. For the test of independence a 5% significance level was used. This means a Chi-square probability (*p-value*) of less than or equal to 0.05 was interpreted as a justification for rejecting the hypothesis, otherwise the hypothesis was accepted.

In addition, observed frequency tables were used to construct graphs to illustrate the comparison between the industrial and commercial populations on the following variables: power interruption frequency per year, satisfaction level, reliability preferences, ability to make-up lost production, ownership of backup power supply.

4.1.1.1 Demographic characteristics

No significance difference ($p > 0.05$) in average monthly electricity bill was found between the two populations. The equivalence in the monthly electricity bill between the industrial and commercial populations can be explained by the fact that the respondents considered in this study are mainly small scale business customers and therefore their electricity use on average can be the same.

Table 4.3: Significance difference of demographic characteristics between industrial and commercial respondents

Fixed/ Explanatory Variables Demographic characteristics:	Industrial respondents (n)	Commercial respondents (n)	Chi-square value	df	<i>p - value</i>
Number of employees	91	184	56.6655	1	0.000
Average monthly electricity bill	61	93	2.6667	1	0.102
Daily operational hours	91	184	62.8572	1	0.000

However, significant differences ($p < 0.05$) were found between the two populations in number of employees (Industrial mean number of employees 17 vs commercial 11) and daily operational hours (industrial mean 11.8 vs commercial 10.8). These findings might suggest that industrial customers are labour intensive and therefore require a lot of employees to carry out their work. In commercial customers sometimes only the owner of the firm is regarded as the employee. The industrial customers also operated longer period of time of the day.

⁷ For evaluation, *p-values* equal to 0.05 or less were deemed to have statistical significance difference at 5% significance level

4.1.1.2 Power interruption frequency

The question asks the respondents to indicate the number of power interruptions they have experienced during the past twelve months. Table 4.4 below shows the mean and standard deviation of the number of power interruptions per year experienced by both industrial and commercial populations.

Table 4.4: Number of power interruptions/year for industrial and commercial customers

Type	Mean	Standard deviation	Maximum	Number of respondents
Industry	3.93	4.61	19	91
Commercial	3.40	4.61	22	184

Fig 4.1 below presents the distribution of the number of power interruptions reported by both commercial and industrial respondents. There was no statistically significance difference ($p > 0.05$) between the industrial and commercial populations regarding the power interruption frequency. Therefore generalisation of the population could be applied by treating both populations as a homogeneous group with regard to power interruption frequency. In both cases almost 40% of the respondents indicated that they did not have any power interruption for the past 12 months. This is as expected since the period when the customer survey was conducted falls out of the time when load shedding was being implemented by the power suppliers.

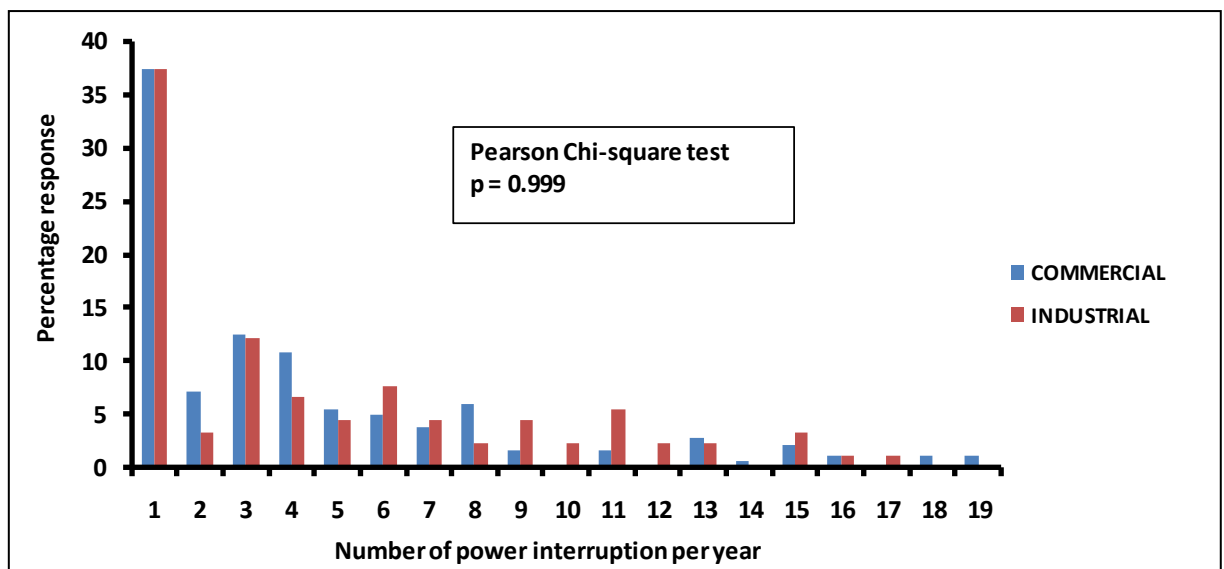


Fig 4.1: Percentage response of industrial and commercial populations regarding power interruption frequency: The p-value is greater than 0.05 and therefore there is insignificant difference between the two populations at the 5% significance level

Figs 4.2 and 4.3 below shows the actual probability distribution of all the customers' perceived frequency of interruptions per year (CAIFI). A beta probability distribution function was used to emphasize the dispersion as well as the skewness in the distribution of the variable being investigated. Fig 4.4 shows the distribution of number of power interruptions per customer per year (SAIFI). The figure (Fig 4.4) shows that there was a high probability of having power interruptions per customer per year in the industrial population than in the commercial population.

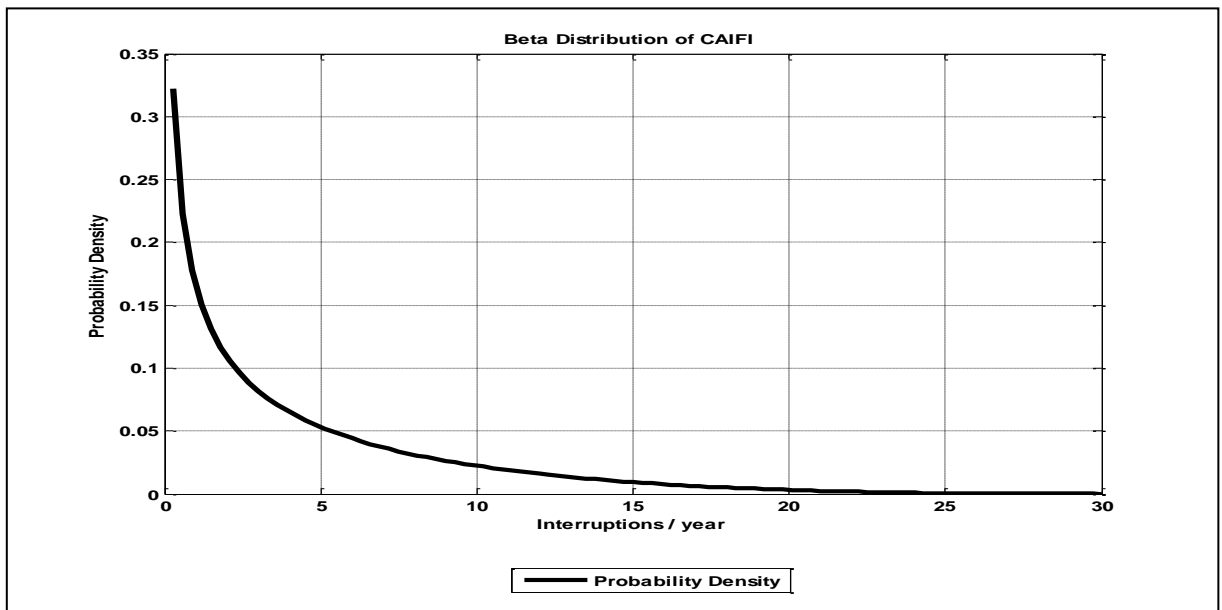


Fig 4.2: Beta probability function of power interruptions/year for industrial population

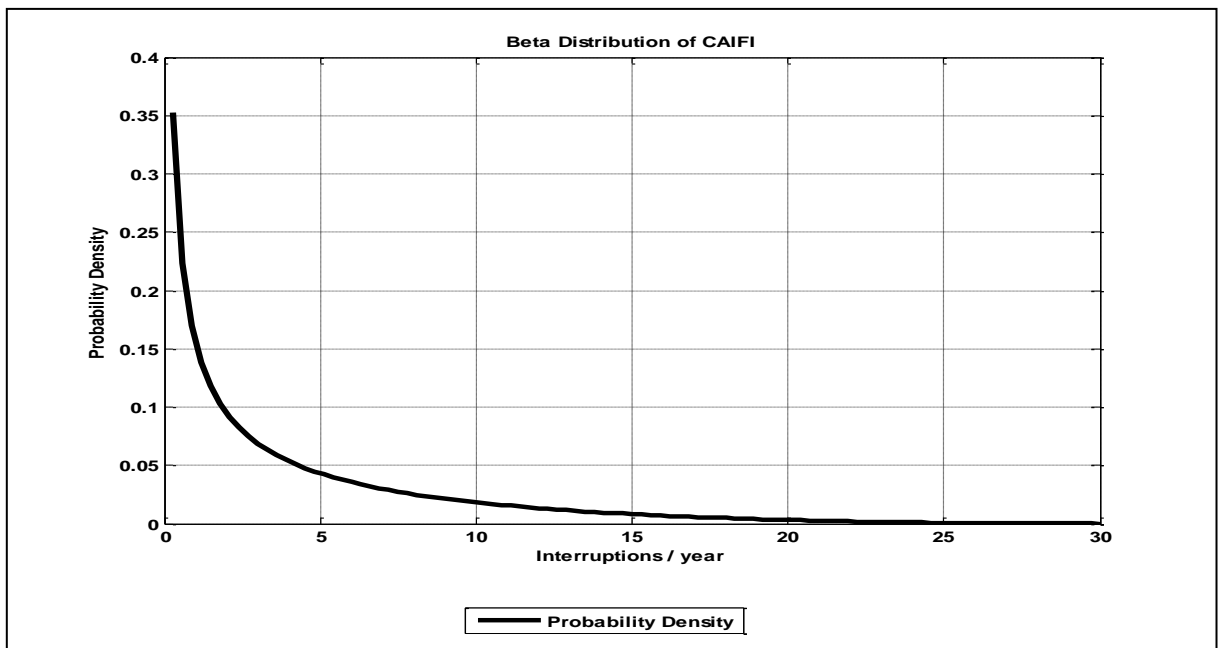


Fig 4.3: Beta probability function of power interruption/year for commercial population

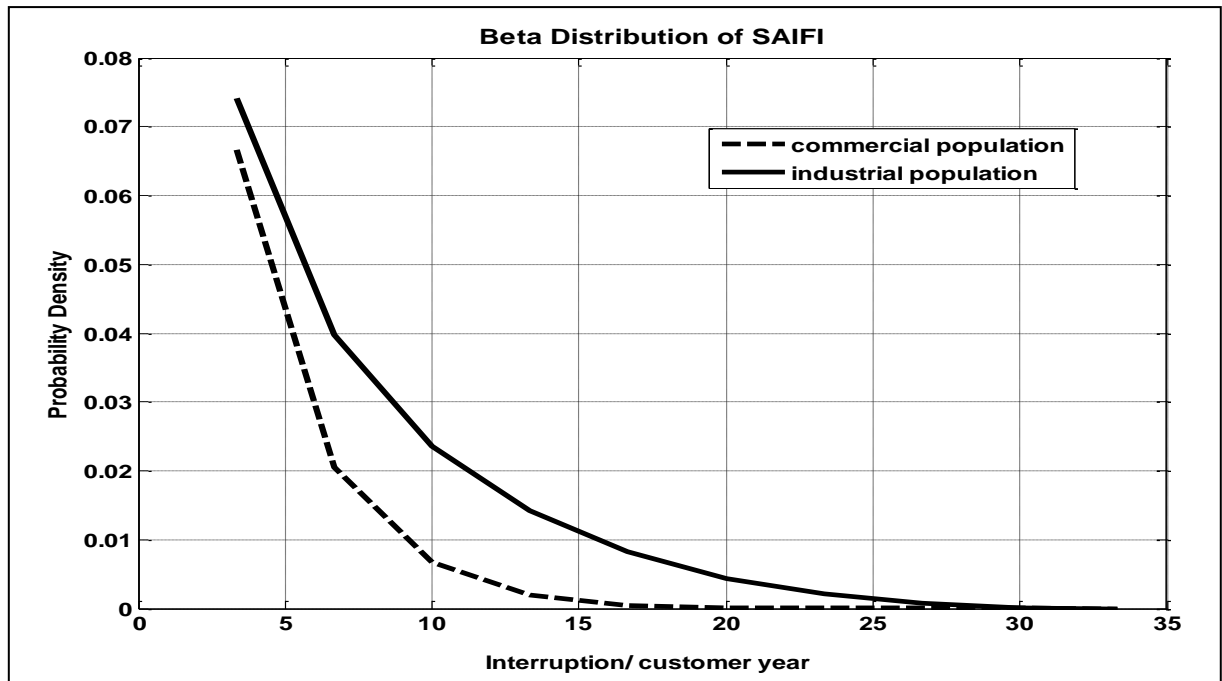


Fig 4.4: Beta probability function of power interruption/ customer year of both industrial and commercial populations

4.1.1.3 Satisfaction Level

Respondents were asked to give their opinions regarding the quality of service provided by their power utility. The satisfaction level for both industrial and commercial respondents is shown in Fig 4.4 below. The *p-value* is greater than 0.05 and therefore the two populations are not statistically different. Both populations can thus be regarded as indistinguishable group regarding their satisfaction level. More than 45% of the respondents are either very dissatisfied or dissatisfied with the service they are getting from the power utility, with about 20% being neutral. Only a third of the respondents are satisfied or very satisfied with the power utility service. This means that both populations regard the service provided by their power utility as generally not satisfying the electricity needs.

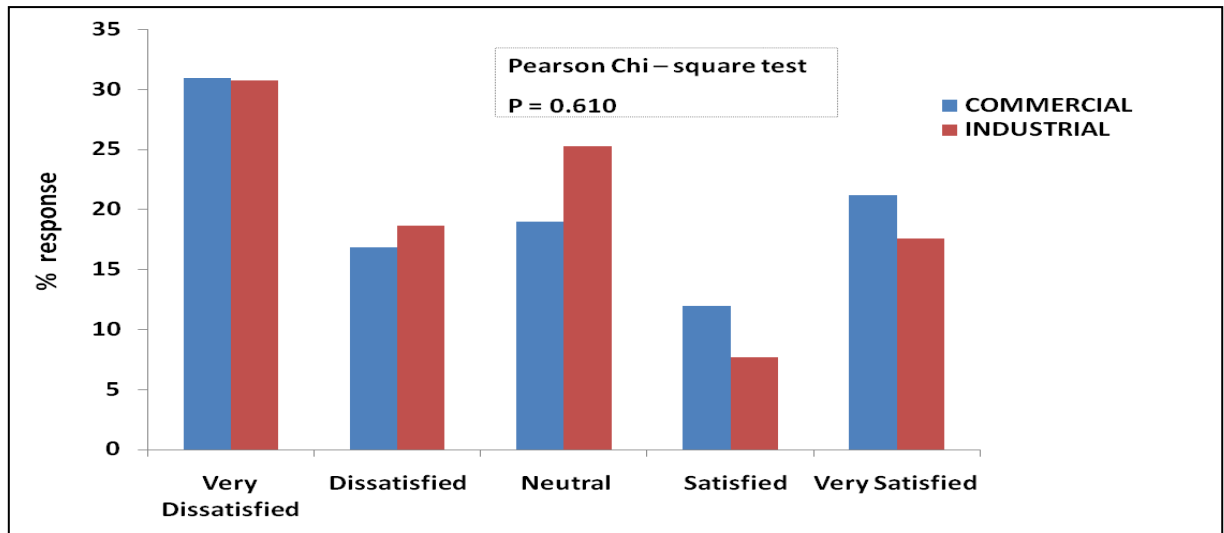


Fig 4.5: Satisfaction level of both commercial and industrial populations: The p-value is greater than 0.05 and therefore there is insignificant difference between the two populations at the 5% significance level

The variation of satisfaction level with power interruption frequency was performed after removing all respondents who have indicated zero power interruptions. It was assumed that those respondents with zero power interruptions were all satisfied with the power supply reliability. Any other satisfaction level indication by these respondents was regarded as a protest answer to other issues concerning the power utility. The two populations were considered as a homogeneous population since there is no statistical significant difference between the two populations regarding the two variables being investigated.

Table 4.5: Variation of Satisfaction Level with Power interruption frequency/year

Satisfaction Level	Mean number of power interruptions/year	Number of respondents
Very satisfied	2.25	4
Satisfied	2.86	14
Neutral	4.00	33
Dissatisfied	5.12	42
Very Dissatisfied	7.44	79

Fig 4.5 below shows that business customers become neutral in their satisfaction level if they experience four power interruptions per year. The satisfaction level of business customers was also shown to decrease as the number of power interruptions increases.

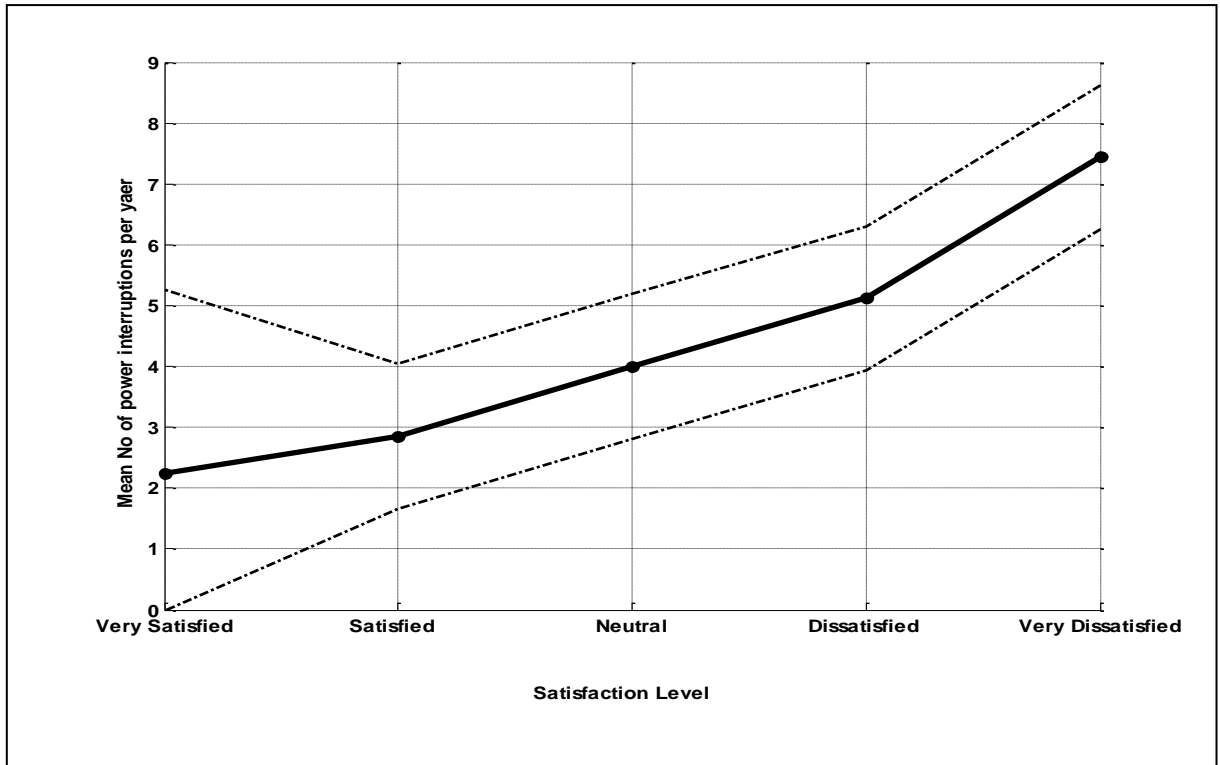


Fig 4.6: Satisfaction Level Versus Number of power interruptions per year: Mean and 95% confidence interval averaged over all respondents. Satisfaction level decreases as the number of power interruptions per year increases.

4.1.1.4 Power Supply Reliability Preferences

Respondents were asked to rate the acceptability of various interruption scenarios for their companies. There was no statistical significant difference ($p > 0.05$) between the two populations. Therefore both industrial and commercial populations could be regarded as a homogeneous population in this respect.

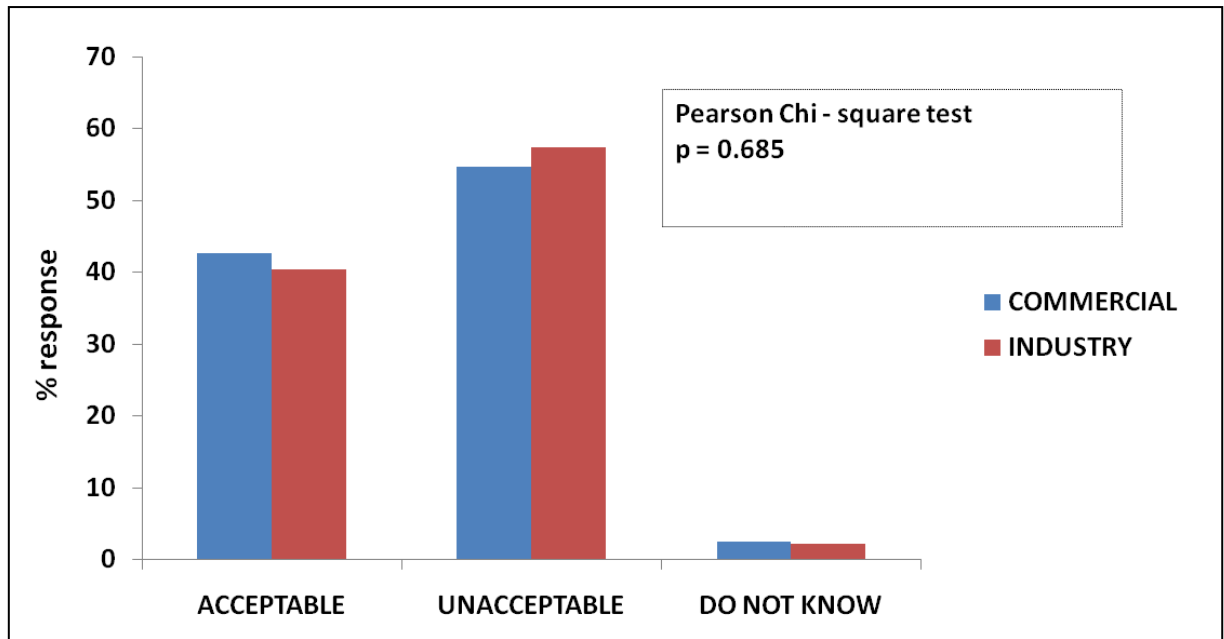


Fig 4.7: Reliability preference of industrial and commercial population: The p -value is greater than 0.05 and therefore there is insignificant difference between the two populations at the 5% significance level. Generally all the power interruption scenarios are unacceptable to both industrial and commercial population.

To investigate the factors that affect the reliability preference of both industrial and commercial customers a three-way analysis of variance (ANOVA) was performed. The industrial and commercial respondents were regarded as a homogeneous group in the analysis. Table 4.6 below presents the ANOVA results.

Table 4.6: Factors that affects reliability preference of industrial and commercial customers

Variable	df	F	p - value
Category	1	0.02	0.8814
Duration	3	6.00	0.0005
Frequency	3	33.68	0.0000
Category*duration	3	1.98	0.1150
Category*frequency	3	0.66	0.5755
Duration*frequency	9	0.53	0.8503
Category*frequency*duration	9	0.62	0.7816

p values ≤ 0.05 are considered to be significant at the 5% significance level

The p -value for frequency and duration are both smaller than 0.05. Therefore the conclusion was that both duration and frequency affect the reliability preference of business (industrial and commercial) customers. The category of the customer does not have a significant effect

on reliability preference. Fig 4.7 below is a two dimensional distribution of the two significant factors showing their effects on the reliability preference.

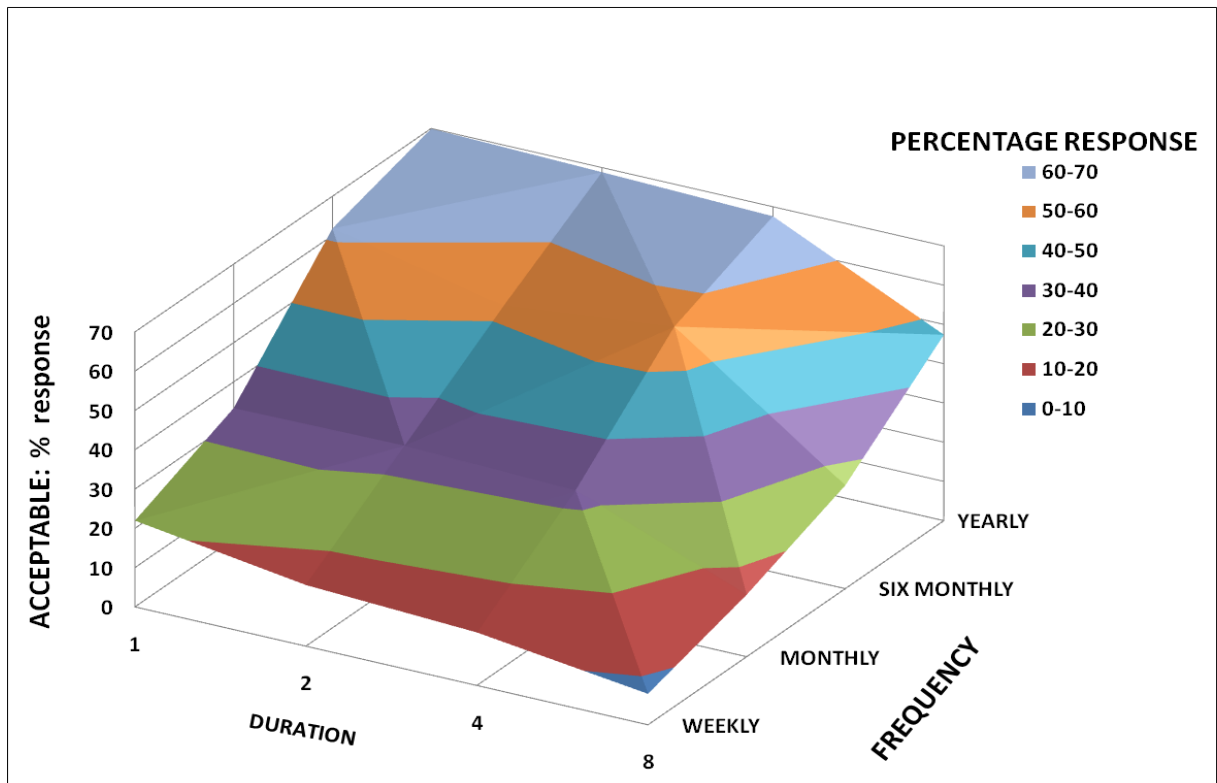


Fig 4.8: Duration and frequency of power interruptions versus acceptability for all respondents: Acceptability increases substantially as frequency decreases and it tends to decrease as the duration increases.

The rated reliability preference increases substantially as the frequency of interruption decreases. A large majority of the respondents considered weekly failures as undesirable. Only about 20% of the respondents have indicated it to be acceptable. Yearly failures were considered to be much preferred to most of the respondents. The results indicated that longer duration failures have great unacceptability than shorter ones. Over 50% of the respondents considered a 4 to 8 hour failure as unacceptable for all the given duration and frequency scenarios. The majority of respondents stated that a 1 to 2 hour failure is tolerable. The reasons may be that, most business customers are able to make up for their lost production (see discussion later), and also these were the type of power failures which were scheduled by the power utility during load shedding programmes and most respondents seem to be used to these types of failures.

4.1.1.5 Ability to make up lost production

Fig. 4.8 below shows the ability of both industrial and commercial populations to make up for their lost production when power supply is restored.

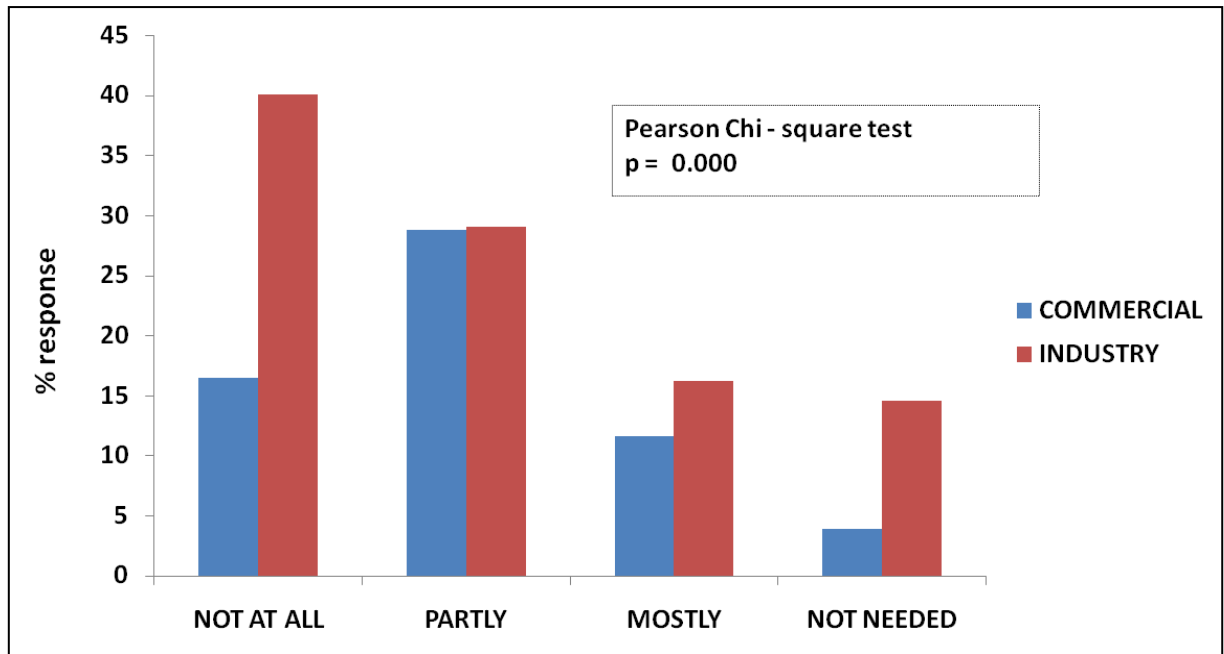


Fig 4.9: Ability to make up lost production by both industrial and commercial populations: The p -value is less than 0.05 and therefore there is significant difference between the two populations at the 5% significance level. Generally most industrial respondents are not able to make up their lost production while most commercial respondents can be able to make part of their lost production.

There was statistical significance difference ($p < 0.05$) between the two populations and therefore could not be regarded as a homogeneous group. A three-way analysis of variance was performed to investigate the factors that affect the ability to make up lost production of both industrial and commercial populations. The industrial and commercial populations were analysed separately. Tables 4.7 and 4.8 below, presents the ANOVA results.

Table 4.7: Factors that affects the ability to make up lost production of industrial population

Variable	df	F	p- value
Duration	3	11.83	0.0001
Time of day	2	27.86	0.0000
Category	2	43.20	0.0000
Category * duration	6	0.16	0.9870
Category * time of day	4	10.77	0.0000
Duration * time of day	6	2.30	0.0347
Category * time of day* duration	12	0.25	0.9956

p values ≤ 0.05 are considered to be significant at the 5% significance level

Table 4.8: Factors that affects the ability to make up lost production of commercial population

Variable	df	F	p- value
Duration	3	11.83	0.0000
Time of day	2	27.86	0.0000
Category	2	43.20	0.0000
Category * duration	6	0.16	0.9870
Category * time of day	4	10.77	0.0000
Duration * time of day	6	2.30	0.0347
Category * time of day* duration	12	0.25	0.9956

p values ≤ 0.05 are considered to be significant at the 5% significance level

In both industrial and commercial populations the two way interactions between category and duration; and duration and time of day were small i.e. $p < 0.05$ and therefore significant. Thus, the conclusion was that category, duration and time of day affect the ability of business customers to make up for their lost production.

Figs 4.9 and 4.10 below, presents the two dimensional distributions of the ability to make up lost production of both industrial and commercial populations respectively. Fig 4.9 shows that the percentage of industrial respondents not able make up for their lost production increases as the duration increases. The reason maybe that as the duration of power interruption increases the production lost becomes significant. The metal segment has the least percentage of respondents not able to make up for their lost production. Perhaps it is because there is least chance of spoilage of products in this segment. Fig 4.10 shows that commercial respondents have significant variations in ability to make up lost production when interruption characteristics such as duration and time of occurrence are considered.

Results showed that commercial respondents have a high level of ability to make up lost production for power interruptions that occur during the morning hours of day. This maybe as a result of that, their customers can still have time to come back for their service. The ability to make up lost production decreases substantially as the duration of the power interruption increases. A large majority of the respondents in both industrial and commercial populations considered 4 to 8 hours failures as the worst and will not be able to make up the lost production.

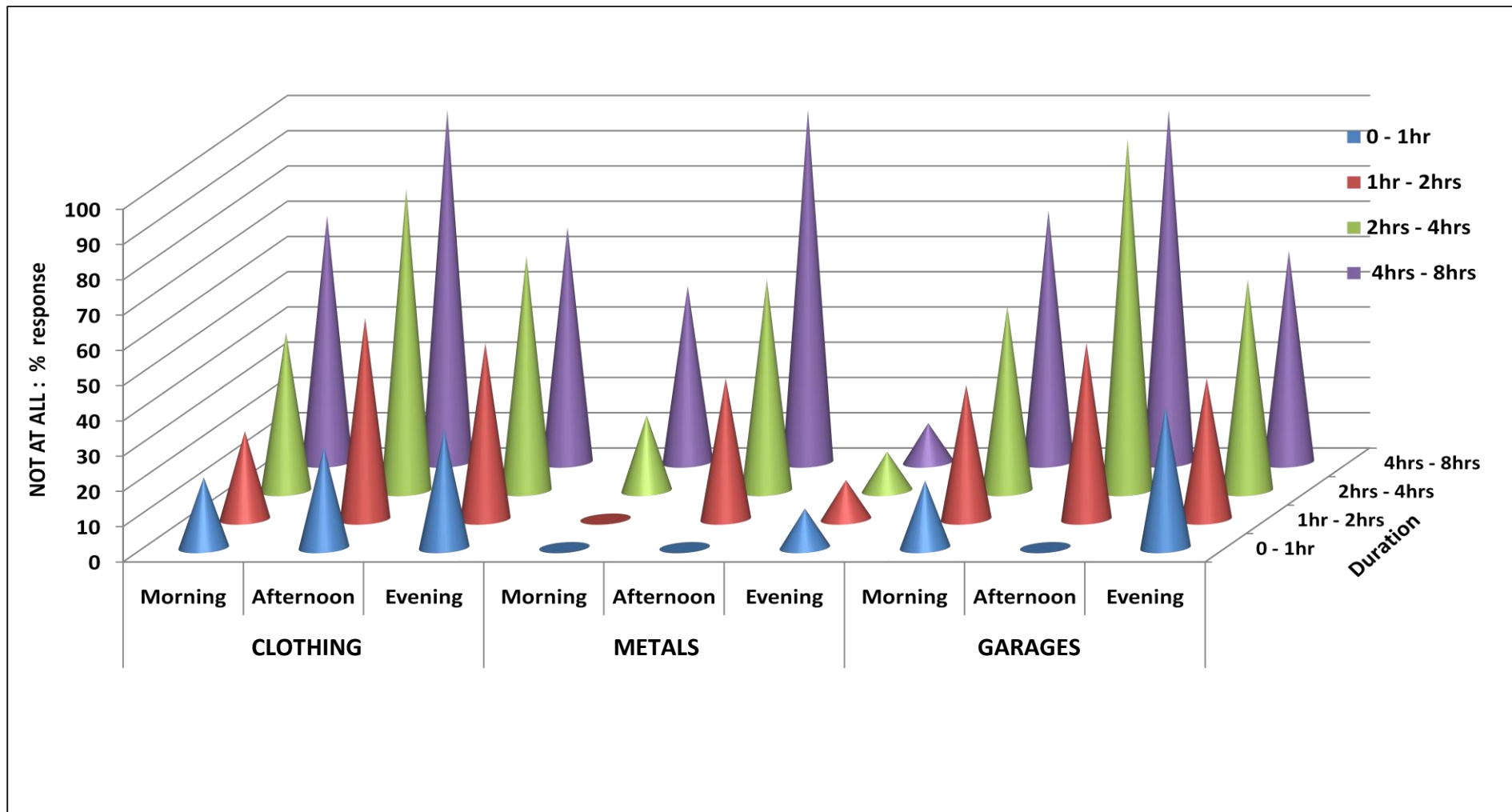


Fig 4.10: Variation of ability to make up lost production with duration, time of day and category for industrial population: The percentage of not able to make up for the lost production increases as duration increases. Afternoon has the highest percentage of respondents not able to make up for their lost production.

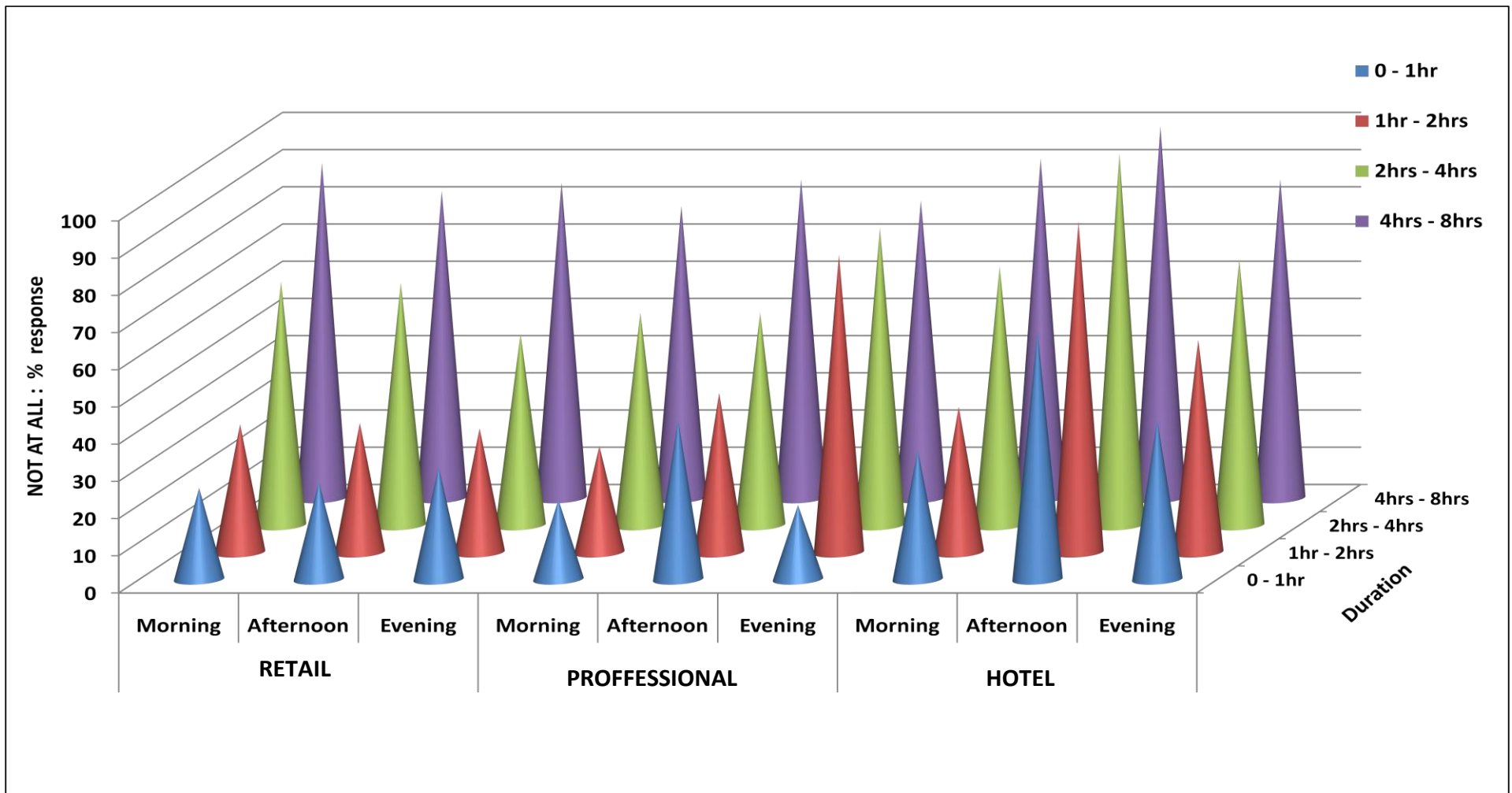


Fig 4.11: Variation of ability to make up lost production with duration, time of day and category for commercial population. The percentage of respondents who are not able to make up for the lost production is very much dependent on duration with the 4 – 8 hours having the highest percentage.

4.1.1.6 Ownership of Backup Power Supply

Respondents were asked to indicate whether they own a backup power supply at their premises. In addition the respondents were asked to indicate the type of backup power supply equipment, purpose, size, installation cost, running cost, year of installation and the percentage coverage of the plant by the backup power supply. The results show that only about 25% of the industrial population has indicated to have a backup power supply installed at their premise. Commercial population has a percentage lower, of about 13%. Over 50% of commercial respondents who indicated to have backup power supply have percentage coverage of their plant below 50%. The purpose of the backup power supply for commercial customers is mainly to maintain business e.g. for most retail shops only the emergency lights, computers and credit card pay point machines are kept running. In contrast to the industrial respondents, almost 50% of the respondents who have backup power supply have more than 80% plant coverage. More than 50% of the generators were installed between 2008 and 2009 (*Fig 4.11 below*). This is as expected since the year 2008 was the year that had most of the load shedding schedules.

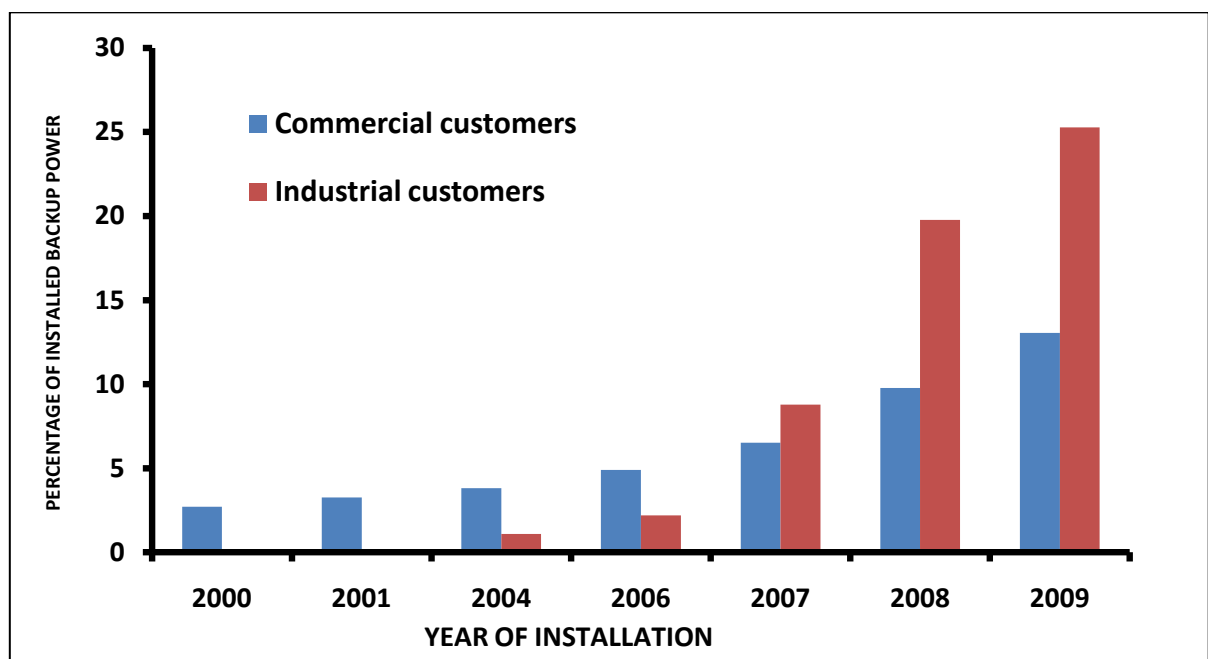


Fig 4.12: Cumulative percentage increase of number of backup power supply installed in each year by both commercial and industrial respondents to the total population surveyed in each respective group. There is a high increase in the number of backup power supply installed between 2006 and 2009.

The size of backup power supply equipment varies from 2.5kVA to 200kVA for industrial population and only two respondents indicated to have UPS i.e. 1.1kVA and 690kVA. For the

commercial customers only three respondents managed to give the size of their backup power supplies – generator i.e. 25, 30, 60kVA. The difference in both size and percentage coverage of backup power supply is possibly as a result of that, industrial customers incur higher interruption costs that commercial customers hence the need to backup their power supply to reduce the costs. No sizes of UPS were provided by respondents in this sector. Most of the respondents indicated that UPS does not have running cost. Additional results are presented in Appendix C1.

Table 4.9: Percentage of coverage of plant by both industrial and commercial populations

Proportion (%) of coverage of plant	Industry (% respondents)	Commercial (% respondents)
≤ 20	13.04	25.00
20 ≤ 50	17.39	37.50
50 ≤ 80	21.74	4.17
> 80	47.83	33.33

Table 4.10: Industrial population: Cost structure for backup power supply (Generator)

Item	Mean	Standard deviation	Number of observations
Installation cost (R/kVA)	1434.30	444.76	11
Running cost (R/kVA-hr)	7.76	2.14	12

4.1.1.7 Business Activity Level

In order to determine the variation of the business activity levels of the industrial and commercial populations with day of month, day of week and time of day, month of year, respondents were asked to estimate their average business activity levels from their busiest business activity level which was set on a scale of 0 – 10. The value of 10 means the busiest activity level and zero indicates that the business was not open. Table 4.11 below shows the variation of the business activity level for both populations. Additional results are presented in Appendix C2

Table 4.11: 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

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	Sunday (6pm – 8am)	Sunday (6pm – 8am)

4.2 CUSTOMER INTERRUPTION COST ANALYSIS

4.2.1 Model Selection

The objective of the modeling exercise was to identify CIC models that allow reasonably accurate prediction of power interruption costs for business customers. The information from the power interruption scenarios and firm characteristics of the survey respondents were used to develop the CIC models. The CIC models expressed power interruption costs as a function of outage duration, season, day of week, time of day and various customer characteristics such as average electricity bill, number of employees, and other variables. The ideal conceptual framework within which to analyse the above described data is statistical regression. As a result, simple linear regression analysis⁸ (standard Ordinary Least Square (OLS)) was found to be the appropriate method of analysis for the typical outage cost data.

Both theoretical approaches and empirical results were used as guides in the statistical analyses. The statistical regression analysis was done using STATA statistical package. Scatter diagrams were used to find the variables that have the highest coefficient of correlation value with power interruption cost. The variable or combination of variables was then used to generate the regression models. In addition, the variable was also used as the scaling factor to generate CDF for the respective customer segment. In conducting the analysis, a set of techniques was used to improve the estimation process. The typical distribution of power interruption costs in addition to having a large number of zeros will also often have very extreme values. In most power interruption cost studies using surveys, a great deal of attention is given to checking and confirming high values or excluding them if they appear to be inappropriate (due, for example, to calculation error or misunderstanding of the question). The Cook's distance⁹ and DFITS¹⁰ techniques were used to check for the influence of all the data values included in the analysis of the regression models.

⁸ See Chapter 7, "Correlation and Simple linear regression" in *Statistics for Engineers and Scientists*, W. Navidi, Second edition, McGraw- Hill, New York, 2008.

⁹ The lowest value that Cook's D can assume is zero, and the higher the Cook's D is, the more influential the point. The convention cut off point that was used in this analysis is $4/n$, where n is the total number of observations.

¹⁰ The cutoff point for DFITS is $2*\sqrt{k/n}$, where k is the number of variable in the analysis and n is the total number of observations. DFITS can either be positive or negative, with numbers close to zero corresponding to the points with small or zero influence.

The interruption attributes were taken as binary coefficients in the regression models i.e. take the value of 1 if present and zero if not present. Thus, the regression model equations were presented in the form of:

$$CIC [d] = a + \beta_1 \beta_2 \beta_3 B (X) \dots\dots\dots (4.1)$$

Where d is the duration of power interruption being studied, a is the regression constant, β_1 , β_2 and β_3 are the binary coefficients representing season, day of week and time of day respectively, B is the regression coefficient and X is the predictor variable being investigated. To simulate the outage cost (dependent variable) for a particular set of outage or customer characteristic, one multiplies the appropriate value for each binary coefficient times the regression coefficient of the predictor (independent) variable under investigation. This is then added to the regression constant (first entry for each model).

The accuracy of the regression model's prediction R^2 is expressed as:

$$R^2 = 1 - \frac{[\sum [y_i - \hat{y}_i]^2]}{[\sum [y_i - \bar{y}]^2]} \dots\dots\dots (4.2)$$

Where \hat{y}_i is the predicted value from the regression model for observation i , y is the actual value for observation i and \bar{y} is the mean for all observations.

The value R^2 is called the coefficient of determination. It expresses the strength of the relationship or association between the dependent and independent variables. It is also be used to define the amount of variation in the dependent variable that is explained by the regression line. The value R^2 varies from 0 to 1. When R^2 is 1, there is no prediction error, and the fit of the regression model is perfect. When it is zero, the prediction error is very large and the regression model has no predictive power at all. The other measure for describing the correlation between two variables is the coefficient of correlation r . The value r varies from 0 (when none of the observed variation in the dependent variable is accounted for by variation in the independent variable) to 1 (when all the observed variation in the dependent variable is accounted for by variation in the independent variable). The relationship between these two measurements of association is:

$$R^2 = (r)^2 \dots\dots\dots (4.3)$$

Only data sets that display coefficient of correlation (r) greater than 0.8 with the power interruption cost data is reported. The results are reported in terms of their R^2 .

4.2.2 Variation of CIC with Average Monthly Electricity Bill

N.B: Additional results are given in Appendix C3.

Interpretation of findings:

The results showed that there is a high linear correlation between power interruption cost and average monthly electricity bill. The coefficient of determination (R^2) values ranges from 0.599 to 0.998 for all the regression models presented. This means average monthly electricity bill was able to explain over 59% variance of power interruption cost incurred by business customers. This finding therefore implies that average monthly electricity bill is a useful variable in predicting the power interruption cost incurred by business customers. The linear correlation between power interruption cost and average monthly electricity bill was positive. The positive correlation means that there is an increase in power interruption cost as the average monthly electricity bill increases. Thus, for the same power interruption, business customers who pay high monthly electricity bills tend to incur high power interruption costs than those who pay less.

The power interruption cost incurred by business customers increases with the duration of power interruption. The increase become significant when a power interruption of 8 hour duration is experienced among the business customers. This means the longer the power interruption the higher the total power interruption costs incurred by business customers. The rate of increase of power interruption cost also increases as the duration of the power interruption increases. Therefore power interruptions of longer duration impose significant amount of power interruption costs on business customers. That is, a 1 hour power interruption have the least power interruption cost and an 8 hour power interruption have the highest power interruption cost.

Power interruption cost incurred by business customers was affected by the time of occurrence of power interruptions. Fig 4.12 and 4.13 below shows the seasonal variation of power interruption cost for the garages segment. The results showed that summer weekday morning costs are higher than winter weekday morning costs. This may be as a result of the increasing use of transport as people prepare for the holidays, for example Christmas holiday in December. For the 1 hour power interruption duration the power interruption costs are almost similar. The difference becomes significant as the duration increases.

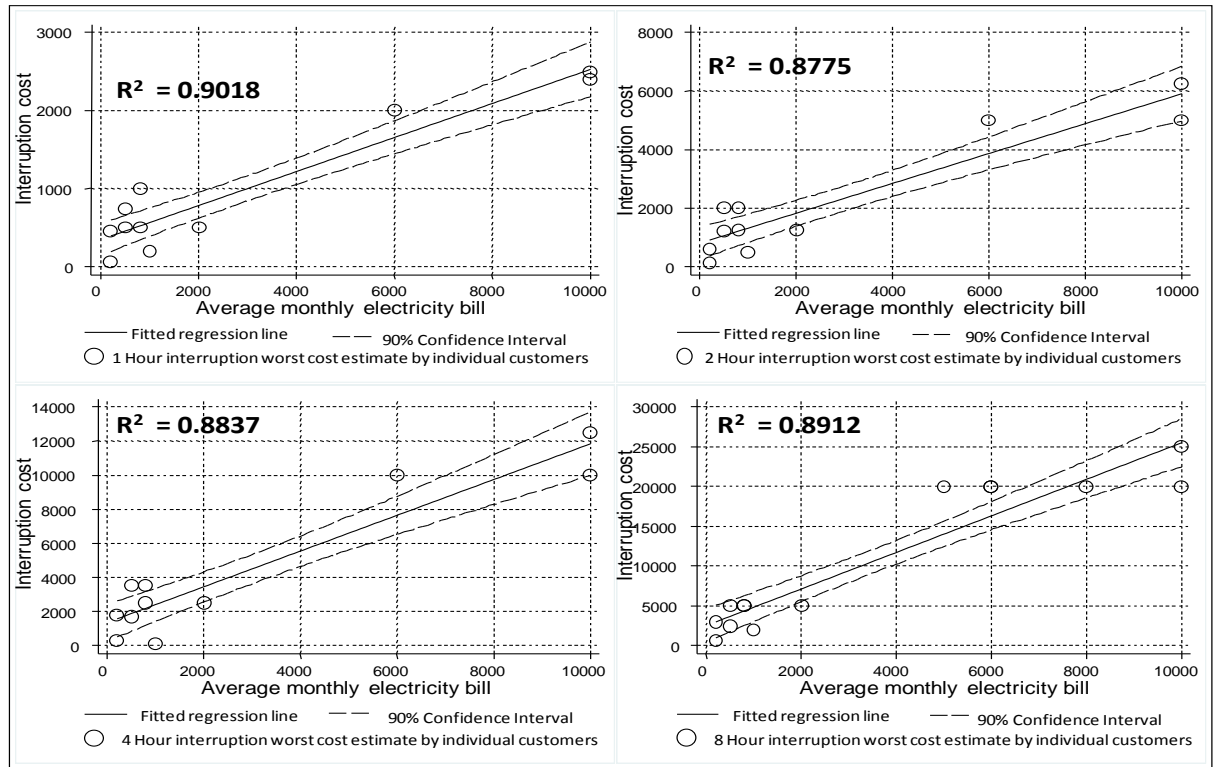


Fig 4.13: Variation of power interruption cost with average monthly electricity bill for a summer weekday morning power interruption: Garage Segment

Table 4.12: Regression model results for summer weekday morning cost estimate of Garage Segment

Duration (hr)	Regression Constant	Regression coefficient	Degree of Freedom
1	353.26	0.21	9
2	803.32	0.51	9
4	1350.19	1.04	9
8	2590.88	2.28	12

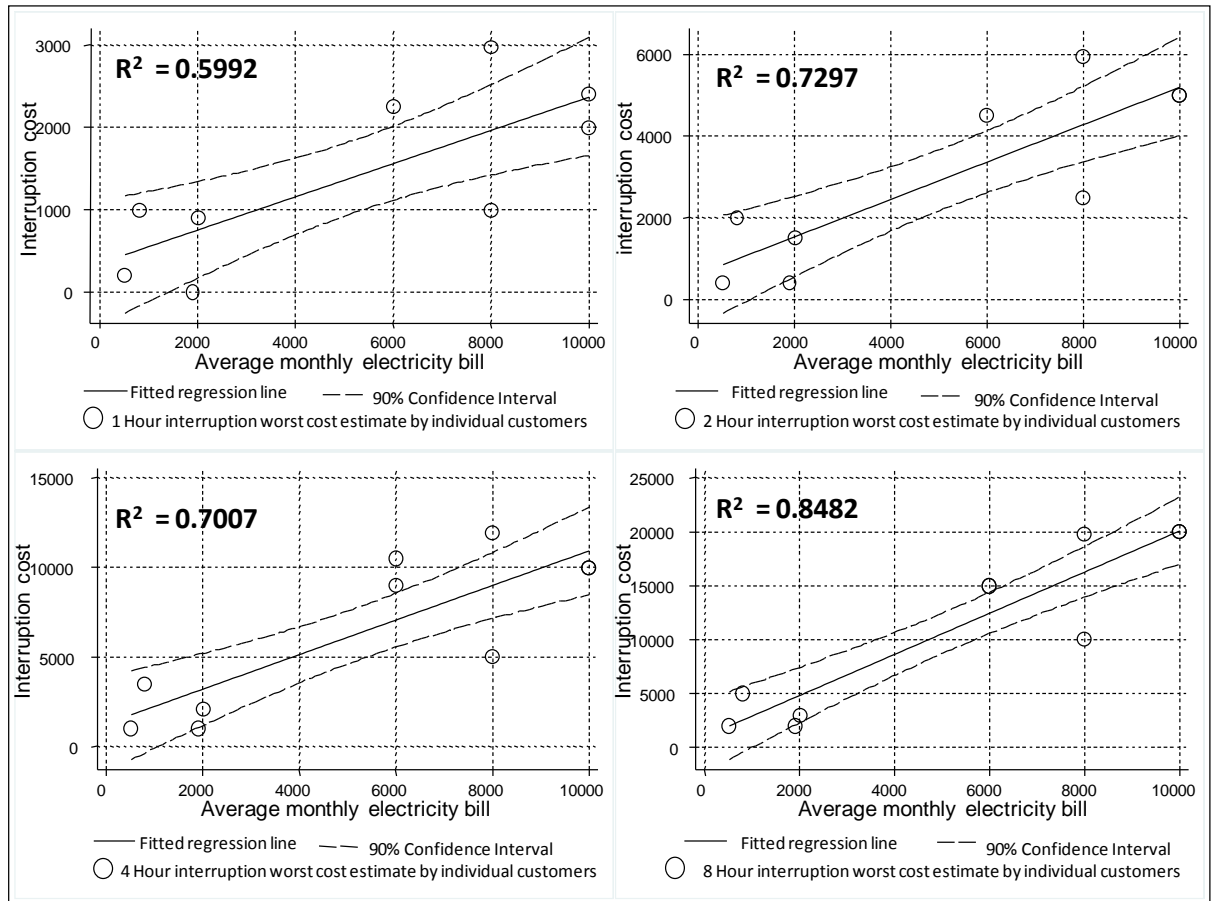


Fig 4.14: Variation of power interruption cost with average monthly electricity bill for a winter weekday morning power interruption: Garage Segment

Table 4.13: Regression model results for winter weekday morning cost estimate of Garage Segment

Duration (hr)	Regression Constant	Regression coefficient	Degree of Freedom
1	353.60	0.20	7
2	625.18	0.45	7
4	1264.96	0.96	8
8	1071.16	1.90	8

Fig 4.14 and 4.15 below show the results of clothing segment respondents who owns backup power supply equipment and those who do not, respectively. The results showed that business customers who own backup power supply tend to incur higher power interruption costs than those who do not have. This finding therefore suggests that respondents own backup power supply in order to reduce the impact of power interruption on their business. Results from the CDF generated (*Appendix C3.7, 8*) show that the power interruption cost for clothing segment respondents who do not have backup power supply increases very rapidly during the first four hours of power interruption. The rate of increase of power interruption cost then decreases after the fourth hour. This could be due to the fact that, after the fourth

hour the firms are expected to take mitigation measures in order to reduce the impact of power interruption such as sending employees back home. On the other hand, respondents in the same segment with backup power supply have their power interruption cost increasing between the second and fourth hour. The increase may possibly be as a result of some emergency backup power supply equipment running out of their fuel and the need to make other mitigation measures to reduce the impact of power interruption. The findings above imply that business customers can be grouped in terms of the investment they make to mitigate the impact of power interruption on their activities. Therefore it can be concluded from this analysis that there are two groups of business customers whose power interruption costs differ because of ownership of backup power supply equipment.

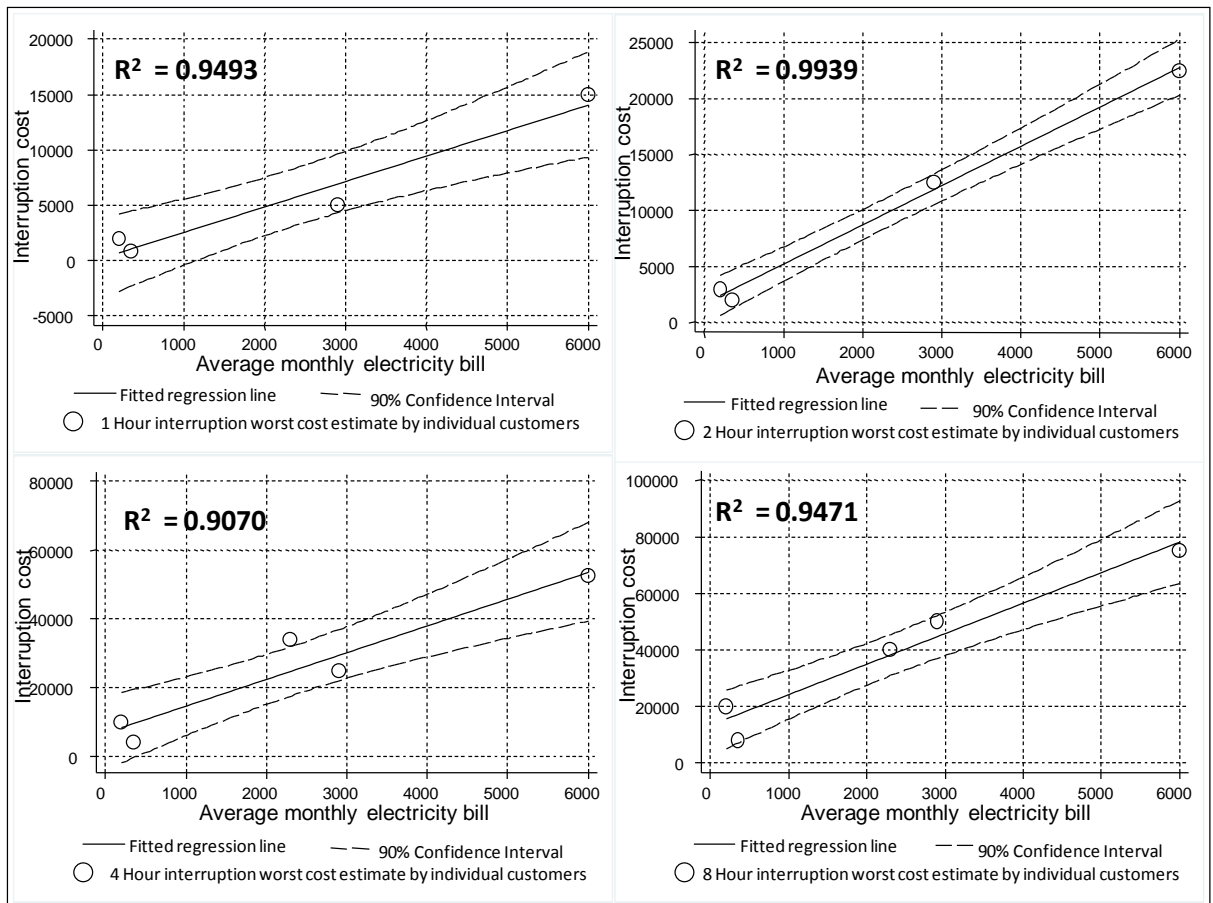


Fig 4.15: Variation of power interruption cost with average monthly electricity bill for summer cost estimate of Clothing Segment respondents with backup power supply

Table 4.14: Regression model results for summer cost estimate of Clothing Segment respondents with backup power supply

Duration (hr)	Regression Constant	Regression coefficient	Degree of Freedom
1	250.61	2.30	2
2	1711.50	3.50	2
4	6703.98	7.82	3
8	13225.28	10.79	3

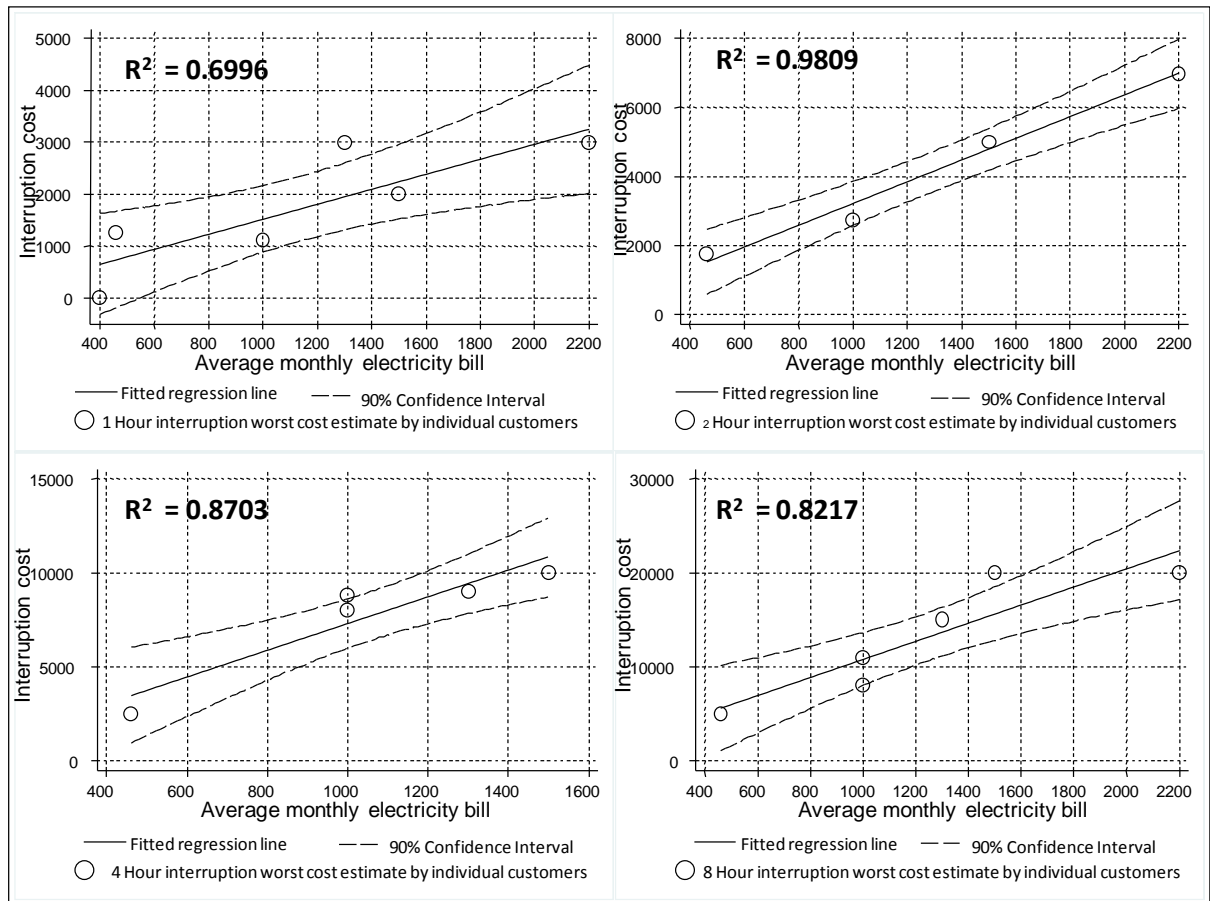


Fig 4.16: Variation of power interruption cost with average monthly electricity bill for summer cost estimate of Clothing Segment respondents without backup power supply.

Table 4.15: Regression model results for summer cost estimate of Clothing Segment respondents without backup power supply

Duration (hr)	Regression Constant	Regression coefficient	Degree of Freedom
1	76.35	1.44	4
2	71.20	3.14	2
4	241.80	7.05	3
8	1158.32	9.65	4

Results showed that the clothing segment customers have their power interruption cost far outstripping those of any other business activity. They incur more than double than those in

retail and garages segments for the same power interruption scenario. This finding therefore implies that different customer segments experience different power interruption costs for the same power interruption scenario. Therefore combining different customer segments to form one homogeneous group when estimating power interruption costs, may provide overestimate and/or underestimate to some customer segments. This makes customer segment a very important variable to consider in power interruption cost analysis. It therefore points out that significant difference in power interruption cost can be as a result of how business customers are defined.

It should be noted that in some cases the number of data points in the analysis are very low and therefore big gaps exists between data points. However, this cannot make the above mentioned conclusions invalid.

The positive regression constants of the linear regression models means a company with zero energy bill will incur power interruption cost. It is therefore clear that the regression constant is meaningless. Nonlinear regression analysis was therefore used in order to try and force the regression line models to pass through the zero point. The nonlinear regression analysis used was in the form of:

$$Y(d) = AX^b \dots\dots\dots 4.3$$

Where Y is the power interruption cost for duration d , A is the regression constant, X is the predictor variable (average monthly electricity bill), b is the power

Fig 4.16 below shows an example of how the linear regression line model would change for the Garages segment. The nonlinear regression model agrees with the assumption that for a zero energy bill, a business customer would incur zero power interruption cost. The graph shows that the nonlinear regression model generates smaller predicted values for both lower and high values of energy bill. The gradient is high at the start of the graph and it decreases as the average monthly electricity bill increases. This means that business customers who pay low average monthly electricity bill are more susceptible to power interruptions than those who pay more. The linear regression model predicts a constant increase in power interruption costs as the average monthly electricity bill increases. Hence, it overestimates the power interruption cost incurred by business customers in the early

hours of a power interruption and also later. However, it should be noted that the accuracy of the nonlinear models (R^2) is lower than that of the linear regression models. It was also seen that the power (b) to the predictor variable for the nonlinear regression models is close to one. Thus, the linear regression model can be regarded as the superior model for business customers who do not have close to zero and very large energy bill.

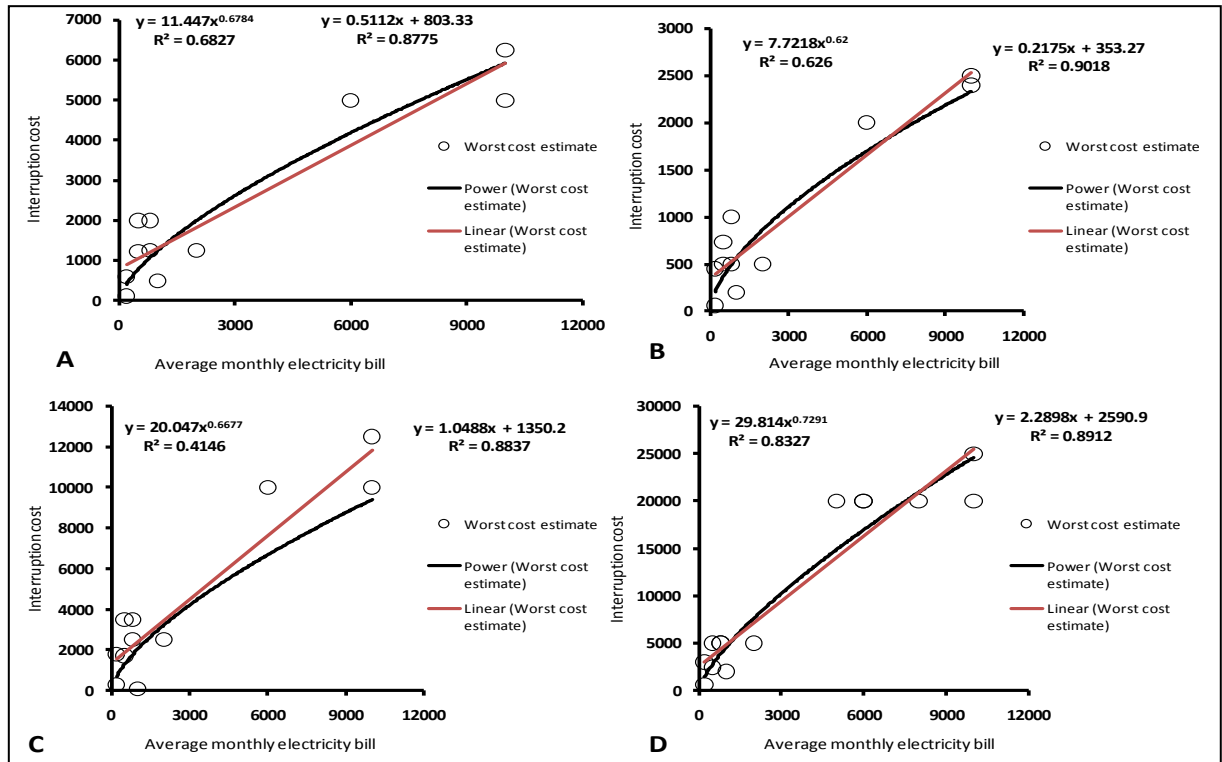


Fig 4.17: Variation of power interruption cost with average monthly electricity bill for a winter weekday morning power interruption: Garage Segment

4.2.3 Variation of CIC with Other Customer Characteristics

The relationship between the number of employees and the worst case cost estimates was examined using scatter grams. Fig 4.17 below shows the relationship between number of employees and worst case cost estimate for the hotel segment customers. Such scatter grams clearly indicated that there is no apparent linear relationship between the worst case cost and the number of employees. However, the accuracy of the quadratic regression models (R^2) is high but it was not consistent for all the customer segments. Similar scatter grams were prepared for the individual customer segments and levels of other user characteristics variables without any success in finding an apparent linear correlation. Therefore it was concluded that normalisation process using these variables does not reduce the variation of worst case costs. The variables were therefore dropped from the analysis.

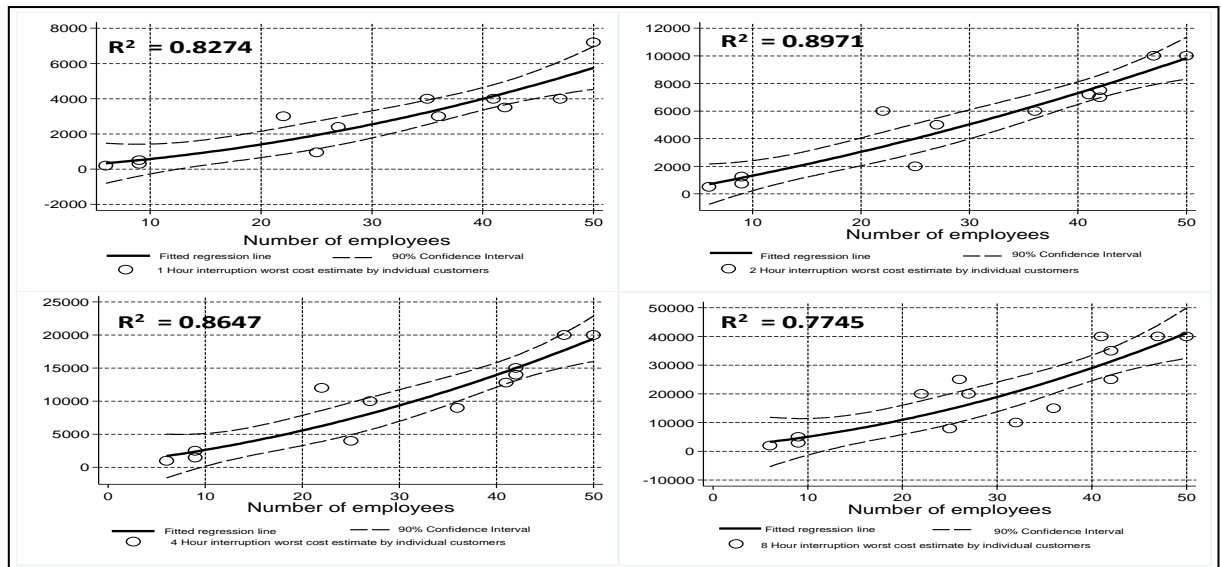


Fig 4.18: variation of power interruption cost with number of employees for a summer weekend morning power interruption: Hotel Segment

Table 4.16: Regression model results for summer weekday morning cost estimate of Hotel Segment

Duration (hr)	Regression Constant 1	Regression Constant 2	Regression coefficient	Degree of Freedom
1	1.55	36.00	61.79	10
2	1.34	132.24	140.31	10
4	4.22	166.90	540.55	10
8	10.43	276.92	1249.9	12

4.3 SUMMARY OF FINDINGS

This chapter presented the statistical analysis of the qualitative and quantitative data generated by the Comprehensive Questionnaire. The regression models and CDF developed are also presented. Table 4.17 below presents a summary of the outage costs for the different customer segments.

Table 4.17: Summary of outage cost for different customer segments

Customer Segment	Time of occurrence	Duration (hr)	Mean (Standard deviation)	Regression constant	Regression coefficient	Beta parameters	
						α	β
Retail	Summer weekday morning	1	0.82 (0.53)	86.79	0.78	-0.3891	-0.085
		2	1.02 (0.50)	198.37	0.96	-1.1032	0.0216
		4	1.72 (1.12)	377.75	1.66	-3.4181	1.4308
		8	5.52 (3.67)	754.49	5.31	-15.745	12.893
Clothing	Summer weekday morning	1	2.20 (1.44)	1203.36	1.56	-5.0009	2.7278
		2	5.48 (3.54)	1622.66	3.57	-16.215	13.256
		4	10.08 (6.82)	1837.79	7.72	-29.915	26.947
		8	20.30 (14.88)	2173.71	15.06	-56.220	53.451
Metal	Summer weekday morning	1	4.65 (6.37)	197.89	3.47	-6.5950	5.1767
		2	8.77 (12.66)	3022.81	4.39	-12.498	11.073
		4	14.08 (19.93)	6609.28	5.36	-20.608	19.144
		8	22.01 (33.62)	17072.90	5.03	-31.014	29.605
Garage	Summer weekday morning	1	0.74 (0.67)	353.26	0.21	-0.4228	-0.1486
		2	1.56 (1.23)	803.32	0.51	-2.4608	0.8834
		4	3.06 (2.76)	1350.19	1.04	-5.5922	3.7647
		8	4.82 (3.66)	2590.88	2.28	-11.445	9.0706
Hotel	Winter weekday morning	1	0.45 (0.18)	257.83	0.36	2.9875	3.6514
		2	0.92 (0.32)	376.97	0.78	-0.2588	-0.0225
		4	1.93 (0.95)	405.44	1.61	-5.7684	2.7796
		8	3.70 (1.93)	585.65	3.06	-13.6232	9.9413

Results show that duration, customer category, season, average monthly electricity bill and backup power supply equipment are important variables that should be considered when modeling CIC models for business customers. The next chapter will look at how these models can be used in practical way in reliability cost/worth assessment of a distribution system network. In addition the variation of worst cost estimate is investigated and how this method differs with the conventional method (CDF). A cost benefit analysis of installing isolators at designated points of the power system network is performed.

CHAPTER 5

RELIABILITY COST/WORTH FOR DISTRIBUTION SYSTEM PLANNING AND MANAGEMENT: CASE STUDY

The previous chapter presented the statistical analysis of qualitative and quantitative data generated by the CQ. In this chapter the developed CIC models are used together with a reliability model and a load model, in management and planning of two test distribution system networks. In the case study, the effect on the estimation of reliability indices such as ECOST from modeling customer interruption costs is investigated. A cost-benefit analysis of adding isolators in the power system network is carried out. This chapter concludes with the findings of the obtained simulation results.

5.1 RELIABILITY COST/WORTH ASSESSMENT OF A DISTRIBUTION SYSTEM

The first step in reliability worth assessment is to acquire the power system network data. The second is to decide the modeling approach to use and formulate the customer interruption cost, reliability and load models. The last step in the reliability worth assessment is to perform Monte Carlo simulations.

5.2 RELIABILITY COST / WORTH INDICES

The basic distribution system reliability indices are the three load point indices of average failure rate λ , the average outage duration r and the annual outage duration U [Billinton and Wang 1998]. Different system indices such as SAIFI and SAIDI can be calculated from these load point parameters [Billinton and Allan 1994]. Reliability cost indices such as expected interruption cost ECOST, expected energy not supplied EENS and interrupted energy assessment rate IEAR can also be calculated. A new reliability index is proposed based on the proposed CIC models derived in this thesis. The new reliability cost/worth indices is called the expected revenue not collected (ERNC). The equations used to calculate these indices are given in the following sections.

5.2.1 Reliability Model Parameters

The failure rates and the restoration times given in Table 5.1 below are adopted from Allan et al 1991. N.B: The failure rate for overhead lines is given in [f/yr-km]

Table 5.1: System Network components reliability data

System Components	λ_p [f/yr]	RT/ RpT [h]	SwT [h]
Transformers 11/0.4 kV	0.015	10	1
Breaker 11kV	0.006	4	1
Overhead lines 11kV	0.065	5	1

Where: λ_p - permanent (total) failure rate RT/ RpT - repair/replacement time
SwT - switching time

The probability distributions for the system network components are shown in Table 5.2 below, and are adopted from [Alvehag 2008]. Note that the probability distribution for the time to failure is exponential with the parameter λ given in Table 5.1.

Table 5.2: System Network components probability distribution

	Distribution	Standard deviation
Time To Failure (TTF)	Exponential	-
Repair Time (RT)		
Overhead lines	Lognormal	1 hr
Breaker	Lognormal	0.4 hrs
Replacement time (RpT)		
Transformer	Lognormal	1 hr
Switching time (SwT)	Lognormal	0.4 hrs
Reclosing time (RcT)	Lognormal	1 minutes

5.3 CASE 1: CASE STUDY DISTRIBUTION SYSTEM NETWORK

The small radial distribution power system network used in the case study is shown in Figure 5.1 below. This power system network is taken from RBTS Bus 2: Feeder 3. The lengths of the 10 overhead lines in the power system network are given in Table 5.3 and these are hypothetical values. The power system network has six load points and the information for all the electricity customers connected to each load point is given in Table 5.4. The power system network consists of one breaker F3 on the 11KV side of a 33/11 KV transformer (not shown in the diagram). It also has six 11/0.4kV transformers, T1 to T6, one at each load point. These transformers have fuses that prevent transformer failure to affect the rest of the power system network. At each T-junction or branch are isolators located on both sides

of lines and breakers, which enables the isolation of these components. The fuses and isolators are assumed to be 100% reliable.

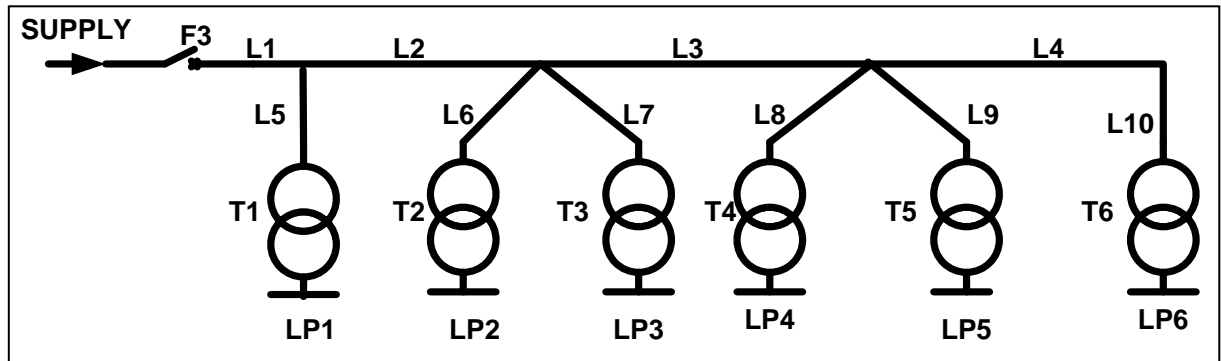


Fig 5.1: Case study distribution system network

Table 5.3: Length of the overhead lines for the Case study distribution system network

Line/ cable	L1	L2	L3	L4	L5	L6	L7	L8	L9	L10
Length (km)	1	2.8	2.4	1.8	1.4	1.5	1.8	1	1.5	2.6

Table 5.4: Load point data for the Case study distribution system network

Load point	Number of customers	Customer type
LP1	10	Industrial (Garage)
LP2	4	Industrial (Clothing)
LP3	15	Commercial (Retail)
LP4	6	Industrial (Metal)
LP5	9	Commercial (Retail)
	5	Industrial (Clothing)
LP6	4	Industrial (Garage)
	2	Industrial (Metal)

5.3.1 Formulation of CIC Model for Customer Segments

In this research study, a multiplicative approach with time-varying cost factors for modelling temporal variations in customer interruption costs is taken. The temporal variations of customer interruption costs with time day, day of week and month are modelled using two time-varying cost weight factors. This approach is described in detail in Billinton and Wangdee [2003], and Billinton and Wangdee [2005]. In this research study the influence on power interruption cost due to time of day and day of week is combined and is modelled through the time of day/day of week weight factor, $f_{h/d}$ and the influence due to month of year is modelled through the month factor, f_m .

The normalised power interruption cost for customer segments due to power interruption of duration d occurring at time t is calculated as:

$$COST_A(t,d) = f_{h/d} f_m C_A(d) \dots \dots \dots (5.1)$$

Where

$f_{h/d}$ is the time-varying cost weight factor for hourly deviation with respect to day of week from the reference time for customer segment A

f_m is the time-varying cost weight factor for monthly deviation from reference time for customer segment A

$C(d)$ = normalised reference (worst case) interruption cost for customer segment A due to a power interruption of duration d .

All the two cost weight factors model the deviation of power interruption from the surveyed reference outage event. When a power interruption occurs at the reference time all the two cost weight factors equal one, and the power interruption cost $COST(t,d)$, equal $C(d)$. The reference cost $C(d)$ can either be modelled using the CDF approach or a probability distribution approach that captures the dispersion in the cost data.

5.3.2 CIC Model Parameters

5.3.2.1 Reference (Worst Case) Power Interruption Cost

The reference worst case power interruption cost is taken as summer weekday morning cost for all the categories considered in the investigation. The CDF generated in the previous chapter for the respective customer segments are used in the analysis. The reference times given in Table 5.5 below were used to derive the time-varying cost weight factors for individual customer segments.

Table 5.5 Reference time for individual customer segments

Customer Segment	Reference Time (Individual Worst Case)
Retail	December: Friday 08 – 12
Clothing	December: Friday 08 – 12
Metal	September: Friday 08 – 12
Garage	December: Friday 08 – 12

5.3.2.2 Time-varying Cost Weight Factors

Table 5.6 and 5.7 below shows the time-varying cost weight factors. The business activity levels for the respective business customer segments were used to generate the

deterministic weight factors. The time-varying cost weight factor for the reference time was set to one and all the other cost weight factors were derived with reference to it.

Table 5.6: Values for time-varying factor that describes the temporal variations in interruptions cost between different day of week and time of day

Category	Day of week	Time of day					
		00 – 08	08 – 12	12 – 14	14 – 18	18 – 21	21 – 24
Retail	Weekday	0.02	0.91	1.18	1.20	0.52	0.01
	Friday	0.02	1.00	1.24	1.30	0.58	0.03
	Saturday	0.01	1.17	1.36	1.16	0.56	0.03
	Sunday	0.00	0.85	1.03	0.82	0.47	0.02
Clothing	Weekday	0.00	0.90	1.21	1.30	0.55	0.00
	Friday	0.00	1.00	1.30	1.43	0.65	0.00
	Saturday	0.00	1.27	1.45	1.41	0.63	0.00
	Sunday	0.00	0.88	1.14	1.06	0.46	0.00
Metal	Weekday	0.18	0.98	0.99	1.01	1.12	0.00
	Friday	0.18	1.00	0.98	0.98	0.06	0.00
	Saturday	0.19	0.83	0.83	0.57	0.00	0.00
	Sunday	0.09	0.53	0.42	0.15	0.00	0.00
Garage	Weekday	0.35	1.00	0.94	0.94	0.55	0.42
	Friday	0.35	1.00	0.94	0.95	0.56	0.49
	Saturday	0.45	1.03	0.89	0.92	0.54	0.53
	Sunday	0.34	0.87	0.59	0.62	0.31	0.28

Table 5.7: Values for time-varying factor that describes the temporal variations in interruptions cost between different months of the year

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec
Retail	0.80	0.75	0.72	0.71	0.64	0.65	0.65	0.66	0.75	0.82	0.93	1.00
Clothing	0.86	0.74	0.71	0.69	0.66	0.73	0.73	0.67	0.74	0.84	0.93	1.00
Metal	0.82	0.88	1.00	0.99	0.97	0.95	0.96	0.97	1.00	0.99	0.93	0.85
Garage	0.85	0.85	0.82	0.76	0.67	0.64	0.65	0.72	0.85	0.91	0.97	1.00

5.3.3 Load Model Parameters

The load model proposed is given in terms of the variation of average monthly electricity bill for the different segments investigated in this research study.

The average monthly electricity bill per hour levels were calculated using median values for the average monthly electricity bill obtained in the Cape Town customer survey presented in the previous chapters. A working day of 30 days was assumed in all the months. The mode of the average daily operational hours for each customer segment being investigated was used in the analysis.

Table 5.8: Average monthly electricity bill for the different customer segments

Customer Segment	Average electricity bill/hour (L') [Rand/hr]	Working Hours/day	Average monthly electricity bill (L) [Rand]
Retail	6.11	12	2200
Clothing	3.19	12	1150
Metal	15	10	4500
Garage	2.78	24	2000

5.4 CALCULATION OF REVENUE NOT COLLECTED (RNC)

The revenue not collected (RNC) can be defined as the amount of money that is equivalent to purchase the energy not supplied (ENS) by the power utility. It therefore expresses the ENS in monetary terms. This index can be valuable when the outage cost for the electricity customers is measured per energy bill. The equation that defines the index (RNC) is given below:

$$RNC = L' r \dots \dots \dots (5.2)$$

Where L' is the average electricity bill divided by the total number of hours in a given period and r is the outage duration experienced by the electricity customers.

5.5 MODELING APPROACHES

Three different modelling approaches have been adapted in order to investigate the impact of considering the dispersion in the customer interruption costs within each customer sector. The three models are parameterised according to the information given in Kivviko et al [2008] (*cited in Alvehag 2008*). The three modelling approaches considered are:

5.5.1 Approach 1

Customer interruption cost model

Customer interruption costs are modelled to depend on outage duration only. The reference (worst case) costs are modelled using the CDF approach and the two time-varying cost weight factors are set to one. Only average (mean) worst case cost values of the respective customers segments presented in Table 4.17 (*Chapter 4*) are used.

Reliability model

The system network component reliability data presented in Table 5.1 is used. The failure rates of the components are assumed to be constant and restoration times non-time

dependent. Standard deviations for time to next failure and restoration times are given in Table 5.2.

Load model

Load model parameters presented in Table 5.7 are used.

5.5.2 Approach 2

Customer interruption cost model

Customer interruption costs are modelled to be time dependent using the time-varying cost weight factors presented in Tables 5.6 and 5.7. The reference (worst case) costs are modelled using the CDF approach and only average (mean) worst case cost values of the respective customers segments presented in Table 4.17 (*Chapter 4*) are used.

Reliability model

The system network component reliability data presented in Table 5.1 is used. The failure rates of the components are assumed to be constant and restoration times non-time dependent. Standard deviations for time to next failure and restoration times are given in Table 5.2.

Load model

Load model parameters presented in Table 5.7 are used.

5.5.3 Approach 3

Customer interruption cost model

Customer interruption costs are modelled to be time dependent using the time-varying cost weight factors presented in Tables 5.6 and 5.7. The beta probability distribution approach is applied to model the reference (worst case) costs. The beta parameters are presented in Table 4.17 (*Chapter 4*).

Reliability model

The system network component reliability data presented in Table 5.1 is used. The failure rates of the components are assumed to be constant and restoration times non-time dependent. Standard deviations for time to next failure and restoration times are given in Table 5.2.

Load model

Load model parameters presented in Table 5.7 are used.

5.6 MONTE CARLO SIMULATION PROCEDURE

The time sequential Monte Carlo simulation technique was used in this thesis. It consists of steps 1 to 11 steps described below. The technique is applied to the three different modelling approaches described earlier. The simulation is performed on an annual basis, and the total annual hours are taken as 8760 hours. In the beginning of each year all components are assumed to be working. The weather condition is assumed to be normal for all the simulations performed. The analysis is done considering events consisting of failure in one component, no second order failures are considered.

Step1: Generate a random number for each component in the system and convert these random numbers into time to failure (TTF) values using the respective component failure probability distributions.

Step2: Determine the component with the least TTF value and its location in the system network that caused the failure event j

Step 3: Generate two random numbers for the component with the least TTF value and convert them into times to repair (TTR) and time to switch (TTS) using the appropriate probability distributions for the component repair and switching times.

Step 4: Identify the load points affected by the failed event j

Step 5: Determine the failure duration r_{ij} for the load point i in the system configuration

Step 6: Evaluate the revenue not collected (RNC_{ij}) and the interruption cost $COST_{ij}$ of the load point i due to the failure event j

$$RNC_{ij} = L_i \cdot r_{ij} \dots\dots\dots (5.3)$$

$$COST_{ij} = c_{ij} L_i \dots\dots\dots (5.4)$$

Step 7: Add the RNC_{ij} and the $COST_{ij}$ to their total values respectively.

Step 8: For each affected load point repeat step 5 – 7.

Step 9: If the total simulations time is less than the specified simulation time, go to Step 10, otherwise, go to Step 11.

Step 10: Generate a new random number for the repaired component and convert it into a new TTF and go to Step 2.

Step 11: Determine the total revenue not collected RNC_i and the interruption cost $COST_i$ of the load point i for the total simulation years

$$RNC_i = \sum L_i' r_{ij} \dots\dots\dots (5.5)$$

$$COST_i = \sum L_i c_{ij} \dots\dots\dots (5.6)$$

The expected energy not supplied $ERNC_i$ and the expected interruption cost $ECOST_i$ can be calculated using the following equations:

$$ERNC_i = RNC_i / N \dots\dots\dots (5.7)$$

$$ECOST_i = COST_i / N \dots\dots\dots (5.8)$$

where N is the total specified simulation period in years.

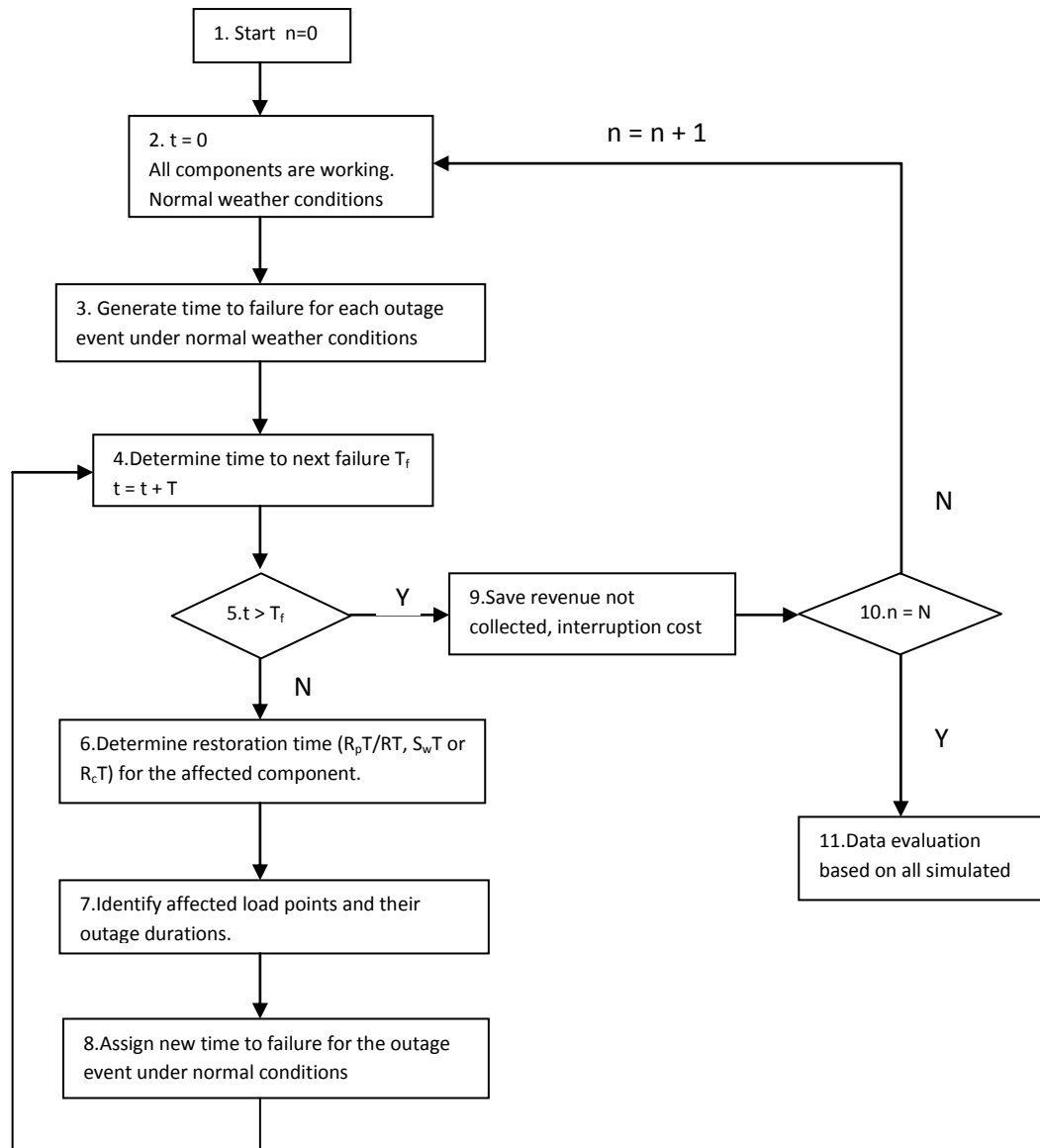


Figure 5.2: Flowchart for the Monte Carlo algorithm, where a time sequential simulation technique is used.

The program was developed using Matlab software. The set of reliability indices provided by the program include the load point cost/worth indices (ERNc and ECOST). The results are given in terms of their average values only. No probability distributions of the indices were done as it was considered to be outside the scope of this research study. A total of 5000 simulated years were performed for the simulations.

5.7 SIMULATION RESULTS FOR CASE 1

This section presents the results of the reliability worth assessment performed for the case study distribution system network presented in Fig 5.1. Fig 5.2 below presents the results of the average expected interruption cost (ECOST) for the six load points using the three different modeling approaches. The results showed that when time of occurrence of power

interruption is taken into account the interruption cost decreases compared to when the worst cost is used for all the power interruptions. ECOST is highest for modeling approach 1 and lowest for approach 2 and 3. It therefore points out that Approach 1 produces an overestimation of ECOST. The ECOST values for Approaches 2 and 3 are almost similar. This is because a large number of draws are made from the reference cost distribution in Approach 3 and therefore the average of the observed reference costs will converge towards the average value used in Approach 2.

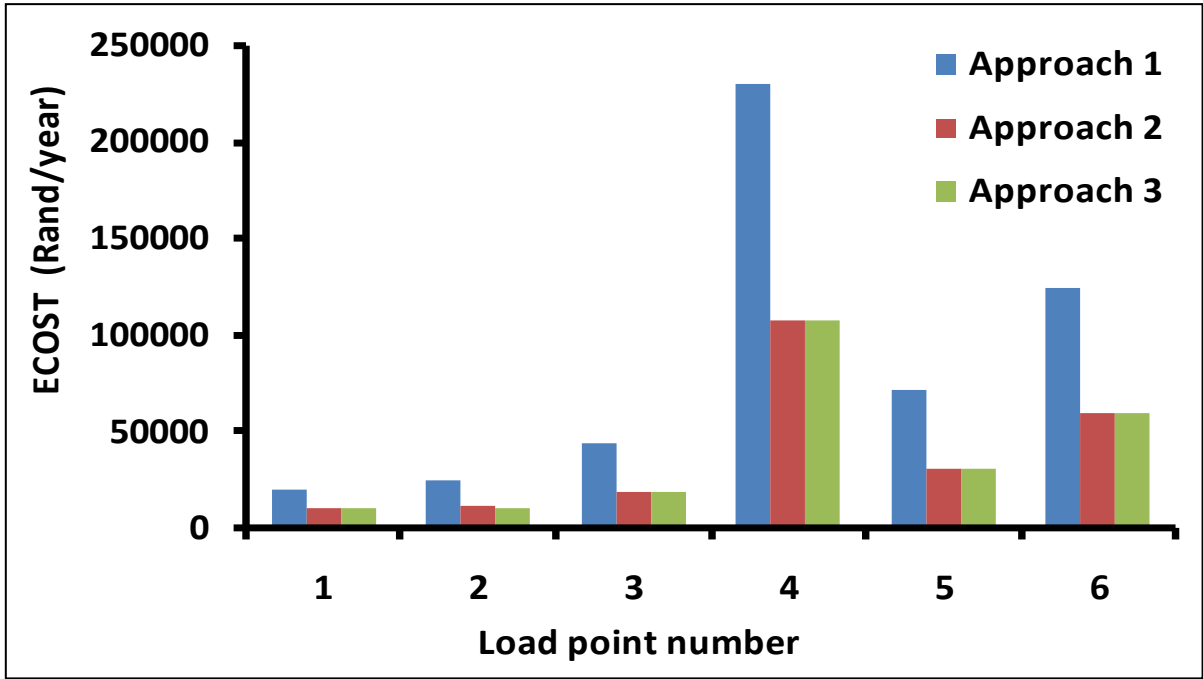


Fig 5.3 Variation of ECOST for different load points

In Fig 5.3 below, the expected revenue not collected (ERNC) for the six load points using the three different modeling approaches are shown. In approach 1 to 3, ERNC is approximately the same.

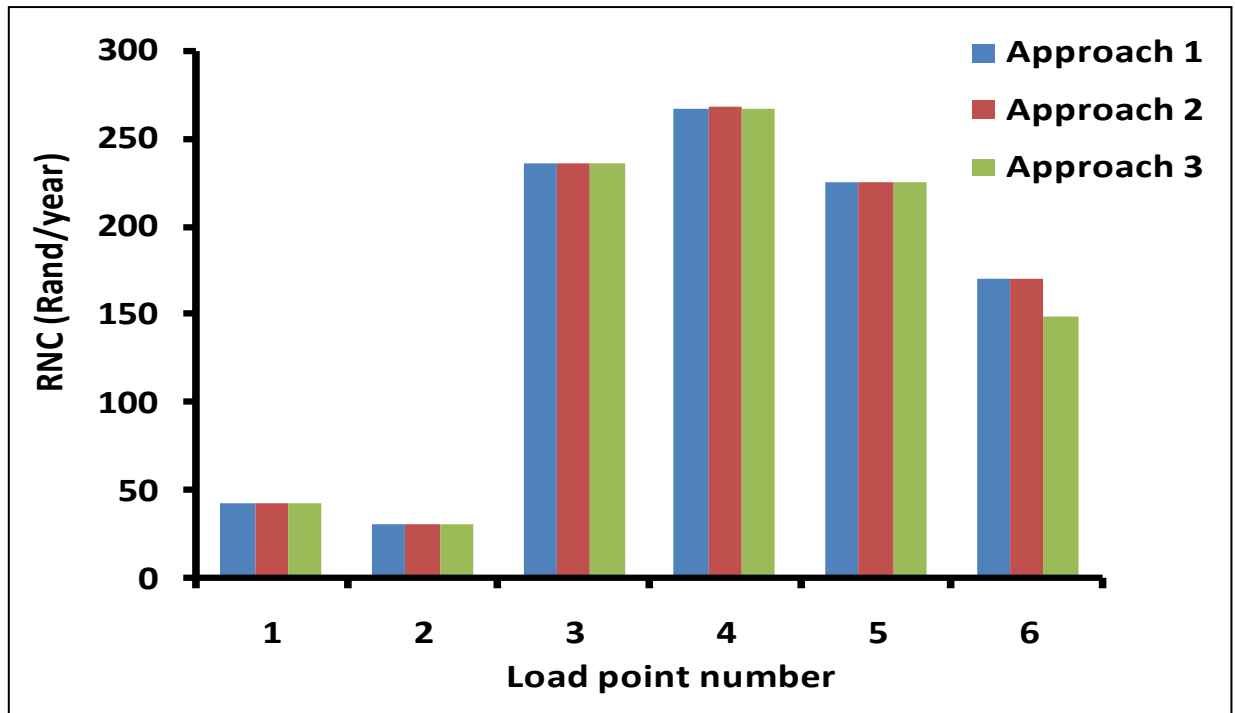


Fig 5.4 Variation of ERNC for the different load points

5.8 CASE 2: A COST/ BENEFIT ANALYSIS – INVESTMENT IN ISOLATORS

A commonly discussed action to increase power system reliability is to add disconnectors or isolators at designated places of the power system network. This investment action enables isolation of power supply to certain parts of the power system network while other parts remain with power supply. The reliability cost/worth assessment of the power system is done by considering two different distribution system network configurations of Fig 5.4 below:

Model 1: No isolators are considered along the main feeder lines

Model 2: Isolators are connected along the main feeder lines at every T – junction of the power system network.

For both system models Approach 3 was used and the ECOST and ERNC were derived.

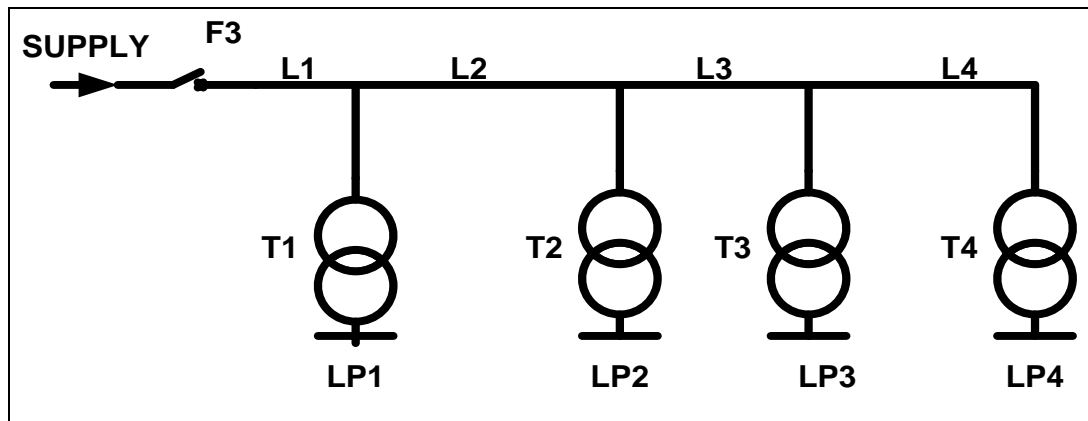


Fig 5.5: Power system network for Case 2

5.9 SIMULATION RESULTS FOR CASE 2

Fig 5.5 below presents the ECOST for the two system models. The results show that ECOST decreases with the subsequent modifications and investments in the power system network. The ECOST of load points 1, 2, 3 and 4 decreased by R12851.2; R5619.4; R2898; R130 respectively. Similar results were obtained for ERNC (Fig 5.6) where load points 1, 2, 3, and 4 decreased by R43.61; R15.96; R47.21; R0.03 respectively. It can be seen that by replacing isolators in the power system network the revenue not collected by the power utility and the expected interruption cost faced by customers is greatly reduced. The ECOST and ERNC values in this case can therefore be considered in conjunction with the investment, operation and maintenance costs associated with each alternative to select the optimum configuration of the system network. The values of ERNC are very small maybe because a small system network was considered and the number of electricity customers considered per load point is very few. Further research is needed to investigate whether these values can be included or excluded in the power system planning models.

Although no general conclusions can be drawn from this simple example, it can be noted that several previous studies have found that the inclusion of isolators in a power system greatly increases the power system reliability and is dependent on the location of placement [Billinton and Wang 1998].

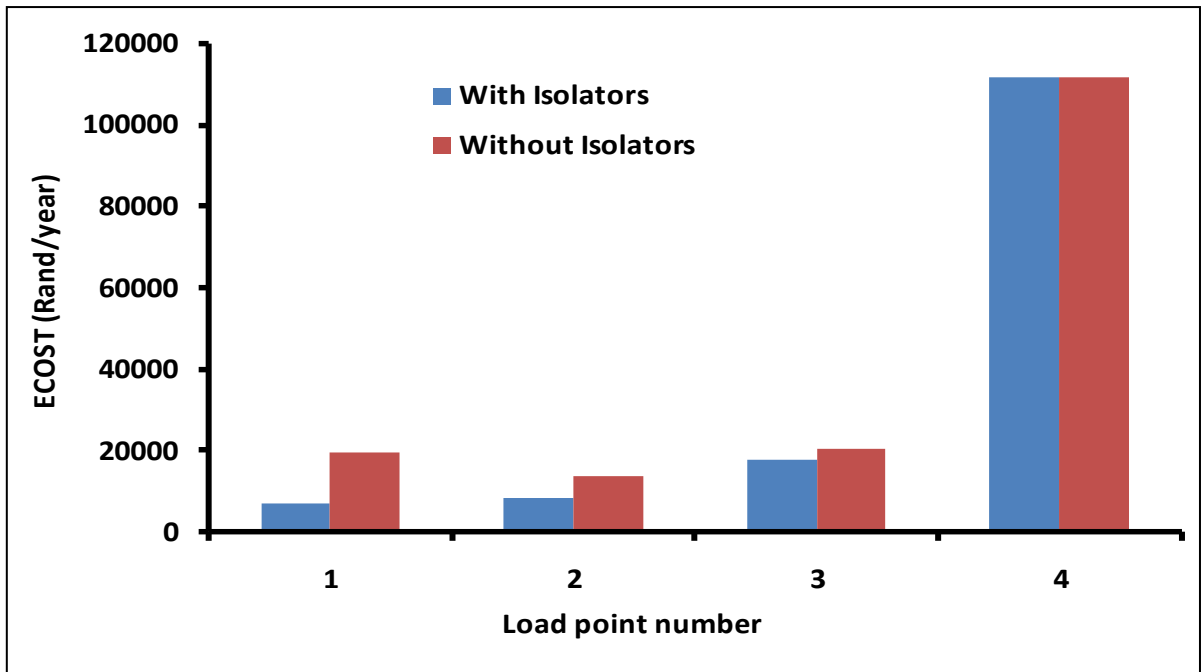


Fig 5.6: Variation of ECOST at different load points

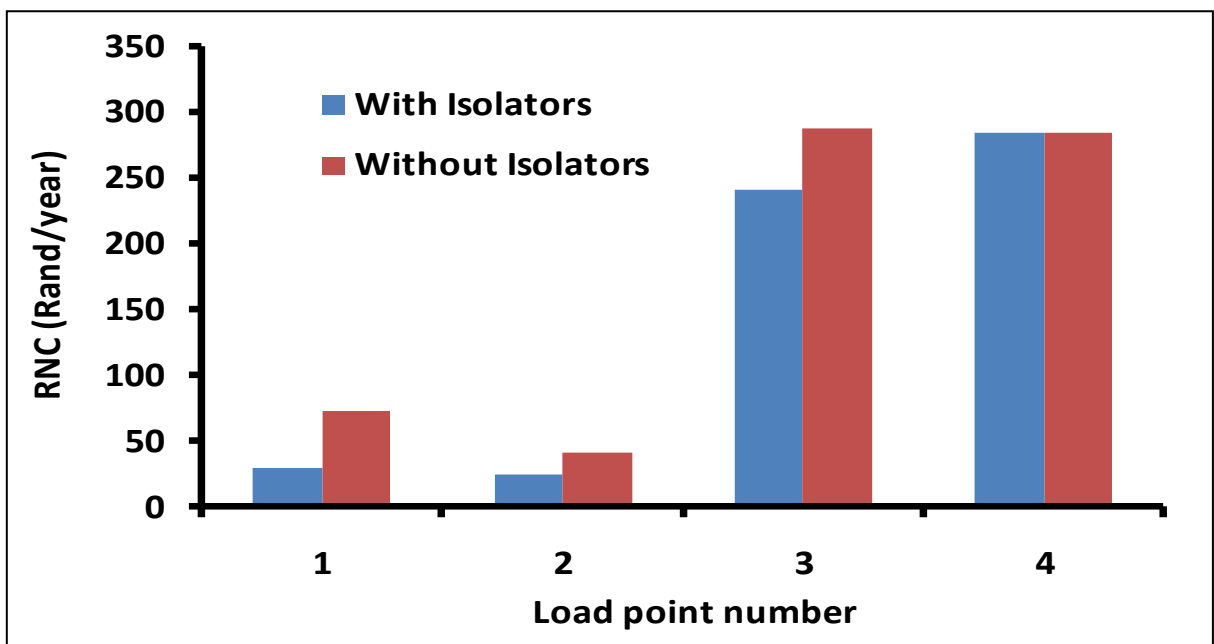


Fig 5.7: Variation of ERNC at different load points

5.10 SUMMARY OF FINDINGS

The simulation results have shown that accounting for time dependencies in customer interruption costs has a significant impact on the estimation of customer interruption costs and revenue not collected due to power interruptions. It was found that ignoring time variations in customer interruption costs severely underestimates the risks of extreme (high and low) values of power interruption cost. For Case 2, a cost benefit analysis of adding

isolator to a power system was performed. The results indicate that for a power system network with isolators the expected interruption cost is more than 10% less than when there are no isolators in the power system network. The inclusion of the isolators also shows that the power utility revenue collection is greatly improved.

CHAPTER 6

DISCUSSIONS, CONCLUSIONS AND RECOMMENDATIONS

This chapter concludes the thesis and areas of future work are discussed.

6.1 RESEARCH ACHIEVEMENTS

The hypothesis tested in this research stated that:

The distributed nature of the Customer Interruption Cost of business customers can be shown as a function of duration and other interruption variables such as frequency, time of occurrence (day of week, time of day, season), and depending on the customer class or segment and this can be applied usefully in planning and management of power system networks.

This research study has demonstrated that the customer survey conducted provides significant insight to the economic value placed by business customers to the power supply reliability. It has further proved the validity of the hypothesis through the statistical analysis done, by showing that customer interruption cost of business customers varies with duration and time of occurrence of power interruptions. It was also shown that power interruption cost for business customers is dependent on the customer segment or category. By use of case studies it was shown that the inclusion of time dependencies greatly improves the accuracy of CIC models. This enables the easy assessment of the impact of the network projects in all business sectors simultaneously within the planning and management of power system networks. Furthermore the case studies done in this thesis showed that the customer interruption cost estimates can be applied usefully in planning and management of the power system network by revealing the worst affected load points. This is an important aspect in planning because it gives provision for projects prioritisation depending on the economic value placed by electricity customers to the power supply reliability level provided.

6.2 DISCUSSIONS AND CONCLUSIONS

Reliability of power supply has and will continue to be a main concern for all the stakeholders in the power industry. Indeed the recent load shedding in South Africa highlights the significant public and private interest in power supply reliability.

However, ensuring reliable power supply to electricity customers is a complex and multi-faceted problem that essentially involves actions taken by both public and private decision makers. Numerous strategies can be employed to provide reliable power supply and some carry hefty tags. Developing the entire power system to achieve a standard reliability target level that costs more than the electricity customers are willing to pay or under-investment in the power system that leads to more power interruptions than electricity customers are willing to bear are both sub-optimal strategies. It is therefore important to consider the economic value attached to power supply reliability by electricity customers, so that noble public and private investments and operating decisions can be undertaken. The power system managers, designers, planners and operators seek to find the optimum level of supply reliability given the economic constraints. The efforts carried out by power utilities seeking to better understand the economic value of power supply reliability by conducting customer interruption cost studies is expensive. Consequently, only a few studies have been conducted. This research study was undertaken as a step towards addressing the current absence of consistent data needed to support better estimates of the economic value of power supply reliability.

The principal contribution of this research study has been to formulate and test the above stated hypothesis through the development of statistical models that can be used to estimate power interruption costs for business customers. These models can be applied to estimate power interruption costs for representative customers in different geographical regions of South Africa and beyond for a variety of power interruption scenarios. Power distribution planners, for example can use the results to estimate power interruption costs for particular customer classes or mix of customers representative of their service territory's customer base. They can, thus, improve generation, transmission and distribution planning processes. In case of the regulator, it can use the results to generate the compensations that can be given to a particular customer class for the different power interruption scenarios.

The results of this research study reveal many facets about CIC in business customers:

Predictor Variables:

The results of this study suggest that customer interruption costs in business customers (commercial and industrial) are linearly correlated to average monthly electricity bill. Of greatest significance is that average monthly electricity bill was supported as a strong or important predictor variable of CIC during this research study. Regarding average monthly electricity bill, a review of the statistical analysis suggests that business customers who pay high monthly electricity bill tend to incur high power interruption costs than those who pay less. It was also shown that, although the main predictor variable is energy bill for all customer categories, the relationship is different for each category. However, the nonlinear regression results showed that business customers who pay less monthly electricity bill are more susceptible to power interruptions than those who pay more. The relationship between power interruption cost and average monthly electricity bill was shown to be nonlinear at both extreme values of the average electricity bill. The general conclusion in this thesis is that the linear regression models were superior to the nonlinear regression models in predicting the power interruption costs of business customers for non-zero energy bill. Further research on different populations is suggested to help explain the importance of average monthly electricity bill as a predictor variable of power interruption cost in more detail. It was therefore difficult to make comparison with other research studies that uses different predictor variables of power interruption cost in business customers.

The linear correlation between power interruption costs of business customers and the other predictor variables: power interruption frequency, number of employees and average daily operational hours was very low – below the cut-off point of 0.8. Average monthly energy consumption and average monthly peak demand were not investigated in this thesis.

Customer Segments:

In general, business customers in the industrial sector tended to incur high power interruption costs than their counterpart in the commercial sector. These findings support Sullivan et al [1997] and Tiedmann [2004] arguments that industrial customers are more vulnerable to power interruptions than the commercial customers. This may be as a result of the finding that commercial customers have high ability to make up for lost production than industrial customers. The difference in the level of vulnerability between industrial and

commercial customers is revealed by the high number of industrial respondents who indicated to have installed backup power supply in the form of standby generators at their premises and the high percentage coverage of their plants.

From the segments investigated, results showed that different segment of customers are affected differently by the same power interruption. Therefore merging different segments of customers to form one segment may not actually yield a good model as in the traditional CDF approach. This is also in support of Tiedmann [2004] research finding that grouping customers into more homogeneous groups would allow for more accurate CC model. The fact that different segments are affected differently by the same power interruption can be used effectively by the power utility to schedule its load shedding programs for the different business customers. The information tends to support the research findings by Alvehag [2008] and has already been proposed in Sweden.

Mitigation Measures:

The findings in this research study revealed that, although business customers may attempt to save their revenue loss by using different mitigation actions like the use of backup power supplies, this strategy may not result in cost savings. The bulk of the costs come in the form of acquisition, maintenance and operation of very expensive backup power equipment. It was also found that business customers who own backup power supplies incur significantly high power interruption costs than those who do not. However, the decision to acquire a backup power supply is actually a rational decision on the part of the firm in order to insure itself from high revenue losses arising from power interruptions in their business activities. Furthermore, as the results of the analysis have shown, industrial customers are more heavily affected by power interruptions than commercial customers. In many instances some are unable to finance the cost of backup power supply equipment necessary to mitigate the negative impact of power interruptions. Hence, they have to bear the full burden of power interruptions. Regardless of the reason for the power interruptions in the business sector, the results of this study suggest that individuals whose businesses are interrupted may use more resources than they would have used if their businesses had been continuous e.g. use of backup power supply. Additional research is needed to validate these findings and explore the causes of power interruptions and the characteristics of CIC so that solutions to this problem can be developed.

Customer Interruption Cost Variation:

Commonly customer interruption costs are modeled as a function of power interruption duration. However, this research study has shown that the time of occurrence of power interruptions has a great effect on the consequences experienced by business customers. To describe customer interruption costs as realistically as possible it is therefore important to take time dependencies into consideration in addition to power interruption duration. For example, business activity level has a significant impact on the consequences of power interruptions for business customers. This thesis proposes a customer interruption cost model for business customers that incorporate time dependencies: business activity level patterns. In this way the model is able to capture extreme (high and low) values of power interruption costs. A conclusion that can be drawn from the simulations results is that taking time dependencies into account is very important when investigating the impact of power interruptions.

It is therefore clear from the results obtained in this research study that assigning a cost to the unserved energy (CUE) is not a good estimate of assessing the impact of power interruptions on electricity customers. Therefore the NERSA [2008b] value of R75/kWh cannot be used as a good estimate of how electricity customers of South Africa were affected by load shedding. From the regression models generated in this thesis the value changes with power interruption duration and category, but some average values might be identifiable.

In summary it can be concluded from the analysis conducted in this research work and described in this thesis that:

- Customer interruption cost in business customers varies with duration and time of occurrence of power interruptions.
- Different customer segments are affected differently by the same power interruption.
- Customer interruption cost is dependent on the customer class or segment.
- Customer interruption cost for business customers has a positive linear correlation with average monthly electricity bill and the relationship is different for each category.
- Business customers who pay low average monthly electricity bill are more susceptible to power interruptions than those who pay more.

- Business customers in the industrial sector incur higher power interruption costs than those in the commercial sector.
- Business customers who own backup power supply incur higher power interruption costs than those who do not have.
- Business customers can be grouped by the investments they make to mitigate the impact of power interruptions.
- Consideration of the dispersed nature of power interruption costs in reliability worth assessment can result in significant differences of reliability cost/worth indices and should be recognised in the evaluation.
- Time varying cost models provide more accurate estimates for the reliability cost/worth indices than those obtained using average cost models
- Reliability cost/worth indices provide an opportunity to include customer concerns into system planning, operation and expansion.

6.3 LIMITATION OF THE STUDY

The conclusion from this effort is that the regression models are producing reasonable estimates of power interruption costs for both commercial and industrial customers. However, a few limitations of this research study should be noted. This research study examined power interruptions in business customers with the use of hypothetical scenarios and did not test whether power interruptions in business customers led directly to the customer interruption costs. It must also be noted that, since linear regression model was used for the basis of quantitative analysis, findings should not be inferred to equate causation. Equally, although collinearity analyses are addressed, interaction effects should not be discounted in studies of very complex phenomena such as CIC. In addition to problems with the collinear nature of the data, the results also show that there is insufficient data for some key variables (some excluded in the analysis), which precludes the effects of those variables from being tested. For example, data on energy consumption or peak load could not be included in the prediction models because these variables were not available for the majority of the cases. Individual business segments were combined to form one homogeneous group so that a bigger sample size could be obtained and this have an influence on the accuracy of the CIC models. Addressing these issues will require future

studies that collect data comprehensively across South Africa rather than what exists today as a series of independent studies by universities or utilities.

Moreover, returning to the theoretical constructs surrounding CIC in business customers, it can be argued that, by its very nature, this dependent variable encompasses far more independent variables than are included in this research study. Future studies investigating more or different variables might help to explain the differences in coefficient analyses. Additionally, studies using both linear and non-linear regression on variables not included in this research study would contribute greatly to the further explanation of CIC in business customers. It is also important to point out that in this analysis the region is closely associated with this individual study. Since most regions are based on a single utility study, the results may compound the effects of methodological differences, climate differences, and unique market conditions. Also, as noted previously, the results do not include any data other than from Cape Town and mostly small scale industrial and commercial customers were surveyed.

Nevertheless, the results of this study serve as a starting point for further investigation of the effects of power interruptions in business customers.

6.4 RECOMMENDATIONS

This study is part of a continuous effort to improve the public availability of information on the economic value of power supply reliability. To address some of the limitation in the current data, I recommends the following:

1. Encourage all S.A electricity providers that have conducted surveys on the economic value of power interruptions to their customers to contribute these data and thereby enhance the coverage and usefulness of these data on a national scale.
2. Support future power utility efforts to collect additional information on the economic value of power supply reliability toward ensuring that ultimately these data also contribute to improving the availability of this type of information on a national basis, by use of consistent methodology for survey design and sampling.
3. Support efforts to conduct additional surveys on topics of high priority. For example collect new data in areas of the country or other electricity customers (large business customers) or on other reliability topics.

In case of this research study, it was observed that business customers had a wide varying cost estimates in relation to the duration of power interruption. The author of this research study, therefore, encourage other researchers in the reliability studies to investigate this phenomenon in further detail, as well as to explore the influence of additional independent variables in the CIC assessment of business customers. Another important area of further research is to examine the institutional transformations that can enhance the public sector delivery of electricity. It is very obvious from the research study that private generation is inefficient relative to that by the public sector. There is need for a comprehensive study of the institutional structure of the power suppliers (Eskom and Municipality of Cape Town) in South Africa and how effective reforms could be carried out to ensure its effectiveness. Likewise, the re-examination of energy policies for electricity customers with great reliability requirement (including individual electricity customers) would also help. Policies that provide individual case management to these at-risk customers might help stabilize their business, for example reliability fee program. Assuming that universal electricity rates with a fixed rate is not working properly; the reliability fee program might enable such individual electricity customers to remain in the business while also maintaining their access to electricity supply and avoiding business shutdowns.

Additionally, state organisations responsible for power supply programs like NERSA might consider steps that enable electricity customers to easily maintain their backup power supplies or giving shopping malls or big companies subsidised backup power supply equipment or fuel. Such steps might reduce the frequency of power interruptions and the cost of administering power reliability benefits. However, this approach assumes that simply giving subsidised backup power supply equipment will ensure that all electricity customers will be able to afford it, which may not be the case. A somewhat challenging issue might be to assess whether backup power supply by shopping mall owners are more beneficial in reducing power interruption costs in business customers as opposed to the normal power supply from the power utility. Along these lines, the power utility can engage the shopping mall owners in providing maintenance and schedules of power interruptions. Further research and contributing dialogue in the professional literature would be needed to investigate this phenomenon in more detail. If power utilities are seeking to reduce the use of electricity among business customers the encouragement of efficient equipment use may also be a better solution than trying to reduce service use by load curtailment.

Finally, increasing socioeconomic pressures to create safe and reliable power systems are being exerted on power utilities by governments, environmental groups and society in general. I hope that the material presented in this thesis will play a significant role in finding acceptable solutions to such pressures and will encourage the increased use of reliability techniques in practical applications.

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APPENDIX A

A.1 SAMPLE 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***

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?***

OLIVER DZOBO
UCT MSc STUDENT
University of Cape Town
Department of Electrical Engineering
Power Engineering Group: Room 455
Private Bag 7701
Rondebosch
E-mail: oliver.dzobo@uct.ac.za
Phone No: 0027 216502936
11/05/2009

SECTION A

The items in this section relate to your experience about power interruptions at your organisation. In completing this survey, a power outage refers to a complete loss of electricity to your organisation. It is assumed that your organisation have been given adequate advance warning about the power outage to occur.

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

1.2 How satisfied are you with the number of outages your organisation has experienced in the last 12 months



1.3 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 1 hour to 2 hours	Once a week			
	Once a month			
	Once every 6 months			
	Once a year			

SECTION B

Now we want to ask you about the mitigation measures you have implemented in order to reduce the risk of power outages to your organisation

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: _____

Outage Cost Measurement

The next questions describe two different power outage scenarios. We would like to know the costs to your organisation of adjusting to each of these power outages. For many organisations, the costs incurred depend upon the particular situation, and may vary from day to day depending upon business conditions. So for each power outage scenario you will be given the opportunity to report the worst cost estimate that your organisation might face under the conditions given.

2.2 **Case 1:** On a **summer weekday 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 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 costs for the highest cost case that you would experience **without considering backup power supply**.

R _____

Highest total outage cost (Worst case)

2.5 With reference to **Case 2**, 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: _____%

2.6 Suppose that the power outage has occurred during the **morning** and 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				

SECTION C

Some background information about your organisation will help us understand how power outages affect your type of organisation. All of your answers are strictly confidential. The information will be used only to report comparisons among different types of organisations. We will never identify individuals or organisations with their responses.

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 daily 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 leather industries	Hotel and restaurants
Any other- please specify:	

In the following questions we want to understand your business activity levels for the different period or time given below.

3.5 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

IMPROVEMENTS:



THANK YOU FOR YOUR PARTICIPATION

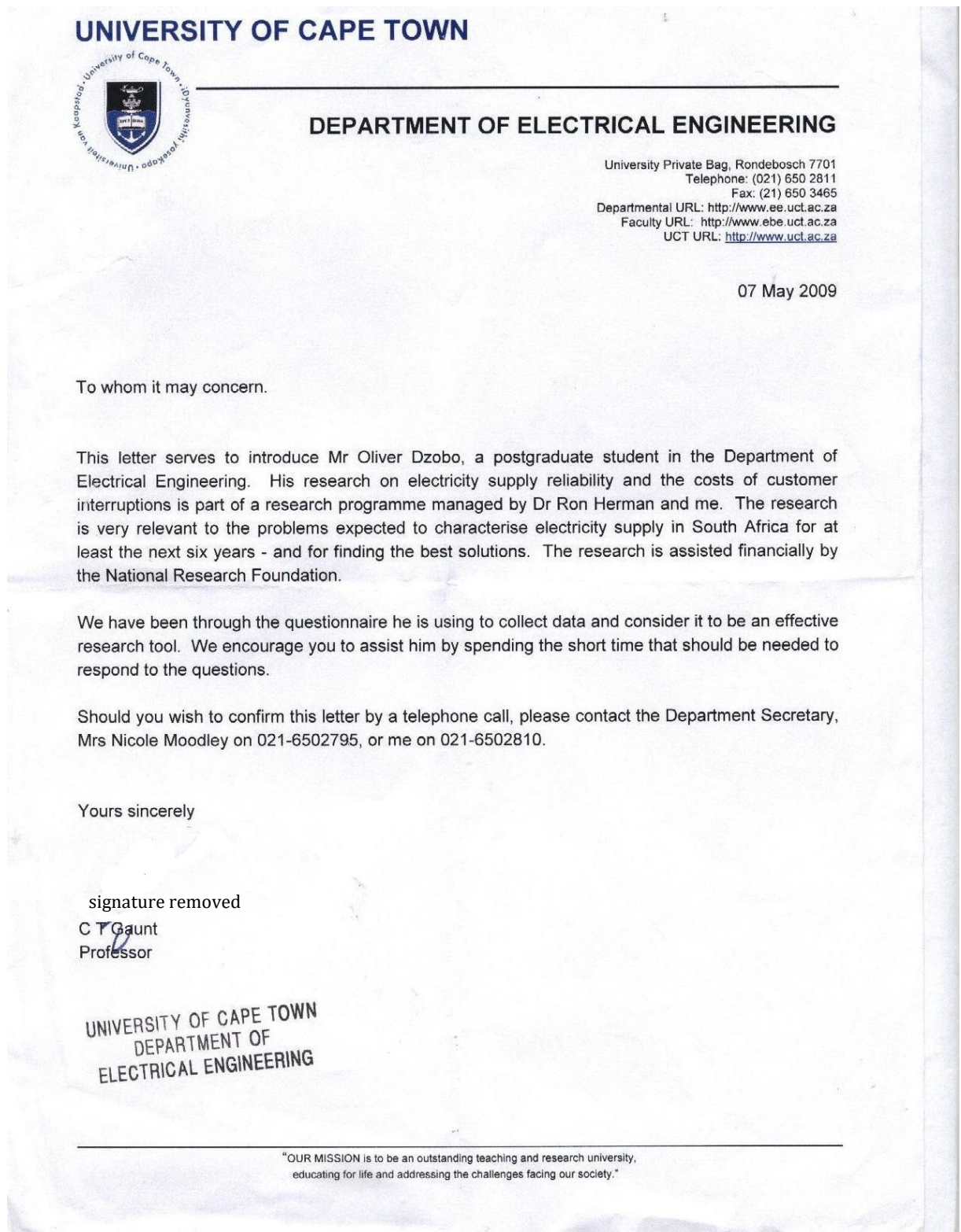
Please return this survey to:

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

APPENDIX B

B1 LETTER OF INTRODUCTION

Fig B1.1 Letter of introduction given to respondents before they answer the comprehensive questionnaire



B2 CODING AND SCORING MEMORANDUM

Table B2.1: Item coding and scoring memorandum for Q1.2 of Section A –Satisfaction level towards the frequency of power interruptions scale

Item No	SCORING OF RESPONSES				
	Very Satisfied	Satisfied	Neutral	Dissatisfied	Very Dissatisfied
1. Satisfaction Level	5	4	3	2	1

Table B2.2: Item coding and scoring memorandum for Q1.3 of Section A– Power System Reliability Level Preference

A.

Item No	SCORING OF RESPONSES			
	Few minutes to 1 hour	1 hour to 2 hours	2 hours to 4 hours	3 hours to 8 hours
1. Duration of Load shedding	1	2	3	4

B.

Item No	SCORING OF RESPONSES			
	Once a week	Once a month	Once every 6 months	Once a year
2. Frequency of Load shedding	1	2	3	4

C.

Item No	SCORING OF RESPONSES		
	Acceptable	Unacceptable	Do not know
3. Acceptability of load shedding	1	2	3

Table B2.3: Item coding and scoring memorandum for Q2.1 of Section B – Power interruption mitigation measures

A.

Item No	SCORING OF RESPONSES	
	YES	No
1. Ownership of backup power equipment	1	0

B.

Item No	SCORING OF RESPONSES		
	UPS	Standby Generator	Others
2. Type of backup power equipment	1	2	3

C.

Item No	SCORING OF RESPONSES		
	Lighting	Computers	Others
3. Purpose of backup power equipment	1	2	3

Table B2.4: Item coding and scoring memorandum for Q2.2 – Q2.4 of Section B – Outage Cost Measurement

A.

Item No	SCORING OF RESPONSES			
	1 hour	2 hours	4 hours	8 hours
1. Duration of power outage	1	2	3	4

B.

Item No	SCORING OF RESPONSES	
	Summer	Winter
2. Season	1	2

C.

Item No	SCORING OF RESPONSES	
	Weekday	Weekend
3. Day of week	1	2

D.

Item No	SCORING OF RESPONSES		
	Morning	Afternoon	Evening
1. Time of day	1	2	3

Table B2.5: Item coding and scoring memorandum for Q2.5 of Section B – Ability to make up lost production

A.

Item No	SCORING OF RESPONSES		
	Morning	Afternoon	Evening
1. Time of day	1	2	3

B.

Item No	SCORING OF RESPONSES			
	Less than 1 hour	Between 1 hour to 2 hours	Between 2 hours to 4 hours	Between 4 hours to 8 hours
2. Duration of power interruption	1	2	3	4

C.

Item No	SCORING OF RESPONSES			
	Not at all	Partly	Mostly	Not needed
3. Ability	1	2	3	4

Table B2.6: Item coding memorandum for Q3.4 of Section C – Categories of respondents

Business Segments	Description of segments
Retail	Retail shops, food and non –food
Professional	Professional practices (legal, finance, engineering consulting)
Offices	Commercial and government offices
Clothing	Clothing textile, furniture, and leather industries
Metal	Metal and Engineering industries
Garages	Service stations, garages, auto workshops
Warehousing	Warehousing, distribution, transport
Hotel	Hotel and restaurants

Table B2.7: Item coding and scoring memorandum for Q3.5 of Section C – Business Activity Level

A.

Item No	SCORING OF RESPONSES			
	Weekday	Friday	Saturday	Sunday
1. Day of week	1	2	3	4

B.

Item No	SCORING OF RESPONSES					
	00 – 08	08 – 12	12 – 14	14 – 18	18 – 21	21 – 24
2. Time of Day	1	2	3	4	5	6

C.

Item No	SCORING OF RESPONSES		
	Beginning of Month	Mid – Month	End of Month
3. Time of Month	1	2	3

D.

Item No	SCORING OF RESPONSES											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec
4. Month	1	2	3	4	5	6	7	8	9	10	11	12

Table B2.8: Item coding and scoring for Q3.6 of Section C – Reduction of the impact of Load Curtailment by power utility

Code	Improvement
0	No response
1	Energy efficient equipments
2	Load shedding outside trading hours (mid-night to early hours of the morning 600hrs)
3	Advance warning + Stick to load shedding schedule

APPENDIX C

ADDITIONAL SURVEY RESULTS

C1: Ownership of Backup Power Supply Equipment by Industrial and Commercial Populations

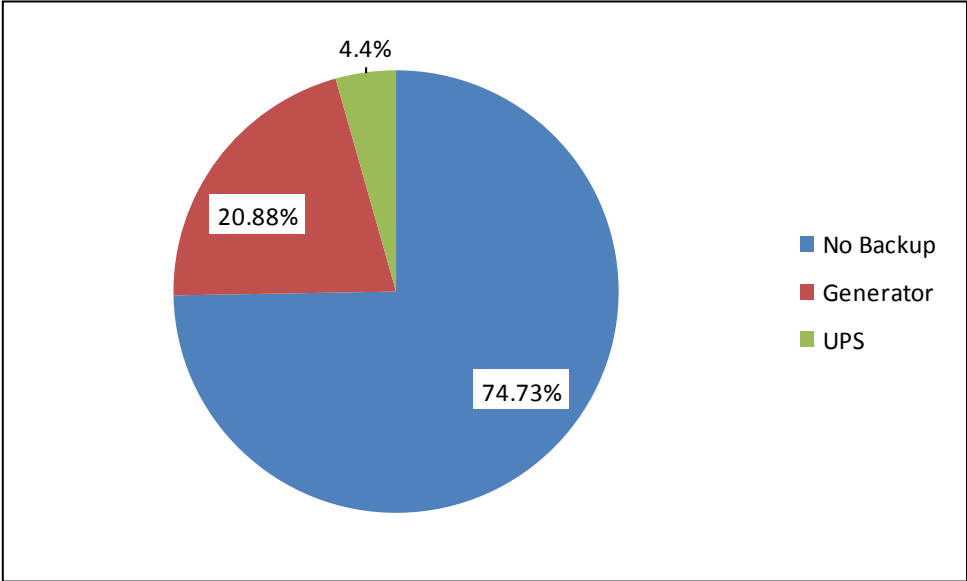


Fig C1.1: Ownership of backup power supply by industrial respondents

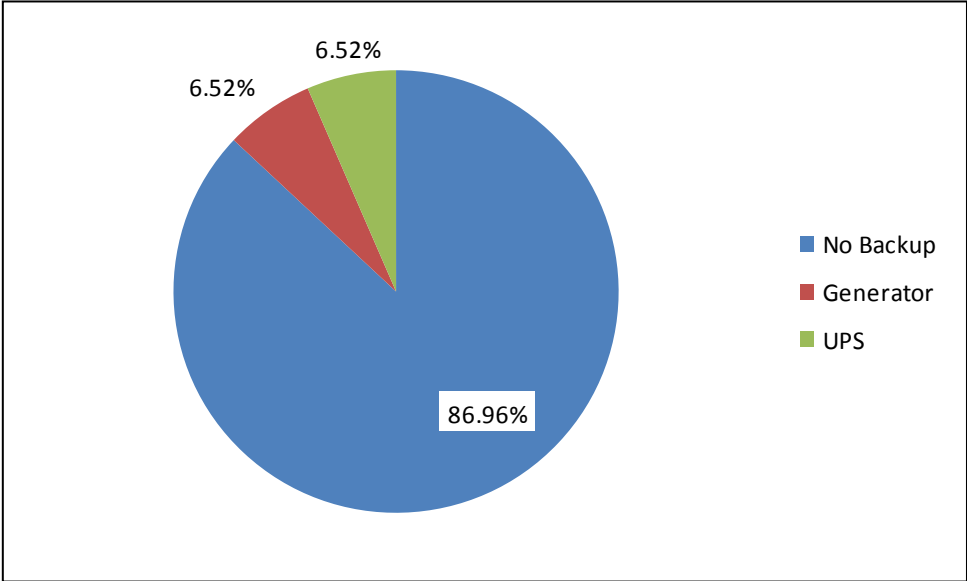


Fig C1.2: Ownership of backup power supply by commercial respondents

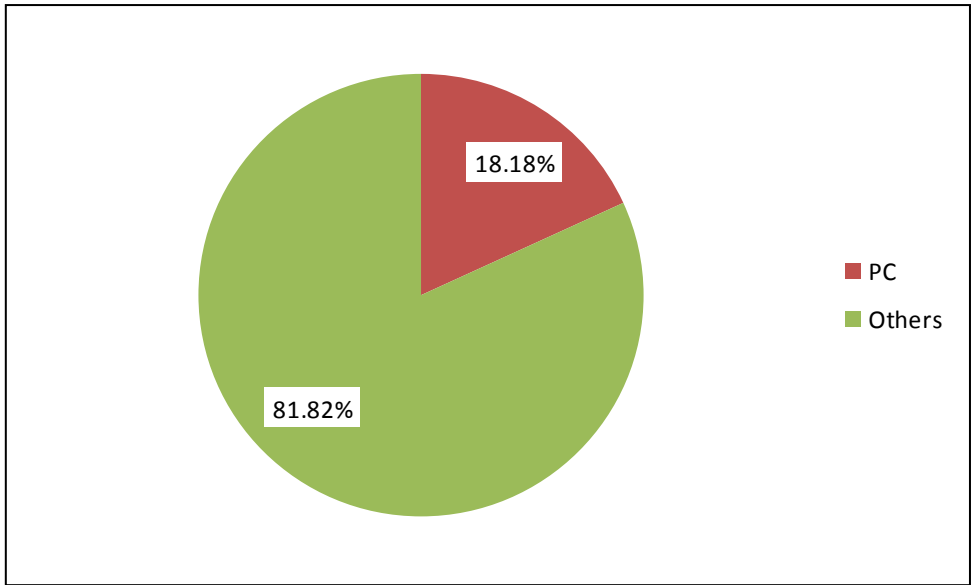


Fig C1.3: Purpose of backup power supply for industrial population

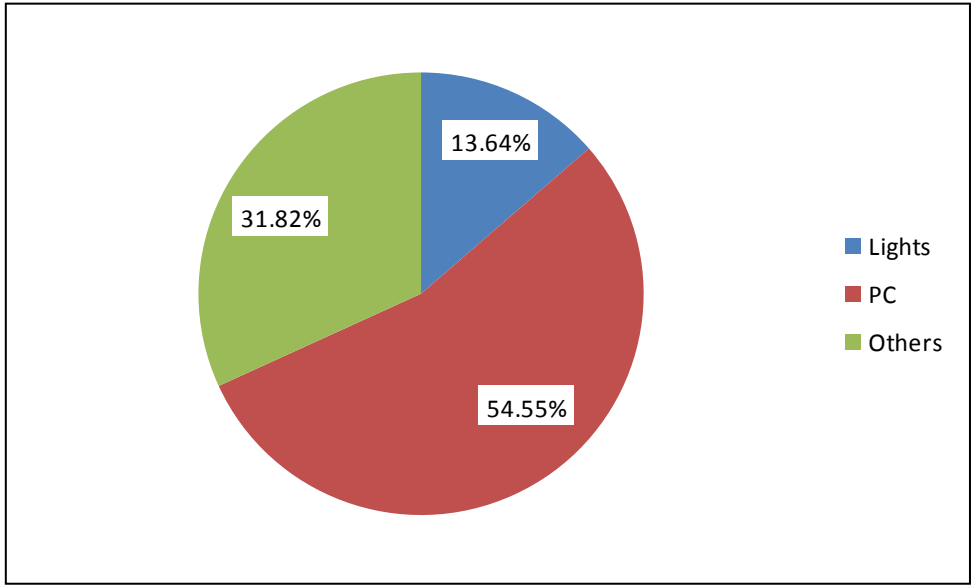


Fig C1.4: Purpose of backup power supply for commercial population

C2: Business Activity Level for Industrial and Commercial respondents

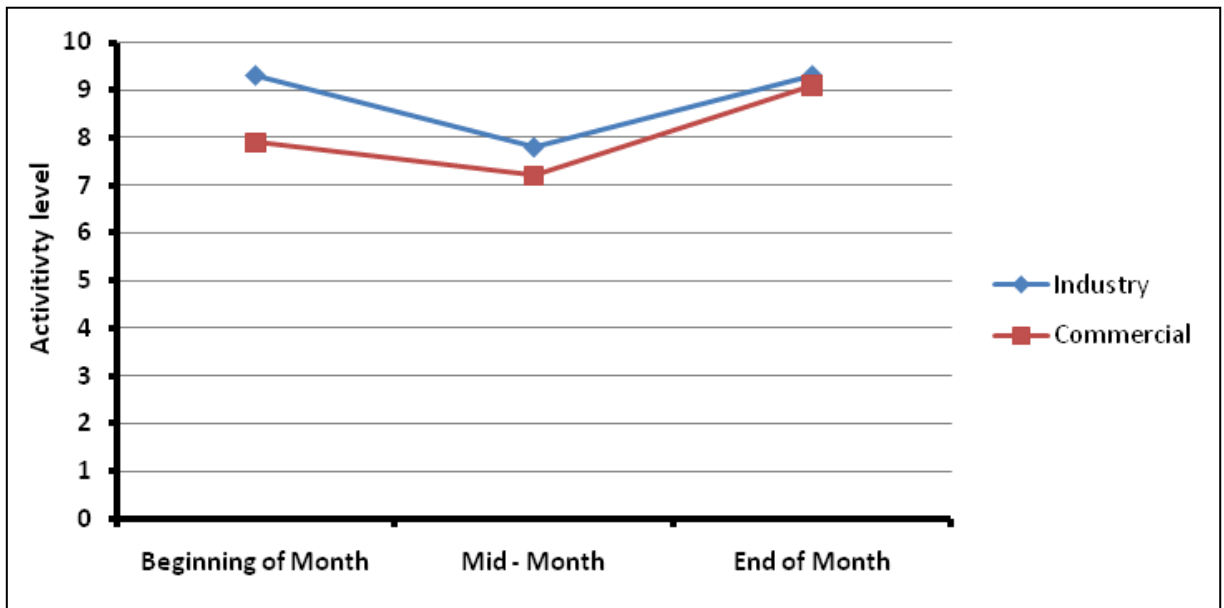


Fig C2.1: Relative variation of business activity level with the time of month

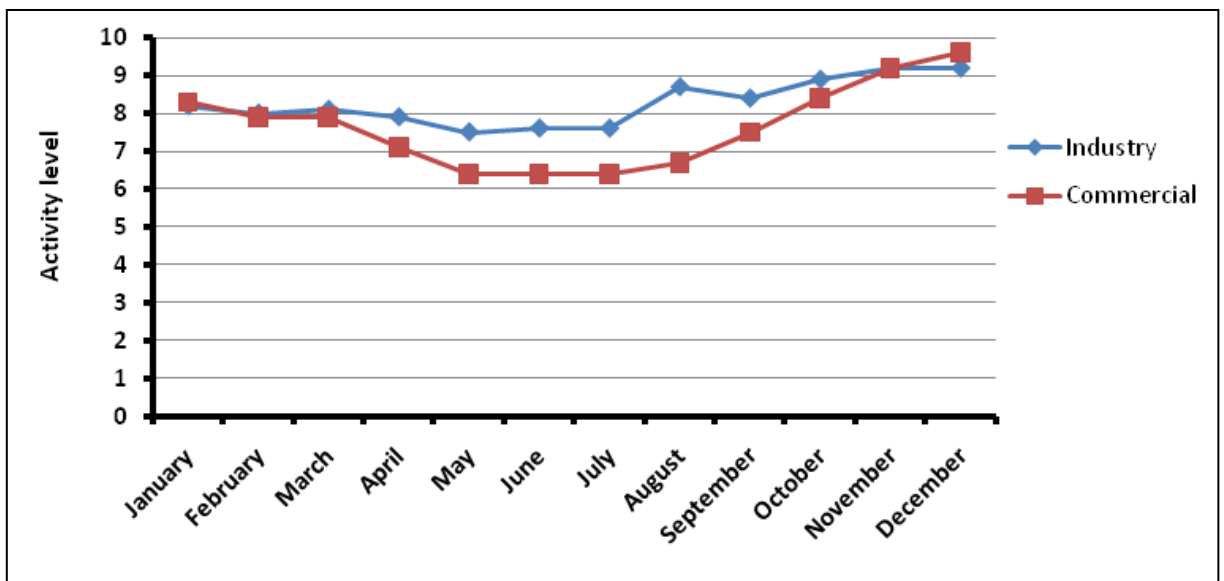


Fig C2.2: Relative variation business activity level with month of the year

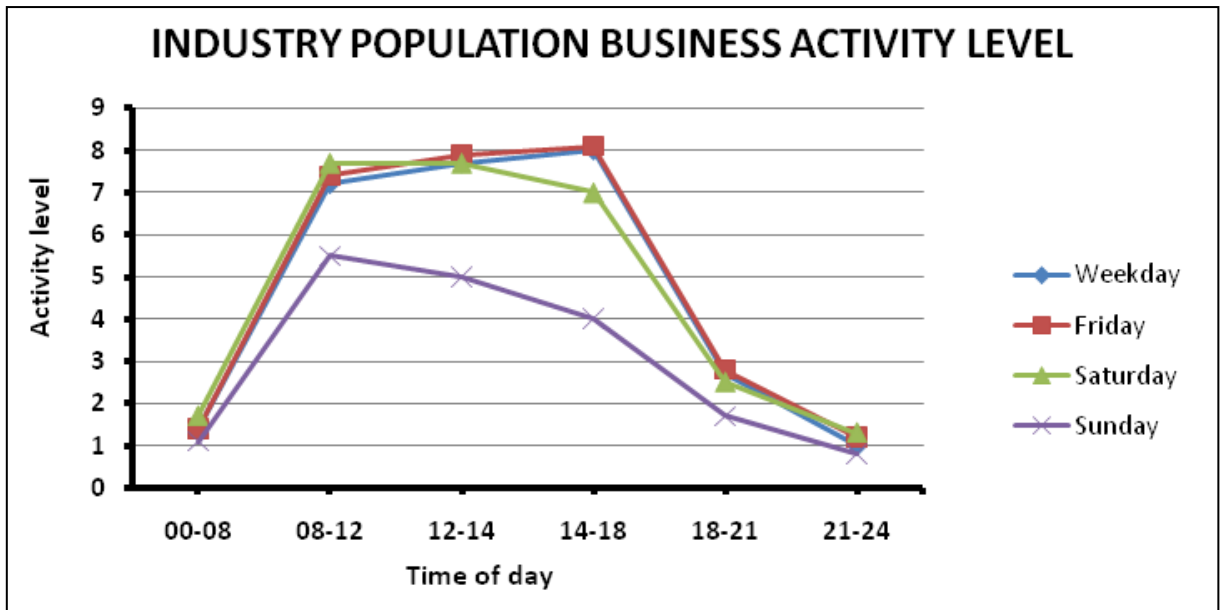


Fig C2.3: Relative variation of business with time of day and day of week for industrial population

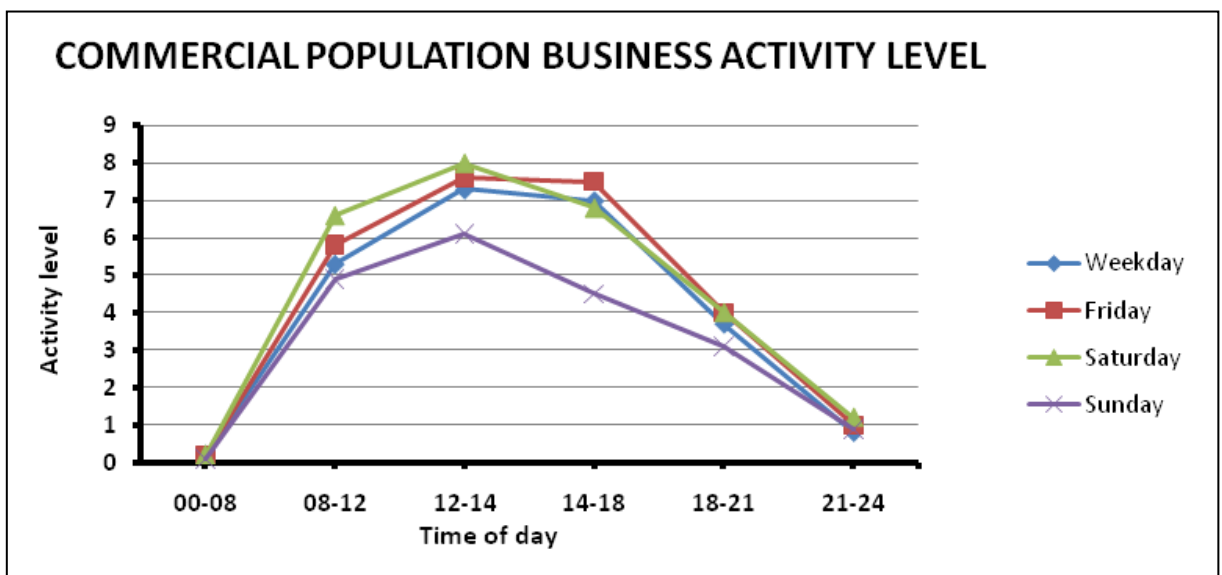


Fig C2.4: Relative variation of business with time of day and day of week for commercial population

C3: Variation of Power Interruption Cost with Average Monthly Electricity Bill

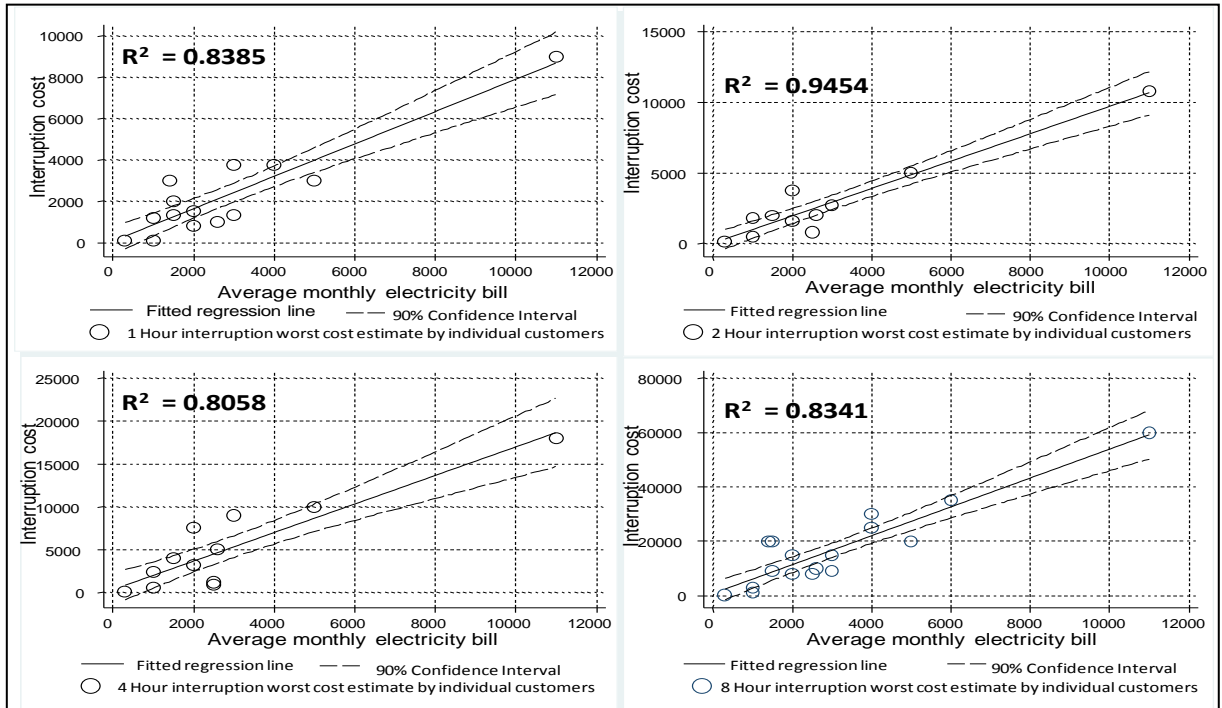


Fig C3.1: Variation of power interruption cost with average monthly electricity bill for a summer weekday morning power interruption: Retail Segment

Table C3.1: Regression model results for summer weekday morning cost estimate for Retail Segment

Duration (hr)	Regression Constant	Regression coefficient	Degree of Freedom
1	86.79	0.78	12
2	198.37	0.96	8
4	377.75	1.66	10
8	754.49	5.31	15

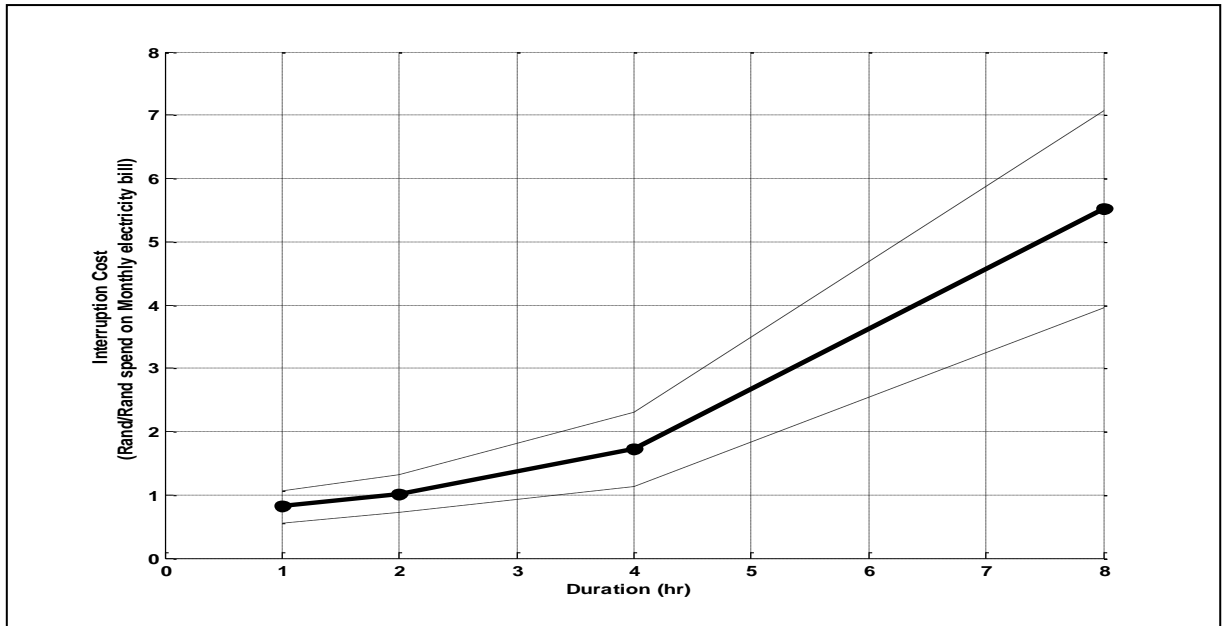


Fig C3.2: Summer weekday morning: CDF for Retail Segment

Table C3.2: CDF results for summer weekday morning cost estimate of Retail Segment

Duration (hr)	Mean	Standard error @ 90% C. I	Standard Deviation	Skewness	No of respondents
1	0.82	0.14	0.53	0.92	14
2	1.02	0.15	0.50	0.52	10
4	1.72	0.32	1.12	0.19	12
8	5.52	0.89	3.67	1.16	17

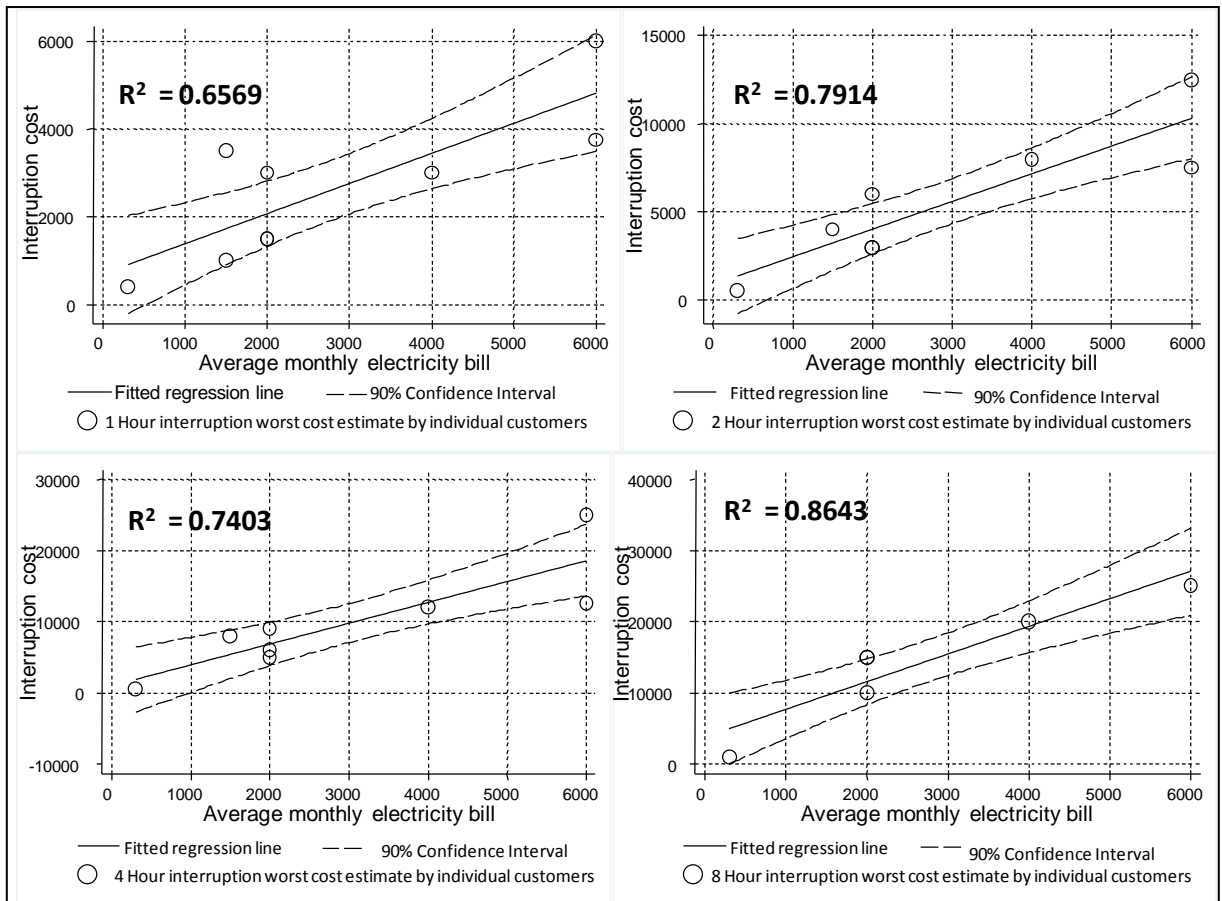


Fig C3.3: Variation of power interruption cost with average monthly electricity bill for winter cost estimate of Retail Segment respondents with backup power supply.

Table C3.3: Regression model results for winter cost estimate of Retail Segment respondents with backup power supply

Duration (hr)	Regression Constant	Regression coefficient	Degree of Freedom
1	705.43	0.68	7
2	867.92	1.57	6
4	1004.71	2.94	6
8	3818.67	3.87	4

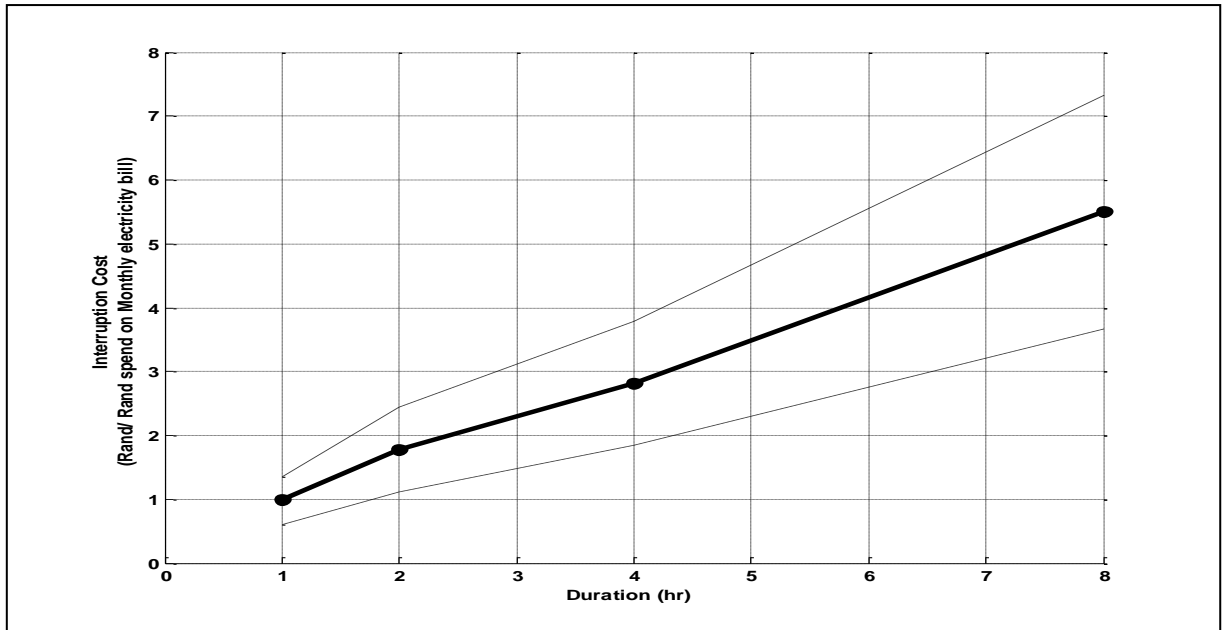


Fig C3.4: Winter cost estimate: CDF for Retail Segment respondents with backup power supply

Table C3. 4: CDF results for winter cost estimate of Retail Segment respondents with backup power supply

Duration (hr)	Mean	Standard error @ 90% C. I	Standard Deviation	Skewness	No of respondents
1	0.99	0.17	0.39	0.42	5
2	1.78	0.31	0.69	1.32	5
4	2.81	0.45	1.02	0.99	5
8	5.5	0.85	1.91	0.13	5

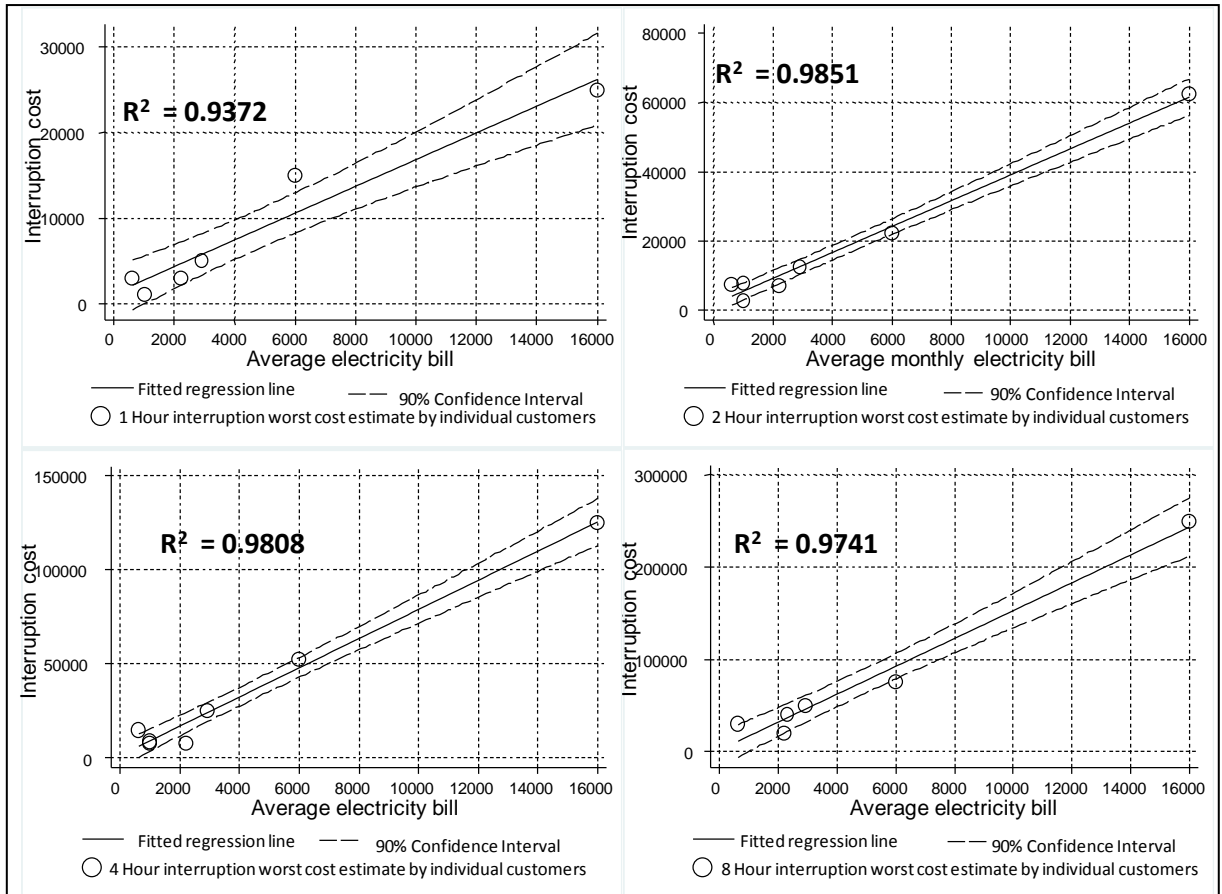


Fig C3.5: Variation of power interruption cost with average monthly electricity bill for a summer weekday morning power interruption: Clothing Segment

Table C3.5: Regression model results for summer weekday morning cost estimate of Clothing Segment

Duration (hr)	Regression Constant	Regression coefficient	Degree of Freedom
1	1203.36	1.56	4
2	1622.66	3.75	5
4	1837.79	7.72	5
8	2173.71	15.06	4

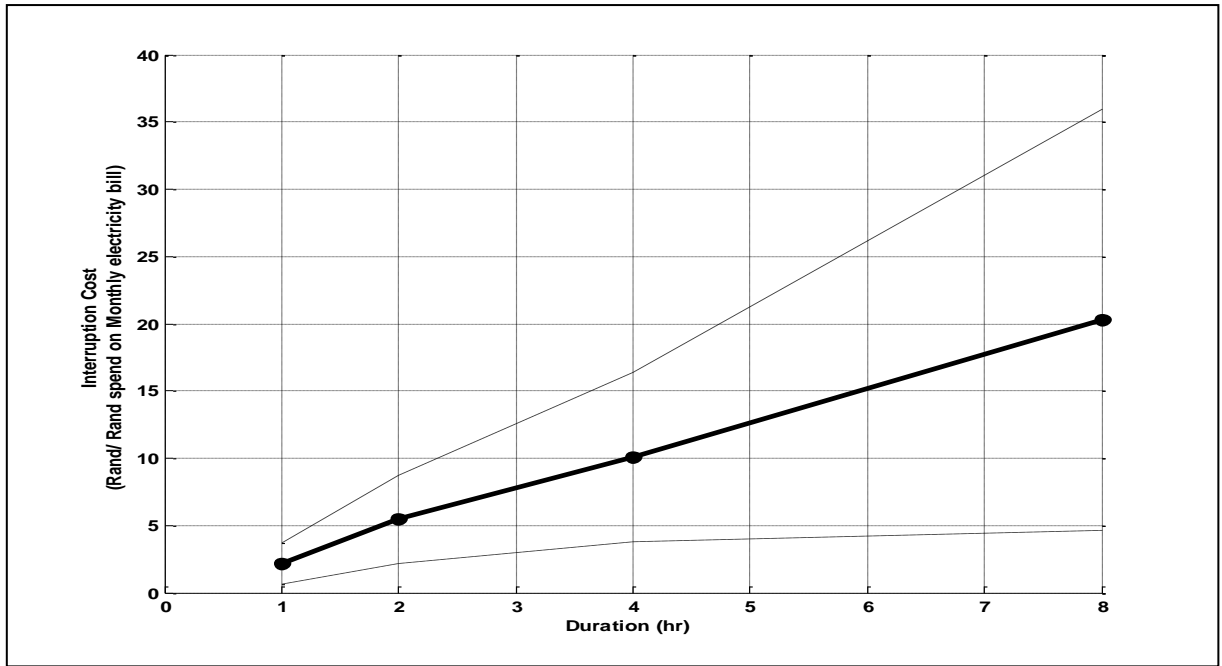


Fig C3.6: Summer weekday morning: CDF for Clothing Segment

Table C3.6: CDF results for summer weekday morning cost estimate of Clothing Segment

Duration (hr)	Mean	Standard error @ 90% C. I	Standard Deviation	Skewness	No of respondents
1	2.20	0.59	1.44	1.40	6
2	5.48	1.33	3.54	1.28	7
4	10.08	2.57	6.82	1.71	7
8	20.30	6.07	14.88	1.60	6

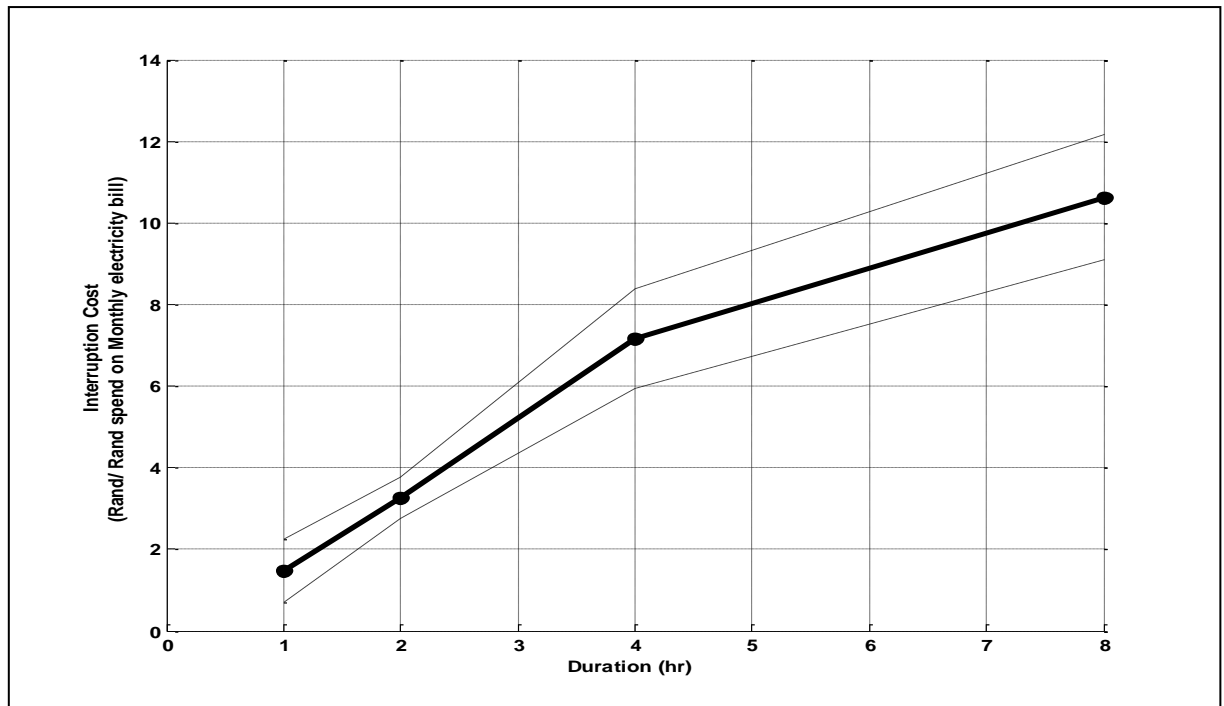


Fig C3.7: Summer cost estimate: CDF results for Clothing Segment respondents without backup power supply

Table C3.7: CDF results for summer cost estimate of Clothing Segment respondents without backup power supply

Duration (hr)	Mean	Standard error @ 90% C. I	Standard Deviation	Skewness	No of respondents
1	1.47	0.38	0.94	-0.14	6
2	3.26	0.21	0.43	0.07	4
4	7.16	0.57	1.29	-0.04	5
8	10.63	0.76	1.87	-0.05	6

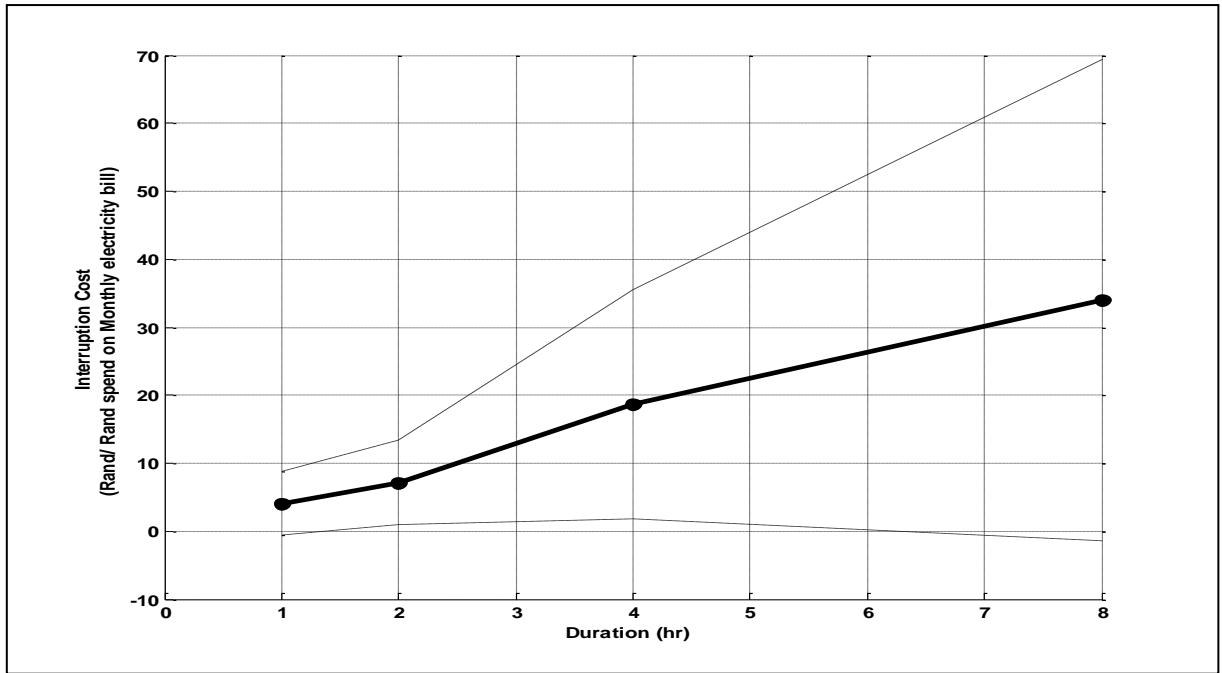


Fig C3.8: Summer cost estimate: CDF for Clothing Segment respondents with backup power supply

Table C3.8: CDF results for summer cost estimate of Clothing Segment respondents with backup power supply

Duration (hr)	Mean	Standard error @ 90% C. I	Standard Deviation	Skewness	No of respondents
1	4.12	1.96	3.92	1.13	4
2	7.19	2.63	5.26	1.07	4
4	18.71	7.90	17.66	1.42	5
8	33.99	16.58	37.07	1.46	5

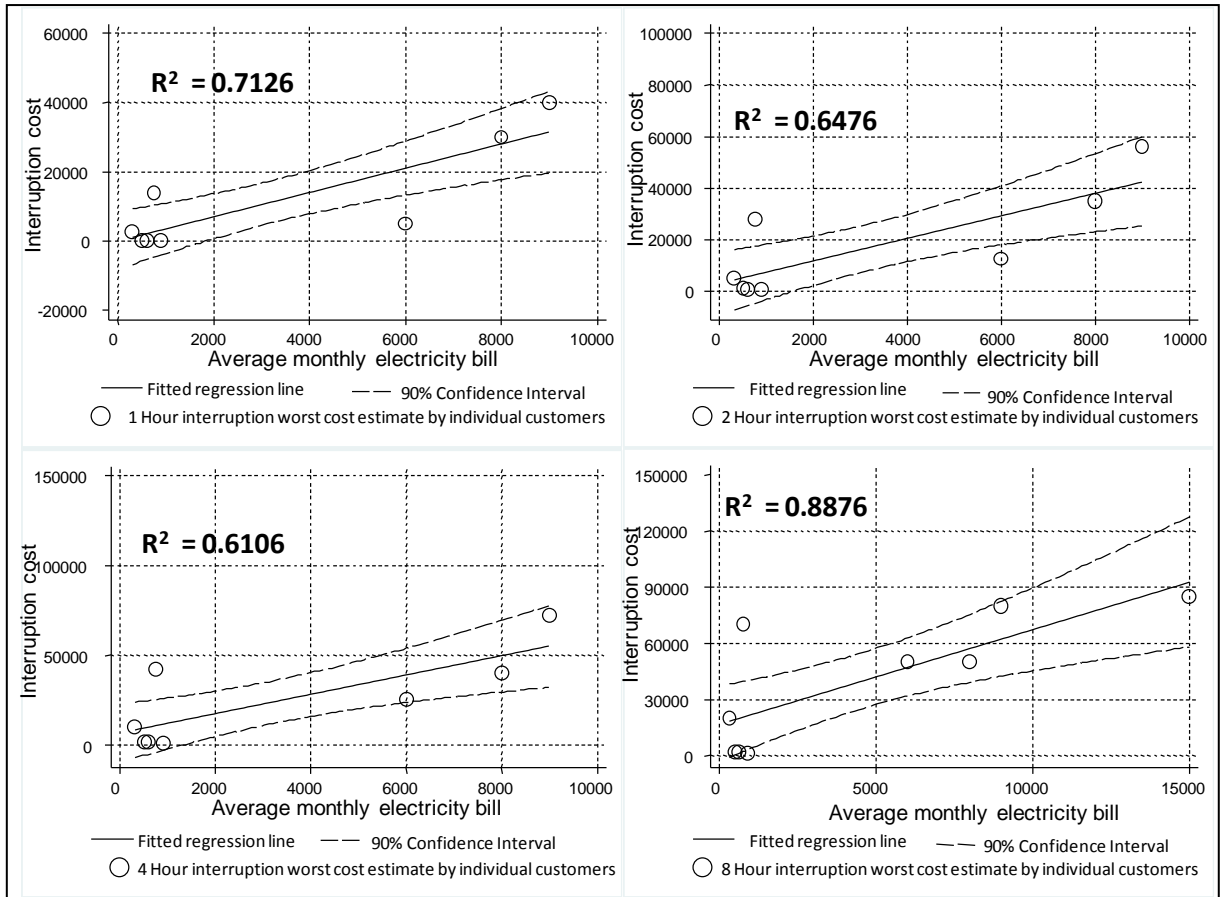


Fig C3.9: Variation of power interruption cost with average monthly electricity bill for a summer weekday morning power interruption: Metal Segment

Table C3.9: Regression model results for summer weekday morning cost estimate of Metal Segment

Duration (hr)	Regression Constant	Regression coefficient	Degree of Freedom
1	197.89	3.47	6
2	3022.81	4.39	6
4	6609.28	5.36	6
8	17072.9	5.03	7

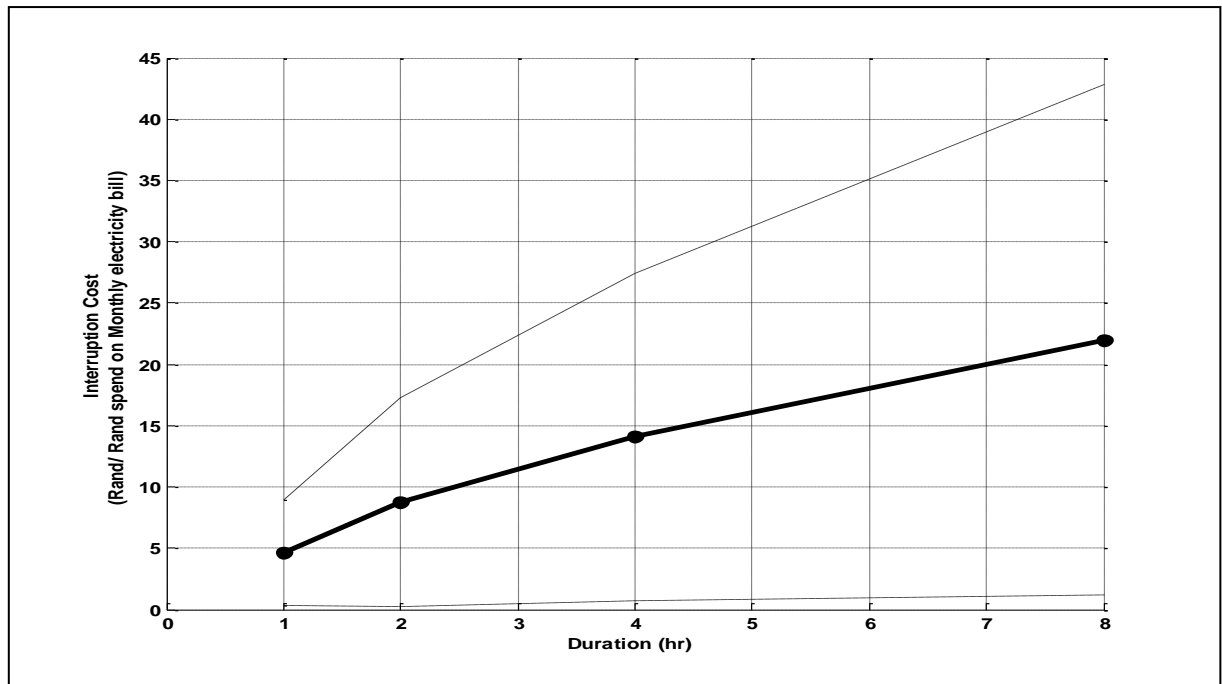


Fig C3.10: Summer weekday morning: CDF for Metal Segment

Table C3.10: CDF results for summer weekday morning cost estimate of Metal Segment

Duration (hr)	Mean	Standard error @ 90% C. I	Standard Deviation	Skewness	No of respondents
1	4.65	2.25	6.37	1.47	8
2	8.77	4.47	12.66	1.65	8
4	14.08	7.04	19.93	1.41	8
8	22.01	11.20	33.62	1.45	8

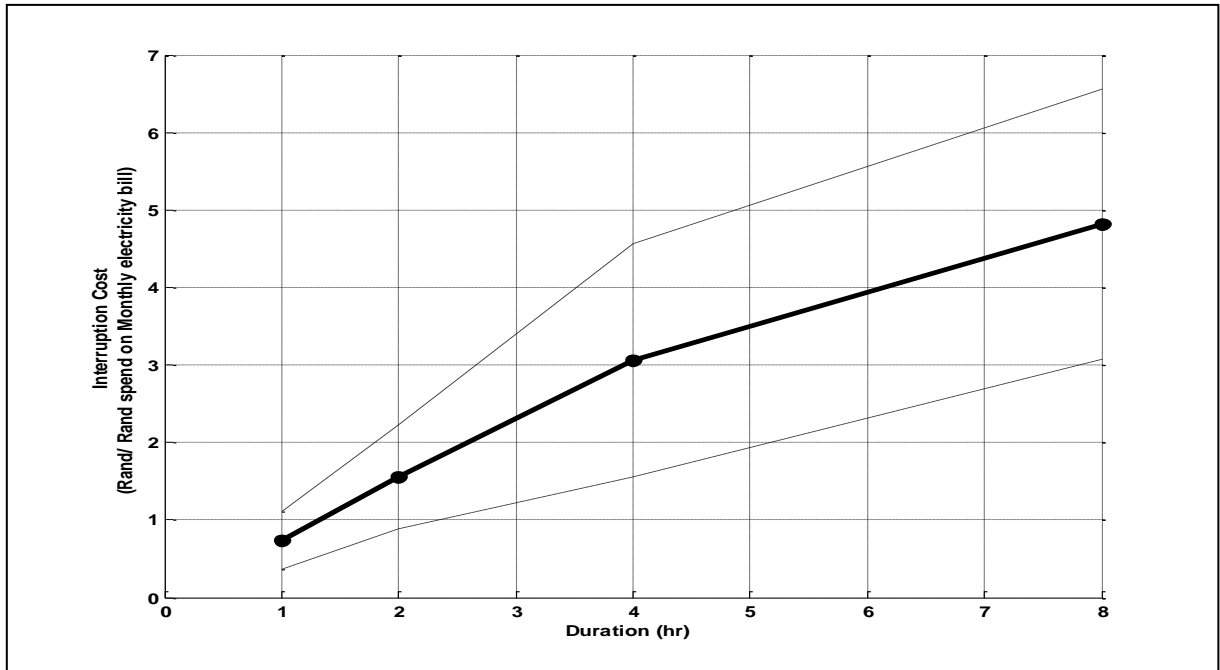


Fig C3.11: Summer weekday morning: CDF for Garage Segment

Table C3.11: CDF results for summer weekday morning cost estimate of Garage Segment

Duration (hr)	Mean	Standard error @ 90% C. I	Standard Deviation	Skewness	No of respondents
1	0.74	0.20	0.67	1.12	11
2	1.56	0.37	1.23	0.76	11
4	3.06	0.83	2.76	1.08	11
8	4.82	0.98	3.66	1.77	14

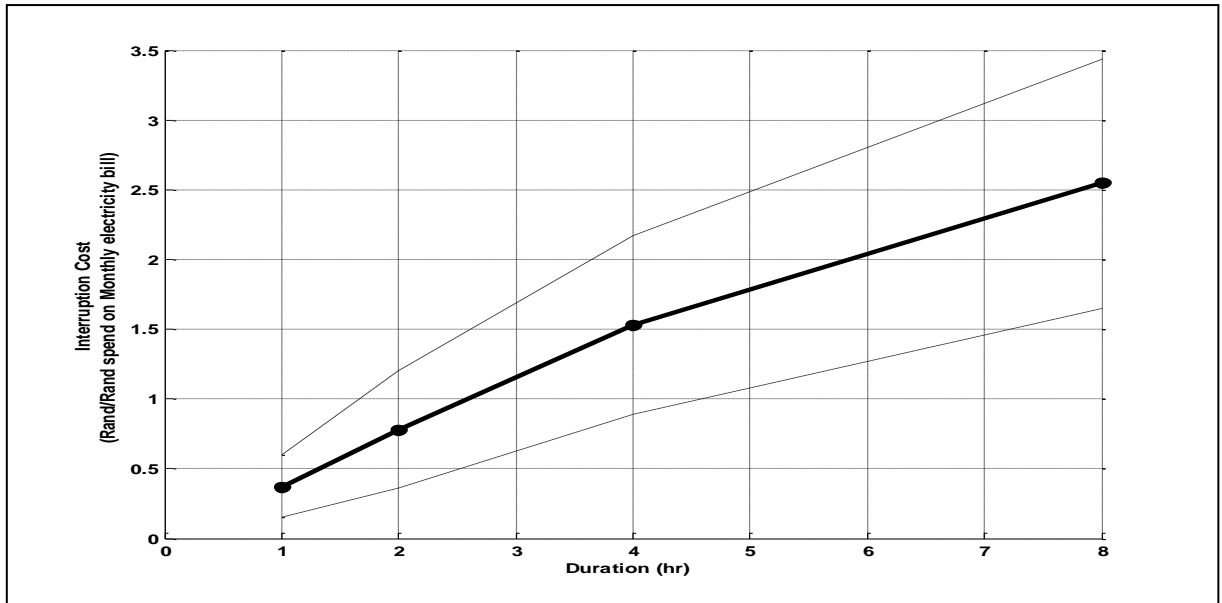


Fig C3.12: Winter weekday morning: CDF for Garage Segment

Table C3.12: CDF results for winter weekday morning cost estimate of Garage Segment

Duration (hr)	Mean	Standard error @ 90% C. I	Standard Deviation	Skewness	No of respondents
1	0.37	0.11	0.35	1.68	9
2	0.78	0.22	0.67	2.01	9
4	1.53	0.34	1.10	1.81	10
8	2.55	0.48	1.54	1.48	10

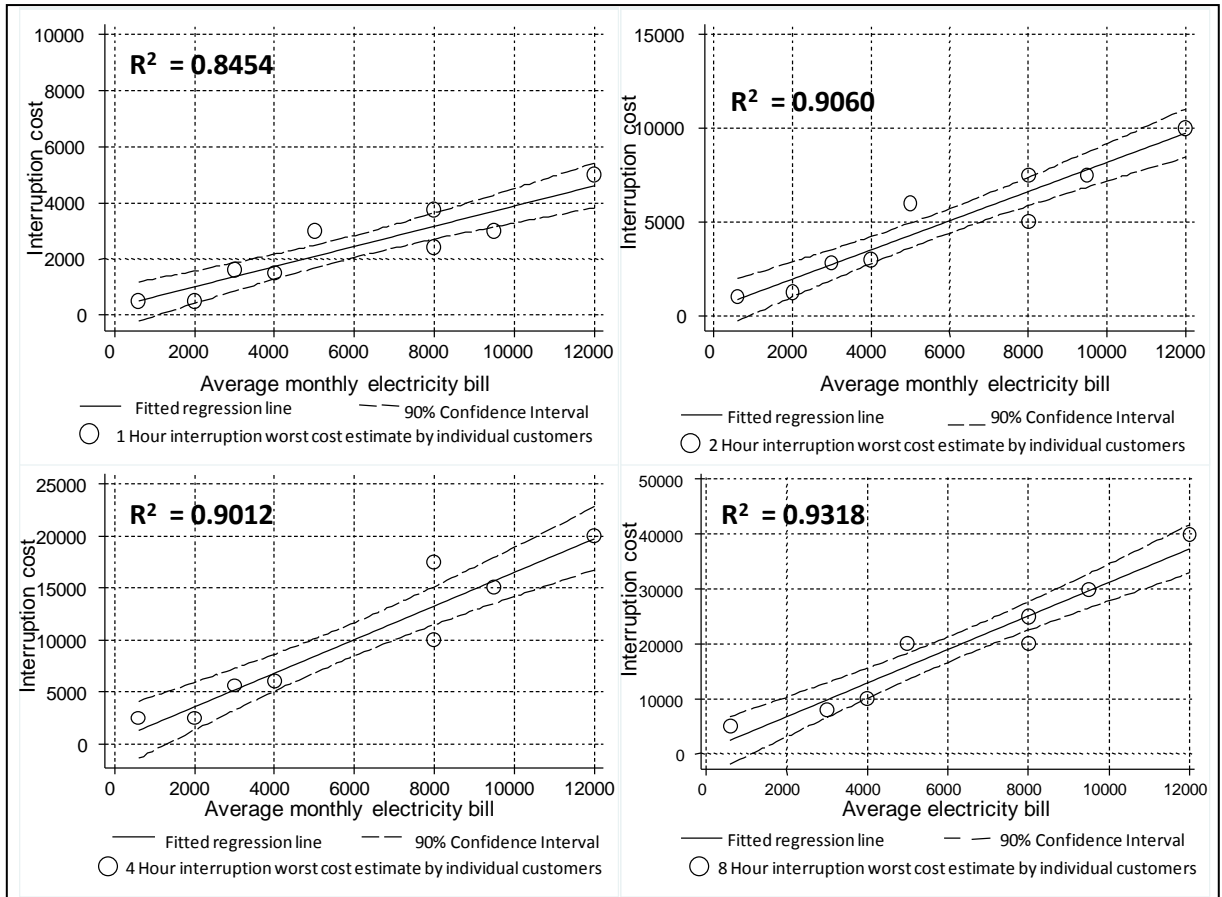


Fig C3.13: Variation of power interruption cost with average monthly electricity bill for a winter weekday morning power interruption: Hotel Segment

Table C3.13: Regression model results for winter weekday morning cost estimate of Hotel Segment

Duration (hr)	Regression Constant	Regression coefficient	Degree of Freedom
1	257.83	0.36	7
2	376.97	0.78	7
4	405.44	1.61	6
8	585.65	3.06	6

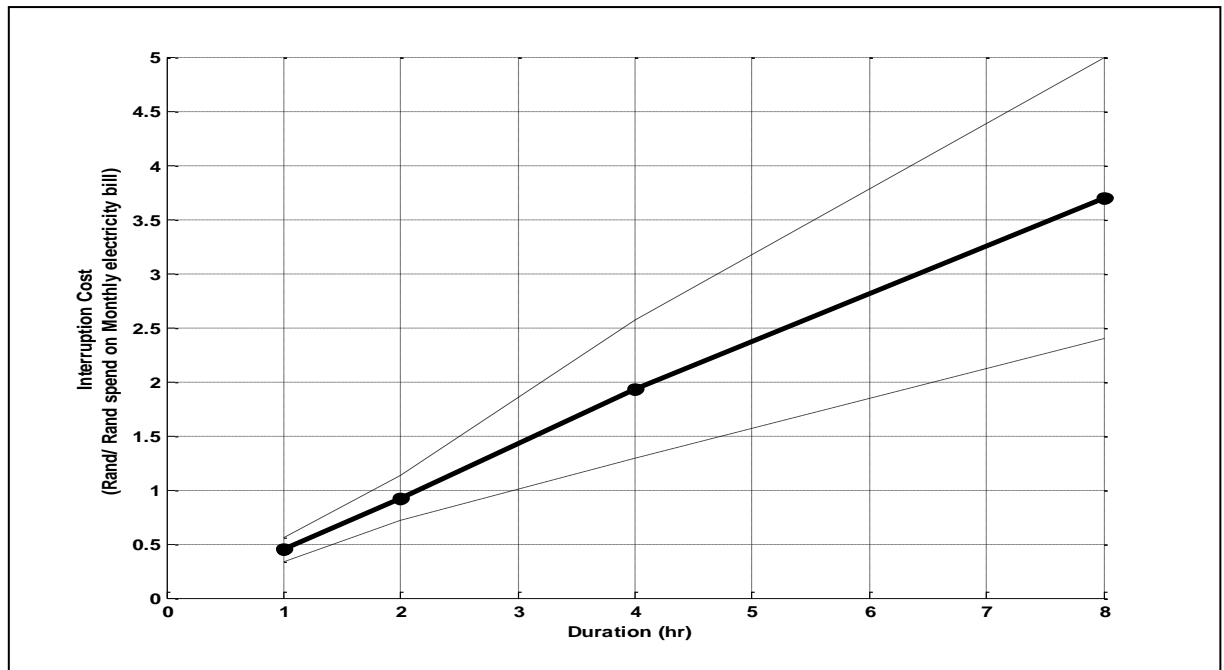


Fig C3.14: Winter weekday morning: CDF for Hotel Segment

Table C3.14: CDF results for winter weekday morning cost estimate of Hotel Segment

Duration (hr)	Mean	Standard error @ 90% C. I	Standard Deviation	Skewness	No of respondents
1	0.45	0.06	0.18	0.93	9
2	0.92	0.10	0.32	1.33	9
4	1.93	0.33	0.95	1.82	8
8	3.70	0.68	1.93	1.98	8

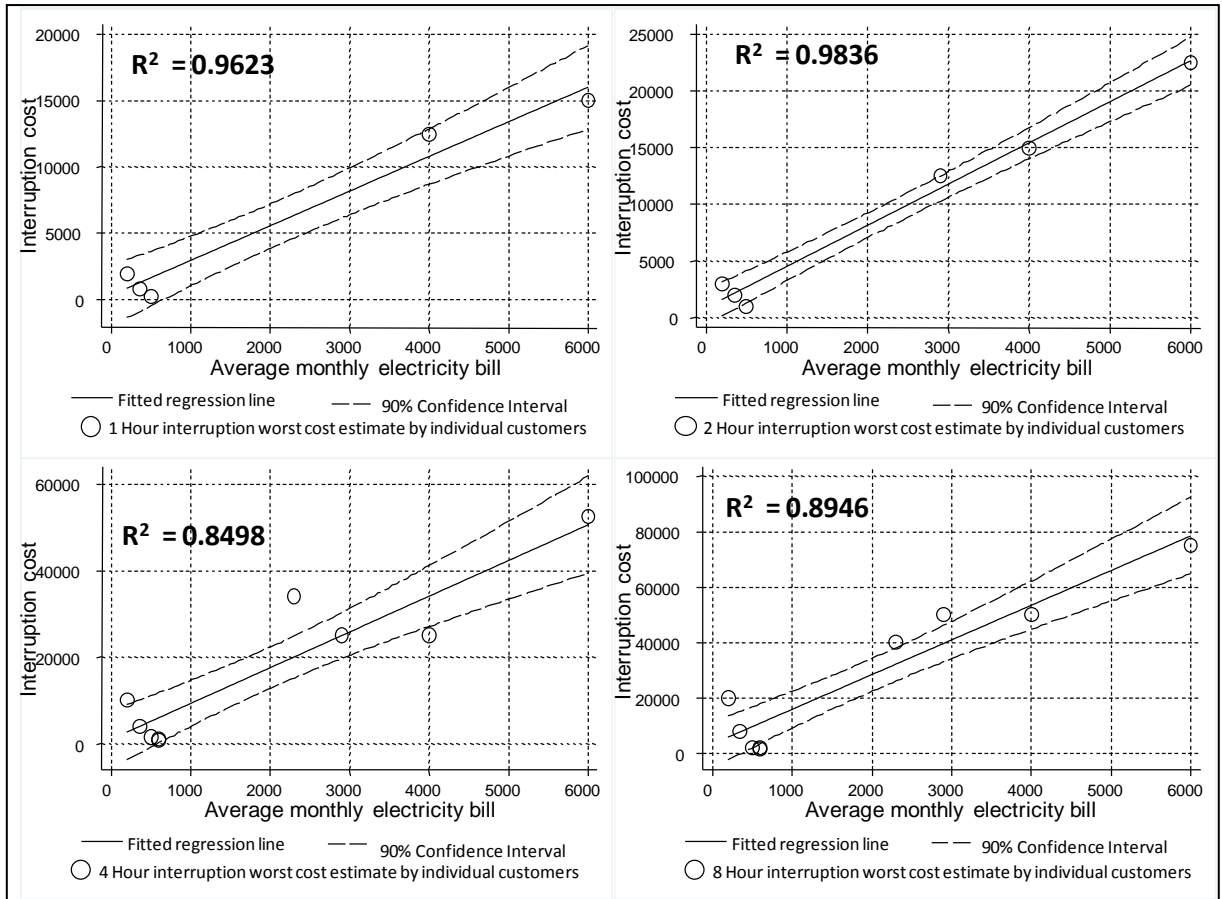


Fig C3.15: Variation of power interruption with average monthly electricity bill for summer morning cost estimate of Industrial respondents with backup power supply

Table C3.15: Regression model results for summer morning cost estimate of Industrial respondents with backup power supply

Duration (hr)	Regression Constant	Regression coefficient	Degree of Freedom
1	306.96	2.62	3
2	910.05	3.62	4
4	1121.90	8.25	7
8	3241.21	12.57	7

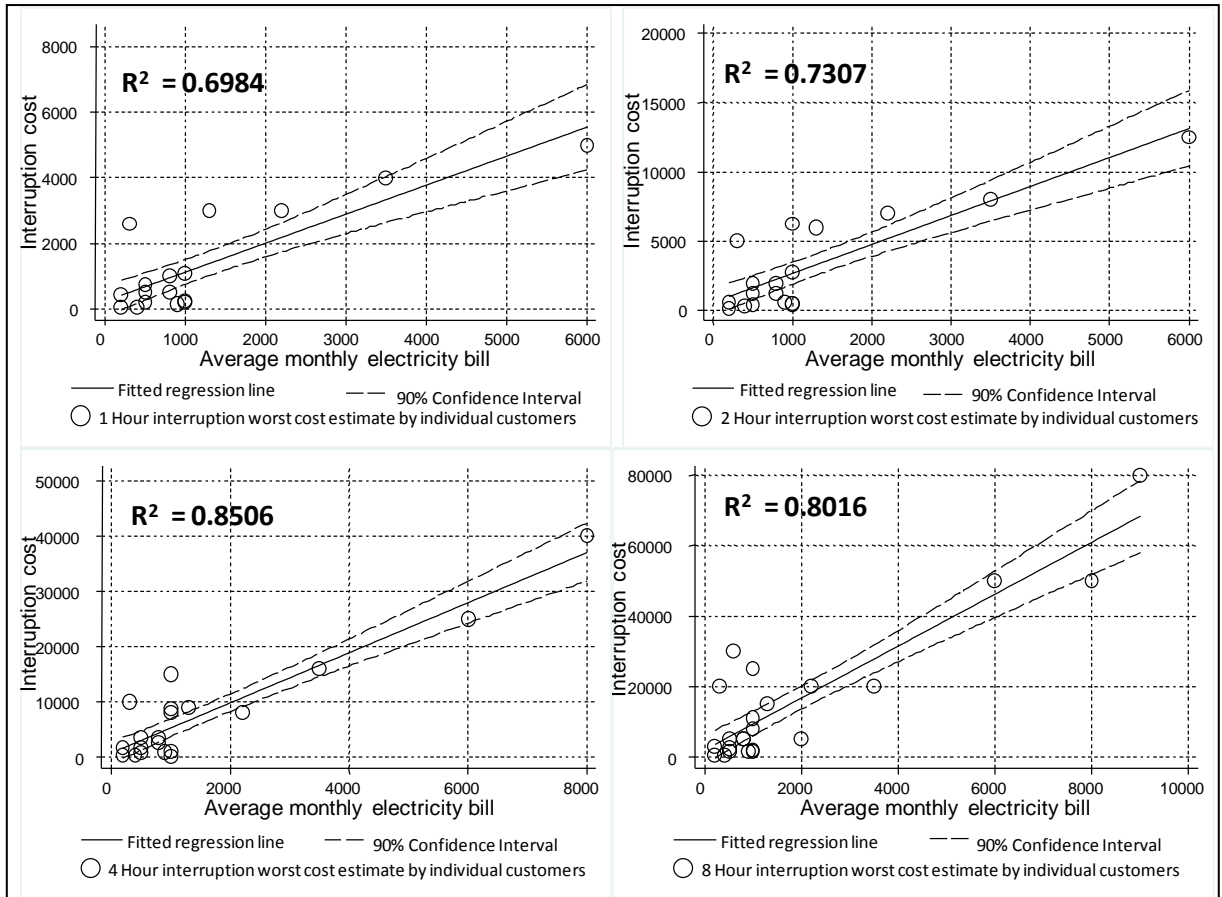


Fig C3.16: Variation of power interruption cost with average monthly electricity bill for summer morning cost estimate of Industrial respondents without backup power supply

Table C3.16: Regression model results for summer morning cost estimate of Industrial respondents without backup power supply

Duration (hr)	Regression Constant	Regression coefficient	Degree of Freedom
1	243.83	0.88	15
2	593.06	2.09	16
4	749.21	4.54	18
8	2117.90	7.34	21

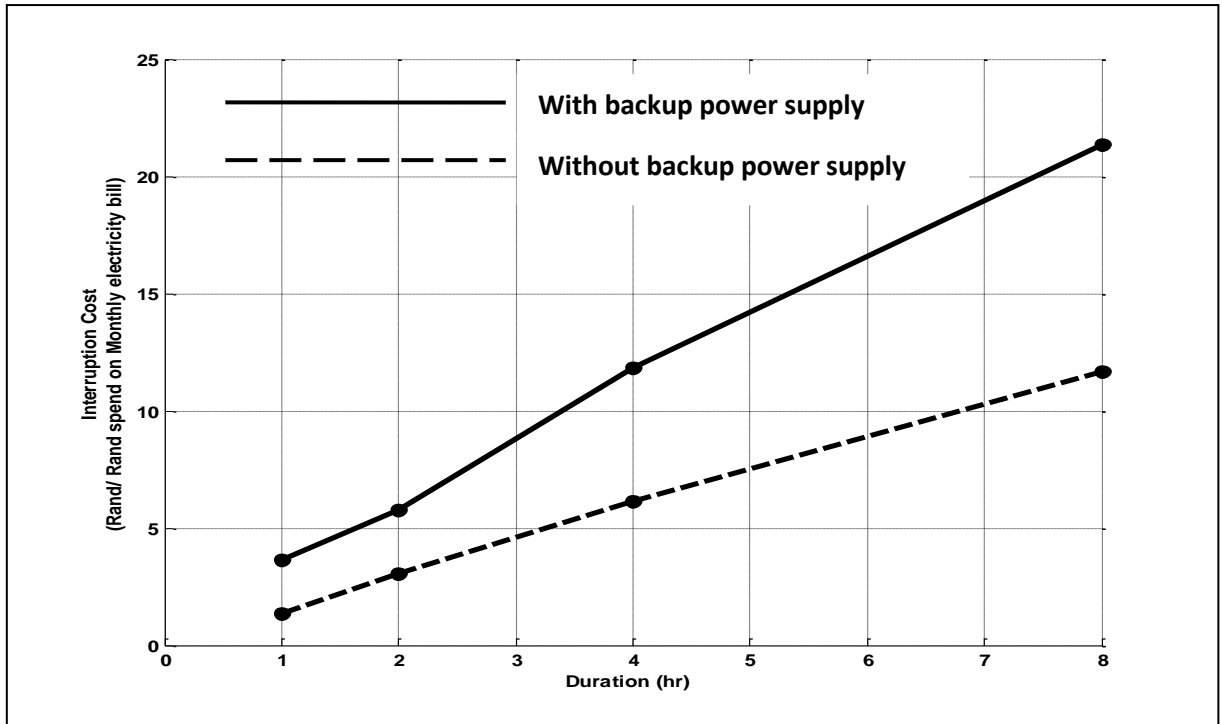


Fig C3.17: Summer morning cost estimate: CDF for industrial respondents with/without backup power supply

APPENDIX D

MATLAB CODE

A. CUSTOMER DAMAGE FUNCTION (CDF) SIMULATION CODE

```
clear all

tic
v=0; h=0;e = 0;
for i = 1:50
FLA = 0; unavailLA = 0;ecost=0;
rand( 'state', sum(100*clock));
for N=1:5000;

t1=0;td1=0; t2=0;td2=0; t3=0;td3=0; t4=0;td4=0;
t5=0;td5=0; t6=0;td6=0; t7=0;td7=0;

c1=0;c2=0;c3=0;c4=0;c5=0;
c6=0;c7=0;

l1=0.065/8760;l2=0.182/8760;l3=0.156/8760;l4=0.117/8760;l5=0.169/8760;
l6=0.006/8760;l7=0.015/8760;

t = 0;

a1=rand; a2=rand; a3=rand; a4=rand;a5=rand;
a6=rand; a7=rand;

T1 =(-1/l1)* reallog(a1);T2 =(-1/l2)* reallog(a2);
T3 =(-1/l3)* reallog(a3);T4 =(-1/l4)* reallog(a4);
T5 =(-1/l5)* reallog(a5);T6 =(-1/l6)* reallog(a6);
T7 =(-1/l7)* reallog(a7);

y = [T1, T2,T3,T4,T6,T7];
x = min(y);
while x < 8760
    t=0;
    t= t + x;
    if x == y(1,1)
        Tr1 = lognrnd(1.60944, (0)^2);
        t1 = t1 + 1;
        td1 = td1 + Tr1;
        c1 = c1 + (1.72 + (0.95)*(Tr1 - 4));
        a1 = rand ;
        T1 =(-1/l1)* reallog(a1);
        t = t + Tr1 + T1;
        T1 = t;
        y = [T1, T2,T3,T4,T6,T7];
        x = min(y);
    elseif x == y(1,2)
        Tr2 = lognrnd(1.60944, (0)^2);
        t2 = t2 + 1;
        td2 = td2 + Tr2;
        c2 = c2 + (1.72 + (0.95)*(Tr2 - 4));
        a2 = rand;
        T2 =(-1/l2)* reallog(a2);
        t = t + Tr2 + T2;
        T2= t;
        y = [T1, T2,T3,T4,T6,T7];
        x = min(y);
    elseif x == y(1,3)
        Tr3 = lognrnd(1.60944, (0)^2);
        t3 = t3 + 1;
```

```

        td3 = td3 + Tr3;
        c3 = c3 + (1.72 + (0.95)*(Tr3 - 4));
        a3 = rand;
        T3 = (-1/13)* reallog(a3);
        t = t + Tr3 + T3;
        T3=t;
        y = [T1, T2,T3,T4,T6,T7];
        x = min(y);

elseif x == y(1,4)
    Tr4 = lognrnd(1.60944, (0)^2);
    t4 = t4 + 1;
    td4 = td4 + Tr4;
    c4 = c4 + (1.72 + (0.95)*(Tr4 - 4));
    a4 = rand;
    T4 = (-1/14)* reallog(a4);
    t = t + Tr4 + T4;
    T4=t;
    y = [T1, T2,T3,T4,T6,T7];
    x = min(y);

elseif x == y(1,5)
    Tr6 = lognrnd(1.386294, (0.4)^2);
    t6 = t6 + 1;
    td6 = td6 + Tr6;
    c6 = c6 + (1.72 + (0.95)*(Tr6 - 4));
    a6 = rand;
    T6 = (-1/16)* reallog(a6);
    t = t + Tr6+T6;
    T6=t;
    y = [T1, T2,T3,T4,T6,T7];
    x = min(y);
elseif x == y(1,6)
    Tr7 = lognrnd(2.302585, (0)^2);
    t7 = t7 + 1;
    td7 = td7 + Tr7;
    c7 = c7 + (1.72 + (0.95)*(Tr7 - 4));
    a7 = rand;
    T7 = (-1/17)* reallog(a7);
    t = t + Tr7 + T7;
    T7=t;
    y = [T1, T2,T3,T4,T6,T7];
    x = min(y);

end
end
% failure rate
fLA= (t1 + t2 + t3 + t4 + t6 + t7);
FLA= FLA + fLA;
% unavailability
unavaiLLA = (t1).* td1 + (t2).* td2 + (t3).* td3+(t4).* td4 + ...
    (t6).* td6 + (t7).*td7;

unavaiLLA= unavaiLLA + unavaiLLA;
cost = c1 + c2 + c3 + c4 + c6 + c7;
ecost = ecost + cost;
end

v= v + FLA/N;
h = h + unavaiLLA/N;

```

```

    e = e + ecost/N;
end
g(d,:) = v/(i);
k(d,:) = h/(i);
m(d,:) = (e/(i));
z(d,:) = (h/(i));
end
g;
k;
mean(m) * 33000
mean(z) * 33000

```

```
toc
```

B. TIME VARYING CDF SIMULATION CODE

```
clear all
```

```

tic
v=0; h=0; e = 0;
for i = 1:50
    FLA = 0; unavailLA = 0; ecost=0;
    rand('state', sum(100*clock));
    for N=1:5000;

        t1=0;td1=0; t2=0;td2=0; t3=0;td3=0; t4=0;td4=0;
        t5=0;td5=0; t6=0;td6=0; t7=0;td7=0;

        c1=0;c2=0;c3=0;c4=0;c5=0;c6=0;c7=0;

        l1=0.065/8760;l2=0.182/8760;l3=0.156/8760;l4=0.117/8760;l5=0.169/8760;
        l6=0.006/8760;l7=0.015/8760;

        L3 = [0.80 0.75 0.72 0.71 0.64 0.65 0.65 0.66 0.75 0.82 0.93 1.00 1.00];
        L4 = [0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.90 0.90 0.90 0.90...
            1.21 1.21 1.30 1.30 1.30 1.30 0.55 0.55 0.55 0.00 0.00 0.00;
            0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.90 0.90 0.90 0.90...
            1.21 1.21 1.30 1.30 1.30 1.30 0.55 0.55 0.55 0.00 0.00 0.00;
            0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.90 0.90 0.90 0.90...
            1.21 1.21 1.30 1.30 1.30 1.30 0.55 0.55 0.55 0.00 0.00 0.00;
            0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.90 0.90 0.90 0.90...
            1.21 1.21 1.30 1.30 1.30 1.30 0.55 0.55 0.55 0.00 0.00 0.00;
            0.02 0.02 0.02 0.02 0.02 0.02 0.02 0.02 0.91 0.91 0.91 0.91...
            1.18 1.18 1.20 1.20 1.20 1.20 0.52 0.52 0.52 0.01 0.01 0.01;
            0.02 0.02 0.02 0.02 0.02 0.02 0.02 0.02 1.00 1.00 1.00 1.00...
            1.24 1.24 1.30 1.30 1.30 1.30 0.58 0.58 0.58 0.03 0.03 0.03;
            0.01 0.01 0.01 0.01 0.01 0.01 0.01 0.01 1.17 1.17 1.17 1.17...
            1.36 1.36 1.16 1.16 1.16 1.16 0.56 0.56 0.56 0.03 0.03 0.03;
            0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.85 0.85 0.85 0.85...
            1.03 1.03 0.82 0.82 0.82 0.82 0.47 0.47 0.47 0.02 0.02 0.02];
        t = 0;

        a1=rand; a2=rand; a3=rand; a4=rand;a5=rand; a6=rand;
        a7=rand;

        T1 =(-1/l1)* reallog(a1);T2 =(-1/l2)* reallog(a2);
        T3 =(-1/l3)* reallog(a3);T4 =(-1/l4)* reallog(a4);
        T5 =(-1/l5)* reallog(a5);T6 =(-1/l6)* reallog(a6);
    end
end

```

```

T7 =(-1/17)* reallog(a7);

y = [T1, T2,T3,T4,T6,T7];
x = min(y);
while x< 8760
    t=0;
    t=t + x;
if x == y(1,1)
    Tr1 = lognrnd(1.60944, (0)^2);
    t1 = t1 + 1;
    td1 = td1 + Tr1;
    a = floor(y(1,1)/(720));
    b = floor( (rem(y(1,1),168)/24));
    c = floor((rem(y(1,1),24)));
    c1 = c1 + L3(1,a+1)*L4(b+1,c+1)*(1.72 + (0.95)*(Tr1 - 4));
    a1 = rand ;
    T1 =(-1/11)* reallog(a1);
    t = t + Tr1+T1;
    T1 = t;
    y = [T1, T2,T3,T4,T6,T7];
    x = min(y);
elseif x == y(1,2)
    Tr2 = lognrnd(1.60944, (0)^2);
    t2 = t2 + 1;
    td2 = td2 + Tr2;
    a = floor(y(1,2)/(720));
    b = floor( (rem(y(1,2),168)/24));
    c = floor((rem(y(1,2),24)));
    c2 = c2 + L3(1,a+1)*L4(b+1,c+1)*(1.72 + (0.95)*(Tr2 - 4));
    a2 = rand;
    T2 =(-1/12)* reallog(a2);
    t = t + Tr2+T2;
    T2= t;
    y = [T1, T2,T3,T4,T6,T7];
    x = min(y);
elseif x == y(1,3)
    Tr3 = lognrnd(1.60944, (0)^2);
    t3 = t3 + 1;
    td3 = td3 + Tr3;
    a = floor(y(1,3)/(720));
    b = floor( (rem(y(1,3),168)/24));
    c = floor((rem(y(1,3),24)));
    c3 = c3 + L3(1,a+1)*L4(b+1,c+1)*(1.72 + (0.95)*(Tr3 - 4));
    a3 = rand;
    T3 =(-1/13)* reallog(a3);
    t = t + Tr3+T3;
    T3=t;
    y = [T1, T2,T3,T4,T6,T7];
    x = min(y);

elseif x == y(1,4)
    Tr4 = lognrnd(1.60944, (0)^2);
    t4 = t4 + 1;
    td4 = td4 + Tr4;
    a = floor(y(1,4)/(720));
    b = floor( (rem(y(1,4),168)/24));
    c = floor((rem(y(1,4),24)));
    c4 = c4 + L3(1,a+1)*L4(b+1,c+1)*(1.72 + (0.95)*(Tr4 - 4));
    a4 = rand;
    T4 =(-1/14)* reallog(a4);
    t = t + Tr4+T4;

```

```

    T4=t;
    y = [T1, T2,T3,T4,T6,T7];
    x = min(y);

elseif x == y(1,5)
    Tr6 = lognrnd(1.386294,(0.4)^2);
    t6 = t6 + 1;
    td6 = td6 + Tr6;
    a = floor(y(1,5)/(720));
    b = floor( (rem(y(1,5),168)/24));
    c = floor((rem(y(1,5),24)));
    c6 = c6 + L3(1,a+1)*L4(b+1,c+1)*(1.72 + (0.95)*(Tr6 - 4));
    a6 = rand;
    T6=(-1/16)* reallog(a6);
    t = t + Tr6+T6;
    T6=t;
    y = [T1, T2,T3,T4,T6,T7];
    x = min(y);
elseif x == y(1,6)
    Tr7 = lognrnd(2.302585,(0)^2);
    t7 = t7 + 1;
    td7 = td7 + Tr7;
    a = floor(y(1,6)/(720));
    b = floor( (rem(y(1,6),168)/24));
    c = floor((rem(y(1,6),24)));
    c7 = c7 + L3(1,a+1)*L4(b+1,c+1)*(1.72 + (0.95)*(Tr7 - 4));
    a7 = rand;
    T7=(-1/17)* reallog(a7);
    t = t + Tr7+T7;
    T7=t;
    y = [T1, T2,T3,T4,T6,T7];
    x = min(y);

end
end
% failure rate
fLA= (t1 + t2 + t3 + t4 + t6 + t7 );
FLA= FLA + fLA;
% unavailability
unavaiLLA = (t1).* td1 + (t2).* td2 + (t3).* td3+(t4).* td4 + ...
    (t6).* td6 + (t7).*td7 ;

unavaiLLA= unavaiLLA + unavaiLLA;
cost = c1 + c2 + c3 + c4 + c6 + c7;
ecost = ecost + cost;
end

v= v + FLA/N;
h = h + unavaiLLA/N;
e = e + ecost/N;
end
g(d,:)= v/(i);
k(d,:)= h/(i);
m(d,:)= (e/(i));
z(d,:) = (h/(i)) ;
end
g;
k;
mean(m) * 33000
mean(z) * 33000

```

```
toc
```

C. TIME VARYING BETA CDF SIMULATION CODE

```
clear all
```

```
tic
```

```
v=0; h=0; e = 0;
```

```
for i = 1:50
```

```
FLA = 0; unavailLA = 0; ecost=0;
```

```
rand( 'state', sum(100*clock));
```

```
for N=1:5000;
```

```
t1=0;td1=0; t2=0;td2=0; t3=0;td3=0; t4=0;td4=0;
```

```
t5=0;td5=0; t6=0;td6=0; t7=0;td7=0;
```

```
c1=0;c2=0;c3=0;c4=0;c5=0;c6=0;c7=0;
```

```
l1=0.065/8760;l2=0.182/8760;l3=0.156/8760;l4=0.117/8760;l5=0.169/8760;
```

```
l6=0.006/8760;l7=0.015/8760;
```

```
L3 = [0.80 0.75 0.72 0.71 0.64 0.65 0.65 0.66 0.75 0.82 0.93 1.00 1.00];
```

```
L4 = [0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.90 0.90 0.90 0.90...
```

```
1.21 1.21 1.30 1.30 1.30 1.30 0.55 0.55 0.55 0.00 0.00 0.00;
```

```
0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.90 0.90 0.90 0.90...
```

```
1.21 1.21 1.30 1.30 1.30 1.30 0.55 0.55 0.55 0.00 0.00 0.00;
```

```
0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.90 0.90 0.90 0.90...
```

```
1.21 1.21 1.30 1.30 1.30 1.30 0.55 0.55 0.55 0.00 0.00 0.00;
```

```
0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.90 0.90 0.90 0.90...
```

```
1.21 1.21 1.30 1.30 1.30 1.30 0.55 0.55 0.55 0.00 0.00 0.00;
```

```
0.02 0.02 0.02 0.02 0.02 0.02 0.02 0.02 0.91 0.91 0.91 0.91...
```

```
1.18 1.18 1.20 1.20 1.20 1.20 0.52 0.52 0.52 0.01 0.01 0.01;
```

```
0.02 0.02 0.02 0.02 0.02 0.02 0.02 0.02 1.00 1.00 1.00 1.00...
```

```
1.24 1.24 1.30 1.30 1.30 1.30 0.58 0.58 0.58 0.03 0.03 0.03;
```

```
0.01 0.01 0.01 0.01 0.01 0.01 0.01 0.01 1.17 1.17 1.17 1.17...
```

```
1.36 1.36 1.16 1.16 1.16 1.16 0.56 0.56 0.56 0.03 0.03 0.03;
```

```
0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.85 0.85 0.85 0.85...
```

```
1.03 1.03 0.82 0.82 0.82 0.82 0.47 0.47 0.47 0.02 0.02 0.02];
```

```
t = 0;
```

```
a1=rand; a2=rand; a3=rand; a4=rand;a5=rand; a6=rand;
```

```
a7=rand;
```

```
T1 =(-1/l1)* reallog(a1);T2 =(-1/l2)* reallog(a2);
```

```
T3 =(-1/l3)* reallog(a3);T4 =(-1/l4)* reallog(a4);
```

```
T5 =(-1/l5)* reallog(a5);T6 =(-1/l6)* reallog(a6);
```

```
T7 =(-1/l7)* reallog(a7);
```

```
y = [T1, T2,T3,T4,T6,T7];
```

```
x = min(y);
```

```
while x< 8760
```

```
    t=0;
```

```
    t=t + x;
```

```
if x == y(1,1)
```

```
    Tr1 = lognrnd(1.60944, (0)^2);
```

```
    t1 = t1 + 1;
```

```
    td1 = td1 + Tr1;
```

```
    a = floor(y(1,1)/(720));
```

```

b = floor( (rem(y(1,1),168)/24));
c = floor((rem(y(1,1),24)));
c1 = c1 + L3(1,a+1)*L4(b+1,c+1)* betarnd(-3.4181, 1.4308);
a1 = rand;
T1 =(-1/11)* reallog(a1);
t = t + Tr1+T1;
T1 = t;
y = [T1, T2,T3,T4,T6,T7];
x = min(y);
elseif x == y(1,2)
Tr2 = lognrnd(1.60944, (0)^2);
t2 = t2 + 1;
td2 = td2 + Tr2;
a = floor(y(1,2)/(720));
b = floor( (rem(y(1,2),168)/24));
c = floor((rem(y(1,2),24)));
c2 = c2 + L3(1,a+1)*L4(b+1,c+1)* betarnd(-3.4181, 1.4308);
a2 = rand;
T2 =(-1/12)* reallog(a2);
t = t + Tr2+T2;
T2= t;
y = [T1, T2,T3,T4,T6,T7];
x = min(y);
elseif x == y(1,3)
Tr3 = lognrnd(1.60944, (0)^2);
t3 = t3 + 1;
td3 = td3 + Tr3;
a = floor(y(1,3)/(720));
b = floor( (rem(y(1,3),168)/24));
c = floor((rem(y(1,3),24)));
c3 = c3 + L3(1,a+1)*L4(b+1,c+1)* betarnd(-3.4181, 1.4308);
a3 = rand;
T3 =(-1/13)* reallog(a3);
t = t + Tr3+T3;
T3=t;
y = [T1, T2,T3,T4,T6,T7];
x = min(y);

elseif x == y(1,4)
Tr4 = lognrnd(1.60944, (0)^2);
t4 = t4 + 1;
td4 = td4 + Tr4;
a = floor(y(1,4)/(720));
b = floor( (rem(y(1,4),168)/24));
c = floor((rem(y(1,4),24)));
c4 = c4 + L3(1,a+1)*L4(b+1,c+1)* betarnd(-3.4181, 1.4308);
a4 = rand;
T4 =(-1/14)* reallog(a4);
t = t + Tr4+T4;
T4=t;
y = [T1, T2,T3,T4,T6,T7];
x = min(y);

elseif x == y(1,5)
Tr6 = lognrnd(1.386294, (0.4)^2);
t6 = t6 + 1;
td6 = td6 + Tr6;
a = floor(y(1,5)/(720));
b = floor( (rem(y(1,5),168)/24));
c = floor((rem(y(1,5),24)));

```

```

        c6 = c6 + L3(1,a+1)*L4(b+1,c+1) * 10.* betarnd(1.7808, 8.5725);
        a6 = rand;
        T6 =(-1/16)* reallog(a6);
        t = t + Tr6+T6;
        T6=t;
        y = [T1, T2,T3,T4,T6,T7];
        x = min(y);
elseif x == y(1,6)
        Tr7 = lognrnd(2.302585, (0)^2);
        t7 = t7 + 1;
        td7 = td7 + Tr7;
        a = floor(y(1,6)/(720));
        b = floor( (rem(y(1,6),168)/24));
        c = floor((rem(y(1,6),24)));
        c7 = c7 + L3(1,a+1)*L4(b+1,c+1) * 25.* betarnd(2.5776,6.1072);
        a7 = rand;
        T7 =(-1/17)* reallog(a7);
        t = t + Tr7+T7;
        T7=t;
        y = [T1, T2,T3,T4,T6,T7];
        x = min(y);

end
end
% failure rate
fLA= (t1 + t2 + t3 + t4 + t6 + t7 );
FLA= FLA + fLA;
% unavailability
unavaiLLA = (t1).* td1 + (t2).* td2 + (t3).* td3+(t4).* td4 + ...
(t6).* td6 + (t7).*td7 ;

unavaiLLA= unavaiLLA + unavaiLLA;
cost = c1 + c2 + c3 + c4 + c6 + c7;
ecost = ecost + cost;
end

v= v + FLA/N;
h = h + unavaiLLA/N;
e = e + ecost/N;
end
g(d,:)= v/(i);
k(d,:)= h/(i);
m(d,:)= (e/(i));
z(d,:) = (h/(i)) ;
end
g;
k;
mean(m) * 33000
mean(z) * 33000
toc

```