Cost of Electricity Interruption to Commercial and Industrial End-Users

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Submitted in fulfilment of the

Academic Requirements for a

Master of Science in Electrical Engineering

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February 2019

Declaration

A lot of literature consultation was undertaken in the preparation of this dissertation. Due care has been taken to properly reference all work used. The rest of the dissertation is my work.

The number of words in the main text of the dissertation does not exceed 50 000.

Signed by candidate

KINGSLEY AKPEJI

Dedication

To my parents, siblings, and dear friends.

Acknowledgement

To the King eternal, immortal, invisible, the only wise God, I give honour and glory for navigating me through a rather wavy path of my MSc research and bringing me to a desired haven!

To my academic supervisors, Prof. K. A. Folly and Mrs K. O. Awodele, the project leader of the Geomagnetically Induced Current (GIC) mitigation research project group, Prof. C.T. Gaunt, and Dr David Oyedokun, I am very grateful for your guidance and support throughout the course of my program. Thank you for your patience and understanding, for the time you availed for consultation, for the helpful criticisms and feedback that refined this dissertation.

To my co-student researchers involved with the GIC mitigation project, you made the journey fun and worthwhile. Azeez, I appreciate the zeal and concertedness you brought to our work package. You inspire progress!

Registrations for my degree and subsistence through it would have been financially burdensome without the scholarship from the Open Philanthropy Project team provided through Prof. C. T. Gaunt. Thank you!

To my parents and siblings, extended family, friends near and far, thank you for your love, prayers, encouragement, and support of every kind. You brought warmth on very cold days.

Abstract

The question *'what is the cost of electricity interruptions?'* is fraught with lots of complexities as electricity interruption is not a tradable commodity. A closely associated question is '*from whose perspective should this cost be assessed – the electric utility or its customers?*' Extant research has shown that the primal focus should be on the electricity customer as the electric utility's revenue loss after an electricity interruption event is significantly less than customers' interruption cost (CIC).

Existing methods of assessing the cost of electricity interruptions are not always consistent, because analysts make different assumptions, primarily in the incorporation of key parameters of electricity interruptions and customer characteristics in their analyses. However, one thing is important: *the chosen assessment method should suit the decision-making context in which the cost data will be applied.* In this dissertation, both micro- and macro-level approaches were applied to the assessment of the cost of electricity interruptions to commercial and industrial electricity customers. However, the central investigation is the micro-level assessment of the direct financial cost of electricity interruptions to suit value-based reliability planning and power system operations management. The cost assessment was done from the business customer's viewpoint via a firm-level survey of commercial and manufacturing businesses in Cape Town.

Three CIC models were developed from an analysis of the survey data viz. *a time-invariant average interruption cost (TIAIC) model, a time-varying average interruption cost (TVAIC) model, and a time-varying probabilistic interruption cost (TVPIC) model.* All three models were applied in an assessment of reliability worth indices for a case study distribution system to demonstrate the practical application of the cost data. The results showed that the TVPIC model is more effective for describing CIC as it accounts for the time-dependencies and uncertainty in CIC estimates. The TVPIC allows for an evaluation of the impact of different confidence levels in decision-making. Reliability worth indices like ECOST derived based on the TVPIC can be expressed as Rands@Risk in different season-time windows. This allows for optimal implementation of contingency measures like load shedding or reliability improvement programs like switch/disconnect placement on distribution feeders.

An exploratory macroeconomic analysis was also done using an input-output (IO) model that allowed the investigation of the effect of the removal of the electricity sector from intersectoral interactions in South Africa's economy. Based on the model's framework and assumptions, the potential economy-wide cost of a day-long blackout was estimated to be approximately R2.2 billion. Compared to estimates of the economic cost of past load shedding events, this figure seemed to be a very optimistic estimate and a potential lower bound of a day-long blackout in South Africa. Also, the relationship between the firm-level survey and the macroeconomic IO approaches to estimating the cost of electricity interruptions was assessed via a case study of the weekly cost of load shedding to South Africa's trade and manufacturing sectors. The ensuing discussions show that caution must be exercised in quoting *blanket figures* of the cost of load shedding to the South African economy without appropriate description of the basis for estimation.

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List of Abbreviations

ASAI	Average system availability index
ASUI	Average system unavailability index
BL_D	Backward linkage impact (daily estimate)
CAIDI	Customer average interruption duration index
CAIFI	Customer average interruption frequency index
CDF	Customer damage function
CGE	Computable general equilibrium
CIC	Customer interruption cost
CIS	Critical infrastructure systems
CoUE	Cost of unserved energy
CPA	Consumer protection act
CPI	Consumer price index
CQ	Comprehensive questionnaire
CR	Contingent ranking
CST	Chi-squared test of independence
CV	Contingent valuation
DC	Direct costing
ECOST	Expected customer interruption cost
EENS	Expected energy not supplied
ERNC	Expected Revenue not collected
FET	Fisher’s exact test
FL_D	Forward linkage impact (daily estimate)
GDP	Gross domestic product
GVA	Gross value added

HEM	Hypothetical extraction method
HILF	High impact low frequency
IEAR	Interrupted energy assessment rate
IO	Input-output
IOT	Input-output table
kV	Kilovolt
kVA	Kilovolt-ampere
kWh	Kilowatt-hour
LP1	Load point 1
MV	Megavolt
MWh	Megawatt-hour
NERSA	National energy regulator of South Africa
PDF	Probability distribution function
PF	Production function
PIC	Purchase and installation cost
R	South African Rand
R/kWh	South African Rand per kilowatt-hour
R2 billion	Two billion South African Rand
RBTS	Roy Billinton Test System
RP	Revealed preference
SA	South Africa
SAIDI	System average interruption duration index
SAIFI	System average interruption frequency index
SAM	Social accounting matrix
SIC	Standard industrial classification

SSA	Sub-Saharan Africa
Stats SA	Statistics South Africa
TIAIC	Time-invariant average interruption cost
TS-MCS	Time-sequential Monte Carlo simulation
TTF	Time to failure
TTR	Time to repair
TTS	Time to switch
TVAIC	Time-varying average interruption cost
TVPIC	Time-varying probabilistic interruption cost
UPS	Uninterrupted power supply
USA	United states of America
VBRP	Value-based reliability planning
VoLL	Value of lost load
WRST	Wilcoxon rank sum test
WTA	Willingness to accept
WTP	Willingness to pay

1 Introduction to The Study

This chapter presents the background for the research undertaken in this dissertation. The relationship between power system risk and reliability is described. The potential impacts of power system risks and the need for a value-based approach to power system management are highlighted. The hypothesis on which this dissertation is based and the ensuing research questions and scope are also clearly stated. The chapter concludes with the outline of the dissertation.

1.1 Concept of risk and reliability in power systems

The socioeconomic sustainability of modern societies is heavily dependent on a reliable and resilient electricity infrastructure. Generally, electric power system reliability is assessed in terms of adequacy and security. Adequacy refers to the existence of enough generation and other resources including transmission networks and demand response to satisfy consumers demand. Security refers to the ability of the power system to respond to disturbances and transients caused by large load changes, faults, switching operations, or lightning strikes [1]. Ideally, perfect power system reliability is desired, but the power system is vulnerable to risks from its immediate operating environment and space weather. Thus, the failure rates of system components can be significantly influenced by these risks resulting in planned, forced or unplanned component outages that might cause electricity interruption to electricity customers.

Risk in the context of power systems encompasses not only the possibility of component outages and electricity interruptions – but also the consequence of such occurrences. Generally, risk may be viewed as the answers to three key questions: *what can happen? how likely is it to occur? What are the consequences?* [2]. The severity of the impact of power system risks is considerably dependent on the vulnerability of the system. Two main levels of vulnerability exist: personnel and cyber-physical. Day-to-day system operation requires a properly trained and specialized workforce, thus threats to system personnel are also system threats. Personnel may be vulnerable to health risks like pandemics or coordinated union actions that might result in workforce unavailability during system contingencies. At the cyber-physical level, power systems have three functional zones which can be combined to form hierarchical levels (Figure 1.1) [3]. The functional zones are generation facilities, transmission facilities, and distribution facilities. Research and field experience have shown that the degree of vulnerability of the cyber-physical power system is influenced by:

- Power utility service territory or geography [4-6];
- Network exposure and design (including substation layout and protection, ratio of underground to overhead line miles, and network redundancy) [7-9];
- Network condition (age and maintainability) [10, 11];
- Degree of automation and reliance on communication infrastructure [12].

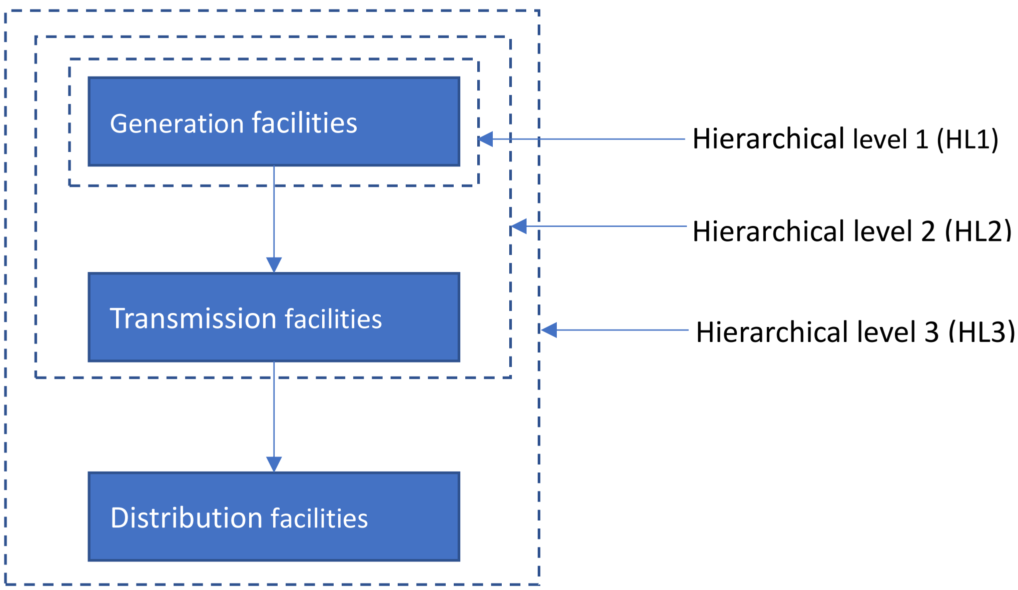

Figure 1.1: Power system functional zones and hierarchical levels

Various risks may affect more than one functional zone of the system. The stress on the system is usually higher if a higher functional zone is affected and there is little or no mitigation in place. Distribution component outages and failures are the most commonly reported [3]. They result primarily from adverse to extreme weather events including lightning, wind, storms, precipitation, equipment ageing, component maloperation, accidents (e.g. cars crashing into poles), theft or vandalism of cables and transformers. Distribution system failures are usually localized and may only cause electricity interruptions to electricity customers connected to affected parts of the network. However, the strong spatial mismatch between electricity supply and demand due to the large distances separating generation and load centres in large electricity grids [13] implies that the impacts of local generation and transmission failures in the system are often not isolated but can propagate easily to locations distant from the point of failure, causing electricity interruption to many electricity customers downstream or wide-area blackouts (Figure 1.2).

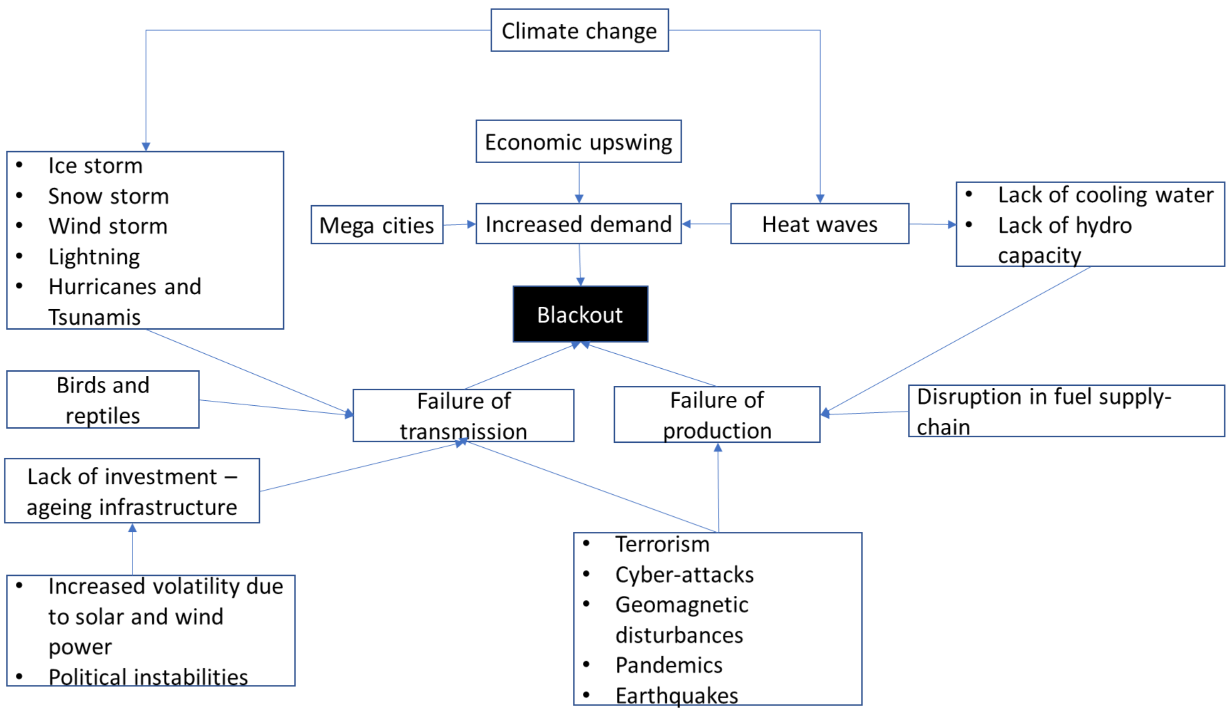

Figure 1.2: Potential causes of wide-area blackouts (adapted from [14])

Terrorism, cyber-attacks, natural disasters (earthquakes, tsunamis, tornadoes, hurricanes, volcanic eruptions), solar storms causing geomagnetic disturbances (GMDs), and pandemics have been classified as high-impact low frequency (HILF) risks [5, 15]. Traditional power system planning scarcely incorporates these risks in risk assessment [15]. This is because HILF risks present a unique challenge to system planners and operators. Since HILF risks occur infrequently, little real-world operational experience exists to respond to them effectively, yet they might have significant impact (up to a regional scale) if they occur [5].

1.2 Impacts of power system reliability events in South Africa and across the globe

With the pervasive use of electricity dependent technologies and systems in modern societies, extended and frequent electricity interruptions may be considered a disaster. Disasters may affect societies in five different categories: economy, quality of life, institutions, environment, health, and life [16]. A consideration of the impacts of past and recent power system reliability events in South Africa (SA) and across the globe provides fact-based evidence of the value of power system adequacy and security and the need for optimum power system reliability and resilience.

Deficient policy outlook that delayed the planning and execution of generation capacity expansion programmes, regulatory oversight from the national energy regulator of South Africa (NERSA), inept management on the part of SA's national electric utility – Eskom, sharp decline in Eskom's coal stockpile and an unseasonably cold and wet weather led to recurrent load shedding in SA between late 2007 and early 2008 [17]. Twenty-three days of load shedding between November 2007 and January 2008 was estimated to have cost SA's economy approximately R50 billion i.e. an average of R2.17 billion per day, based on NERSA's cost of unserved energy (CoUE) of R75/kWh at that time [18]. This was approximately 2.3% of SA's 2008 gross domestic product (GDP) [19]. The mining sector experienced a 22.1% contraction in output for the first quarter and a major mining company had to lay off 5 000 workers [17]. The manufacturing, services and tourism sectors were also badly hit.

The 2008 events received government and public support for Eskom to plan and invest in building new generating plants to improve system adequacy. However, after a few years of improvement in electricity generation and delivery, load shedding was reintroduced between late 2014 and early 2015. Chris Yelland [20], an energy expert estimated the cost of these events as R20 billion, R40 billion, and R80 billion per month for stage 1, 2, and 3 load shedding[1] respectively. Yelland's estimates were based on the following assumptions: cost of unserved energy of R100/kWh, 10

[1] Up to 1000 MW of SA's national load is shed at each load shedding stage e.g. 1000 MW, 2000 MW, and 3000MW at stage 1, 2, and 3 respectively.

hours of load shedding per day, and 20 days of load shedding per month [20]. These imply a daily cost of R1 billion, R2 billion, and R4 billion for stage 1, 2, and 3 load shedding respectively. The estimates of NERSA and Yelland are not contained in peer-reviewed academic studies, but they provide an indication of the economic cost of 2007/2008 and 2014/2015 recurrent load shedding events.

Investment in generation capacity expansion improves system adequacy, but without a viable framework for such investments, the extra cost will be passed on to electricity customers in tariff increases. Limited financial support from the government and the threat posed to its credit ratings by unhealthy debt profiles made Eskom resort to tariff increases to fund its investment programmes [21]. In addition, there appears to be an investment backlog in Eskom's transmission and distribution networks [21, 22]. Regular and HILF risks, increase in grid-integration of renewable energy sources, existing and prospective governmental and environmental policies still threaten the reliability of the grid, and in some countries extensive system collapses have occurred [1, 14, 15]. Table 1.1 highlights some recent blackouts across different countries and their impacts. South Africa (SA) is relatively unprepared for extreme events that might result in wide-area blackouts, and Eskom's last resort to grid contingencies is load shedding. Eskom asserts that the likelihood of a national blackout in SA remains low given the existence of what it terms *"various layers of protection"* including [22]:

- Scheduled rotational load shedding, in terms of the National Code of Practice for Emergency Load reduction (NRS 048-9);
- Unscheduled load shedding in the event of system constraint exceedance after the implementation of scheduled load reduction as per NRS 048-9;
- Resort to blackout restoration plan following the occurrence of a blackout. The components of the restoration plan are deemed to be tested through physical and simulation exercises. Eskom's black start facilities namely Kendal and Drakensberg were reported to be fully tested every six years in compliance with the SA Grid Code;

- Generation unit islanding on some power stations to reduce the time required to restart the national system.

Despite the low likelihood of a national blackout, any event that could significantly precipitate its occurrence should be prevented where possible. Accordingly, there is a need to implement deliberate measures to ensure grid reliability and resilience.

Table 1.1: Recent blackouts across different countries and their impacts [1, 14, 15, 23-25]

Date	**Location**	**Cause**	**Duration (approximate values)**	**Population affected (estimate)**	**Impacts**
13/03/1989	Eastern Canada	Geomagnetic disturbance	83% restoration after 9 hours	6, 000, 000	NA*
02/01/2001	India	Technical failure - Failure of substation in Uttar Pradesh.	12 hours	226, 000, 000	Economic losses estimated to be USD110 million.
14/08/2003	USA (North-East) + Canada (Central)	Combination of lack of maintenance, human error, and equipment failure.	4 days	50, 000, 000	Economic losses estimated to be USD6 billion.
28/09/2003	All Italy except Sardinia	Technical failure causing a domino effect that led to a separation of the Italian grid from the rest of the European grid.	18 hours	56, 000, 000	4 deaths
25/05/2005	Moscow	Technical failure: tripping of aging transformers in Chagino substation, causing a domino effect that led to the blackout.	100% restoration after 10 weeks	4, 000, 000	Economic losses estimated to be USD70 million.
04/11/2006	Southwest Europe (parts of Germany, France, Italy, Belgium, Spain and Portugal)	Human error. Fault originated from the Netz control area in Germany when a high voltage line was switched off to allow a ship pass underneath it.	2 hours	15, 000, 000	NA*
04/02/2011	Brazil	Technical failure – failure of electronic component in a	16 hours	53, 000, 000	NA*

		protection system in affected substation.			
29/10/2012	Northeast U.S.A.	Hurricane	95% restoration after 10 days	5, 770, 000	NA*
23/12/2015	Ukraine	Cyber-attack	6 hours	225, 000	NA*
30/7/2012	India	Network overload in India's northern grid led to cascaded tripping of circuit breakers on High voltage lines beginning with the 400 kV Bina–Gwalior line.	15 hours	350, 000 000 – 400, 000, 000	NA*
31/7/2012	India	Network overload caused a drop in system frequency and a tripping of inter-state and inter-region HV lines. India's Northern, Eastern and North-Eastern electricity grids were affected.	8.5 hours	620, 000, 000	NA*

NA - Information not available.*

1.3 Value-based decision-making in power system planning and operations

The average time required to respond to different power system reliability events ranging from normal to extreme varies depending on the type and speed of the failure and the need for coordination [15]. There is no solution to fully prevent reliability events and blackouts. However, effective decision-making can provide optimal risk management. Decision-making in power systems can be categorized based on timeframe as long-term and short-term (Table 1.2). Most long-term decisions address system planning and industry regulation, while short-term decisions address system operations.

In performing risk management whether in the system planning or operational framework, it is necessary to perform a quantitative risk evaluation, determine risk reduction measures and justify an acceptable level of risk (Figure 1.3) [26].

Table 1.2: Power system risk management decision-making needs

Long-term Decisions	Short-term Decisions
• Reliability planning– adequacy and security • Regulation • National strategies on High impact low frequency risks (HILFs) • Policy decisions on proliferation of backup generators (e.g. emission concerns) and grid integration of renewable energy sources	• Operations planning: economic dispatch (hours - days) • Voltage and frequency control (seconds – minutes): real-time dispatch, forced outages or load shedding

Figure 1.3: Process flow of power system risk management

Traditionally, power system reliability levels have been planned based on deterministic techniques. Reserve margins are determined using the **N – X** criterion i.e. the ability of the system to supply forecast peak loads with a specified number of units out of service [27]. This technique is based mainly on historic reliability levels and the expertise of power system operators and planners. It does not account for variation in the needs and expectations of electricity customers when setting reliability targets or evaluating power system improvement [28]. Also, quantitative distribution reliability indices like 'system average interruption duration index' (SAIDI), 'system average interruption frequency index' (SAIFI), 'customer average interruption duration index' (CAIDI) and 'customer average interruption frequency index' (CAIFI) which are commonly used to measure and compare the performance of the networks of electric utilities are single-average-value indices. They only provide a snapshot of the performance of the grid [29]. A major disadvantage of these indices in determining a satisfactory reliability level is that they do not reflect the financial, economic, and socio-political effects of poor reliability [30]. Thus, it is also necessary to carry out a non-technical assessment of reliability from the electricity customer's viewpoint.

As electricity customers become more knowledgeable about electric service delivery, they have an expectation of an *acceptable level* of service reliability at an *affordable price*. Since the electricity market is a natural monopoly, electricity customers might not be able to change service providers at will[2]. Many of these customers desire that the "lights stay on" perpetually, but such idealistic expectation might not be justifiable financially. Electric utilities face increasing uncertainties due to political, environmental, societal and economic constraints, thus it is necessary to justify an acceptable level of system risk financially. A value-based approach that embeds a rigorous cost-benefit analysis is required for this purpose. The goal is to determine a value-at-risk that can be used for decision making in system reliability planning and operation, designing effective regulatory schemes and energy policies.

The cost of investment to meet certain reliability targets can be readily quantified by evaluating the necessary capital and operational expenditures. On the other hand, quantifying the benefits or worth of the set reliability target is rather difficult. Although the benefits of very high power system reliability is readily perceptible, the value that electricity customers place on reliable electricity supply is not exactly known. Recourse to markets to derive this information might be futile, as there is no market where electricity interruptions are traded[3] [31]. Since a direct evaluation of the value of electric service reliability is not feasible, assessing the *cost of the impacts of unreliability to electricity customers and society* has evolved as a rational alternative. These impacts may be tangible or intangible, economic or social. The cost of these impacts may be described as *'customer interruption cost (CIC)'*. Other description of this cost in existing literature include *'value of lost load (VoLL)'* and *'cost of unserved energy (CoUE)'*.

In a value-based reliability planning (VBRP) framework, a system reliability level is sought that allows significant reduction of CIC with feasible and optimal investments by electric utilities (Figure 1.4). Traditional regulatory schemes require electric utilities to achieve certain targets in reliability indices such as SAIDI and SAIFI. However, the attainment of minimum standards in

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[2] An exception is when electricity customers decide to fully go off-grid and provide for their electricity needs themselves.

[3] This might not apply to very large power users who have provisions in their contracts to reduce their demands during system peaks. But even for these users, it is not a total interruption of supply that is often contracted.

SAIDI or SAIFI might not yield optimal reliability level. When electric utilities meet minimum standards, they have no incentive to further improve their networks. If there is an incentive based on CIC, electric utilities always have an incentive to provide optimal reliability [32]. The optimal reliability level is that where the total net cost of reliability is minimum (Figure 1.4).

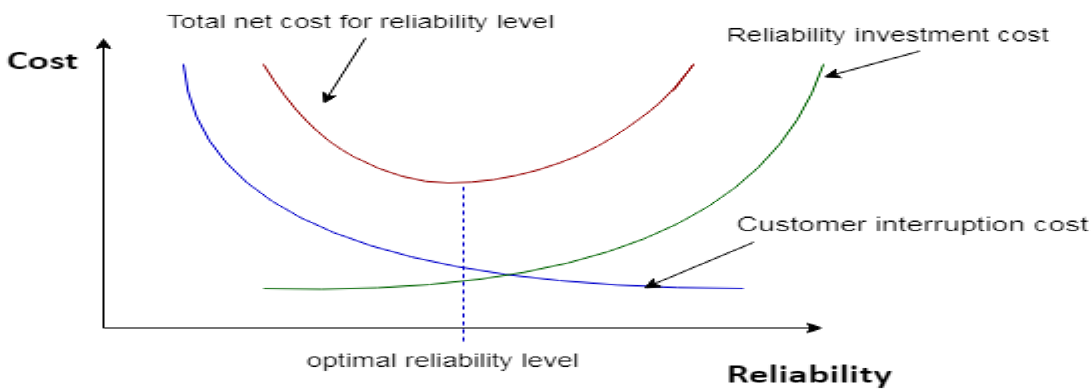


Figure 1.4: Reliability cost-benefit valuation

1.4 Research motivation and hypothesis

Choice of power system functional level and customer categories for research

Reliability worth assessment studies can be performed at any power system functional level – generation, transmission, or distribution. A holistic reliability worth analysis that includes all functional levels is very complex and might not be tractable. Since generation and transmission failures might reflect at distribution level and approximately 80% of power system failures occur at the distribution level [33], reliability worth assessment at the distribution level yields an approximate system reliability worth [33]. Hence, this research primarily studies the cost of electricity interruptions at the distribution functional zone.

Assessing CIC is quite difficult especially when the impacts of unreliability cannot be readily monetized. Nonetheless, significant research has been done on the assessment of CIC in various countries. CIC assessment has been done for the residential sector and economic sectors - agricultural, commercial, and industrial. In several studies, CIC for commercial and industrial customers (otherwise called *business customers* in this dissertation) have been found to be significantly higher than that for residential customers [34]. In considering the impacts of electricity interruptions on a local or national economy, it is necessary to focus on business customers [35]. Furthermore, the impacts of unreliability on these customers can be readily monetized. Hence, business customers are the focus of this research.

Challenges with business customers interruption cost assessment

The methods of data collection and analysis applied by CIC researchers assume different conditions prevailing at the times of electricity interruption, mainly whether the interruptions are chronic or sporadic. Also, cost assessment is usually carried out within the specific context of the region or country for which the study is undertaken. Methods applied in one country might not be readily applicable in another and the cost estimates may not be readily extrapolated. Accordingly, published results of business customers' interruption cost are not always consistent and comparison is very difficult [36]. The inconsistencies are mainly in the incorporation of key spatiotemporal and customer-related factors that influence the electricity interruption cost of business customers [37].

Business customers have different activity levels, electricity usage patterns and resilience to electricity interruptions. Different business customers will be affected in different ways by electricity interruptions of different durations occurring at different time of day, day-of-week and season of the year. For instance, an electricity interruption of about 2 hours occurring between 5pm – 7pm will have more impact on a restaurant that has peak activity in the evenings and uses mainly electrical equipment for cooking and other activities than another that has peak activity between morning and lunchtime and uses mainly gas for cooking. Extending the foregoing example, the sizes of the restaurants may be significantly different. Generally, three size groups may be identified within any business sector – small, medium and large [38]. This highlights that the segmentation of business customers is an important factor that should be considered when modelling their CIC. Intuitively, grouping business customers into more homogenous groups should yield more accurate CIC results [39].

The conventional approach to describing the CIC of business customers is to average or aggregate their CIC estimates for a certain electricity interruption duration [40-43]. Neither cost averaging nor aggregation adequately captures the variation in CIC, hence they might not provide a good representation of business customers, nor do they allow for exploring the impact of different risk or confidence levels in power system decision making. In the context of SA, there is a need for the assessment of the cost of electricity interruption to business customers and the economy using approaches that yield cost estimates in a form that can be readily applied for optimal decisions in power system planning and operation, electric utility performance regulation and energy policy designs. Load shedding might be necessary to prevent wide-area blackouts in the event of extreme system contingencies, thus it is necessary that *the right load or set of loads be shed at the right time*. Logically, loads should be shed in order of their CIC i.e. starting with loads with minimum CIC.

Although most of the published research on business customers interruption cost have been done in developed countries [34], some electricity interruption cost studies have been performed in SA and other Sub-Saharan African (SSA) countries [44-47]. These studies provide methodical insights for electricity interruption cost studies in SA and other SSA countries. Accordingly, in this research, these studies will be critically reviewed to explore which factors, data collection and analysis approach allow for a comprehensive modelling of the CIC of business customers considering the need for risk-based decision making by electric utilities and regulators.

Furthermore, most of the existing methods of assessing the cost of electricity interruptions neglect the sectoral independencies that characterize modern economies. They limit the assessment of electricity interruption cost to individual business customers or sectors. However, the complex cross-linkages in modern economies imply that sectoral or regional shocks may ripple throughout an economy. Economy-wide models that capture inter-sectoral flows have been applied to study the potential economy-wide impact that may be caused by disasters, market instabilities, policy, or institutional changes. These models will be reviewed in this research and an exploratory analysis of the economic impact of electricity interruptions will be carried out using a model that suits the South African context.

Given the foregoing discussions, this research aims to test the validity of the following hypothesis.

A time-based probabilistic model of the cost of electricity interruptions to business customers which can be applied for effective power system management can be developed through

appropriate data collection and analysis that incorporates key parameters of the interruption, characteristics of business customers and the uncertainty in their interruption cost estimates.

To test the validity of this hypothesis, the following research questions are investigated:

1. What is the nature of the various electricity interruptions business customers are subjected to and how do they respond?
2. What key factors best describe the CIC of business customers?
3. What is the best approach to assessing the cost of electricity interruptions to businesses and an economy?
    - What are the data requirements of the existing approaches and how are these data collected?
    - In what context have these approaches been applied and what decision-making needs do they suit?
4. What is the best way for describing the CIC of business customers?
    - What quantitative and qualitative insights does a probabilistic representation of their CIC provide over average CIC?
5. How do the results of past SA studies on the cost of electricity interruption compare with the results of this research? Do they corroborate each other? What factors explain the difference?

1.5 Scope and limitations of the study

This study focuses on the assessment of the cost of electricity interruptions to business customers through appropriate data collection and analysis. The actual collection of data is not as extensive as that required by electric utilities and regulators for power system planning, operations and regulation. A sufficient sample size that allows for the demonstration of the analysis and application of electricity interruption cost data in power system reliability worth assessment will be determined. Also, the assessment of the cost of power quality events – voltage sags, dips, and harmonics – and the social impact of electricity interruptions are not considered in this study.

The use of hypothetical electricity interruption scenarios to obtain CIC estimates in this study does not allow for ascertaining whether electricity interruptions directly led to the incursion of cost. Thus, it is plausible that the CIC of the survey respondents in actual electricity interruption events might differ significantly from those reported in this study. This can be validated by collecting more data during a period of load curtailment. Also, while the regression analyses in this dissertation shows positive correlation between average monthly electricity bill and CIC, causation is not implied. The regression models should only be considered as an approximation of the relationship between CIC and average monthly electricity bill. Applying the models for extrapolation outside the range of the sample data *assumes* that the approximate relationship observed will be valid for other sample data or the entire population. The *estimate* of the potential worst-case CIC for a given electricity interruption duration based on business customers' average monthly electricity bill is *imperfect*. While the regression models capture the underlying trend in the collected survey data, no business customer interruption cost for an electricity interruption occurring at their busiest time-of-day, day-of-week, and season-of-the-year will be perfectly predicted. The CDFs developed in the study are deemed to be mainly valid for the range of electricity interruption duration studied i.e. 30 minutes to 8 hours. The CDFs are inappropriate for estimating the cost of power quality events or electricity interruptions of only a few cycles. Also, the variation in demography and market activity across different regions in SA implies that the results of this study might not be directly extrapolated to other regions without sound and justifiable assumptions.

Lastly, the derived estimates of the daily macroeconomic cost of a nation-wide blackout in this dissertation are not absolute values but are optimistic indicators of the potential macroeconomic impact of such a sporadic electricity interruption event. The exploratory case study may also be carried out within provincial contexts if provincial input-output (IO) tables are available or derivable from the national IO table.

1.6 Dissertation outline

Chapter 2 reviews the literature on the cost of electricity interruptions. Customer interruption impacts are discussed. Key features and drawbacks of different methods that are used to evaluate the cost of electricity interruptions are discussed. The power system decision-making needs that different cost assessment methods suit are also highlighted. The research findings in this chapter form the basis of the design of the CIC survey in this study, the analysis of the survey data and a macroeconomic analysis that was done to assesses the potential economy-wide cost of electricity interruptions in SA.

Chapter 3 discusses the protocol for the firm-level survey. The procedure for the selection of the study population and samples, questionnaire design and administration, data capturing and coding are described in detail. The chapter ends with a summary of the data collection.

Chapter 4 presents descriptive statistics and graphical comparisons of the characteristics of the commercial and manufacturing population represented in the survey. The results of statistical tests applied to compare both populations are discussed. Comparisons are also made with findings in past studies where applicable.

Chapter 5 discusses the procedure and the results of the analysis done on the quantitative CIC data retrieved from the firm-level survey. The use of average monthly electricity bill to normalize the CIC estimates of survey respondents is validated via statistical regression analyses.

Chapter 6 focuses on a reliability cost-worth assessment done for a distribution test feeder to demonstrate the practical application of the analysed survey data. Three CIC models namely *time-invariant average interruption cost (TIAIC) model, time-varying average interruption cost (TVAIC) model, and a time-varying probabilistic interruption cost (TVPIC) model* were developed and compared using time-Sequential Monte Carlo simulations (TS-MCS) done on the distribution test feeder. The effects of different operation philosophies on the test feeder were also analysed. The algorithm and results of the TS-MCS are presented and discussed.

Chapter 7 discusses the procedure and results of an exploratory macroeconomic analysis done to assess the potential economy-wide cost of a nation-wide blackout in SA due to a hypothetical large-scale transmission system failure, as may be induced by an extreme geomagnetic disturbance, natural disaster, civil disorder, extensive union action or some other HILF risk.

Chapter 8 consolidates the research findings in this dissertation. Answers to the research questions, validation of the research hypothesis, and recommendations for further research are presented.

2 Cost of Electricity Interruptions: Review of Influencing Factors and Assessment Methods

This chapter presents an extensive review of the literature on the cost of electricity interruptions. Customer interruption impacts, factors influencing customer interruption cost and the different methods for assessing it are discussed. Macroeconomic models for assessing the economy-wide cost of electricity interruptions are also discussed. The chapter ends with a discussion on the research questions that were considerably answered through the literature review.

2.1 Customer interruption impacts

Electricity interruptions causes two broad categories of impact on electricity customers – economic and social.

2.1.1 Economic impacts

Generally, any interruption impact that can be directly assigned a monetary value is considered an economic impact [48]. Economic impacts may be further distinguished as direct, induced and indirect. The temporal and spatial extent of economic impacts are often used as a basis for providing clear description and distinctions of these impact categories [49].

Direct impacts result primarily from electricity customers' economic activities or processes that are directly affected by a discontinuity in electricity supply i.e. the impacts experienced during the duration of an electricity interruption (Table 2.1). Induced impacts usually accompany direct impacts (Table 2.1). Induced impacts reflect the responses of electricity customers to electricity interruptions and are sometimes unpredictable [48, 49].

Indirect impacts or higher-order impacts result from the diffusion of direct impacts (especially lost sales and production) across the wider economic system [49, 50]. In the case of business customers, quantifying these higher order impacts accounts for the fact that the impact of an electricity interruption on a business customer sets off a *domino effect*. For instance, the shutdown of a certain factory **A** may reduce its supplies to factories **B** and **C**, who in turn may be forced to reduce their production due to unavailability of necessary inputs. Also, factories **B** and **C** will be forced to reduce their supplies to other factories, and the chain continues. These types of effects are called *downstream, forward, or supply-side linkages*. Their counterparts refer to *upstream, backward-linkage or demand-side indirect effects*.

Table 2.1: Direct and induced impacts of electricity interruption

Broad customer category	**1. Direct impact**	**2. Induced impact**
Business	• Lost production • Equipment damage • Inventory loss (food or product spoilage, etc. • Lost paid staff-hours	• Lost Production (post event) • Post-event equipment damage due to fault development. • Overtime payment • Change in business operation plans • Business relocation • Security equipment installation costs • Backup power system costs
Government	• Transit revenue loss • Tax revenue loss	• Tax and transit revenue loss (post-event) • Emergency aid • Overtime payments • Investigation and research costs
Insurance	___	• Unemployment • Indemnification for private property, business property losses, and health issues.
Public health and safety	• Food and medical specimen spoilage • Lost revenue	• Increased patient load - overtime costs • Backup power system costs • New contingency plan costs
Other Public services	• Revenue loss • Equipment damage	• Backup power system costs • Overtime costs • Litigation costs
Electric utilities	• Revenue loss • Overtime costs (for supply restoration) • Capital expenses for restoration	• Extra capital expenses mandated • Legal fees • Investigation and research costs • Potential effect on rates

2.1.2 Social impacts

Social impacts associated with electricity interruptions refer mainly to the changes in social activities which are ordinarily facilitated by electricity dependent technology (e.g. leisure, cooking, and security monitoring), and the social adaptations – short and long term – which are made in response to these changes [48]. There is considerable degree of fuzziness in distinguishing between direct and indirect social impacts, hence no such distinction is made. A non-exhaustive list of some social impacts of electricity interruptions includes:

- Inconvenience due to unavailability of public services e.g. water supply and sanitation
- Loss of leisure time
- Crime
- Loss of goodwill
- Civil disorder
- Risk of injury and death

One special interest when considering the social impacts of electricity interruptions is the inconvenience experienced by residential customers [51]. On the side of electric utilities, a key social impact is the loss of their customers' confidence in their ability to provide reliable service. In unbundled power systems and competitive electricity markets where electricity customers can choose their service providers, this can have a significant effect on an electric utility's profitability.

2.2 Key factors influencing customer interruption cost

The severity of electricity interruption on electricity customers and society is influenced mainly by temporal, spatial, and customer-related factors.

2.2.1 Temporal factors

2.2.1.1 Electricity interruption duration

The reliability events which electricity customers experience can be broadly classified as *momentary or sustained* interruptions [52]. A major distinguishing feature between the duo is the threshold adopted for momentary interruption. This threshold varies among electric utilities, regulators and international standards (Table 2.2).

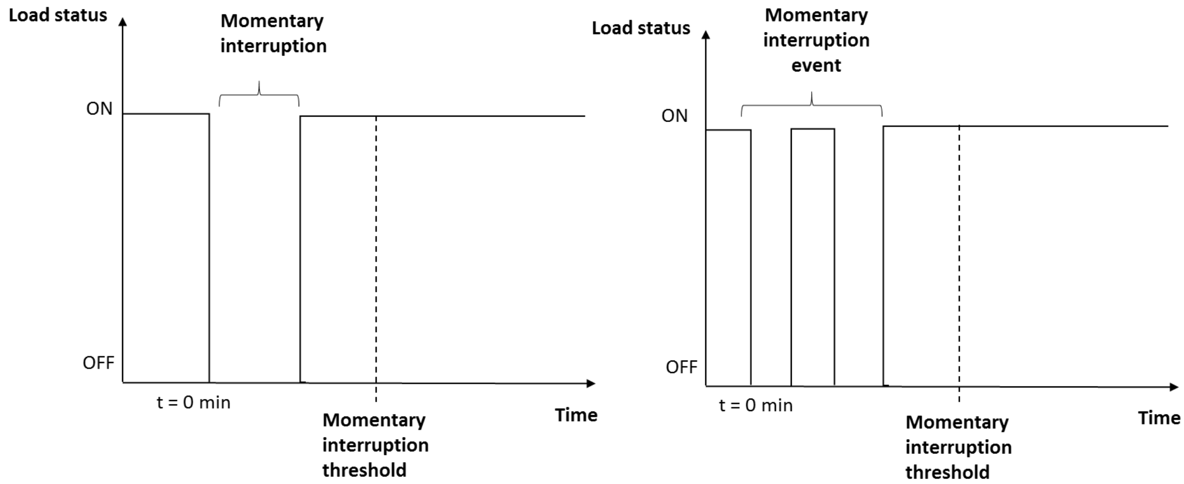
Table 2.2: Different thresholds for momentary interruption

Source	**Country**	**Year**	**Momentary interruption duration thresholds**	**Remark**
[52]	N/A	2012	< 5min	IEEE 1366 standard. Defined for distribution networks.
[53]	N/A	2004	≤ 3min	EN50160 standard defined for LV and MV networks. LV: ≤1kV MV: 1kV - 35kV
[54]	South Africa	2004	< 2min	Eskom Distribution. Defined for MV and HV network.
[55]	South Africa	2003	3s < t ≤1min (EHV and HV) 3s < t ≤ 5mins (MV and LV)	NERSA: NRS048-2
[56]	Australia	2014	< 1min	Changes made by the Australian Energy Market Commission (AEMC)
[57]	Brazil	________	≤ 3min	________

LV – low voltage. MV – medium voltage. HV – High voltage. EHV – Extra-high voltage.

Momentary interruption

Momentary interruptions (Figure 2.1(a)) may be caused by self-clearing faults or permanent faults [58]. Several momentary interruptions may occur within the duration threshold defined for momentary interruption (Table 2.2), causing a *momentary interruption event* (Figure 2.1 (b)). In this case, the successful restoration of electricity supply after any number of momentary interruptions is taken to be the end of the momentary interruption event [56]. The total number of momentary interruptions that each electricity customer can expect can be computed as the sum of the number of momentary interruptions due to self-clearing faults plus the number of those due to all permanent faults.



(a) (b)

Figure 2.1: (a) Momentary interruption (b) momentary interruption event
(N.B. t is measured from the onset of the interruption)

Switching actions (e.g. opening and closing of a circuit breaker, switches or similar device) to avoid high-impact sustained interruptions due to these faults are done manually or through distribution automation technologies. Although distribution automation cannot prevent permanent faults, they can mitigate the impact on certain electricity customers by reducing sustained interruptions to momentary interruptions [58]. Nonetheless, improvements gained through automation are sensitive to the number and location of switches. In some cases, this presents a somewhat dicey situation in power system operation, as some electricity customers consider that a single long duration electricity interruption is better than many short duration interruptions [57].

Sustained interruption

Electricity interruptions with duration exceeding the duration threshold for momentary interruptions are generally designated sustained interruptions (Figure 2.2). Figure 2.2 (b) represents a sustained interruption where there are unsuccessful attempts to restore electricity supply before the momentary interruption duration threshold is exceeded.

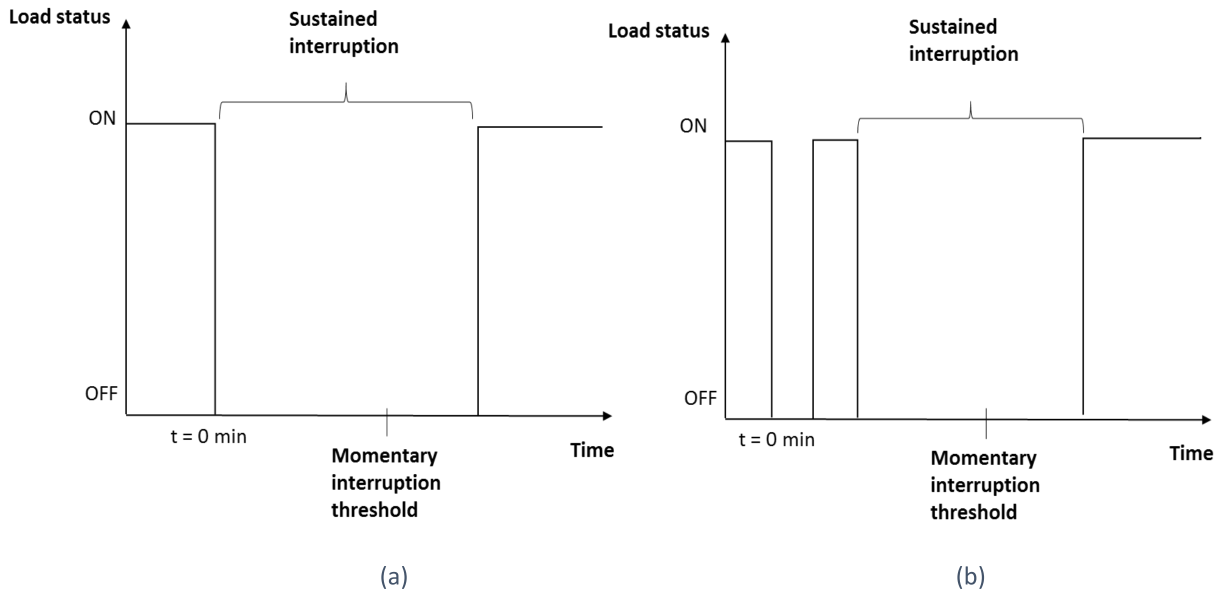


Figure 2.2: (a) Sustained interruption - no immediate attempt to restore supply (b) Sustained interruption after a few unsuccessful attempts to restore electricity supply.
(N.B. t is measured from the onset of the interruption)

Sustained interruptions could be either planned or unplanned. A key test to describe whether a sustained interruption is planned or unplanned is described as follows: "If it is possible to defer the interruption, then the interruption is a planned interruption, otherwise the interruption is an unplanned interruption" [52]. A planned electricity interruption is usually due to planned maintenance activities on some components of the network. Usually, the component(s) associated with the electricity interruption is taken out of service. On the other hand, unplanned electricity interruptions are usually due to the exploitation of the power system's vulnerabilities by different risks (section 1.1). Unplanned electricity interruptions that typically occur on the network can be described as 'normal' and these are mostly included in reliability reports [52, 59]. However, when the electricity interruption is due to an unusual event and has a somewhat lengthy duration than the average, it can be described as 'major' event.

Also, planned and unplanned electricity interruptions can be viewed from the perspective of the advance notifications given to electricity customers. For instance, Eskom makes prior agreements with large business customers to shed large blocks of load rapidly to save the system during severe contingencies [60]. When load shedding is planned, and adequate notifications given to electricity customers, they are better prepared to minimize the impacts of load shedding [61-63]. The converse is also true.

Effects of electricity interruption duration on CIC

The primary models for estimating CIC are based on electricity interruption duration [43, 46, 47, 64-68]. A general finding is that a sustained interruption exacerbates CIC. Although, there is evidence that the relationship between CIC and electricity interruption duration is not exactly linear [39], several studies approximate the relationship using linear or piece-wise linear models, especially for an electricity interruption duration up to 12 hours [67, 69, 70]. Generally, the value of CIC increases from zero to a positive value at the instant of electricity interruption (especially, for business customers that run continuous processes). Beyond this point in time, CIC continues to increase with electricity interruption duration. However, as the interruption becomes protracted, the effect of electricity interruption duration on CIC diminishes [16, 39]. The increase in CIC with electricity interruption duration becomes marginal (Figure 2.3). This is because electricity customers begin to adapt and employ mitigation measures to reduce their cost e.g. running backup power supply, sending workers home, outsourcing jobs, or rescheduling operations.

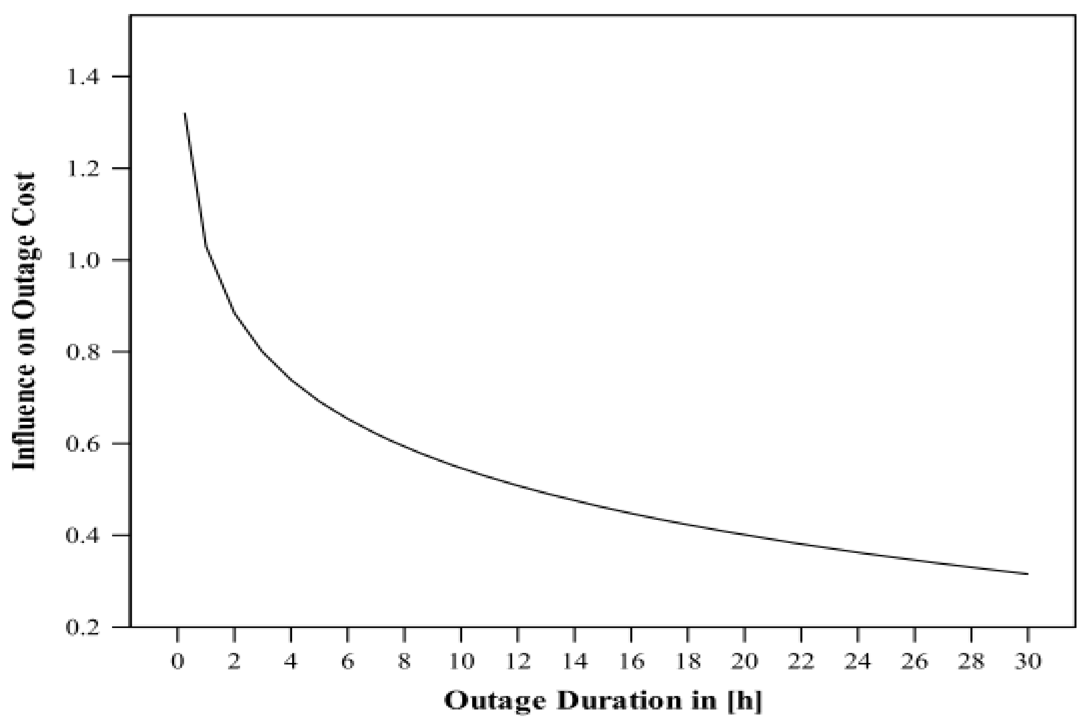


Figure 2.3: Influence of electricity interruption duration on CIC
(Adapted from [16])

2.2.1.2 Electricity interruption frequency

Generally, most electric utilities target reduced SAIDI and SAIFI. Reduced SAIFI mainly implies reduced occurrence of sustained interruptions recorded by electric utilities. However, in a bid to reduce sustained interruptions, momentary interruptions occur (section 2.2.1.1). The frequency of momentary interruptions is assessed using MAIFI (momentary average interruption frequency index) – a counterpart of SAIFI. MAIFI is not often reported in reliability data, because it is difficult to establish provenance of momentary interruptions [58]. In the cases where it is reported, it is generally only measured at the substation level [30]. This implies that momentary faults on medium and low-voltage feeders could go unrecorded. This creates a disparity between the assessment of system reliability by the affected electricity customers and the corresponding electric utilities that serve them

In terms of CIC assessment, inconsistent or inaccurate tracking of momentary interruptions can lead to an underestimation or overestimation of CIC depending on either of the following cases:

- If the cost assessment is based majorly on data collated by electric utilities at the substation level, a significant number of momentary interruptions experienced by electricity customers might be omitted, leading to a possible underestimation of the cost.
- If the assessment is based largely on response gotten through customer surveys (section 2.3.2), the tendency is for the cost to be overestimated. This is because the survey data can be biased by emotive and strategic responses.

Several studies that consider the effect of electricity interruption duration on CIC do not assess the sensitivity of the impacts on the electricity customer to electricity interruption frequency. There is research evidence that these frequent electricity interruptions can cause significantly high costs to business customers [30, 57, 71-74]. The increased digitalization of many industrial processes and commercial activities make power quality problems and momentary interruptions very critical. In many industrial processes, an electricity interruption duration of only a few cycles can cause several hours of plant equipment downtime, especially those requiring an accurately synchronized production process e.g. paper manufacturing and semiconductor production. In such cases, the impact for business customers should not be viewed from the electricity interruption duration, but from the perspective of the business downtime.

Apart from 'fault-clearing momentary interruptions', another major contribution to increase in electricity interruption frequency is chronic load shedding [46]. Chronic load shedding is predominant in many developing and 'third-world' countries, and is due mainly to generation and transmission inadequacy, and poorly maintained distribution networks.

2.2.1.3 Electricity interruption time and season

Business activity levels vary with season, day-of-the-week, and time-of -the-day [42]. For instance, in 2016, 6 out of the 9 major South African industries (at the 1-digit level of SA standard industrial classification (SIC) [75]) generated their highest quarterly gross value added (GVA) in the 4th quarter (October – December) [76]. The impact of electricity interruptions on economic activities during these periods will be more significant than in other time windows with lower activity levels.

Also, weather which varies with time and season influences electricity dependence level and usage. During winter, there is an increase in the number of heating degree days especially for northerly countries like Sweden, Finland, and Canada. This increases the need of electricity for water and space heating. This implies that electricity interruptions (especially those of long durations) during winter can adversely impact comfort levels of electricity customers compared to similar interruptions in autumn and spring. The same discussion holds sway for summer season, where space cooling and refrigeration are predominant electricity dependent needs.

Thus, in studying the impact of electricity interruptions on business customers, it is important to also account for the effect of time-of-day, day-of-week and season on impact levels. The risks of extreme (high or low) values of business customers' interruption cost can be can significantly underestimated when temporal factors are ignored. In several studies [28, 70, 77, 78], a worst-case electricity interruption scenario is chosen for CIC assessment, and CICs for other scenarios are derived by applying time-weight factors to the CIC in the reference scenario. However, Herman and Gaunt [79] proposed that using time-element matrices is a more robust approach to capture the effect of the variation of time and season on CIC.

2.2.2 Spatial/geographic factors

Risk susceptibility and electricity customer demographics (e.g. population, ethnic diversity, income, housing characteristics, density, settlement types, etc.) vary across different geographical locations within a country or region. The resulting distribution of political and socio-economic activities across regions is inconsistent. This can lead to significant regional variation in interruption costs as shown in [35, 65, 72-74, 79]. Thus, CIC assessment on a large regional footprint (e.g. country-wide) needs to consider spatial variations.

Extrapolating the results of a CIC study for a case study region has to be done using sound and justifiable assumptions, because the results for the case study region might not be representative of other regions. The drawback of an aggregate country-wide analysis disregarding spatial variations is that it suppresses meaningful information such as knowing the regions within a country for which electricity interruption is most significant. Information on the regional distribution of impacts can allow for evaluating equity considerations and communicating risk to stakeholders, thus facilitating their input in relevant policy processes. This way, affected parties can see what stake they have in dealing with electricity interruptions [49]. Regions for which electricity interruptions is most significant represent significant contributors to economic viability of a country and should be primarily considered in grid resiliency and reliability improvement programs.

A recent study [35] accentuates the importance of including the spatial factor in CIC assessment, although this adds an extra level of complexity in the assessment. A starting point will be identifying unique regions based on a chosen criterion. The following criteria may be explored:

- Susceptibility to risk [35];
- Census-based geographical regions [65, 72-74];
- Settlement type – rural or urban;
- Utility or municipality service territory.

2.2.3 Electricity customer characteristics

Electricity customers connected to a power system network may be classified into homogenous groups based on their economic activity or size – which may be electrical, economic, or physical. Different customer segmentation methods may be derived by combining segmentation criteria (Table 2.3). These segmentation methods are mainly applied in CIC studies that are based on customer surveys (section 2.3). The choice of customer segmentation method can cause significant difference in CIC estimates [72].

Table 2.3: Customer segmentation methods

Customer segmentation method	Segmentation criteria
One-dimensional (1-D)	Economic activity i.e. SIC[4]
Two-dimensional (2-D)	Economic activity and one size parameter (could be electrical e.g. maximum demand, energy consumption, voltage level, or economic e.g. turn-over)
Multi-dimensional (Multi-D)	Economic activity and more than one size parameter e.g. Energy consumption and turn-over as electrical and economic size parameters respectively.

The 1-D customer segmentation method has been adopted in many CIC researches [46, 80-82]. This allows for grouping electricity customers of similar economic activities together and has the advantage that CIC estimates can be obtained for each customer segment down to the last digit of the SIC. However, there is a disparity in this method. For instance, in the segmentation of business customers, large business customers may be grouped with smaller ones. Thus, in the CIC data, the CIC estimate for some business customers will appear as outliers. Some other authors have adopted the 2-D customer segmentation. These combine economic activity with a size parameter such as energy consumption [83], voltage level [84], or turnover [73].

Dzobo et al [85] identified the following drawbacks with the 1-D and 2-D customer segmentation methods for segmenting business customers: the high cost of extensive survey to survey all the

[4] The South African SIC includes 99 individual economic activity categories aggregated into 21 sections, and further into 9 sections; with each section containing categories with semblance in their economic activity.

customer segments formed under the 1-D, and significant variation in electricity intensities of various business customers in the segments formed under the 1 and 2-D segmentation methods. Consequently, a multi-D segmentation based on business customers' economic activity, electricity consumption and turnover was proposed as a more effective customer segmentation method that yields CIC estimates with lower uncertainty. The multi-D customer segmentation involves the aggregation of customer segments via hierarchical clustering. The application of this method requires that ancillary data on the economic activity and size parameters of the business customers to be surveyed are available beforehand to allow for the adoption of a stratified random sampling of prospective respondents. However, such data might not be publicly available to researchers due to restrictions on electric utilities and public enterprises (like chambers of commerce) by the consumer protection act (CPA) to protect consumer privacy. Thus, the application of this method is limited to instances when collaborations can be made with researchers, electric utilities or public enterprises who might be willing to divulge such data.

2.3 Customer interruption cost assessment methods

Many CIC studies assess mainly the cost of sustained interruptions using different methods [34]. Two major categories can be identified for the variety of methods that have been applied in these studies: indirect (analytical) and direct (survey) methods (Figure. 2.4). Direct methods require actual CIC valuations by the electricity customer, while indirect methods are based on some proxy approach.

2.3.1 Indirect methods

Indirect analytical methods generally assess CIC using macroeconomic production functions or market study of revealed preferences of electricity customers e.g. their investments in backup power supplies or power conditioning equipment.

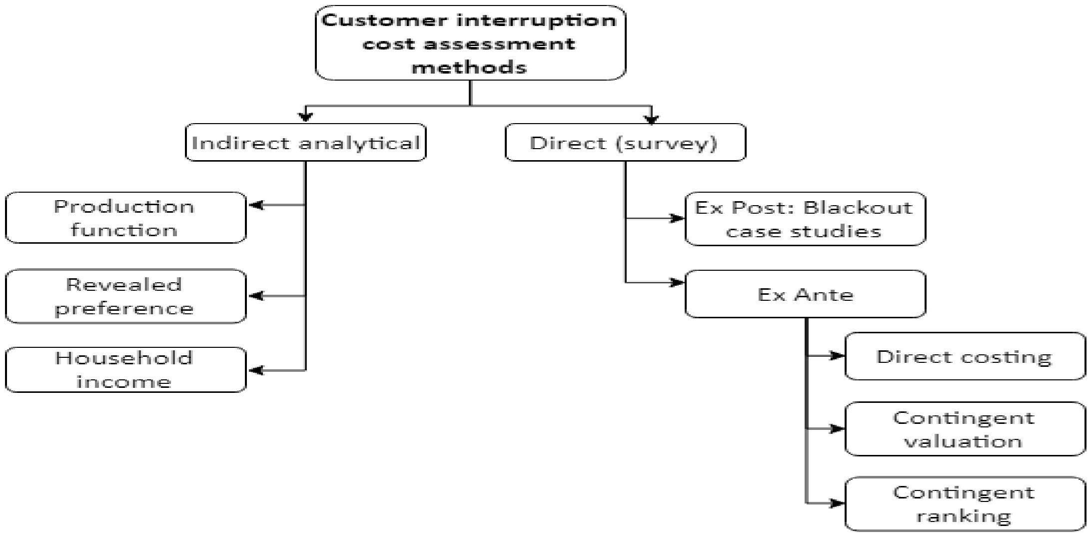


Figure 2.4: Classification of CIC assessment methods.

2.3.1.1 Production function (PF) method

The production function method assesses the cost of electricity interruptions based on global economic indices and variables. It is a simplistic approach to assessing the cost of electricity interruptions to economic sectors, a region or country. Many studies based on this method describe reliability worth using terms like *"value of lost load (VoLL)"* or *"Cost of unserved energy (CoUE)"*. For an economic sector, country, or region, VoLL or CoUE is determined by assessing the ratio of its productivity – proxied by gross domestic product (GDP) or gross value added (GVA) – to a certain amount of electricity consumption (peak load (kW) or energy (kWh)) [16, 31, 51, 81, 86-89]. For instance, if an economic sector consumes 10^6 kWh of electricity to produce R100 million output, each kWh consumed translates to R100 in productivity. Hence, the interruption cost for this sector is estimated as R100/kWh. The key assumptions in this interruption cost assessment approach include [88]:

- Electricity is an irreplaceable factor of production in the short term.
- Economic output is a linear function of electricity use.
- Exact time and duration of electricity interruption do not make a difference. Firms can change

their production schedules to different times of the day without economic losses.

The production function approach is readily applicable for estimating the interruption costs of business customers whose activities can be linked with a direct economic output. However, there have been efforts to extend its application to residential customers [16, 51, 62]. A concept termed *leisure time monetization* has been applied to link the activities of residential customers with economic output. The premise is that marginal values of leisure and labour are equal i.e. wage corresponding to one hour of labour equals the value of one hour of lost leisure. The application of the method to residential customers may be improved by eliciting data on leisure time usage for individuals in various households via surveys to derive a factor of substitution of home activities [16].

The application of the production function approach has been increasing in recent times for estimating VoLL in European Union countries [16, 31, 51, 62, 81, 86-88]. These countries normally have high electricity reliability and concerns about electricity security centers mainly on energy policy issues e.g. deciding on grid-integration of renewable energy sources [90]. Another reason for this trend could be because analysts are seeking to avoid the costs and technicalities of acquiring and analysing survey data. It could also be as a result of seeking a uniform framework for electricity interruption cost estimation that allows for international comparability [36]. Generally, the required data for the production function method viz. GDP, GVA, wages, electricity tariffs, and annual electricity consumption are usually published by government agencies, philanthropic organizations, private companies or associations (e.g. the insurance industry), and independent researchers, thus they are considered to be generally objective and low cost.

However, there are certain drawbacks with the production function method. It estimates cost for macroeconomic sectors, thus it yields broad and average results that might not be too helpful to electric utilities who seek specific customer-based results. Furthermore, it ignores the time-dependencies of CIC. This may result in an overestimation or underestimation CIC depending on the incidence of an electricity interruption. In a few recent VoLL studies [86, 88], the importance of including temporal factors in the cost assessment has been recognized. The estimated VoLLs for economic sectors were scaled using their respective load profiles.

2.3.1.2 Revealed preference (RP) method

This method is based on data that reveals the actual market behaviour of electricity customers in response to electricity interruptions, instead of their stated preferences in hypothetical electricity interruption scenarios. Seminal studies on electricity interruption cost assessment using the revealed preference method were undertaken in references [91-93]. The primary assumption in these studies is that businesses and individuals are rational and will act as to minimize the impact of electricity interruptions on their productive processes. The acquisition of facilities to enhance electricity supply reliability has a negative impact on the cost competitiveness of most businesses, thus loss quantification is usually based on a business' investment in mitigation measures like backup generators and power conditioning equipment [45, 94, 95], or its insurance claims for electricity interruption impacts [96].

The revealed preference method is suitable for assessing CIC in areas with chronic electricity interruptions that prod electricity customers to employ mitigation measures. However, it depends on the availability of data on the cost of mitigation measures. In cases where such data are not publicly available, they might be obtained via surveys [45, 94]. The use of non-market mitigation measures adds complexity to the monetary quantification of impacts. Furthermore, risk-neutral individuals and businesses generally equate at the margin where the benefits of measures to improve electricity reliability equals the cost of such measures. Thus, unless both mitigation cost and unmitigated losses are accounted for, CIC might be underestimated [45].

2.3.2 Direct method – Customer surveys

Customer surveys generally involve the design, administration of questionnaires, and analysis of survey responses to estimate CIC. This method is mostly preferred by electric utilities and has also been widely applied by academic researchers [34]. Electric utilities normally execute surveys to suit their system improvement needs, and sometimes, consider the information from these surveys to be proprietary [66]. This could be attributed to the competitive nature of the deregulated power markets in which many electric utilities now operate.

Customer surveys may be ex ante or ex post. Ex ante surveys often precede an actual recent experience of electricity interruption. Ex post surveys are conducted immediately after an electricity interruption event and are otherwise called *event-chasing* surveys [47]. Ex post surveys may be conducted immediately after large scale blackouts to assess CIC. These are called *blackout case studies* [48]. Since the cost assessment follows immediately after an actual event, reliable and accurate CIC estimates can be obtained from blackout case studies. However, the application of blackout case studies to derive CIC is limited to the occurrence of actual blackouts. The cost figures obtained from a study might not be readily usable for estimating electricity interruption costs generally, as each blackout has unique characteristics.

Between the late 1980s and early 2000s, the application of customer surveys to estimate CIC gained predominance after the success of Canadian seminal CIC surveys between 1980 and 1985 [97-100]. Through experienced gained from several past surveys, guidelines for executing customer surveys have been published [38, 47, 101, 102]. Customer surveys could be designed to investigate the effect of customer characteristics and spatiotemporal factors CIC (Section 2.2). The survey design process usually involves deciding on electricity interruption scenarios, cost valuation method, and questionnaire administration method.

Electricity interruption scenarios

An electricity interruption scenario is a combination of an electricity interruption event and context [47]. The electricity interruption event refers to the occurrence of an electricity interruption, while the electricity interruption context refers to temporal factors of interruption like frequency and duration. Actual scenarios are more appropriate when the experience of electricity interruptions is recent or chronic. Where this is not the case, hypothetical scenarios may be adopted. A respondent's estimation of cost based on hypothetical scenarios may differ considerably from that in an actual scenario. Estimating this difference is difficult, because actual costs cannot be ascertained prior to the occurrence of an electricity interruption. Presenting respondents with both hypothetical and actual scenarios might yield interesting results, but this might make the survey too lengthy, induce boredom in respondents and eventually result in inaccurate responses. Hybrid electricity interruption scenarios that improve the quality of CIC data collection may be developed without increasing the length of the survey [47]. The electricity interruption scenarios are developed as a combination of hypothetical electricity interruption events or context with actual electricity interruption events or context (Table 2.4). Respondents can be asked about the cost of actual events as experienced (W), or about the cost of an actual event in a different (hypothetical or conceptual context) that did not apply at that time (X). Also, respondents can be asked to estimate the cost of a hypothetical event in their own real context (Y), or they can be asked to estimate the costs of conceptual events in hypothetical contexts.

Table 2.4: Electricity interruption scenarios

		Context	
		Actual	***Conceptual***
Event	***Actual***	W	X
	Conceptual	Y	Z

Valuation Methods

The major valuation methods applied in several customer surveys include direct costing, contingency valuation (i.e. willingness to pay (WTP) or willingness to accept (WTA)), contingency ranking [40, 102, 103]. Key features, advantages and drawbacks of these methods are summarized in Table 2.5.

Table 2.5: Customer survey valuation methods

Direct costing (DC) method	
Description	• Respondents quantify the direct financial cost they may incur due to real electricity interruptions or hypothetical electricity interruptions using worksheets provided in the surveys.
Customers	• Commercial and industrial. Applications to residential customers is limited.
Advantages	• Provides consistent results in situations where losses are tangible and directly quantifiable e.g. lost production, equipment damage, spoilage of perishables, etc.
Drawbacks	• Respondents' ability to adequately assess their losses depends on their level of education and knowledge of the dependence of their productive activities on electricity. Respondents may not give extreme scenarios serious consideration. • The activity of completing worksheets can be time-demanding, thus requiring significant effort from the respondent. Accuracy of the results might be impaired if questions are complex and include many scenarios. • Cannot be effectively used in cases where losses are mostly intangible and cannot be readily quantified monetarily e.g. in the residential sector. • There is the risk of emotive and strategic responses i.e. electricity customers deliberately provide inaccurate responses to influence the results of the study.

Contingent valuation (CV) method	
Description	• Based on the assumption that electricity customers derive a certain utility from electricity consumption and a decrease in this utility is contingent upon a forced decrease in consumption. • Establishes the value of electric service reliability worth by estimating lost consumer surplus using proxies such as "willingness to pay" (WTP) to avoid electricity disruptions or "willingness to accept" (WTA) compensation for disruptions. WTA and WTP values establish a range of CIC.
Customers	• Residential. (Applications to commercial and industrial customers is limited).
Advantages	• It allows the consideration of options without experience of actual positive or negative changes in reliability, thus is readily applicable in the context of developed countries with high power system reliability.
Drawbacks	• Results are impaired by the subjectivity of respondents. Since most residential customers consider electricity a social right, they generally have a low WTP and a high WTA. • Electricity markets are natural monopolies, thus electricity customers cannot generally choose among suppliers. Accordingly, their responses to CV questions may be influenced by their concerns for potential rate changes.
Contingent ranking (CR) method	
Description	• CIC is inferred from an electricity customer's choice or ranking of a series of electricity interruption options, each accompanied by a rate increase or decrease.
Customers	• Residential
Advantages	• Respondents experience less stress in choosing between alternatives. • Yields accurate result due to close duplication of actual choice procedure. • Presents a more realistic situation than a direct evaluation of WTP and reduces the probability of strategic or emotive responses. • Non-monetary cost can be included in the cost assessment.
Drawbacks	• The volume of data to be analysed can be very large if many attributes are considered. • Complex econometric methods are required to estimate CIC. This is quite tedious and may yield vague results. • Setting the right prices for alternative choices may be challenging. • Respondents may be unaware of what their actual choices might be in real electricity interruption scenarios. This can affect the validity of their responses.

Questionnaire Administration

Well-designed customer survey questionnaires may be administered to respondents via one or a combination of: (e)mail, telephone call or field interview. Field interview have been mostly used for business customers. It yields better response rate than email, post-mail and telephone call

(Table 2.6). Thus, it is a more effective approach for getting the relevant data. The researcher can help respondents in answering questions that are not readily understood. However, there is the concern of introduction of “researcher’s bias” in the study. This bias can be minimal when the researcher has no proprietary interest in the study. It is believed that this is largely the case with academic researchers. Another drawback with field interviews is the high cost involved. A trade-off needs to be made between cost, high response rate and reasonably accurate data.

Table 2.6: Data collection and valuation approaches used in past customer interruption cost surveys

Reference	**Survey Year**	**Country**	**Customer Category***	**Response Rate (%)**	**Sample size**	**Questionnaire Administration method**	**Valuation approach**
[103]	1980	Canada	Res	58	3148	Post-mail	CR
			Com	19	3494		DC
			Ind	18	4461		
[104]	1985	Canada	Agr	36.6	-	Post-mail	CR, DC, WTA.
[94]	1998	Nigeria	Ind	162	300	-	RP – marginal cost of backup generation.
[105]	1999	Nepal	Res	62	944	Field interview	CR, WTP.
[106]	1999	Nepal	Com	80	800	Field interview	DC
			Ind	78.3	300		
[63]	2005	Finland	Com	54	236	e-mail	DC
[68]	2005	Finland	Ind	73	126	Field interview, email, and telephone.	DC, WTP, WTA.
[46]		South Africa	Com & Ind	96	275	Field interview	DC
[83]	2006	Bangladesh	Res	27.5	400	Field interview, Telephone.	DC
			Com	22.04	304		
			Ind	23.08	234		
[107]	2006-2007	Thailand	Ind	67	134	Field interview	DC
[108]	2007	South Africa	Res	25	-	-	DC, WTP
[16]	2011	Germany	Res	-	859	-	WTA, WTP.
[81]	2013	Austria	Res	48.1	894	Field interview – 78.75% of sample. Online tool – 21.25% of sample.	
[62]	2015*	Finland	Res	30	-	-	DC, WTP, WTA.

**Res – residential. Com – commercial. Ind – industrial. Agr – agricultural*

2.3.2.1 Customer interruption cost data normalization and customer damage functions

CIC estimates retrieved from survey respondents are absolute cost values. To consistently apply the cost data in power system reliability planning or operation, it is necessary to transform the CIC data by normalization with an appropriate factor. This allows for the calculation of aggregate or average cost of different electricity customers with similar cost characteristics [28]. Normalization also reduces the magnitude of the cost data and speeds up computational procedures. The normalized CIC for a respondent in a electricity interruption scenario at a time reference time *t* may be represented as:

$$C_{n,i}(d,t) = \frac{C_i(d,t)}{NF_i}\,(R/kWh\ or\ kW) \tag{2.1}$$

$C_{n,\ i}(d,t)$ is the normalized CIC estimate for respondent *i* for an electricity interruption of duration *d,* occurring at time *t.* $C_{n,\ i}(d,t)$ can be also called the *individual customer damage function (ICDF).*

$C_i(d,t)$ is the CIC estimate for respondent *i* for an electricity interruption of duration *d,* occurring at time *t.*

$\mathrm{N}F_i$ is the chosen normalization factor for respondent *i*.

The customer damage function for sector *j* (i.e. $C_{n,j}(d,t)$) consisting of *N* electricity customers may be calculated by:

I. Averaging the *ICDF* for the electricity customers in that sector:

$$C_{n,j}(d,t) \ = \ \frac{1}{N}\sum_{i=1}^{N} c_{n,\ i}(d,t) \tag{2.2}$$

II. Aggregating the CIC estimates for sector *j* and dividing the aggregate by a chosen normalization factor for the sector.

$$C_{n,j}(d,t) \ = \ \frac{\sum_{i=1}^{N} C_{\ i}(d,t)}{NF_j} \tag{2.3}$$

III. Fitting a suitable probability distribution function (PDF) to the *N* data points of individual normalized cost of the electricity customers in sector *j*. Normalized CIC data for a sector having a finite range may exhibit significant skewness. Thus, the chosen PDF must be versatile enough to accommodate these characteristics of the data. The effectiveness of the beta PDF in characterizing CIC data probabilistically has been demonstrated and validated by past researches [28, 79, 109, 110]. A concise mathematical and graphical description of the beta distribution is presented in Appendix A. Describing CIC probabilistically allows for a probabilistic evaluation of a network's performance in terms of value-at-risk (e.g. Rands@Risk).

Normalized CIC estimates for a reference electricity interruption scenario may be temporally differentiated using time-weight factors [42, 78]. A time-element matrix may also be developed that characterizes the activity levels of electricity customers into distinct time-season cells [79]. Each time-season cell may represent periods where the power system is susceptible to certain types of risk [6].

Choosing normalization factors

The intended application of CIC data and availability of ancillary data during a study or project period influences the choice of a normalization factor. Dzobo [28] summarizes various normalization factors based on electrical energy or load and their data requirements (Table 2.7). The predominant CIC normalization factors in the literature include annual electricity consumption (kWh/MWh) and peak load [34]. In some cases, electricity customers may be able to provide data on their monthly or annual electricity consumption. Where electric utilities are involved or interested in the CIC study, they can also provide such data. Otherwise, annual electricity consumption may be deduced from tariff information. Information on peak load at a reference electricity interruption time are not usually publicly available but can be estimated from load curves [28].

Several opinions have been aired by different authors on the most suitable normalization factor for specific customer types or electricity interruption scenarios. For instance, Ghajar and Billinton [111] claim that the effect of peak load on CIC is more significant for short electricity interruption duration, while the effect of annual electrical energy consumption on CIC is more significant for longer duration. Thus, peak load should be used for normalizing CIC for very short electricity interruption duration, while annual electrical energy consumption should be used for normalizing CIC for longer duration. However, Sullivan et al [38] opine that normalization based on peak load and that based on annual electrical energy consumption do not yield similar reliability worth evaluation results. Alternatively, the unsupplied energy for a sector may be used to normalize the estimated CIC for the sector [112]. Normalizing CIC by unsupplied energy requires estimation of the unsupplied energy for the reference electricity interruption scenario from load curves. However, it might be difficult to ascertain whether the variation in CIC results directly from a variation in unsupplied energy or from assumptions and approximations made during the estimation of unsupplied energy [113]. Some other authors [114] opine that a more appropriate normalization factor for large industries is their annual turnover. They argue that annual turnover has a more prominent effect on CIC than electricity consumption, because the annual turnover for such large industries is significantly higher than their annual electrical energy consumption. However, annual turnover is seldom used for normalizing CIC.

Table 2.7: Normalization factors based on electrical energy demand or load [28]

Factor	**Definition**	**Data requirement**
Annual electricity consumption (kWh or MWh)	Total annual electricity units consumed.	Total annual electricity consumption monitored as input to the electricity bill.
Average load (kW)	Annual electricity consumption / 8760	Total annual electricity consumption monitored as input to the electricity bill.
Peak load (kW)	Maximum hourly load in a year	Load data: 8760 hourly loads based on hourly metering or general load curves.
Interrupted load (kW)	The estimated power that would have been supplied at the time of the electricity interruption (or voltage disturbance) if the interruption (disturbance) did not occur	Load data: 8760 hourly loads based on hourly metering or general load curves.
Energy not supplied	The estimated energy that would have been supplied if an electricity interruption did not occur.	Load data: 8760 hourly loads based on hourly metering or general load curves.
Monthly energy cost	The total amount of money paid by the electricity customer to buy electricity for a month.	Total monthly electricity bill.

Academic researchers may not be able to obtain accurate information from survey respondents on their annual or monthly electrical energy consumption [70, 115] and electric utilities might be unwilling to divulge such data or may not have it at a disaggregated level. In such cases, average monthly electricity cost may be used for CIC normalization. High correlation has been observed between average monthly electricity bill and CIC for electricity customers with similar economic activity [47, 70].

2.4 Assessing the economy-wide costs of electricity interruptions

The methods for assessing CIC discussed in section 2.3 neglect the intersectoral interdependencies that exists within an economy. Customer surveys are customer-centric and assess mainly the direct financial cost of electricity interruptions to electricity customers or sectors. Macroeconomic production functions for economic sectors or an aggregate economy assess mainly the direct economic cost of electricity interruptions. The complex cross-linkages that exists in modern economies imply that sectoral or regional shocks may ripple throughout an economy. As businesses adopt 'just-in-time' technologies to reduce inventory costs, they become vulnerable to demand-supply chain disruptions. Economy-wide models that capture inter-sectoral flows and interdependencies have been applied to study the potential economy-wide impacts of sectoral or regional shocks that may be precipitated by disasters, market changes, policy changes, institutional changes [49]. These models include the input-output (IO), computable general equilibrium (CGE), and econometric models. Although these models have featured frequently in disaster impact analysis [116-118], their application to assessing the economy-wide cost of electricity disruptions is not so extensive. Given a predetermined level of regional aggregation, they can be applied to analyse the region-wide economic costs of sporadic electricity disruptions of extended durations[5] [35]. Key features and drawback of each model with respect to economy-wide cost of electricity disruption assessment are discussed subsequently.

[5] Up to several weeks as in the case of a severe geomagnetic storm destroying several extra-high voltage transformers or a coordinated cyber-physical or terrorist attack targeted at key generating stations, transmission lines or transformers.

2.4.1 Input-output (IO) model

The IO model is the predominant framework used for economic impact analysis. It has a simple data structure that provides a transparent view of an economy. Production or sectoral interdependencies in an economy are modelled using a system of linear equations [119]. It allows the use of engineering and economic data for intra- or inter – sectoral (or regional) economic impact assessment. Direct and indirect economic losses due to economic shocks (e.g. from electricity disruptions) can be quantified through an analysis of the effect of economic changes in affected sectors or regions on other sectors or regions. The disaggregation of an economy into sectors within the model makes it suitable for an analysis of the distribution of economic shocks within an economy. The model is best suited to short-term recovery periods i.e. before major adaptive mechanisms are put in place.

The simplicity of the IO model translates to certain drawbacks [49]. The assumption of infinite supply elasticities and fixed coefficients between inputs required to produce final outputs neglects the possibility of input or import substitution. Adaptive behaviours and resilience of economies are not explicitly incorporated, hence it can overstate losses and is not suitable for analysing very long-duration electricity interruptions that allow the adoption of different resiliency options like the use of backup generation or focusing on production activities that are not electricity intensive to minimize economic losses. Furthermore, it is deterministic and is limited for risk-based analysis. Attempts to improve the accuracy of IO models by accounting for adaptive behaviours and time lags have redounded in development of relatively advanced IO models [120, 121].

Despite its drawbacks, the IO model has been applied by several researchers to determine the economy-wide cost of electricity interruptions. Minnaar et al [89] used a basic IO framework to assess the direct and total economic CoUE for short unplanned electricity interruptions (up to 3 hours) in SA. Based on the 2013 IO data for SA, direct and total CoUE for SA were estimated as R22.30/kWh and R77.30/kWh respectively. However, the authors did not validate their claim on the applicability of the estimated CoUEs for unplanned electricity interruptions up to 3 hours. Oughton et al [35] also used an IO framework to assess the daily economic cost for the hypothetical scenario of a total USA transmission system shutdown due to a severe geomagnetic storm. Results obtained showed that indirect (or higher order) economic losses in the event of a sporadic electricity interruption can be significantly higher than direct losses.

2.4.2 Computable general equilibrium (CGE) Model

CGE models extends basic IO models to include disaggregated institutional accounts in the form of social accounting matrices (SAM). They incorporate input or import substitution and resilience, and accounts for finite supply elasticities, thus are more suitable for analyzing very long duration electricity interruptions spanning several weeks, within which different resilience options can be adopted. Like IO models, they are suitable for distributional analysis, can quantify both direct and indirect economic impacts, but they typically produce lower estimates of economic impacts.

The development of a CGE model involves complex mathematical formulations that can reduce solution tractability [49]. The quantification of resilience requires empirical data of businesses or sectors within an economy, thus the model is data intensive, and might not be readily applied in regions for which the required data is unavailable. Furthermore, CGE models assume an economy that is always at equilibrium which is not always valid. The flexible adjustment feature attributed to the modelled economy may result in an underestimation of the impact of economic shocks.

However, there have been successful attempts at their application to analyze the impacts of electricity disruptions of several weeks. Rose et al [122], used a CGE model to estimate the economic losses from business customer impacts in the hypothetical context of a two-week long total blackout that might be caused by terrorist activities in Los Angeles, USA.

2.4.3 Econometric model

The econometric model uses empirical data and statistically estimated parametric equations to represent the aggregate workings of an economy and predict the impact of potential shocks. In the case of electricity interruption cost assessment, rigorous statistical methods are used to establish the dependence of economic activities on electricity and the consequent effects of electricity interruptions of time-scales in the order of days or greater [116]. The model possesses forecasting capabilities. The difference in economic activity with and without a shock can be assessed. The model does not assume market equilibrium. The results of the analysis are mainly influenced by the data used. The uncertainty around estimates of economic impacts is usually assessed using stochastic estimation [49, 117].

Applying the econometric model for electricity interruption cost assessment requires significant amount of reliable data on the effects of previous disasters on economic growth rate. Its weakness in predicting post-disaster economic growth rate lies in the fact that future disaster impacts might not follow the trajectory of past ones. Also, it lacks an explicit description of behavioural content like adaptive mechanisms of economic agents. Furthermore, the model does not allow for distinguishing between direct and higher-order effects of disasters or economic shocks and is unsuitable for modelling rare events [49].

2.5 Discussion

The following important remarks which provide a basis for the investigative procedures in this dissertation ensue from the foregoing discussions:

1. On the nature of electricity interruptions and the response of electricity customers

Electricity interruptions may be characterized in terms of their duration and frequency of occurrence. In terms of duration, electricity interruptions may be momentary or sustained. In several countries, an electricity interruption duration less than or equal to 5minutes is momentary, while an electricity interruption duration greater than 5minutes is sustained. In terms of frequency, electricity interruptions may be chronic or sporadic and the scale and nature of the effects differs in each case. Many sub-Saharan African countries experience chronic electricity interruption.

Chronic and sporadic electricity interruptions might result in different set of electricity customer behaviors based on expectations of electric service reliability. For instance, chronic interruptions may prod business customers to invest in backup power systems. This can potentially affect their cost competitiveness. Thus, it is necessary to investigate the cost of such mitigation measures.

2. On the key factors influencing the interruption cost of business customers

The CIC of business customers is influenced by their characteristics and the temporal factors of electricity interruptions. The predominant factors include electricity interruption duration, time and season, business customers economic activity, activity level, and electricity intensity. These factors need to be carefully incorporated in assessing business customers' interruption cost.

3. On the best approach to assessing the cost of electricity interruptions to businesses and an economy

The approaches to assessing the cost of electricity interruption may be customer-centric (customer surveys), market-based (the study of revealed preferences) or macroeconomic (production functions and economy-wide models). Each approach differs mainly in the assumptions made by analysts and the spatiotemporal context of the study. Thus, there is no '*one size fits all'* approach to assessing the cost of electricity interruptions. Different approaches and the resulting cost estimates will suit different decision-making needs, such as for regulation, integrated electricity plans, value-based reliability planning, or estimating the high impact of infrequent events. For holistic power system reliability and resilience planning, both chronic and sporadic events should be given due consideration and an appropriate reliability worth evaluation approach selected. Economy-wide models seem more applicable for long-term strategic planning, while customer-centric approaches seem more applicable for short-term planning and operations, and electric utility regulation.

A major interest in this research is the evaluation of the cost of electricity interruption from the electricity customer's perspective. Thus, a customer survey was conducted to demonstrate the collection of CIC data to support the modelling of the cost of electricity interruption and application of the resulting cost model for reliability worth evaluation. Of the different data collection approaches applied in CIC surveys conducted in several countries, field (in-person) interview was observed to yield the highest response rate. Thus, field interview was adopted as the primary data collection method in this research.

Conventional approaches to representing the CIC of a given sector average or aggregate its normalized CIC estimates. However, some past CIC researches have demonstrated that a time characterization and probabilistic description of the CIC of business customers is more suitable for risk-based decision making [42, 78, 79, 109]. A probabilistic description of CIC accounts for the uncertainty in cost estimates and allows for an evaluation of the impact of different confidence levels in decision making. To corroborate this findings, three CIC models will be compared based on the survey data in this study viz. a *time-invariant average interruption cost (TIAIC) model, time-varying average interruption cost (TVAIC) model, and a time-varying probabilistic interruption cost (TVPIC) model.*

2.6 Summary

This chapter extensively reviewed the literature on reliability events and the cost of electricity interruptions. The different factors influencing CIC and the economy-wide cost of electricity interruptions were discussed. The various assessment methods applied to assessing these costs were also discussed. Accordingly, important remarks which provide a basis for the investigative procedures in this dissertation were put forward. Some of the research questions in this study were considerably answered in the foregoing remarks, however conclusive answers are only advanced after a corroboration of these findings from the literature with the findings in this study. The next chapter describes in detail the protocol of the firm-level survey conducted for this study and provides a summary of the data collection. The data retrieved from the survey provides a basis for answering some of the research questions that were not answered in this chapter.

3 Firm-level Survey: Protocol and Data Collection Summary

This chapter discusses the investigative procedures undertaken for this research. The rationale guiding the selection of the study population and sample are clearly outlined. Also, the design of the comprehensive questionnaire used for data collection is discussed. The research findings in the previous chapter formed the basis for the comprehensive questionnaire design and administration. The chapter ends with a summary of the data collection process.

3.1 Selection of population

The survey was directed at business customers (i.e. commercial and manufacturing customers) around Cape Town. The primary reasons for selecting these populations include:

Contribution to Cape Town's GDP: The commercial and manufacturing sectors accounted for 60.0% and 14.8% of Cape Town's 2015 GDP respectively [123].

Accessibility: Many of these business customers are located within the vicinity of the University of Cape Town. The ease of accessibility allows for obtaining a sufficient sample while minimizing time and transportation cost.

Ability to answer survey questions: The questions in the survey require participants with formal reasoning capabilities. Owners of businesses, managers, or other senior business staff who are knowledgeable about their business facilities and operating costs will be able to comfortably answer the survey questions.

Cost quantification: Surveying business customers allows for an understanding of a broad range of electricity interruption impacts including lost revenue, spoilt goods or inventory, and other third-party costs. Since the economic activities of these business customers can be represented in monetary value, the impact of electricity interruptions to them can be easily represented in monetary value.

3.2 Provisional sample size estimation and sample selection

A simple random sample or a stratified random sampling approach can be used to develop representative samples for a CIC survey [38]. The stratified random sampling is more effective in obtaining representative samples, however it requires some background data on each unit (i.e. business) in the population for stratification e.g. annual or monthly electricity consumption, annual turnover, size in square meters (m^2). These data were not available to the researcher beforehand[6]. Thus, a simple random sampling was used in this research. Since an official sampling frame could not be obtained, the researcher adopted an alternative means for estimating a provisional sample size to indicate a target minimum number of responses to be collected. The following considerations were made in the provisional sample size estimation:

1. Businesses to be surveyed are either in the commercial or manufacturing sectors.
2. Two important characteristics distinguish these businesses:
   a. Possession of a backup or parallel power supply.
   b. Business size. This could be based on physical size in m^2, electrical size (proxied by average monthly electricity bill (Rand) or energy consumption (kWh) or turnover (Rand).
3. Three reference electricity interruption durations were to be investigated.
4. Statistically, for many random variables, a sample size less than 30 limits the general assumption that a population is normally distributed [124]. Thus, without prior knowledge of the distribution of the random variable to be studied, a general assumption of normality can be made for a sample size greater than or equal to 30. If due to certain conditions, a sample size less than 30 is collected, an assumption of a t-distribution[7] can be made.

[6] The Cape Chamber of Commerce was contacted for a business listing with information like business contact and size that could be used as a sampling frame, but they could not provide such data as they were restricted by the consumer protection act (CPA).
[7] The t-distribution is derived from the normal distribution to accommodate small sample sizes (less than 30).

The provisional sample was determined based on (1), (2b), and (4) above. There are two cases in (1), and three cases in (2b) for any size parameter i.e. small, medium, and large. Allowing for a non/partial response rate of 30%[8], the provisional sample size was estimated as:

$$Provisonal\ sample\ size\ = 30\ \times 2\ \times 3 + 0.3 \times (\ 30\ \times 2\ \times 3) =\ \mathbf{234}$$

The basic order adopted for reaching prospective respondents is outlined below:

- Use a search string to get listings of business under the standard industrial classification (SIC) sub-categories to be surveyed the from Yellow Pages online business directory [125] and from Google search. The yellow pages online directory is made available for free by Trudon (PTY).
- Make telephone calls to identify appropriate respondents[9] in the businesses who can answer the survey questions.
- Visit different business sites and make direct request for participation in the survey.
- Get prospective respondents' consent to participate in the research.
- Schedule interviews with prospective respondents who consent to participate via interviews, send emails with link to web-survey to those who prefer emails, and make telephone calls to those who prefer telephone calls.

Visiting different business sites to make direct request for participation in the study could introduce convenience sampling bias in the study, however it was necessary to adopt this approach to improve the response rate for the study (Appendix B4). To minimize the convenience sampling bias, several business sites across Cape Town were visited.

3.3 Ethical considerations

The firm-level survey was conducted with strict conformance to the Ethics standards of the University of Cape Town. No harm or risk was posed to the prospective respondents. The design of the survey protocol ensured data were not collected without the consent of the respondents.

[8] 30% non/partial response rate was arbitrarily chosen; however, considering the response rate observed in past surveys conducted elsewhere (section 2.3.2), 30% non/partial was an optimistic expectation.

[9] The appropriate respondent is a business owner or manager who can answer questions related to the financial implications of electricity interruptions to the business.

Besides the pre-survey telephone call and email that explain the nature of the research, the comprehensive questionnaire (Appendix B1) also included a cover page that reminded respondents of the nature of the study, assured them that neither their identity nor that of the business they represent will be disclosed, and the information they provide will not be disclosed to parties outside the research group. Respondents were told that their participation is voluntary, and they could quit whenever they felt like without stating any reason. The predetermined means for data sharing within the researcher's research group was the research group's Vula site or secure folders on a shared drive. Completed data sheets were safely kept for future use or reference.

3.4 Data collection instrument

A comprehensive questionnaire was designed for the face-to-face interviews and web-based survey. Hardcopy forms were used for the face-to-face interviews and Survey Monkey[10] for the web-based survey.

The object 'type' that defines the cases in a research is the unit of analysis [126]. In this study, the unit of analysis is each business represented in the sample, thus the questionnaire focused on a business entity a respondent represents and not the individual. Business owners and managers are quite busy and are reluctant to answer questions which they deem risky to their business. Some are constrained by business policy or proprietary concerns, hence they might not provide exact information to certain questions. The survey questions were phrased in a way that minimizes misinterpretation, discomfort of respondents and completion time. The questions follow a logical sequence and were mostly close-ended to allow for an average completion time of 10 minutes. Besides, reducing the survey completion time, close-ended questions offer other advantages [127]: they are easy to answer and are familiar to most respondents, provide reliable measurements, are very suitable for online surveys, and allow faster data capturing and processing. In predetermining the response options for the closed-ended questions, care was

[10] https://www.surveymonkey.com/

taken to ensure that the response options were exhaustive, mutually exclusive[11] and consistent to ensure coherent understanding of the questions by respondents.

Where necessary, open-ended questions were asked. Open-ended questions allow respondents to answer questions in their own words/figures by entering their response into an empty text box [127]. They are very useful when exhaustive and mutually exclusive response options cannot be accurately predetermined by the researcher beforehand. They provide interesting insights when investigating new topics and allow for learning unexpected information. For the online survey, response boxes were calibrated to ensure that responses of the right data type were entered.

3.5 Comprehensive questionnaire structure

Three versions of the comprehensive questionnaire (CQ) were developed. The contents of each CQ variant were the same apart for the reference electricity interruption duration presented for CIC estimation - one reference electricity interruption duration was presented in each variant. The CQ was divided into four sections:

- Section A - Business' experience with power outages.
- Section B - Backup/parallel power supply information.
- Section C - Business' power outage cost
- Section D – Background (demographic) information

A pre-test survey was initially done for the retail trade sector to acquaint the researcher with the practicalities of surveys and to aid revision of survey questions where necessary. Some modifications were made to the CQ from field learnings during the early survey period. Thus, in some cases, respondents were not asked the same set of questions. Modifications were mainly in a few questions perceived to improve the researcher's knowledge of businesses' experience

[11] Exhaustive response options cover all possible responses related to a study; mutually exclusive options do not allow a respondent to select more than one answer choice at a time. The formats of the close-ended questions used in this study include multiple choice, rankings, and rating scales.

with power outages and their demographics. Questions in sections B and C that were central to estimating respondents' CIC were consistent.

3.5.1 Section A of comprehensive questionnaire – Business experience with power outages

Electricity interruption frequency

There might often be disparity between electricity interruption frequency as perceived by a business customer and that recorded by electric utilities at the substation level. Since a major objective of CIC surveys is to get electricity customers' perception about their electricity reliability and reliability worth, respondents were asked to estimate the number of electricity interruptions they had experienced in the last two years. A timespan of 2 years was used because the electricity supply around Cape Town has was quite reliable in the year preceding the survey.

Satisfaction level and backup/parallel supply availability

It is expected that poor reliability results in dissatisfaction in business customers. But the tolerances of electricity customers differ, so two business customers experiencing the same annual frequency of electricity interruption may express different satisfaction levels. To gain further insight on this, respondents were asked to rate their satisfaction level using a 4-point scale: *very satisfied, satisfied, dissatisfied, and very dissatisfied.* Respondents were also offered the flexibility of not indicating their satisfaction level by ticking a *not applicable (N/A)* box.

Respondents were also asked if they had installed Backup/parallel power supply to mitigate the effects of electricity interruptions. Those who indicated availability of Backup/parallel power supply were asked to continue with section B, while those who did not skipped to section C.

3.5.2 Section B of comprehensive questionnaire – Backup power supply information

Respondents were asked the following information related to their backup/parallel electricity supply:

- Percentage of organization's facilities powered
- Whether the Backup/parallel power supply is owned or provided as a service (service charge

was requested if it was provided as a service).

- Type of Backup/parallel power supply owned
- Installation period
- Size and cost (including purchase and installation cost, monthly maintenance cost, and running cost).

Since a business' Backup/parallel power supply might only provide partial mitigation during an electricity interruption, respondents who answered this section were also asked to answer section C.

3.5.3 Section C of comprehensive questionnaire– Power outage cost

Business activity level

Understanding the business activity levels of respondents provides a temporal context for describing their CIC. Accordingly, the first question in this section asked respondents to describe the variation in their business activity levels across a typical weekday, typical weekend, and across seasons of the year.

A 5-point activity level scale was used, and four daytime and season intervals respectively were presented in the CQ. The use of a 5-point scale allowed for effective capturing of low, medium and high activity levels without making respondents think across a wide-range scale. The choice of four daytime intervals was based on findings in earlier reliability and reliability worth studies in South Africa [6, 79] that reliability events in South Africa can be characterized temporally using 4-by-4 time-element matrices.

CIC estimation

A power outage or electricity interruption scenario is the basis for CIC estimation by respondents of CIC surveys. The composite approach to devising electricity interruption scenarios proposed by Herman and Gaunt [47] was used in this research i.e. a combination of a hypothetical event with an actual context that businesses might have experienced in the past.

The electricity supply in SA improved considerably since the load shedding events of 2014/2015, especially for metropolitan areas like Cape Town. Three years is quite long for respondents to accurately recount the actual costs they incurred due to those load shedding events. However, the durations of the load shedding they experienced are actual electricity interruption contexts. Load shedding schedules for the 2007/2008 and 2014/2015 load shedding events were designed mainly in 2-hour blocks. 4-hour blocks were also included for high contingency periods. Thus, one reference outage duration of 2 hours, 4 hours, or 8 hours was presented in each of the three CQ variants used.

Respondents were asked to estimate the cost of an electricity interruption of an indicated duration, occurring at their busiest time-of-day and season-of-the-year. Next, respondents were asked to indicate what percentage of this cost estimate they would incur, if the duration was shorter. The combination of reference and reduced interruption duration is shown in Table 3.1.

Table 3.1: Reference and reduced electricity interruption duration in the comprehensive questionnaire

Reference electricity interruption duration	**Reduced electricity interruption duration**
2 hours	30 minutes
4 hours	2 hours
8 hours	4 hours

This percentage reduction in cost approach was applied in [70, 115]. It avoids making respondents estimate costs for several interruption durations and allows for a cross-examination of costs directly estimated for a reference electricity interruption duration and those estimated as percentages of the cost for the reference electricity interruption duration.

CIC differentiation across loss components.

Respondents were asked to differentiate their estimated cost on the following basis:

- Percentage of cost due to lost production or sales not made during outage duration
- Percentage of cost due to extra financial costs incurred in stock damages, restarts, labour overtime, and operational difficulties.

This cost differentiation allows for understanding respondents' perception of their main loss component for an indicated outage duration. Furthermore, it allows for validating the primary assumption in the production function method of assessing electricity interruption cost i.e. the value of lost load to economic sectors can be regarded as their lost value added (production or sales volume not made due to unavailability of electricity supply) (section 2.3.1.1).

Ability to make up lost production or sales

The production or sales not made during an electricity interruption may be regarded as 'lost revenue' depending or whether it can be made up after power is restored. Knowledge of businesses ability to make up for lost production or sales aids an understanding of the production and operational flexibility of businesses and gives an indication of the post-outage resilience of businesses. Accordingly, respondents' were asked to estimate what percentage of lost production or sales they can make up, when power is restored after an electricity interruption that occurred in the morning and lasted for the reference duration indicated in the CQ.

3.5.4 Section D of comprehensive questionnaire– Demographic information

To put the responses in sections A – C of the CQ in context, some demographic information was requested from respondents i.e. electrical load size, number of employees, business SIC category, dependence of business activities on electricity, and location.

The question on electrical load size required information on business maximum demand and average monthly electrical energy consumption, but it has been found in past studies [70, 115] that respondents might not understand these technical terms and may not be able to provide this information. Hence, information on average monthly electricity cost was also requested as an alternative measure for a business' electrical load size.

In a time of proliferation of business technologies driven by electricity, a general assumption can be made that most businesses are 100% dependent on electricity. This is a core assumption in the production function method to estimate VoLL/CoUE. The question on dependence of business activity on electricity allows for validating this assumption.

Since there was no financial/material incentive for participating in the survey, the researcher considered that some respondents might be interested in receiving a summary of the survey results, thus at the end of section D, respondents were asked about their willingness to be contacted to acknowledge receipt of their completed CQ, for limited queries, short telephone interviews, to receive a summary report on the survey results, or to participate in another year. Respondents who consented were asked for their contacts.

3.6 Data capturing and coding

Responses from all the survey platforms used were collated in an excel spreadsheet in a format convenient for further data analysis. Appendix B5 shows the numeric codes used for coding responses to close-ended questions to aid easy data verification, and programmatic analysis using MATLAB 2017b Statistics Toolbox.

3.7 Data collection summary

The survey spanned a period of $2\frac{1}{2}$ months. A breakdown of the participation requests and response rate is outlined in Appendix B4. Overall, 227 responses (both partial and complete) were logged. Table 3.2 gives a summary of response count by survey method. Face-to-face interviews accounted for 87.2% of logged responses. Of these, 69.2% were done via direct requests at business sites. Thus, scheduling or making direct requests for face-to-face interviews was the most effective means of achieving a high response rate in this study. This is very similar to findings in past surveys conducted in other countries (Table 2.6). Despite efforts to send personalized emails in order to minimize the consideration of emails as spam, the response rate on the e-mail/web-survey was still significantly low. Generally, three form completion levels (CL) were identified in the two broad economic sectors surveyed (Table 3.3).

Also, 11 facility managers were contacted specifically for information on cost of Backup/parallel power supply. Four (4) responded (36.4% response rate).

Table 3.2: Summary of response count by survey method

Data collection method	No. of responses	% of logged responses
Face-to-face interviews	198	87.2%
Telephone interviews	6	2.6%
Web survey (Survey Monkey)	8	3.5%
Retrieved hard copy forms	15	6.6%
Total	227	100.0%

Table 3.3: CQ completion rate

CL	**Description**	**Number of responses**	
		Commercial sector	**Manufacturing sector**
1	Fully completed	85	38
2	Data provided enough for CIC analysis (reasonable assumptions can be made)	21	3
3	Data provided for CIC analysis insufficient.	70	10
Total		**176**	**52**

3.8 Summary

This chapter discussed the protocol for the firm-level survey in this study and summarized the outcome of the data collection process. The rationale guiding the population selection, sampling method, sample size estimation, adopted survey methods, data collection instrument design and structure have been succinctly discussed. The ethical considerations in the study were clearly outlined. Details of data capturing and coding have been explained. Also, a summary of the survey response rate and effectiveness of the chosen survey methods were presented. In the next chapter, the results of statistical analyses carried out on the survey data are discussed.

4 Descriptive Statistics and Statistical Hypothesis Tests on Survey Data

This chapter discusses the characteristics of the commercial and manufacturing population represented in the survey. Descriptive statistics and graphical representation of measured variables are presented. Also, the results of statistical hypothesis tests applied to compare both populations are discussed.

4.1 Overview of assessed explanatory variables and statistical hypothesis tests

The survey data on explanatory variables measured for both the commercial and manufacturing populations allow for assessing the characteristics of both populations. The explanatory variables in this assessment in no strict order include: electricity interruption frequency, satisfaction with electricity reliability, availability of backup supply, business activity level, contribution of different loss components to cost estimates, perception of dependence on electricity for business activities, and firm demographics (average monthly electricity bill and number of employees). Summary descriptive statistics for both populations with respect to these variables were assessed and graphical comparisons made.

Besides descriptive statistics and graphical comparisons, statistical hypothesis tests were used to determine if there was statistically significant evidence that the manufacturing and commercial populations are significantly different based on the values measured for the aforementioned variables, provided that these variables are assumed to be relatively constant within each unit of analysis during the duration of the study [70]. Several statistical tests can be used for group comparisons [126]. Two broad categories of such tests are the parametric and non-parametric tests. Most parametric tests assume a normal distribution and independence in the groups to be compared. Non-parametric tests make no assumption of the underlying distribution of the groups. Non-parametric tests were considered in this dissertation. Key features of the non-parametric tests considered in this dissertation are summarized in Table 4.1 [124, 126].

Table 4.1:Description of the statistical hypothesis tests considered in the study

Non-parametric test	Application and assumptions
Chi-squared test (CST) of independence	It is applied to test the relation between two categorical variables. It assesses whether the sample data on a categorical variable measured on two or more populations are homogenous, or whether the samples of two categorical variables measured for a population are independent. The p-values produced by a Chi-square test are inappropriate if the expected count is less than 5 in more than 20% of the cells in the contingency table.
Fisher's Exact test (FET)	It provides an alternative to the CST for small samples, or samples with very uneven marginal distributions i.e. it does not depend on large-sample distribution assumptions, rather it calculates an exact p-value based on the sample data. A 2-sided FET is equivalent to the CST for independence.
Wilcoxon rank sum test (WRST)	It is a test for two populations when the samples are independent. It determines whether the data in two groups are samples from continuous distributions with equal medians. The two groups can have different sample sizes. *The key assumption is that the two samples are independent. WRST does not assume that the data in the groups are normal nor that they have approximately equal variance.*

FET was preferred over CST for the comparison of the two populations based on categorical variables, because of the relatively small sample size in this study. The categorical variables considered for FET include satisfaction with reliability and availability of backup power supply . FET was also applied to some continuous and discrete numerical variables measured with open-ended questions after converting them into categorical variables by defining appropriate categories. These variables include: percentage contribution of cost components to cost estimates, average monthly electricity bill, and number of employees. The number categories (n) in some of these variables is greater than 2, resulting in *2-by-n* contingency tables[12].

The null *(H_0)* and alternative hypothesis *(H_A)* for the FET as applied in this dissertation are:

H_0: There is no statistically significant difference between the commercial and manufacturing populations based on the levels observed in Var X (i.e. both populations have equal outcome probabilities).

[12] MATLAB 2017b statistics toolbox only supports FET for 2-by-2 contingency tables, hence the FETs in this study were performed in R software. R uses a hybrid approximation to compute probabilities for larger than 2-by-2 contingency tables. The approximation only fails with an error when the counts in the cells of the contingency table are too large; in this case R uses a Monte Carlo procedure.

H_A: There is statistically significant difference between the commercial and manufacturing populations based on levels observed in Var X (i.e. both populations do not have equal outcome probabilities).

Var X is a pseudonym for each categorical variable on which the comparison of the populations was done. The hypothesis for the FET on *Var X is* for establishing a basis for concluding whether respondents' responses as contained in *Var X* is dependent on the economic sector they belong to.

A 5% statistical significance level was chosen for rejecting the null hypothesis i.e. the null hypothesis is rejected for an FET p-value less than 0.05. The choice of a significance level above 1% is to minimize the chance of failing to reject the null hypothesis when it is false.

The Wilcoxon rank sum test (WRST) was used for comparison of the two populations based on only discrete and continuous numerical variables[13]: average electricity interruption frequency per year, perception of dependence on electricity, percentage contribution of cost components to cost estimates, average monthly electricity bill, and number of employees. The null *(H_0)* and alternative hypothesis *(H_A)* for the WRST are:

H_0: The data on Var X measured on the commercial and manufacturing populations respectively come from continuous distributions with equal medians or similar central tendency.

H_A: The data on Var X measured on the commercial and manufacturing populations respectively do not come from continuous distributions with equal medians or similar central tendency.

5% statistical significance level was also used for WRST i.e. the null hypothesis for the WRST is rejected when the p-value is less than 0.05. The WRST was still done even when the medians computed from the sample data were the same in order to have a statistically-based conclusion about the populations.

[13] The choice of a statistical comparison test based on the median instead of the mean was informed by the robustness of the median over the mean as indicator of central tendency over a wide range of distributions, especially those with large skew.

4.2 Business size parameters

As anticipated prior to the survey, most respondents were not able to provide information on their maximum demand (kW) and average monthly electricity consumption in (kWh). Some did not even understand what these terms meant. Generally, it was easier for respondents to report their electrical size in terms of their average monthly electricity bill (Rands).

The survey data indicates that the manufacturing sector is generally more electricity and labour intensive than the commercial sector as indicated by the respective mean and median of their electricity bills and number of employees (Table 4.2). Also, the electricity bills in the manufacturing sector has a wider range as indicated by the minimum and maximum bills. The medians of average monthly electricity bill and number of employees indicate that majority of the businesses represented in the sample were small-medium scale. In some cases, in the commercial sector, the business owner is the only employee. Only a few large businesses participated in the study. In most cases, the appropriate respondent in large businesses was too busy to participate. P-values less than 0.05 were obtained for the FET and WRST on both average monthly electricity bill and number of employees (Table 4.3). This implies that the commercial and manufacturing populations are significantly different based on these two size parameters.

Table 4.2: Summary statistics on business size parameters

Business size parameter	Sectors	Number of responses	Mean	Std*	Min*	Med*	Max
Average Monthly electricity bill (Rands)	Commercial	110	11 134.7	18 874.18	300	5 625	150 000
	Manufacturing	42	165078	692 408.3	1400	14 836.52	4 500 000
Number of employees	Commercial	92	20	39	1	9	300
	Manufacturing	37	106	234	3	30	1200

**Here and elsewhere in this dissertation: std - standard deviation; Min - Minimum; Med – Median; Max – Maximum.*

Table 4.3: Fisher's exact test and Wilcoxon rank sum test on business size parameters

Business size parameter	**Fisher's exact test**		**Wilcoxon rank sum test**	
	Degree of freedom	p-value	z-statistic	p-value
Electricity bill	4	**0.0007676**	-4.1675	**3.08E-05**
Number of employees	3	**9.57E-05**	-4.7134	**2.44E-06**

4.3 Perceived electricity interruption frequency

The distribution of the number of electricity interruptions experienced at respondents' business site in the last two years is right-skewed for both populations (Figure 4.1). The mean and standard deviation of the number of electricity interruptions are equal and the same for both sectors i.e. 3 interruptions (Table 4.4). This implies an annual average of 1 interruption per year at most business sites. One respondent reported 50 interruptions in the last two years. This reflects the susceptibility of surveys to emotive and strategic responses and underscores a need to mitigate the influence of outliers on the analysis of survey results.

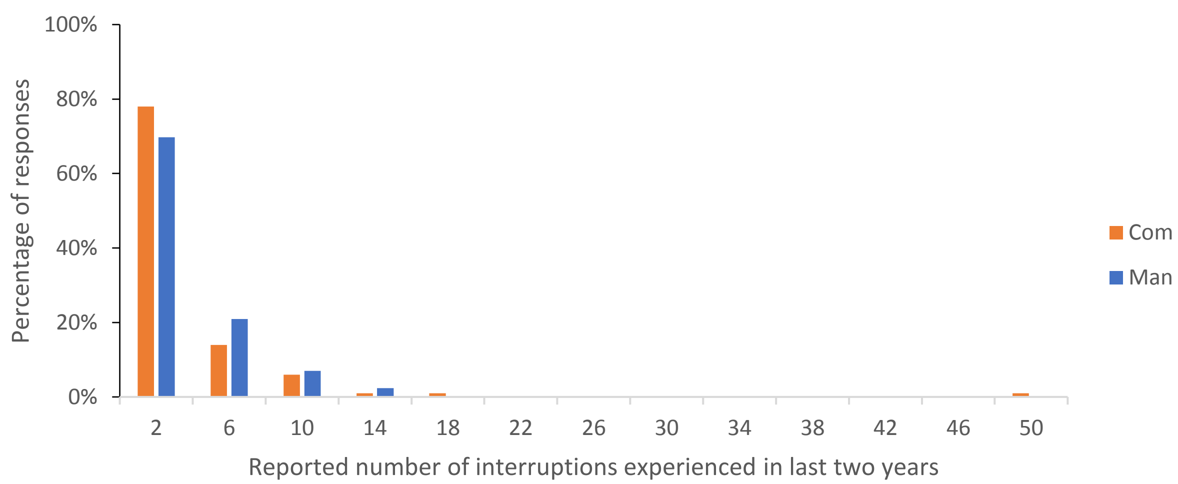


Figure 4.1: Reported number of electricity interruptions experienced in the last two years by respondents in the commercial (Com) and manufacturing (Man) sectors.

Table 4.4: Statistics on respondents' reported electricity interruption frequency in the last 2 years

Sector	Number of respondents	Mean	Std*	Min*	Med*	Max*	Wilcoxon rank sum test	
							z-statistic	p-value
Commercial	136	3	3	0	1	50	-1.3308	0.18324
Manufacturing	43	3	3	0	2	15		

Only the Wilcoxon rank sum test was used in comparing the industrial and manufacturing populations on the basis of electricity interruption frequency. The p-value of the Wilcoxon rank sum test is greater than 0.05 (Table 4.4), hence the null hypothesis is not rejected. There is statistically significant evidence that the sample data on electricity interruption frequency measured for the commercial and manufacturing populations come from continuous distributions having equal medians or similar central tendency. This is evident when Figure 4.1 is closely observed.

In general, the electricity supply to businesses around Cape Town has been fairly reliable. The minimum and maximum yearly average number of electricity interruptions across all the surveyed areas is 1 and 3 respectively (Figure 4.2). The area labels are described in Table 4.5.

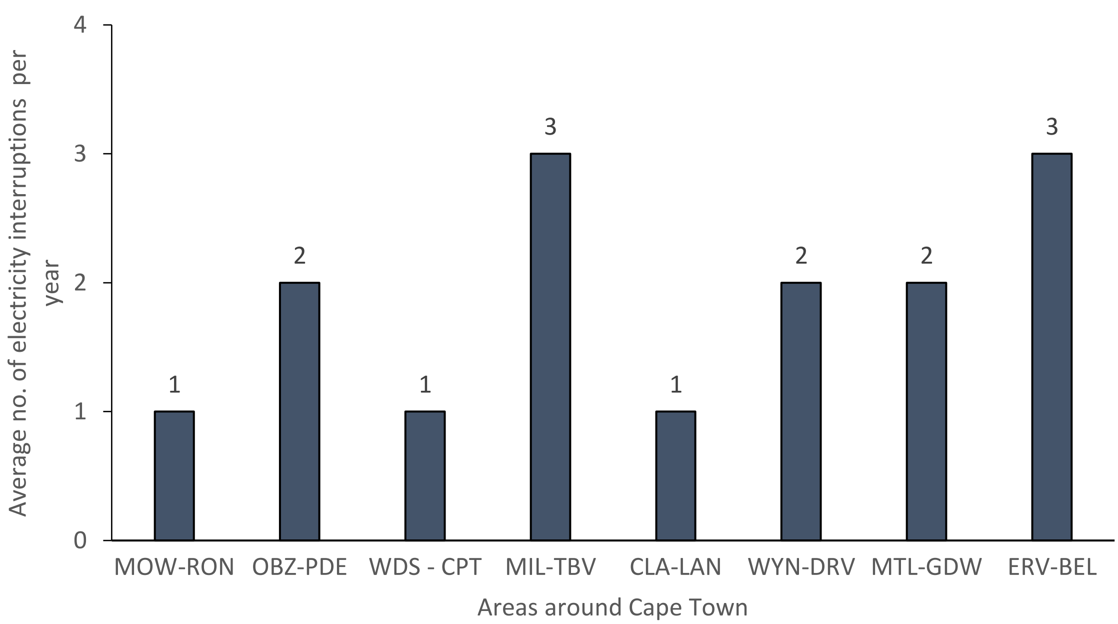


Figure 4.2: Average annual electricity interruption frequency across surveyed areas in Cape Town

Table 4.5: Survey areas and area label

Area label	Group Areas
MOW-RON	Mowbray, Rondebosch, Athlone
OBZ-PDE	Observatory, salt river, Paarden Eiland
WDS – CPT	Woodstock, Cape Town Central Business District. Waterfront, Sea Point
MIL-TBV	Milnerton, Montague Gardens, Killarney Gardens, Tableview
CLA-LAN	Claremont, Kenilworth, Lansdowne
WYN-DRV	Wynberg, Ottery, Diep River, Plumstead
MTL-GDW	Maitland, Kensington, Thorton, Epping, Goodwood
PAR-BRA	Beaconvale, Parow, Bellville, Durbanville, Branckenfell

4.4 Satisfaction level

Most respondents were either *very satisfied* or *satisfied* with their electricity supply reliability (Figures 4.3 and 4.4). The satisfaction levels of respondents in this study are quite the opposite of those in a past survey conducted in 2009 – quite close to the 2008 load shedding events, where approximately 48% of respondents in the commercial and industrial sectors respectively were either dissatisfied or very dissatisfied [70]. Generally, satisfaction level is higher for lower annual average electricity interruption frequency. The 4% of respondents in the commercial sector who were very dissatisfied had an annual average electricity interruption frequency of 5 interruptions per year. A p-value greater than 0.05 for the Fisher's exact test on satisfaction level (Table 4.6) indicates that the null hypothesis is not rejected: there is no statistically significant difference between the manufacturing and commercial populations based on available sample data on satisfaction level with electricity supply reliability.

Table 4.6: Results of Fisher's exact test on satisfaction level

Number of respondents		**Fisher's exact test**	
Commercial	Manufacturing	Degrees of freedom	p-value
137	43	3	0.5217

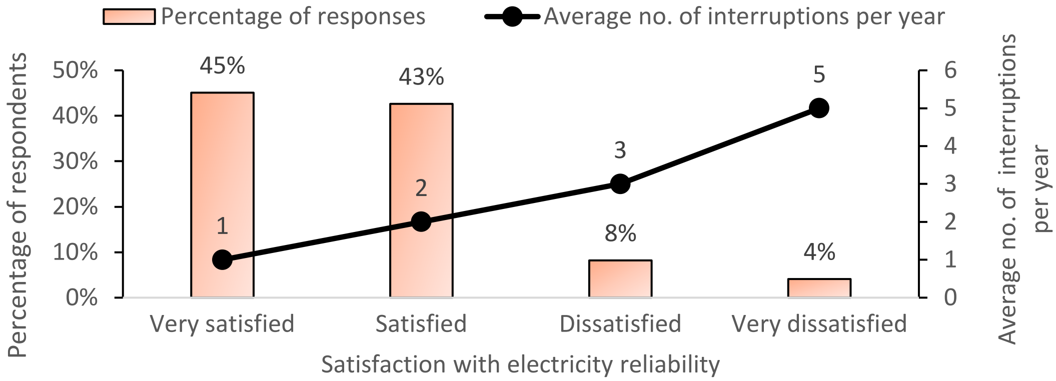


Figure 4.3: Average annual electricity interruption frequency and satisfaction level in the commercial sector

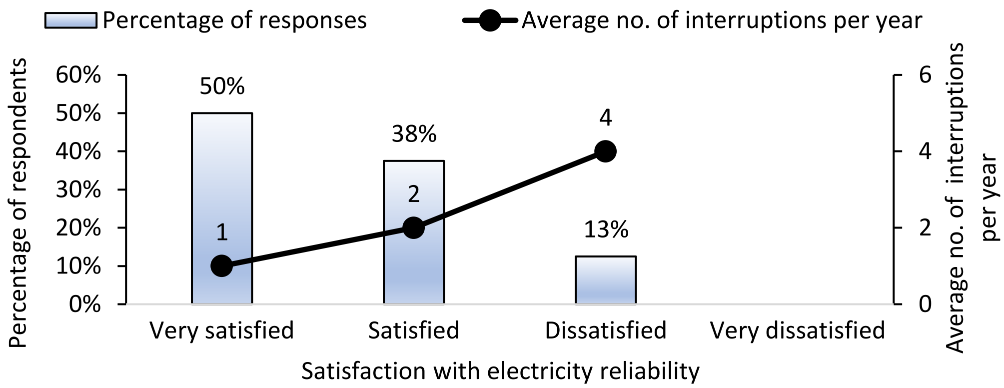


Figure 4.4: Average annual electricity interruption frequency and satisfaction level in the manufacturing sector

4.5 Business activity level

Business activity level was measured on a 5-point scale. Weekdays are generally busier than weekends in both manufacturing and commercial sectors (Figures 4.5 and 4.6). Only few businesses run continuous processes, hence business activities in both sectors occur mainly in the 06:00 – 12:00 and 12:00 – 18:00 time blocks on weekdays, and 06:00 – 12:00 block on weekends. On a typical weekday, the difference between the average business activity level in the 06:00 – 12:00 and 12:00 – 18:00 time blocks is minimal in both sectors. Generally, across seasons, the average business activity level in both the commercial and manufacturing sector is highest between October and December (Figure 4.7). This could be because of businesses working to meet annual targets for production and sales volume, tourism, and other holiday activities. Although these activity trends were perceptible before the survey, the survey responses allowed for determining activity level weights from the business customer's standpoint. Time-element matrices of season-day-time activity weights were developed for each commercial subsector and the manufacturing sector (section 6.3 and Appendix C1).

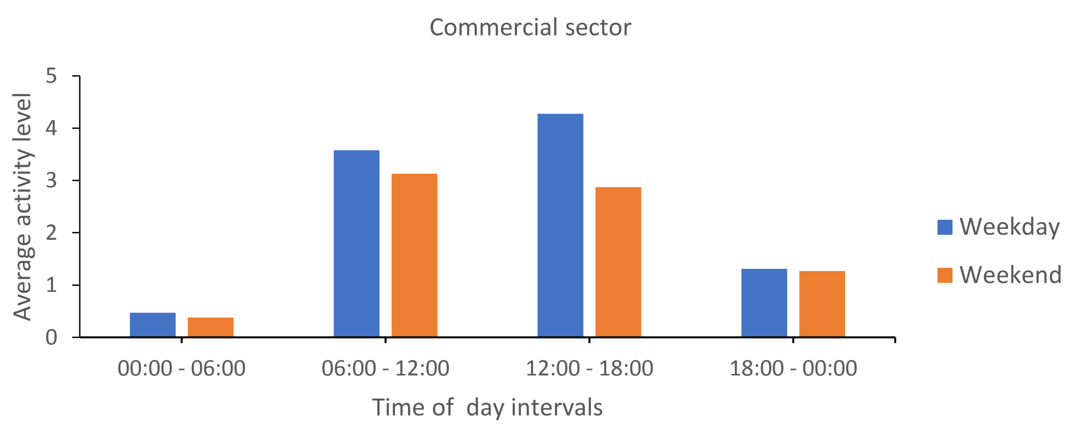


Figure 4.5: Business activity levels across time of day in the commercial sector

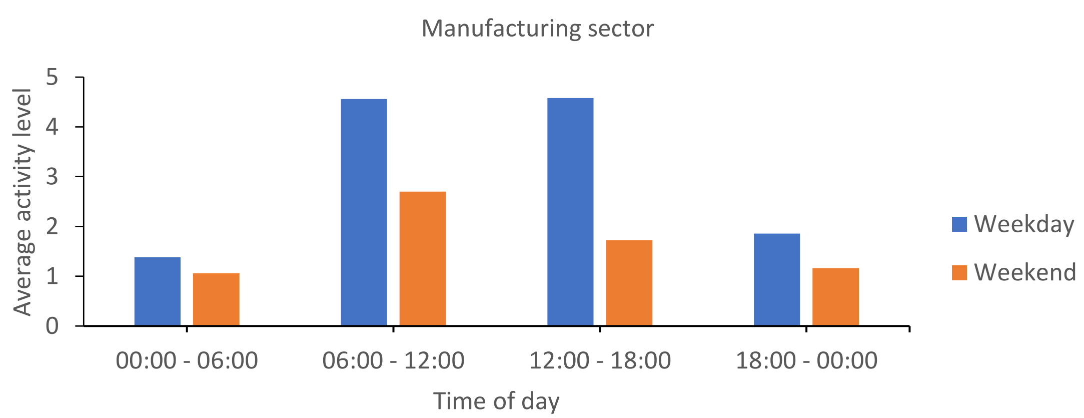


Figure 4.6: Business activity levels across time of day in the manufacturing sector

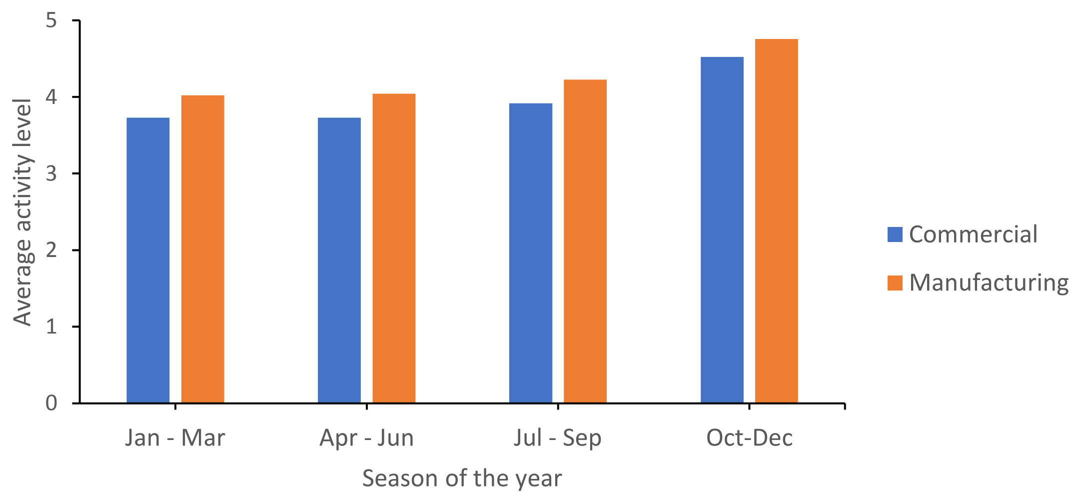


Figure 4.7: Business activity level across seasons of the year in the commercial and manufacturing sectors

4.6 Perception of dependence on electricity for business activities

The perceived level of dependence of business activities on electricity is higher in the manufacturing sector than the commercial sector (Table 4.7). Respondents' perception of the dependence of their business activities on electricity does not necessarily connote their electricity intensity, rather it is an indication of their need for availability of supply. The level of dependence on electricity might also be regarded as an indicator of the shock level a sector might experience during an unplanned sporadic electricity interruption [120]. Olasoji et al [128] used an arbitrary factor of 70% to relax the assumption of total dependence of economic sectors on electricity and scale the results of an input-output model used to estimate the daily economy-wide cost of a sporadic electricity interruption to SA's economy. This factor is approximately 25% lower than the average percentage dependence on electricity measured for both the commercial and manufacturing sectors in this study (Table 4.7). Hence the caveat by the authors that their results are optimistic and conservative estimates might be valid. The observed difference might be because the sample for this study was drawn from Cape Town and its environs and did not include all sectors in SA's SIC, while an economy-wide input-output data [129] was used in [128].

The Fisher' exact test on level of dependence on electricity has a p-value greater than 0.05 (Table 4.8), thus its null hypothesis is not rejected. This indicates that there is no statistically significant difference between the level of dependence on electricity in the commercial and manufacturing populations.

Table 4.7: Summary statistics on percentage of business activities that are dependent on electricity

Sectors	Number of responses	Mean	Std	Min	Med	Max	Fisher's exact test	
							Degree of freedom	p-value
Commercial	92	91%	17%	30%	100%	100%	1	0.09776
Manufacturing	42	97%	8%	60%	100%	100%		

4.7 Components of CIC

Two major loss components were considered in the comprehensive questionnaire (section 3.5.3). For all the electricity interruption scenarios, respondents in both sectors indicated that their CIC[14] was due mainly to lost sales/production (LSP) (Figure 4.8). However, the percentage of estimated CIC due to lost sales/production in the manufacturing sector is lower than the commercial sector in all electricity interruption scenarios. The percentage of CIC due to extra financial cost (EFC) in restarts, labour overtime, potential stock or material damages was generally higher in the manufacturing sector. Some respondents in the manufacturing sector stated that the effects of an electricity interruption on their operation is not primarily determined by the duration of the interruption itself but the potential production downtime due to clean-ups and restart procedure, thus a 2-hour and a 4-hour electricity interruption could have the same effect on their operation.

Statistical hypothesis tests were only done on the percentage of estimated CIC due to lost sales and production. The results of the Wilcoxon rank sum test (Table 4.8) indicate a rejection of its null hypothesis for the 2 – 4 hour electricity interruption scenario, but a non-rejection in the 8-hour scenario. There is no statistically significant evidence that the median of the sample data on percentage of CIC due to lost sales/production in the 2 – 4 hour electricity interruption scenario measured on commercial and manufacturing population respectively come from the continuous

[14] Analysis of CIC estimates provided by respondents is in Chapter 5.

distributions with equal medians. The converse holds for the 8 - hour electricity interruption scenario. This disparity in the Wilcoxon rank sum test results in the two cases could be due to the small sample size.

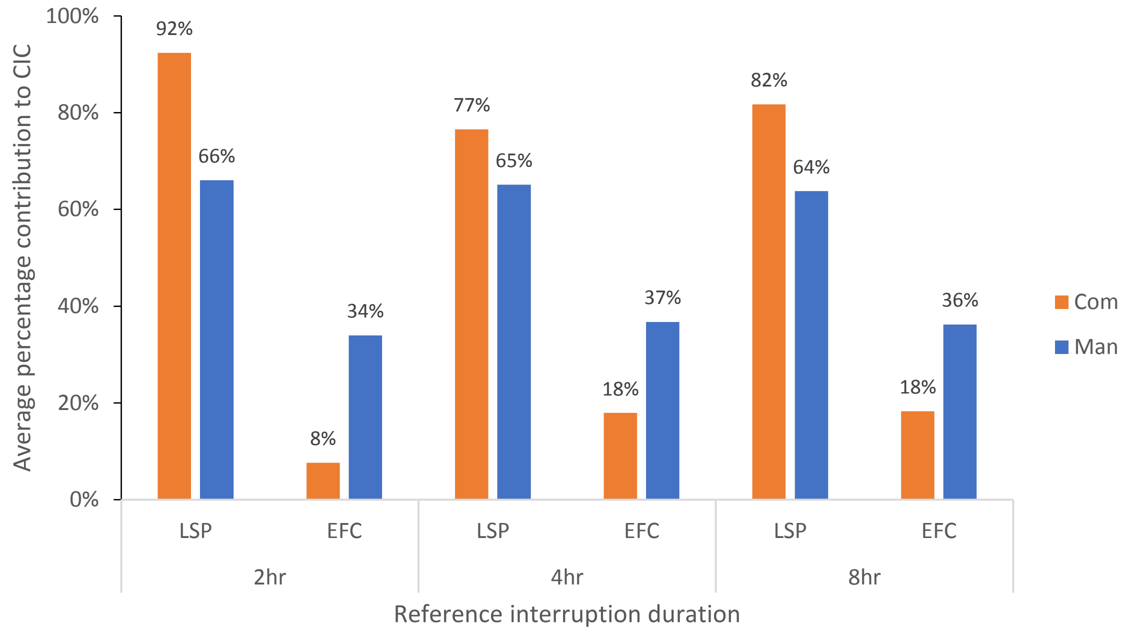


Figure 4.8: Average percentage contribution of lost sales / production (LSP) and extra financial cost (EFC) to estimated CIC

Table 4.8: Fisher's exact test and Wilcoxon rank sum test on average percentage contribution of lost sales and production to CIC

Outage duration	**Number of respondents**		**Wilcoxon rank sum test**	
	Commercial	Manufacturing	z -statistic	p-value
2 – 4 hours	43	16	2.3886	**0.016915**
8 hours	15	7	1.7612	0.07821

4.8 Backup/parallel power supply (non-cost factors)

Availability and type

Most respondents in the commercial and manufacturing populations indicated that they do not own a Backup/parallel power supply, nor have it provided as a service (Table 4.9). Backup power supply ownership is higher in the manufacturing sector than the commercial sector. This could be due to the sensitivity of the processes of manufacturing businesses. Approximately 24% of manufacturing businesses surveyed ran continuous processes. Generally, a higher risk mitigation is expected when risks prospects are high. The primary type of backup power supply owned in both sectors is diesel/petrol generator (Table 4.9).

The Fisher's exact test on backup power supply availability has a p-value greater than 0.05 (Table 4.10). There is no statistically significant difference between the commercial and manufacturing populations; both can be regarded as a homogenous group based on the availability of backup power supply at their business sites.

Table 4.9: Primary backup power supply availability in the commercial and manufacturing sectors

Sector	**Percentage of respondents**			
	Primary backup power supply owned		Backup power supply provided as a service	No backup power supply
	Diesel/petrol generator	UPS[a]		
Commercial	23%	8%	3%	66%
Manufacturing	42%	-	-	58%

[a]Uninterruptible power supply or battery – inverter systems

Table 4.10: Fisher's exact test on backup power supply availability

Number of respondents		**Fisher's exact test**	
Commercial	Manufacturing	DoF	p-value
54	21	1	0.3175

Procurement of backup power supply across recent years

The procurement period of backup power supply among respondents who indicated ownership of backup power supply is depicted in Figure 4.9. The cumulative percentage of respondents who indicated ownership of backup power supply rose from 13% and 24% before 2008 in the commercial and manufacturing sector respectively to 72% and 95% between 2014 – 2016. This indicates that chronic electricity interruption causes proliferation of backup power supply, especially diesel/petrol generators. Following the improvement in electricity supply just after the

2008 load shedding events, the rate of backup power supply procurement among respondents in both the commercial and manufacturing sectors dropped significantly, but increased again during the 2014/2015 load shedding events and dropped thereafter.

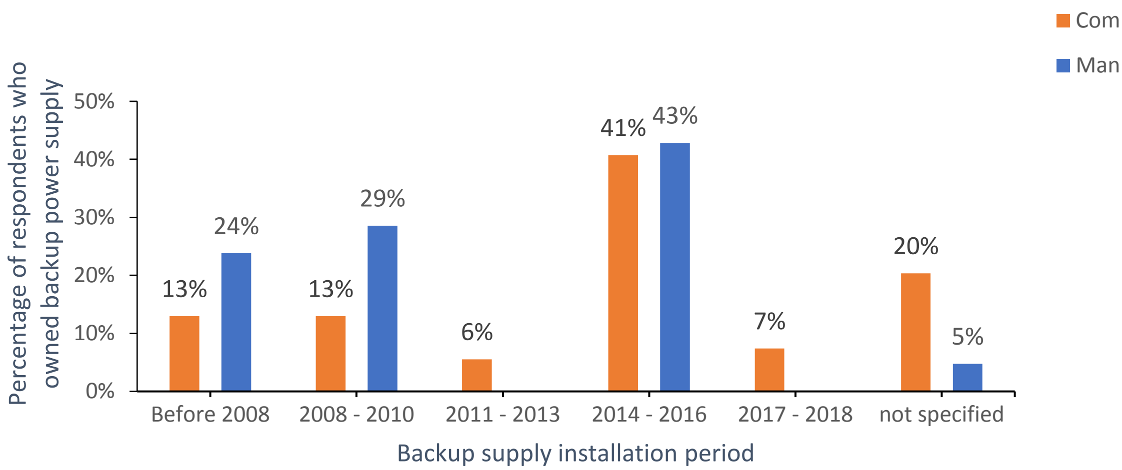


Figure 4.9: Backup power supply procurement in the commercial and manufacturing sectors across recent years

Unfortunately, many sub-Saharan countries experience chronic electricity interruptions. Besides the cost to businesses of procuring and operating backup generators, they may increase emissions of greenhouse gases, and may affect the quality of life of individuals around the operating premises if appropriate legislations are not enforced. However, a seemingly counterintuitive, but interesting and plausible observation in this study is that:

Chronic electricity interruption may have positive outcomes. The increased purchase and installation of backup power supply indicates increased economic activity for the backup power supply industry. Also, some respondents indicated that procuring a backup generator during the load shedding event offered them competitive advantage over their competitors who didn't install backup power.

Business facilities powered by backup power supply

Most respondents were not able to report their maximum demand (kW), hence an objective estimation of the percentage of their business facilities powered by their backup power supply could not be ascertained. However, from the subjective responses obtained, approximately 50%

and 24% of respondents in the commercial and manufacturing sector respectively had 75 – 100% of their facilities powered by their onsite backup supply (Figure 4.10). The backup power supply of 29% and 47% of respondents in the commercial and manufacturing sector respectively achieved less than 50% facility coverage.

In face-to-face interviews, several respondents in the manufacturing sector indicated that the *cost of investing in backup/parallel power supply to power all their facilities was prohibitive because of their electrical size*. Hence, backup power was mainly for administrative functions, security and safety. In the commercial sector, backup power supply was mainly for powering PCs, tills, lighting and security.

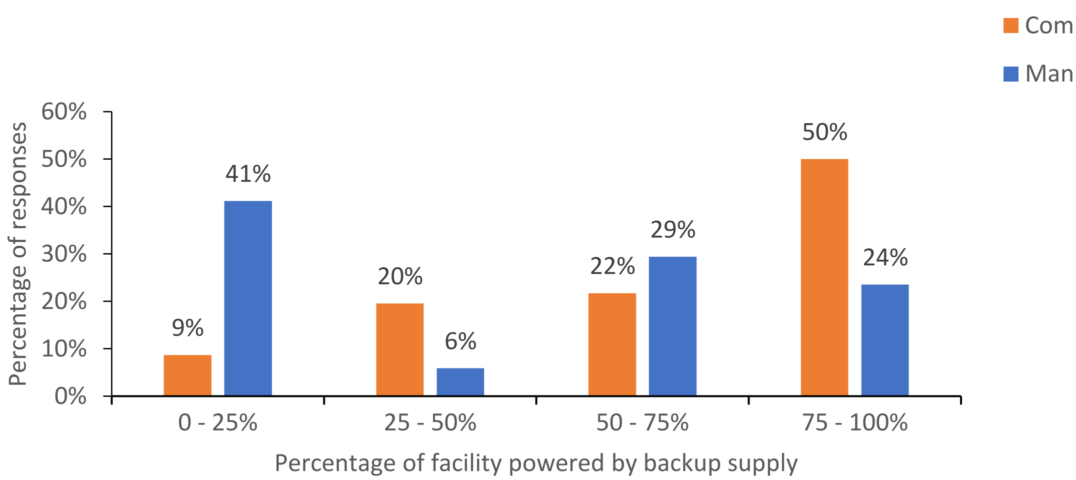


Figure 4.10: Percentage of business facility powered by backup power supply in the commercial and manufacturing sectors

4.9 Validating assumptions in the production function method

The validity of 3 Important assumptions in the production function method for estimating CoUE/VoLL (section 2.3.1.1) were assessed based on the results of the analyses in this chapter.

Assumption 1: The activities of economic sectors are 100% dependent on electricity.

The results in section 4.6 – (*Perception of dependence on electricity for business activities*) considerably validates this assumption, especially for the manufacturing sector. The average of the percentage of business activities dependent on electricity in the commercial and manufacturing sectors was 91% and 97% respectively.

Assumption 2: An economic sector's interruption cost for a particular interruption duration equals value added/GDP for that duration

The results in section 4.6 (*components of CIC*) considerably validate this assumption, especially for the commercial sector. For all electricity interruption duration presented in the CQ, respondents in the commercial sector indicated that over 75% of their CIC was due to lost sales/production which is often proxied by GVA/GDP in studies that estimate CIC with the production function method. Also, respondents in both commercial and manufacturing sector consider that their CICs varies linearly with electricity interruption duration.

Assumption 3: An economic sector's interruption cost does not vary with day type, time-of-day, or season.

The results in section 4.5 (*business activity level*) do not validate this assumption. Business activity level varies across sectors, day-type, time-of-day, and season. Respondents consented that the intensity of their business activity in an electricity interruption scenario will influence their CIC. Accordingly, their CIC will not be the same in different season – time windows. The values of GVA/GDP used in the production function method are annual aggregates that obscure their temporal variation. Appropriate weighting factors need to be applied to differentiate the average interruption cost estimates from the production function method across different time - season windows.

4.10 Summary

This chapter presented descriptive statistics and graphical comparison of the characteristics of the commercial and manufacturing population represented in the survey sample. Statistical hypothesis tests that assessed the homogeneity of both populations based on different explanatory variables were also presented. In certain cases, observations in this study were compared with those in past studies. Also, the findings in this chapter were used to assess the validity of three important assumptions in the production function method whose application for assessing interruption cost (VoLL and CoUE) is increasing especially in Europe. The next chapter focuses on the analyses of the CIC estimates retrieved from survey respondents.

5 Customer Interruption Cost Analysis

This chapter discusses the analyses of the CIC estimates retrieved from survey respondents. The results of several regression analyses done to validate the use of business customers' average monthly electricity cost as a normalizing factor for their CIC are presented. Also, case studies were done to compare the difference in the cost of using backup power supply to achieve 'zero' CIC versus the cost of electricity from the electric utility.

5.1 Background

CIC estimates were collected from business customers with and without backup power supply. The CIC estimates reported by business customers without backup power supply was considered as their potential worst-case cost[15] for a given electricity interruption duration. For business customers with backup power supply, their CIC was considered as the sum of the cost of running backup power supply (including depreciated purchase and installation cost) and their potential worst-case unmitigated loss (if any) for the electricity interruption duration. The relevant survey data for each group were analysed separately to provide consistent description of its CIC.

5.2 Business customers without backup power supply

5.2.1 CIC normalization

Normalization of CIC estimates based on an electricity-related factor allows for easy application of the cost data in power system management. Most respondents in this study could report their average monthly electricity bill (section 4.2), hence average monthly electricity bill was the preferred CIC normalization factor in this study. However, to justify the use of this normalization factor, linear regression analyses was carried out to assess the linearity of the relationship between survey data on average monthly electricity bill and CIC estimates. For some sub-sectors, the complete pair of CIC and average monthly electricity bill data for one or more of the reference

[15] This is because the busiest time-of-day, day, of the week, and season of the year was the context for the interruption scenario presented (Section 3.5.3).

interruption duration was too small[16] for meaningful regression analysis. Hence, the data of sub-sectors had to be merged (Table 5.1). The 8-hour CIC – average monthly electricity bill data pair for the hospitality and 'other commercial services' sector were insufficient for regression analysis.

Table 5.1: Sub-sector merging to improve CIC – average monthly electricity bill data pair count

Main sector	Merged sub-sectors in CQ
Manufacturing	All manufacturing subsectors listed in CQ
Trade	Food/grocery retail trade, other retail trade, wholesale trade, service station
Hospitality	Restaurants and hotels
Other commercial	salons, printing, auto-services.

The general form of the linear regression model output from the curve fitting for a sector is given by equation (5.1):

$$CIC_{nb}^{d} = b_0 + b_1 E \tag{5.1}$$

Where CIC_{nb}^{d} is the worst-case CIC estimate of business customer without backup power supply for an electricity interruption of duration d; E is the business customer's average monthly electricity bill; b_0 and b_1 are intercept and slope parameters respectively for the fitted regression line. The coefficient of determination, R^2 was used to evaluate the goodness of linear fit [124]. It lies in the range $0 \leq R^2 \leq 1$. In equations (5.1), R^2 describes the amount of variation in CIC_{nb}^{d} that can be explained by *E.* When R^2 is 1, all the variation in CIC_{nb}^{d} can be explained by E.

For each electricity interruption duration, an initial visualization of the CIC and average monthly electricity bill data pair in each sector using scatterplots showed significant number of zero, near-zero, and extreme CIC values. This phenomenon was also observed in [41, 69, 70, 128]. To assess

[16] In some cases, respondents provided CIC estimates, but not electricity bill. In other cases, respondents said they could not quantify the cost they might incur in the interruption scenario presented to them, thus they declined from estimating their interruption cost.

the effect of these outliers on the linear regression results, two types of linear fit were applied to the data and compared i.e. a *regular non-robust linear fit* and a *bisquare robust fit*[17].

Alternative modelling approach

Equation (5.1) may have a R^2 that is near 1, but b_0 that is significantly different than zero. This implies that for an average monthly electricity bill of zero, there is an interruption cost, which may be positive or negative if b_0 is less than or greater than zero respectively. Thus b_0 conveys no practical meaning. This 'intercept problem' necessitated the consideration of an alternative non-linear model – a single-term power model (equation 5.2). The general form of the power model implies that an average monthly electricity bill of zero should yield zero interruption cost. R^2 was also used as the goodness of fit metric for the power model.

$$CIC_{nb}^{d} = \gamma E^{n} \tag{5.2}$$

CIC_{nb}^{d} and *E* are as defined for equation (5.1). γ and n are parameters of the single-term power model.

Results of regression analyses on CIC and average monthly electricity bill

Graphical representations of the scatterplots and fitted models are in Appendix C2. The data on average monthly electricity bill and CIC were scaled down by 1000 (i.e. represented in R1 000) in the regression models. With the non-robust linear fit, average monthly electricity bill could only explain less than 50% of the variation in CIC for most of the electricity interruption scenarios in each sector (Table 5.2). This due to the sensitivity of this linear fit to the outliers in the data set. With the bisquare linear fit, average monthly electricity bill could explain 54% – 97% of the variation in CIC for most of the electricity interruption scenarios in each sector (Table 5.2). The only exception was in the 30-minute electricity interruption scenario in the trade sector, where only 23% of the variation in CIC could be explained by average monthly electricity bill. This is due

[17] The *bisquare linear fitting technique in* MATLAB's 2017b Curve Fitting Toolbox is a robust fitting technique minimizes a weighted sum of squares. The weight given to each data point depends on how far the point is from the fitted line. Points near the line get full weight; points farther from the line get reduced weight; points farther from the line than would be expected by random chance get zero weight. This technique is generally preferred because it simultaneously seeks to find a line that fits most of the data using the least squares approach, while minimizing the effect of outliers.

to the small sample size and high variability of the data for this electricity interruption scenario. A robust curve fitting was used for the single-term power model i.e. bisquare power fit, hence its evaluated model parameters and R^2 values were not significantly affected by the outliers in the data set. With this model, average monthly electricity bill could explain 60% - 99% of the variation in CIC in most of the electricity interruption scenarios (Table 5.3).

The positive values evaluated for b_1 (Table 5.2) and n (Table 5.3) in the robust linear and single-term power models respectively indicate that across all sectors there is a positive correlation between average monthly electricity bill and CIC for a given electricity interruption duration. This implies that for business customers with similar economic activity, those with high average monthly electricity bill tend to report high CIC. This corroborates findings in prior studies [47, 70, 83, 105]. However, the scatterplots from the regression analyses (Appendix C2) show that for a given electricity interruption duration in a sector, business customers with relatively low average monthly electricity bills might report higher interruption cost estimates than those with higher average monthly electricity bills. In such cases, normalizing CIC estimates by average monthly electricity bill might result in some very high and very low normalized CIC values[18].

Summary statistics of normalized CIC estimates for the different electricity interruption scenarios in each sector in this study were evaluated (Table 5.4). In deriving these statistics, values greater than three standard deviations (3σ) from the mean were considered as outliers and excluded from the data set [68, 124]. These outliers exert a disproportionate effect on the mean of the normalized CIC data. The 'reduced data set' were characterized probabilistically to account for the risk of high or low CIC values that are less than 3σ from the mean. The beta probability distribution function was used because of the high skewness of the normalized CIC data[19]. The evaluated parameters of beta distribution of the normalized CIC for each electricity interruption scenario in each sector are in Table 5.4.

[18] The very high normalized CIC are due to customers who report high CIC but have low average monthly electricity bills. The very low normalized values are due to customers who report low CIC but have high average monthly electricity bills.

[19] As discussed in section 2.3.2.1, the beta distribution has been found to be versatile for characterizing data of varying skewness.

Table 5.2: Parameter estimates and goodness of fit of linear models describing relationship between average monthly electricity bill and CIC for business customers without backup power supply

Sector	**Electricity interruption duration**	**Non-robust linear fit***			**Bisquare linear fit***			**DFE*** **
		Parameter estimates		R^2	**Parameter estimates**		R^2	
		b_0**	b_1		b_0**	b_1		
Trade	30 mins	2.903	0.388	0.225	2.408	0.627	0.226	5
	2 hours	7.669	0.571	0.109	6.345	0.078	0.730	19
	4 hours	12.850	2.097	0.312	19.110	0.382	0.609	17
	8 hours	38.450	8.682	0.548	25.900	9.075	0.532	7
Hospitality	30 mins	0.572	0.114	0.146	-0.501	0.232	0.614	10
	2 hours	0.385	0.666	0.390	2.597	0.317	0.689	20
	4 hours	2.427	0.716	0.266	5.403	0.226	0.542	11
Other commercial services	30 mins	-9.758	4.301	0.663	-2.208	1.265	0.853	5
	2 hours	14.250	0.830	0.041	4.088	0.583	0.769	12
	4 hours	37.340	-0.424	0.005	9.085	0.422	0.722	10
Manufacturing	30 mins	-5.713	0.567	0.977	-5.960	0.569	0.972	3
	2 hours	24.230	0.344	0.162	13.950	0.132	0.760	16
	4 hours	21.400	0.287	0.371	3.938	0.345	0.871	20
	8 hours	42.110	0.466	0.383	12.680	0.626	0.787	8

**Values are reported to 3 decimal places. **Estimated intercept is in R1000s. ***DFE: Degree of freedom in error: the difference between number of observations (n) and number of regression model parameters (p) i.e. DFE = n – p.*

Table 5.3: Parameter estimates and goodness of fit of power model describing relationship between average monthly electricity bill and CIC for business customers without backup power supply

Sector	Electricity interruption duration	Power model*			DFE
		Parameter estimates		R^2	
		γ	n		
Trade	30 mins	3.459	0.254	0.246	5
	2 hours	5.222	0.466	0.725	19
	4 hours	6.875	0.715	0.610	17
	8 hours	22.440	0.774	0.838	7
Hospitality	30 mins	0.539	0.541	0.039	10
	2 hours	0.772	0.961	0.703	20
	4 hours	2.737	0.574	0.616	11
Other commercial services	30 mins	0.000	5.898	0.999	5
	2 hours	11.640	0.410	0.780	12
	4 hours	42.590	-0.166	0.723	10
Manufacturing	30 mins	0.035	1.553	0.990	3
	2 hours	9.515	0.447	0.773	16
	4 hours	10.010	0.392	0.865	20
	8 hours	26.740	0.292	0.763	8

**Values are reported to 3 decimal places.*

5.2.2 Customer damage functions for customers without backup power supply

The CDF for each sector was derived as an interpolant showing the relationship between average normalized CIC estimates and electricity interruption duration for the reference electricity interruption context surveyed. Only the CDFs for the trade and manufacturing sectors include all interruption duration investigated in the survey (30 minutes, 2 hours, 4 hours, and 8 hours). As discussed in section 5.2.1, the data of the 8-hour interruption cost in the hospitality and other commercial services sectors was insufficient for meaningful statistical analyses. To allow for a uniform basis of comparison and illustration, the discussion on CDFs in this section is mainly on the trade and manufacturing sectors.

The CDFs for all the sectors were evaluated with and without outliers. All CDFs are piecewise linear i.e. CIC increases with electricity interruption duration, albeit at different rates for the different sectors (Figure 5.1 and Appendix C3). In all sectors, the CDF without outliers has lower normalized CIC for some of the electricity interruption duration e.g. the 4-hour electricity interruption duration in the trade and manufacturing sectors. The gradient of the CDFs without outliers for the trade and manufacturing sectors is highest between the 4-hour and 8-hour electricity interruption scenarios. This implies that respondents in these sectors consider that their CIC would increase significantly if the duration of an unplanned electricity interruption lasted beyond 4 hours.

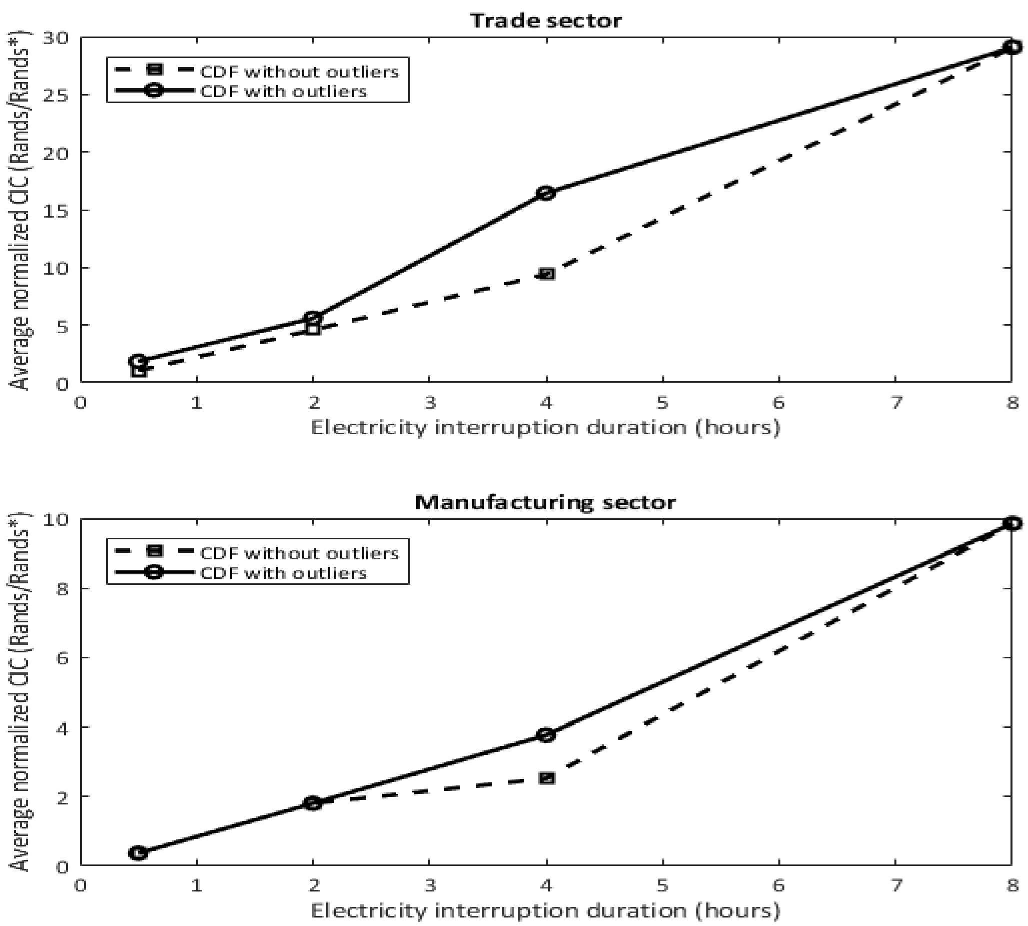


Figure 5.1: CDFs for the trade and manufacturing sectors
(Rands → Average monthly electricity bill)*

Table 5.4: Summary statistics on normalized worst-case CIC

Sectors	Duration (hours)	Mean	Std	Min	Med	Max	*Std error	Skewness	Beta distribution parameters	
									α	β
Trade	0.5	1.029	1.358	0.000	0.569	4.496	0.297	1.513	0.214	0.720
	2	4.581	6.211	0.000	2.470	25.000	0.935	1.872	0.261	1.164
	4	9.403	15.536	0.000	3.104	50.000	2.102	1.957	0.109	0.472
	8	29.090	61.108	0.000	6.680	198.462	9.199	2.433	0.047	0.273
Hospitality	0.5	0.183	0.287	0.000	0.060	0.960	0.053	1.871	0.137	0.584
	2	0.794	0.646	0.000	0.725	2.500	0.169	1.068	0.712	1.531
	4	1.065	0.870	0.000	1.000	2.500	0.295	0.529	0.434	0.585
Other Commercial Services	0.5	1.039	1.734	0.000	0.300	4.806	0.393	1.730	0.065	0.237
	2	2.149	2.279	0.000	1.500	7.680	0.596	1.156	0.360	0.927
	4	4.674	7.578	0.150	1.429	25.600	1.409	2.151	0.128	0.575
Manufacturing	0.5	0.370	0.414	0.000	0.286	1.000	0.165	0.644	0.132	0.226
	2	1.811	2.822	0.050	0.414	10.000	0.427	1.866	0.156	0.706
	4	2.527	3.689	0.150	0.625	14.286	0.552	2.048	0.209	0.975
	8	9.850	18.168	0.667	2.763	60.000	3.115	2.388	0.082	0.415

**Std error: Standard error*

The normalized CIC estimates for the trade sector are higher than that of the manufacturing sector across all electricity interruption durations. However, this does not necessarily mean that business customers in the trade sector have higher interruption cost. This observation could be due to the higher electrical size of the business customers in the manufacturing sector (Table 4.2) i.e. normalizing the CIC of business customers in the manufacturing sector with higher average monthly electricity bills results in lower normalized CIC estimates. It is also plausible that business customers in the manufacturing sector were more conservative in estimating their CICs. Trade sector respondents mostly estimated their cost in terms of 'volume of sales' that could have been made during the electricity interruption duration. It is possible that they were quite optimistic of the potential sales they can make at their busiest time of day, day of week and season of the year. For example, during noon on a 'Black Friday' in summer. The different shapes of the CDF for the sectors imply that appropriate customer classification is important for a comprehensive understanding of the CIC of business customers. For instance, grouping the trade and manufacturing sectors together would have obscured the trends observed in this study. Where the sample data is large enough, business customers may be further classified according to size (both economic i.e. based on turnover and electricity intensity) and geographically. This will reduce the variation in CIC and provide insight on whether business customers interruption costs exhibits significant spatial variation.

5.2.3 Caveat on CDFs

The CDFs derived in this study are deemed valid only for the range of the electricity interruption durations studied: 30 minutes to 8 hours for the trade and manufacturing sectors; and 30 minutes to 4 hours for the hospitality and other commercial services sectors. Also, for a business customer without backup power supply, its real CIC for a given electricity interruption duration is the difference between its CIC and the electricity bill it would have paid for that duration. Often, the electricity bill for the electricity interruption duration is significantly smaller than CIC, hence it is appropriate to use estimates from the CDF of a particular sector to evaluate its interruption cost.

5.2.4 Comparison of average normalized CIC estimates with those in a past study

To put the findings in this study within the context of past research, the average normalized CIC estimates (without outliers) in this study were compared with those of a similar CIC study conducted for business customers in Cape Town between 2009 and 2010 [70]. The sector description in this study are not exactly the same as that in [70]. However, the descriptions of the sectors designated 'trade' and 'hospitality' in this study are similar to those designated 'retail' and 'hotel and restaurant' respectively in [70], thus the comparison was done for just these two sectors and for similar electricity interruption durations investigated in both studies. It was not necessary to apply cost weighting factors like *'consumer price index* (CPI)*'* to adjust the results of the 2010 study, because the CIC estimates were also normalized by average monthly electricity bill. Applying the same CPI weight to CIC and average monthly electricity bill implies little or no change in the normalized CIC estimates.

The percentage differences in the estimates were evaluated using the estimates in the 2010 study as a reference. The estimates for the trade sector in this study are over 350% higher than those in the older study (Table 5.5). This substantiates the supposition in section 5.2.2 that trade sector respondents in this study were quite pessimistic about their potential worst-case CIC, even though general satisfaction with electricity reliability evaluated in this study was higher than in reference [70] (section 4.4– on satisfaction level). Hospitality sector respondents in this study seem more conservative in estimating their CICs. The 2-hour CIC estimates for the hospitality sector in both studies are comparable.

A plausible reason for the large difference between the mean of the normalized CIC estimates in this study and the 2009/2010 study is the prevailing conditions around the period each survey was conducted. The survey for the 2010 study was conducted around mid-2009 (not too far from the 2008 load shedding events), thus respondents then would have been more poised to leverage on their recent experience of electricity interruptions when estimating their CIC. The survey for this study was conducted at a time when electricity supply in Cape Town was quite reliable, thus respondents' CIC estimates were mainly hypothetical.

Table 5.5: Comparison of average normalized CIC estimates for the trade and hospitality sector in this study with those in a past study

Sector	**Duration (hours)**	**Mean of normalized CIC (Rands/Rands)**		**Absolute percentage difference in cost**
		This study	Dzobo [70]	
Trade	2	1.02	4.581	349%
	4	1.72	9.403	447%
	8	5.52	29.090	427%
Hospitality	2	0.794	0.92	14%
	4	1.065	1.93	45%

5.3 Customers with backup power supply

The cost of using backup power supply to mitigate the effect of electricity interruption includes its purchase and installation cost depreciated over duration of use, its maintenance cost and running cost for the duration of use. Summary statistics on the survey data on backup power supply cost were derived for customers who owned diesel, petrol or gas generators and those who owned uninterruptible power supply (UPS) or battery-inverter systems[20] (Tables 5.6 and 5.7 respectively). Since the period of purchase and installation of backup power supply differed from respondent to respondent, the reported purchase and installation cost (PIC) were adjusted using CPI weights [130]:

$$\text{Adjusted PIC} = \text{Actual PIC} * \frac{2018\, CPI}{Average\ CPI\ for\ purchase\ and\ installation\ period} \quad (5.3)$$

Table 5.6: Generator cost summary statistics

Cost description	No. of responses	Rands per kVA				
		Mean	Std	Min.	Med.	Max.
Purchase and installation	36	3966.16	2455.19	894.18	3437.02	8941.85
Monthly Maintenance	26	5.35	6.78	0.00	3.79	30.00
Running cost per hour	25	4.58	5.25	0.63	3.20	20.00

Table 5.7: UPS / Battery - inverter system cost summary statistics

Cost description	No. of responses	Rands per kVA				
		Mean	Std	Min.	Med.	Max.
Purchase and installation	5	5909.07	4486.39	484.35	5588.65	12295.04

Obtaining cost summary without regard to the difference in cost features for different backup power supply sizes does not provide an estimated mean cost per kVA that is very representative of the backup power supply equipment in the sample. For instance, the reported generator sizes has a skew and wide range (Appendix C4 – Figure C4.1). The mean purchase and installation cost per kVA for generators less than or equal to 10kVA is approximately R2400, while it is greater than R4500 for generators greater than or equal to 100kVA. Thus, summary statistics for the different generator cost components were evaluated for 4 different generator size ranges (Appendix C4 – Table C4.1). The small number of responses for UPS/Battery-inverter system cost did not allow for cost description according to size ranges.

[20] Respondents in the manufacturing sector who owned uninterruptible power supply (UPS) / battery-inverter systems mainly reported that they were for safe shutdown routines. These backup power supplies were not procured to mitigate the effects of long duration electricity interruptions.

5.3.1 Synopsis of opinions on backup power supply cost from facility managers

One facility manager who was recently involved in the costing and procurement of backup power supply for different departments of his organization indicated that the basic unit purchase cost of a diesel backup generator without other associated installation cost is around R2 000/kVA. This is the same as the median of the purchase and installation cost per kVA of generators between 1 – 10kVA in this study (Appendix C4 – Table C4.1). Most of the generators in this category are petrol-fueled, and do not require extensive installation procedures. This facility manager also highlighted that besides the basic unit cost of purchase, several components contribute to the cost of getting a medium - large sized diesel generator ready for use viz.:

- Rigging and transportation;
- Environmental factors: ensuring that noise and exhaust levels are within regulatory limits specified for the environment the generator is to operate in;
- Structural work e.g. excavations, building generator base and housing;
- Electrical works: trenching, cabling, and distribution board design;
- Building load management system: controls to ensure that generator powers mainly high priority loads and is not overloaded;
- Commissioning and load tests.

All facility managers contacted indicated that the cost of installing backup power supply to cover the whole of a business facility might be prohibitive if its electricity size is significantly high. The cost may not justify the benefits, especially if the uncertainty around power supply reliability is not very high. Appendix C4 contains an excerpt of an email exchange with one facility manager that discussed this significantly. Hence, backup power supply are only installed for high priority loads.

5.3.2 CIC Modelling for customers with backup power supply

From the discussions in the preceding section, in a given sector, the interruption cost of business customers who own backup power supply can be described as the sum of the cost of using the backup power supply and the unmitigated loss if the mitigation provided by the backup is partial equation (5.4):

$$CIC_b(\tau , d) \ = \ \left(B_{PIC}^h + B_{MC}^h + B_{RC}^h\right) B_{SZ} d_b + \ \ L_u(d, B_{Fc}, E, \ \tau) \tag{5.4}$$

Where $CIC_b(\tau , d)$ implies CIC of customers with backup power supply, for an electricity interruption of duration d, occurring in season – time interval τ; B_{PIC}^h, B_{MC}^h, B_{RC}^h are the backup power supply purchase and installation cost per kVA depreciated on a hourly basis, average hourly maintenance and average hourly running cost per kVA respectively; B_{SZ} is the size of the backup power supply (in kVA); d_b is the duration of backup power supply usage; $L_u(d, B_{FC}, E, \ \tau)$ is the unmitigated loss expressed as a function of electricity interruption duration d, percentage of business facility powered by the backup power supply B_{FC}, the business' average monthly electricity bill E, and activity level in season – time interval τ. The expression of backup cost parameters on per kVA basis allows the determination of the potential cost of a given backup generator size to provide 100% mitigation such that L_u is 0. The *straight-line depreciation method*[21] was used to determine B_{PIC}^h (equation 5.5).

$$B_{PIC}^h \ = \ \frac{B_{PIC} - B_{SV}}{H_u} \tag{5.5}$$

Where B_{PIC} is the actual purchase and installation cost per kVA of the backup generator. B_{SV} is the backup generator's salvage value per kVA at the end of useful life. $H_u$is the useful life (in hours) of the backup generator.

A suitable model for L_u can be determined via multivariable regression analysis. However, the data on unmitigated loss for the different electricity interruption scenarios did not allow for such analysis (Appendix C4 – Table C4.2). However, case studies of the difference in cost of running backup generators and the cost of using the electric utility's supply was done for a few selected respondents who provided sufficient information on the size and cost of their backup power supply, and their average monthly electricity bill.

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[21] This is the most widely used and simplest asset depreciation calculation method (https://www.calculator.net/depreciation-calculator.html; https://www.accountingcoach.com/depreciation/explanation)

5.3.3 Case studies: Cost of backup power for full loss mitigation versus the cost of electric utility's supply

The respondents considered reported that during an interruption they would have no unmitigated loss (i.e. $L_u = 0$) besides the cost of running their generator. For each respondent, the average cost per hour of running a generator and the average electricity bill per hour were compared. For some respondents, the relevant backup cost data were incomplete (Appendix C4 – Table C4.3). Missing data were evaluated using the respondent's reported generator size and the average cost estimates computed in Appendix C4 – Table C4.1. It was assumed that each respondent's hourly electricity consumption is identical throughout its operating period. Thus, average hourly electricity bill was derived by dividing reported average monthly electricity bill by average operating period per month. The useful life of the generators was assumed to be 50, 000 hours[22], and salvage (scrap) value was assumed to be 5% of actual PIC.

The results from the case studies provide empirical evidence on the significant increase in operating costs businesses may incur if they were to use generators that provided them full impact mitigation during an interruption. The average hourly cost of using a generator was between 100% - 314% higher than average hourly electricity bill for the respondents considered in the commercial sector. For the manufacturing sector respondents, it was 149% - 1320% higher (Table 5.8). Respondents' average monthly electricity bills and backup generator sizes were major influencers of the cost difference observed (Figure 5.2). This cost difference can be considered the *real interruption cost* of these respondents. Also, the cost of using a generator to achieve full mitigation is a more objective estimate of the respondents' willingness to pay (WTP) to avoid interruptions. These WTPs can be considered as a lower bound of the CIC of these respondents. The corresponding higher bound will be the compensation they will be willing to accept (WTA) for the impact of electricity interruptions. For each respondent, this WTA may be derived as the cost that would have been incurred if there was no mitigation in place.

[22] https://www.homerenergy.com/products/pro/docs/3.11/generator_lifetime.html (accessed 10 December 2018)

Table 5.8: Comparison of average hourly generator cost and average hourly electricity bill for selected respondents

Respondent*	**Average hourly electricity bill, E^h (R/hr)**	**Generator size (kVA)**	**Average hourly generator cost, CIC_{b^h} (R/hr)**	**Cost difference, $CIC_{b^h} - E^h$ (R/hr)**	**Percentage difference $\frac{CIC_{b^h} - E^h}{E^h} \times 100$**
C_1	8.33	5.5	28	19.66	235.97%
C_2	25.93	45	51.84	25.91	99.95%
C_3	24.42	70	101.17	76.75	314.31%
M_1	33.69	250	477.67	443.98	1318.01%
M_2	1250	600	3114.43	1864.43	149.15%
M_3	531.69	1 200.00	3949.03	3417.33	642.73%

**C_i and M_i imply respondent i considered in the commercial and manufacturing sector respectively*

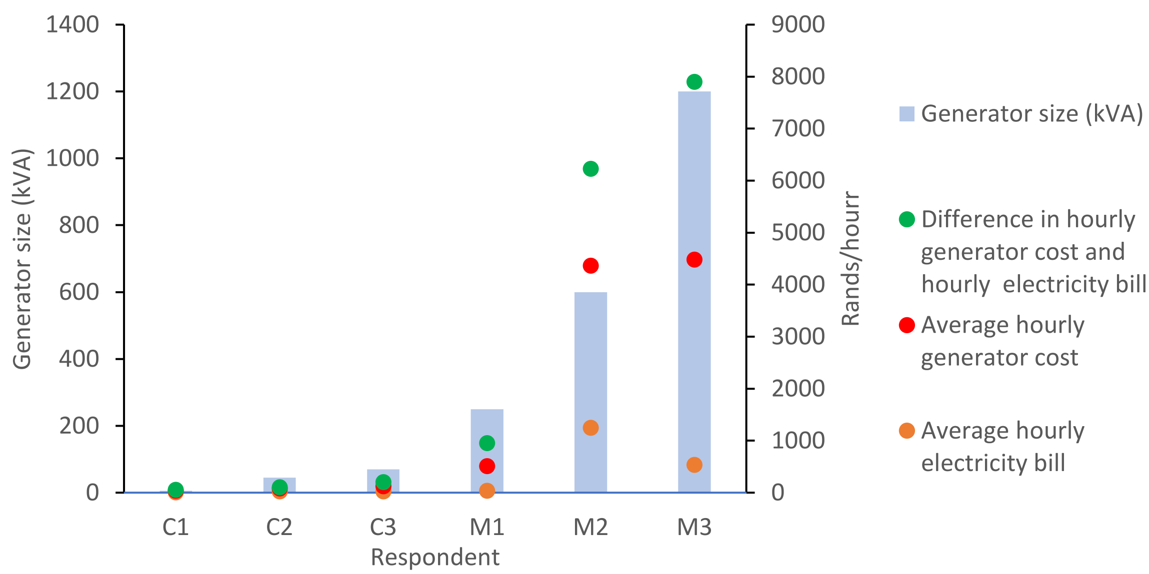

Figure 5.2: Generator sizes and difference in average hourly generator cost and average hourly electricity bill among selected respondents

5.4 Assessing the statistical significance of electricity interruption and customer parameters on CIC

In section 5.2 (customers without backup power supply), regression models for estimating the CIC of customers without backup power supply based on their average monthly electricity bill were derived for different electricity interruption scenarios in different customer sectors. This allowed for specificity in model description. However, a comprehensive understanding of the CIC (*unmitigated loss*)[23] of business customers with and without backup power supply may be obtained using a linear least squares multiple regression framework. Such a framework allows for a reduction in unintentional bias in CIC estimation, and an assessment of the statistical significance of other predictors (besides average monthly electricity bill) that might influence the unmitigated loss of business customers. The multiple linear regression model was specified for the reference electricity interruption scenario considered in the survey: *an interruption of a given duration occurring at the busiest operating time and season of a business.* The generic form of the model is given by equation (5.6).

$$L_U \; = \; \theta_0 + \textstyle\sum_{j=2}^{n} \theta_{1j} Sec_j + \theta_2 \mathrm{d} + \theta_3 \mathrm{E} + \theta_4 B_o B_{FC} + \theta_5 B_o B_{SZ} \tag{5.6}$$

L_U (unmitigated loss) is the response variable. The predictors are economic sector Sec; interruption duration d; average monthly electricity bill E; backup ownership[24] B_o; percentage of business facility powered by backup power supply B_{FC}; backup power supply size B_{SZ}. θ_i's are the model's coefficients. Sec is a nominal variable, hence Sec_j is a dummy (indicator) variable for the *j^th^* economic sector in the dataset (Table 5.9). Its associated model coefficient is θ_{1j}. To evaluate equation (5.6) for the j^{th} economic sector, Sec_j takes the value 1, otherwise it takes the value 0. The hospitality sector is the reference sector i.e. Sec_1. To evaluate the model for this sector only, the second term of equation (5.6) i.e. $\sum_{j=2}^{n} \theta_{1j} Sec_j$ is eliminated.

Table 5.9: Indicators for economic sectors in multiple linear regression model

Identifier, *j*	**Sector**
1	Hospitality
2	Trade
3	Other commercial services
4	Manufacturing

[23] Customers without backup power supply are considered to have zero mitigation in place, hence their reported CIC is taken as their unmitigated loss. The interruption cost besides the cost of running a backup power supply is considered the unmitigated loss of customers who own backup power supply.
[24] Backup ownership is a logical variable; it takes the value 1 if present, otherwise it is 0.

Results from Multiple Regression Analyses

The estimated coefficients for the predictors in equation (5.6) and their statistics are shown in Table 5.10. A 5% significance level was chosen for assessing the statistical significance of the predictors [124]. The p-values of the estimated coefficients for electricity interruption duration, average monthly electricity bill, and the percentage of business facility powered by backup power supply (for customers who have one) were less than 0.05 (Table 5.10). These three are statistically significant predictors of the unmitigated loss of business customers. The intercept, the dummy variables for economic sector, and size of backup power supply are not statistically significant at the 5% significance level. However, the estimated coefficient for the dummy variables for economic sector implies that each has a unique effect on the response variable. The positive estimated coefficients for interruption duration and average monthly electricity bill imply that: controlling for other predictors, a unit increase in each predictor results in a corresponding increase in unmitigated loss that is determined by the value of the predictor's coefficient. The negative estimated coefficients for the percentage of business facility powered by backup power supply and backup power supply size imply that: controlling for other variables, increase in the mitigation capacity provided by a business' backup power supply will reduce its unmitigated loss. The intercept is quite meaningless when all the predictor variables are zero.

The adjusted R^2 i.e. R_{adj}^2 was preferred over R^2 for assessing the strength of the multiple linear regression model. Because of the multiple variables considered, R_{adj}^2 provides a better estimate of the amount of variability explained by the model. Based on R_{adj}^2, 82.5% of the variability in unmitigated loss was explained by the selected predictors (Table 5.11). A final model may be conventionally determined by eliminating predictors with p-values greater than 0.05 [124]. However, eliminating either or both Sec_j and B_oB_{SZ} from equation 5.6 yielded models with reduced explanatory power (R_{adj}^2), hence both predictors were retained in the model.

Table 5.10: Estimated coefficients of multiple linear regression model for interruption cost

Predictor	Parameter estimate	t-statistic	p-value
(Intercept)	-15000.260	-1.386	0.167
Sec_2	19581.680	1.552	0.122
Sec_3	20470.683	1.379	0.169
Sec_4	11521.749	0.863	0.389
d	7084.298	3.800	**0.000**
E	0.348	33.049	**0.000**
B_oB_{FC}	-59.858	-2.005	**0.046**
B_oB_{SZ}	-30183.596	-1.653	0.100

Table 5.11: Goodness of fit of multiple linear regression model for interruption cost

Item description	Value
Number of observations	245[25]
Error degrees of freedom	237
R-squared	0.83
Adjusted R-Squared	0.825
F-statistic vs. constant model:	165
p-value:	2.01e-87

5.5 Chapter summary

This chapter discussed the procedure and the results of the analysis done on the quantitative CIC data retrieved from survey respondents without and with backup power supply. The use of average monthly electricity bill to normalize the CICs estimated by survey respondents was validated via statistical regression analyses. The normalized CIC estimates for the trade and hospitality sectors in this study were compared with those of an earlier study and plausible reasons for the differences observed were explained. The results of the cost analysis done for customers who own backup generators showed that running a backup generator to fully power a business' facilities can significantly increase its operating cost. Also, the multiple linear

[25] There was some 'form of duplication' in the dataset collated for the multiple regression analyses; the data for a given respondent for a particular outage duration was considered as one observation, because the respondent's reported unmitigated loss differed in each of the outage duration presented. Thus, for the four-outage duration considered, four of the observations used in evaluating the model belonged to a single respondent.

regression analysis done showed that average monthly electricity bill, electricity interruption duration, ownership of backup power supply and percentage of facilities powered by backup power supply are statistically significant predictors of business customers' unmitigated loss during a power outage. The next chapter focuses on a reliability cost – worth evaluation for a test distribution test feeder.

6 Case Study of Reliability Cost-Worth Evaluation for a Distribution System

In this chapter, three CIC models, a reliability model and load model are applied in the evaluation of the reliability – worth of a distribution test feeder using a time-sequential Monte-Carlo framework. The results of applying the three CIC models are discussed. The placement of switches/disconnects on the feeder to minimize expected CIC is investigated. Also, the effect of having an alternative feeder supply on expected feeder interruption cost is investigated. The chapter ends with a summary of the results.

6.1 Reliability cost/worth indices

The reliability indices of the distribution system are derived from three basic load point indices – average failure rate λ, average outage duration r and average annual unavailability U [33]. From these, system indices such as SAIFI, SAIDI, CAIDI, ASAI, and ASUI can be evaluated. System reliability assessment based on these indices alone is not holistic without the consideration of the associated economics. For a consistent and holistic appraisal of system reliability, it is necessary to combine reliability criteria with cost considerations [131]. Reliability cost-worth assessment provides a platform for incorporating cost analysis and quantitative reliability assessment into a single structured framework [3, 131].

Reliability cost refers to the investments required by electric utilities to achieve a given level of system reliability, while reliability – worth is the benefit derived by the electric utility, electricity customers and society from the set reliability level. The basic reliability cost-worth indices in existing literature include expected cost of interruption (ECOST), expected energy not supplied (EENS), and interrupted energy assessment rate (IEAR). Basically, three models are required for the evaluation of these indices i.e. system model, load model and CIC models (Figure 6.1). These models can be used in analytical or simulation methods to assess ECOST, EENS, and IEAR. [33].

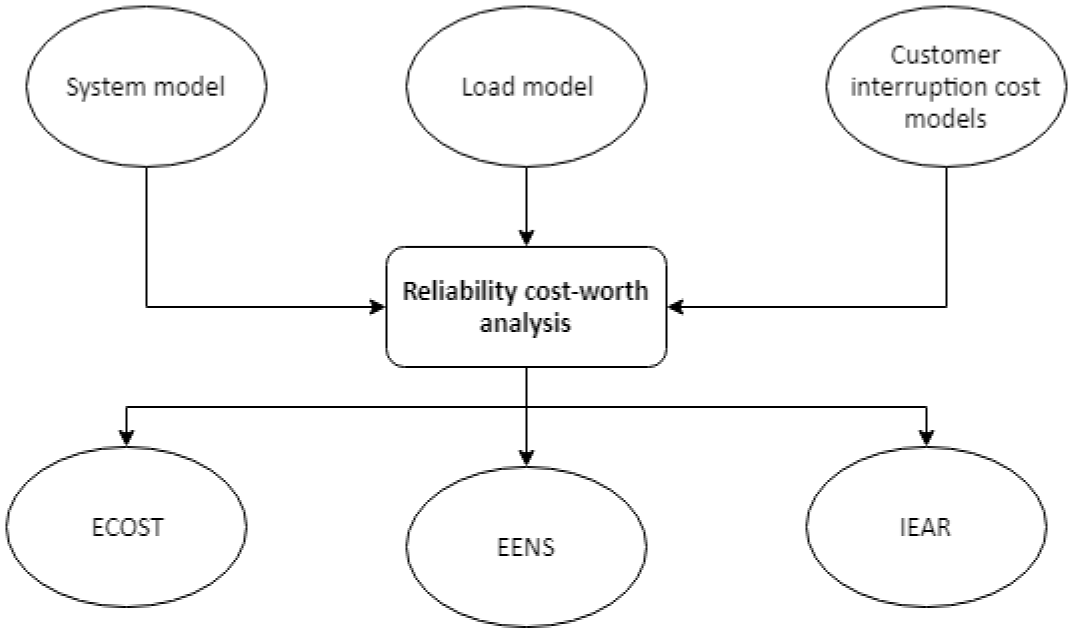

Figure 6.1: Diagrammatic representation of a reliability cost-worth analysis

Analytical methods describe the system using a suitable mathematical model and evaluates system reliability indices via direct numerical solutions of this model. They offer the advantage of computational speed, but they mainly output average/mean values of load point and system reliability indices.

Simulation methods estimate system reliability indices via simulation of the actual process and random behavior of the system i.e. the system is treated as a series of real experiments [3]. The Monte Carlo simulation (MCS) framework is mostly used for this purpose. System and load point indices can be described probabilistically, thus providing information on the variability of the indices. MCS for reliability assessment may be time sequential, nonsequential or pseudo-chronological. The time sequential MCS is predominantly applied in existing literature [109, 131-133] for reliability worth assessment. This is due to its flexibility and algorithmic simplicity. Hence, the time-sequential MCS was applied for the reliability cost-worth assessment in this chapter. The case study network, the load and CIC models, and simulation procedures used are presented in subsequent sections.

6.2 Case study distribution system model

The distribution system adopted for the case study is Feeder 2 of Bus 6 of the Roy Billinton Test System (RBTS)[26] [134]. The feeder is a radial feeder supplied by a 33/11kV transformer. It has seven 11/0.415kV transformers, each supplying a load point (Figure 6.2). Fuses are connected to these transformers to prevent lateral failures from affecting other parts of the network. There is a switch/disconnect at each T-junction on the feeder to allow safe isolation of faulty parts of the network. The feeder has a normally open switch at its far end that allows for connection to an alternate source of electricity supply. In this study, the fuses and switches are assumed to be 100% reliable. The reliability data for other feeder components are presented in Tables 6.1 and 6.2. A single weather state is assumed. The length of each feeder line section is presented in Table 6.3. Business customers in the different sectors considered in the survey were arbitrarily assigned to the load points of the test feeder (Table 6.4).

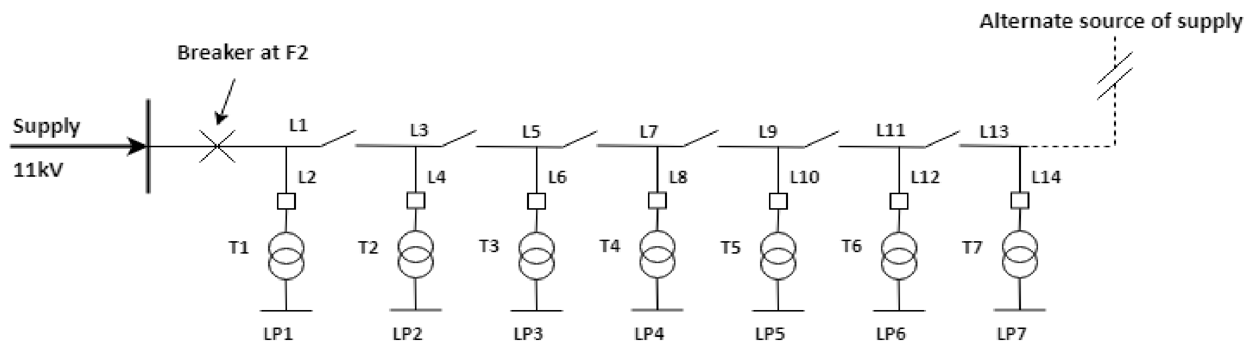

Figure 6.2: Single line diagram of feeder 2 at RBTS Bus 6

Table 6.1: Reliability data of test feeder

Feeder components	**Failure rate λ (failure/year)**	**Mean repair/replacement time (h)**	**Mean switching time (h)**
11/0.415kV Transformers	0.015	10	1
11kV Breaker at F2	0.006	4	1
Overhead lines	0.065*	5	1

**Overhead line failure rate is failure/year-kilometer i.e. 0.065 failure/year-kilometer*

[26] The RBTS is an educational test system developed by the Power Systems Research group at the University of Saskatchewan.

Table 6.2: Probability distribution of network component reliability parameters

Parameter		**Probability distribution**	**Standard deviation (h)**
Time to failure (TTF) – all components		Exponential	–
Repair time	Overhead lines	Lognormal	1
	Breaker	Lognormal	0.4
Replacement time – Transformer		Lognormal	1
Switching time		Lognormal	0.4
Reclosing time		Lognormal	0.0167

Adapted from [135]

Table 6.3: Length of line sections of test feeder

Line section	L1	L2	L3	L4	L5	L6	L7	L8	L9	L10	L11	L12	L13	L14
Length (km)	0.6	0.75	0.75	0.8	0.6	0.8	0.6	0.6	0.8	0.75	0.75	0.6	0.6	0.75

Table 6.4: Business customer assignment to load points of test feeder

Sector	**Number of business customers at each load point**						
	LP1	**LP2**	**LP3**	**LP4**	**LP5**	**LP6**	**LP7**
Trade	7	5	4	6	-	2	4
Hospitality	2	8	3	-	6	-	3
Other commercial services	-	-	3	6	4	3	-
Manufacturing	6	2	4	-	5	5	-
Total	**15**	**15**	**14**	**12**	**15**	**10**	**7**

6.3 Customer interruption cost model

The base CIC model considered in this case study is a time-varying multiplicative model similar to those in [28, 78]. The model is simply derived by multiplying the CDFs evaluated for the worst-case CIC estimates[27] (section 5.2.2) with season – time activity weights evaluated from the business activity levels reported by the firm-level survey respondents (section 4.5).

The season-time activity weights were derived for each sector *i* using equations (6.1) – (6.5):

$$\boldsymbol{AL_{S,WD}^{(i)}} = \overline{AL}_{S}^{(i)} \times \overline{AL}_{WD}^{(i)} \tag{6.1}$$

$$\mathbf{AL_{S,WE}^{(i)}} = \overline{\mathrm{AL}}_{\mathrm{S}}^{(\mathrm{i})} \times \overline{\mathrm{AL}}_{\mathrm{WE}}^{(\mathrm{i})} \tag{6.2}$$

$$\mathrm{AL}_{\max}^{(\mathrm{i})} = \max\left(\mathbf{AL_{S,WD}^{(i)}}, \mathbf{AL_{S,WE}^{(i)}}\right) \tag{6.3}$$

$$\mathbf{T_{S,WD}^{(i)}} = \frac{\mathbf{AL_{S,WD}^{(i)}}}{\mathrm{AL}_{\max}^{(\mathrm{i})}} \tag{6.4}$$

$$\boldsymbol{T_{S,WE}^{(i)}} = \frac{\mathbf{AL_{S,WE}^{(i)}}}{\boldsymbol{AL_{MAX}^{(i)}}} \tag{6.5}$$

Where:

$\overline{AL}_{WD}^{(i)}$ = 1 x 4 vector containing average activity level in each time block of a typical weekday.

$\overline{AL}_{WE}^{(i)}$ = 1 x 4 vector containing average activity level in each time block of a typical weekend.

$\overline{AL}_{S}^{(i)}$ = 4 x 1 vector containing average activity level in each season of the year.

$\mathbf{AL_{S,WD}^{(i)}}$ = 4 x 4 matrix of activity season – weekday time activity level.

$\mathbf{AL_{S,WE}^{(i)}}$ = 4 x 4 matrix of activity season – weekend time activity level.

$\boldsymbol{AL_{MAX}^{(i)}}$ = Maximum season – time activity level (i.e. busiest time and season in sector *i*)

[27] The worst-case interruption cost estimates are those estimated by the survey respondents for the reference time and season investigated i.e. respondents'' business' busiest time-of-day and season-of-the-year.

$\mathbf{T}_{\mathbf{S,WD}}^{(\mathbf{i})}$ = 4 x 4 matrix of season – weekday time weights. $\mathbf{T}_{\mathbf{S,WD}}^{(\mathbf{i})} \in [\mathbf{0}, \mathbf{1}]$.

$\boldsymbol{T}_{\boldsymbol{S,WE}}^{(\boldsymbol{i})}$ = 4 x 4 matrix of season – weekend time weights. $\boldsymbol{T}_{\boldsymbol{S,WE}}^{(\boldsymbol{i})} \in [\mathbf{0}, \mathbf{1}]$.

The computed season-time activity weight matrices are in Appendix C1.

The time-varying CIC model for sector *i* is given as:

$$C_n^{(i)}(\tau, d) = W_i(\tau) \times C_n^{(i)}(\tau_{ref}, d) \tag{6.6}$$

Where:

$C_n^{(i)}(\tau, d)$ = normalized CIC estimate corresponding to season – time-of-day interval τ, and interruption duration *d.*

$W_i(\tau)$ = season – time-of-day activity weight corresponding to season – time-of-day interval *τ.*

For season – weekday time interval, $W_i(\tau)$ = $\boldsymbol{T}_{\boldsymbol{S,WD}}^{(\boldsymbol{i})}(\boldsymbol{\tau})$. For season – weekend time interval,

$W_i(\tau) = \boldsymbol{T}_{\boldsymbol{S,WE}}^{(\boldsymbol{i})}(\boldsymbol{\tau})$.

$C_n^{(i)}(\tau_{ref}, d)$ = normalized CIC estimate corresponding to reference season and time τ_{ref}, and electricity interruption duration *d.*

The time-varying CIC model in equation (6.6) can be modified and represented in any of the following three ways for investigative purposes (Table 6.5).

Table 6.5: Description of CIC models for case study

Model description[28]	Remark
1. Time invariant average interruption cost (TIAIC) model	$C_n^{(i)}(\tau_{ref}, d)$ is described as average normalized CIC. $T^{(i)}(\tau)$ = 1.
2. Time-varying average interruption cost (TVAIC) model	$C_n^{(i)}(\tau_{ref}, d)$ is described as average normalized CIC. $T^{(i)}(\tau)$ is evaluated from the appropriate season – time activity weight matrix in Appendix C1.
3. Time-varying probabilistic interruption cost (TVPIC) model	$C_n^{(i)}(\tau_{ref}, d)$ is probabilistically described using the parameters of the beta distribution evaluated for the normalized interruption cost estimates for τ_{ref} and *d*. $T^{(i)}(\tau)$ is evaluated from the appropriate season – time activity weight matrix in Appendix C1.

6.4 Load Model

Business customers' loads at each load point of a distribution system may be described as average load or time-varying loads as in a chronological load curve [132]. Chronological load curves were not available for use in this study. Hence, a load model based on business customers' average monthly electricity bill and season – time activity weights is used in this dissertation. Considering a 30 – day month and a 6-hour time block in each cell of the season – time activity weight matrices in Appendix C1, the average 6-hour electricity bill for a given sector *i* in season – time interval τ, is computed using a weighted-average approach:

$$E_{6h}^{(i)}(\tau) = \frac{E_m^{(i)}}{30} \times \frac{W_i(\tau)}{W_i^{(s)}(\tau)} \times N_i \tag{6.7}$$

Where:

[28] For the TIAIC and TVAIC, $C_n^{(i)}(\tau_{ref}, d)$ is the interpolant CDF model for sector *i* (section 5.2.2)

$E_{6h}^{(i)}(\tau)$ = Average 6-hour electricity bill for sector *i* in season – time interval *τ*.

$E_m^{(i)}$ = Median of average monthly electricity bill in sector *i* (Table 6.6).

$W_i(\tau)$ = Activity level weight for season – time-of-day window *τ*.

$W_i^{(s)}(\tau)$ = Average activity level weight across all time-of-day intervals in the season associated with *τ*.

N_i = Number of business customers in sector *i*.

The corresponding average hourly electricity bill $E_h^{(i)}(\tau)$ for sector *i* in season – time interval is obtained as:

$$E_h^{(i)}(\tau) = \frac{E_{6h}^{(i)}(\tau)}{6} \tag{6.8}$$

Table 6.6: Median of average monthly electricity bill for the different business sectors

Sector	**Median of average monthly electricity bill (Rands)**
Trade	4500
Hospitality	6000
Other commercial services	3000
Manufacturing	13500

Since business customers' load was proxied by the electricity bill, EENS is not evaluated in this dissertation, rather an alternative reliability worth index called *revenue not collected (RNC)* is evaluated for the electric utility [70]. For an electricity interruption of duration *d*, occurring in a season – time interval *τ,* the revenue not collected from affected business customers at a load point *j* is evaluated as:

$$\mathrm{RN}C_j(\tau) = \sum_{i=1}^{Nc_j} E_h^{(i)}(\tau) \times d \tag{6.9}$$

Where N_{cj} is the number of business customer sectors at load point *j.*

6.5 Time-sequential Monte-Carlo simulation (TS-MCS) algorithm

In quantitative reliability or reliability cost-worth evaluation, the TS-MCS involves the generation of an artificial history of a system components' up and down states in a chronological order [3]. The computational procedure involves the use of random number generators and the probability distributions of component failure and restoration time. The TS-MCS allows for obtaining a sequence of failure-repair cycles from the artificially generated component states. Probabilistic distributions of system reliability or reliability cost-worth indices can be evaluated from this artificial history of the system.

The algorithm for the TS-MCS is outlined below [131, 133]:

1. Define the system viz. system model, CIC model, and load model, and all required input data.
2. Input number of sample years N_s, simulation period T.
3. Start simulation: $n_s = 1$; t = 0.
4. Generate a random number, R_n in the interval [0 1] for each component in the system and convert it into times to failure (TTF), based on the failure time distribution and the expected time to failure of each element.
3. $$\mathrm{TT}F_j = (-log(R_n)/\lambda) \times 8760 \qquad (6.10)$$
5. Determine the component 'c' with minimum TTF in the network of Figure 6.2.
6. Define 'c' as the failed component and do the following:
    a. Compute time to repair (TTR) and time to switch (TTS) using the appropriate probability distribution for component c's repair and switching time.
    b. Determine the location of 'c'.
    c. Find the load points L_j that are affected due to the failure of component 'c'.
    d. For the failure event k, determine the failure duration, d_{jk} for each affected load point L_j.
    e. Evaluate the customer interruption cost $COST_{jk}$ and the electric utility's revenue not

collected RNC_{jk} for failure event k:

$$\mathrm{COST}_{jk} = \sum_{i=1}^{Nc_j} C_{jk}^{(i)}(\tau, d_{jk}) \times E_m^{(i)} \times N_i \tag{6.11}$$

$$\mathrm{RN}C_{jk} = \sum_{i=1}^{Nc_j} E_h^{(i)}(\tau) \times d_{jk} \tag{6.12}$$

Where: $C_{jk}^{(i)}(\tau, d_{jk})$ is the evaluation of the chosen CIC model for sector i at load point j. N_i, N_{cj}, τ, E_m, and E_h are as defined in sections 6.3 and 6.4.

f. Add COST_{jk} and $\mathrm{RN}C_{jk}$ to their respective total values.

g. Repeat steps e – g for all load points.

7. Generate a new random number for repaired component 'c' and convert it into a new TTF.
8. If t < T, go to step 5.
9. Do $n_s = n_s + 1$. If $n_s < N_s$, go to step 4.
10. Determine the total customer interruption cost $COST_j$ and the electric utility's revenue not collected RNC_j of load point j for the total simulation years.

4. $$\mathrm{COST}_j = \sum_k COST_{jk} \tag{6.13}$$
5. $$\mathrm{RN}C_j = \sum_k RNC_{jk} \tag{6.14}$$

The expected customer interruption cost $ECOST_j$, expected revenue not collected $ERNC_j$, and interrupted energy assessment rate $IEAR_j$ for each load point j are evaluated thus:

$$\mathrm{ECOS}T_j = \frac{COST_j}{N_s} \tag{6.15}$$

$$\mathrm{ERN}C_j = \frac{RNC_j}{N_s} \tag{6.16}$$

$$\mathrm{IEA}R_j = \frac{ECOST_j}{ERNC_j} \tag{6.17}$$

The feeder ECOST, ERNC, and IEAR are evaluated as in equations (6.18) – (6.20):

$$\mathrm{ECOST} = \sum_{J=1}^{N_p} ECOST_j \tag{6.18}$$

$$\mathrm{ERNC} = \sum_{J=1}^{N_p} ERNC_j \tag{6.19}$$

$$\mathrm{IEAR} = \frac{ECOST}{ERNC} \tag{6.20}$$

A diagrammatic representation of the TS-MCS algorithm is shown in Figure 6.3

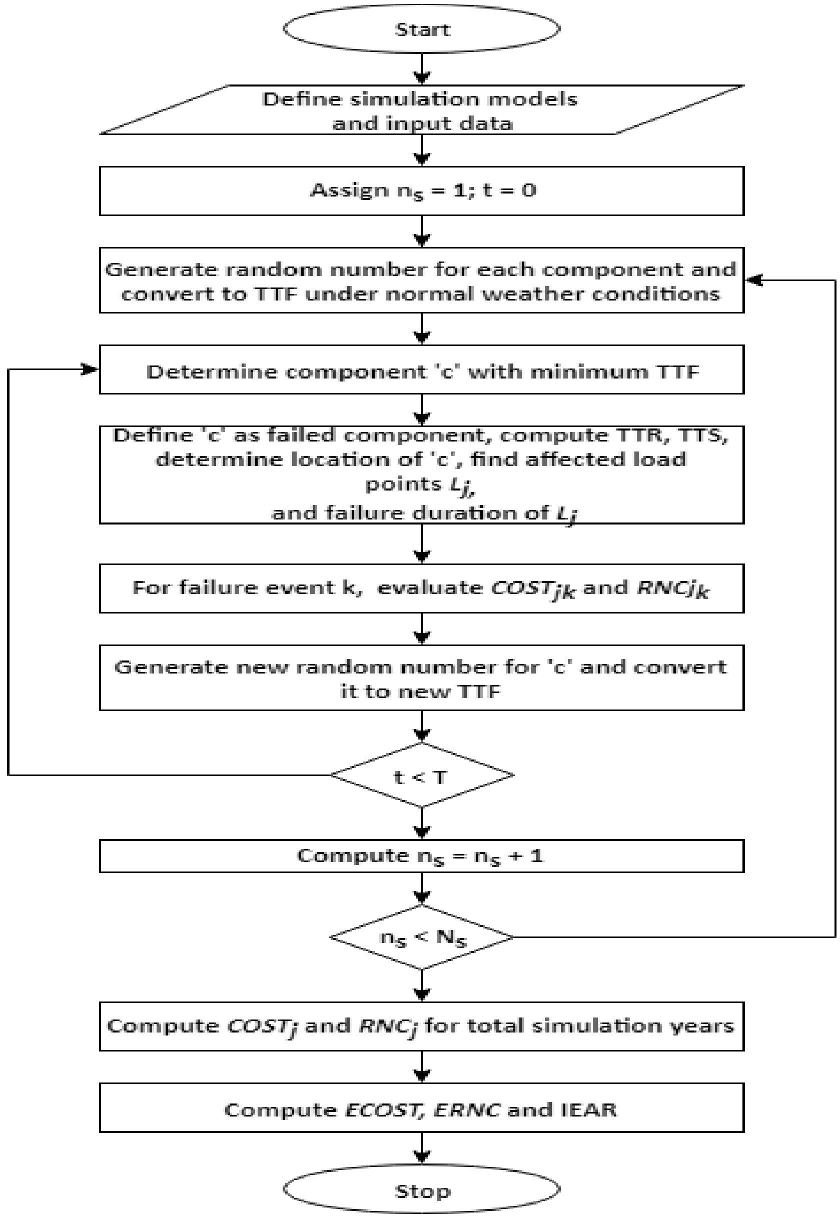

Figure 6.3: Flow chart for the TS-MCS for reliability cost/worth analysis

6.6 Reliability cost – worth simulation cases

Three major cases where considered to investigate the effect of the CIC models in Table 6.5 and different configurations of the test feeder on reliability worth indices. In all cases, the load model in section 6.4, and the test feeder component reliability parameters and load point data in section

6.2 (Tables 6.1 – 6.4) were used. The description of the simulation cases is presented in Table 6.7. All simulations were done using MATLAB 2017b software.

Table 6.7: Description of reliability cost/worth simulation cases

Simulation case	Description
1. Effect of CIC model on ECOST	• The effect of the three CIC models in Table 6.5 were considered. • The test feeder (Figure 6.2) is assumed to have no switch/disconnect and no alternative supply.

2. Effect of alternative electricity supply on ECOST and ERNC	• The Feeder's ECOST and ERNC were evaluated for two cases:
	  o When there is no alternative electricity supply to the feeder.
	  o When there is an alternative electricity supply to the feeder. (The probability of transferring failed load points to an alternative supply is taken as 100%.)
	• It was assumed that there are switches on all feeder sections.
	• Only *the time-varying probabilistic CIC model was* used.

3. Optimal location of switches	• The electric utility was assumed to be budget-constrained and cannot install more than 3 switches on the feeder. • A constrained optimization problem to determine the optimal location of 3 switches that minimizes the feeder ECOST was solved by embedding the TS-MCS in an exhaustive search routine (Appendix D). • The optimal location of switches was evaluated for the scenarios where the feeder has an alternative supply and where it has none. • Only *the time-varying probabilistic CIC model was* used.

6.7 Results of simulation cases

The TS-MCS outputs reliability worth indices consisting of N_s data points corresponding to the number of simulations run. This allows for a probabilistic description of these indices. However, the comparisons in this section are mainly on the computed mean of the output data of the indices.

6.7.1 Case 1: Effect of CIC model on ECOST

Across all the load points, the evaluated mean ECOST from the TS-MCS is highest using the TIAIC model (Figure 6.4). The TIAIC represents the worst-case average CIC model. The load point ECOSTs obtained using the TVAIC model shows that accounting for the time-variation in cost using business activity level weights results in lower ECOST. This is plausible as significant number of electricity interruptions during the simulation runs might have occurred in season – time intervals with low activity weights. Furthermore, combining both the time-dependencies of CIC with a probabilistic description of CIC results in even lower in ECOST. Very high values in the normalized CIC data can exert a disproportionate effect on the average normalized CIC even if they are few. The probability distributions of the normalized CIC estimates for each sector in this study were significantly right skewed (Table 5.4). Thus sampling from the beta probability distribution of the normalized CIC estimates in the TS-MCS implies that smaller CIC values with higher probability will be picked often. This explains why the mean ECOST based on the TVPIC model is smaller than that of the TVAIC model for load points LP1, LP2, LP5. The feeder's mean ECOST computed using all three CIC models is depicted in Figure 6.5.

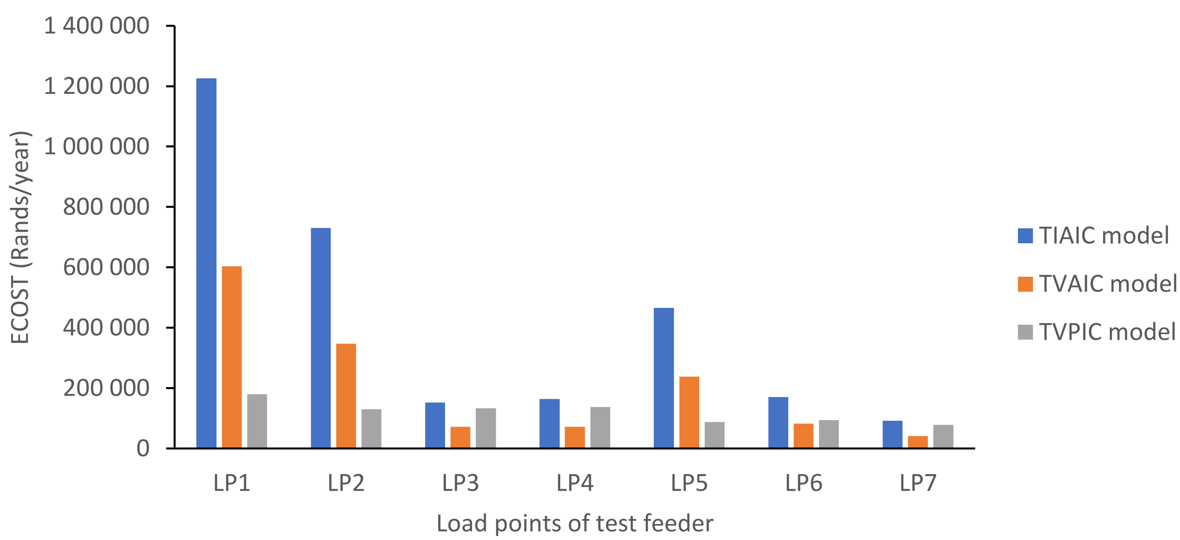

Figure 6.4: Comparison of load point expected interruption cost (ECOST) obtained from the 3 different CIC models described in Table 6.5

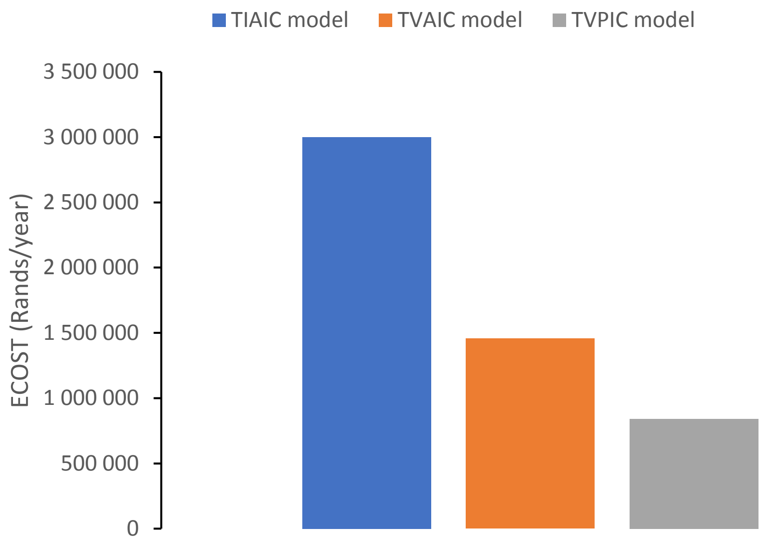

Figure 6.5: Comparison of feeder mean ECOST obtained from the 3 different CIC models described in Table 6.5

Effect of different CIC percentile values on evaluated ECOST for an electricity interruption scenario

The effect of choosing different confidence levels to determine the CIC estimate to use for a particular application was considered for a 4 – hour electricity interruption occurring within the weekday time interval 00:06AM to 12:00PM in the October – December season. The computed normalized 4 – hour CIC data from the survey, median of average monthly electricity bill data (Table 6.6) and the business customer designation adopted for the test feeder (Table 6.4) were used to evaluate average feeder ECOST and risk-based ECOST with the TIAIC, TVAIC and the TVPIC models respectively. Four risk levels were considered for the evaluation of risk-based ECOST viz. 50%, 20%, 10%, and 5% risk. These correspond to the 50th, 80th, 90th percentile and 95th percentile of the beta distribution of the normalized 4 – hour CIC data in the stated season – time interval.

The ECOST computed based on the TIAIC and TVAIC models respectively are almost equal (Figure 6.6) because the time – season window considered in this analysis was the busiest time – season window for the trade, hospitality and manufacturing sectors (i.e. their activity level weights in this time – season window is 1). The activity level weight for 'other commercial services' sector was approximately 0.97. With the TVPIC model, the choice of confidence level results in different ECOST (Figure 6.6). This can lead to different decision making. A 5% risk implies a 95% decision making confidence level which accommodates the possibility of extreme CIC values. ECOST_TVPIC (@50% risk) is significantly lower than ECOST_TIAIC and ECOST_TVAIC because of the heavy right skew of the 4-hour normalized CIC estimates in each sector (Table 5.4) i.e. the 50th percentile value of the beta distribution of the 4 – hour normalized CIC estimates is significantly lower than average value of the estimates.

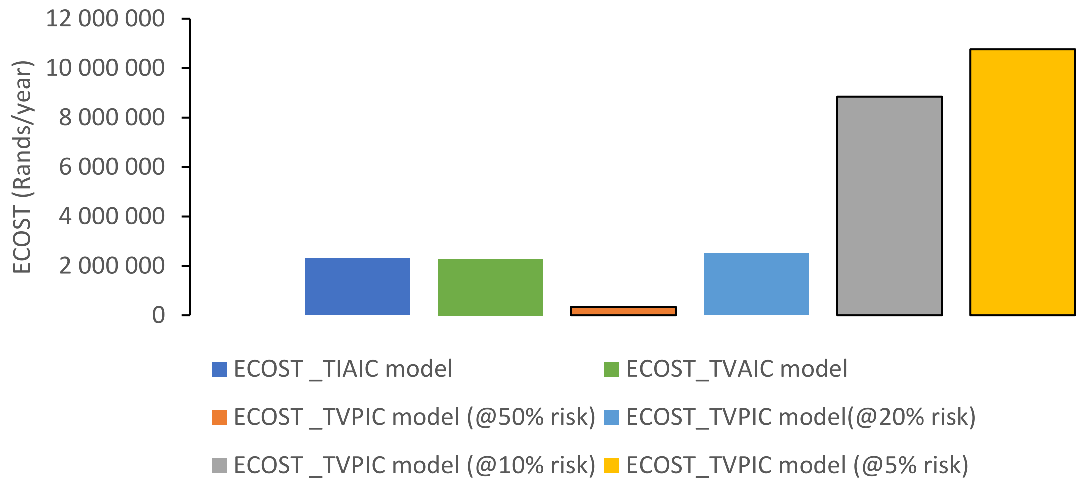

Figure 6.6: Comparison of average ECOST and risk-based ECOST for the scenario of a 4 - hour full feeder outage occurring between 12:00 - 18:00 in October – December season

6.7.2 Case 2: Effect of alternate supply on ECOST *(TVPIC model used)*

The switch configuration for this simulation is different from that in case 1; all feeder sections are assumed to have switches. Without considering alternate supply, the feeder mean ECOST reduced by about 41% when compared with its value for the TVPIC model in case 1 – where the feeder was assumed to have no switches. Comparisons of the load point ECOST and ERNC for simulation case 2 shows that including an alternate supply to the feeder reduces the load point ECOST and ERNC considerably (Figures 6.7 and 6.8 respectively). The reduction in ECOST and ERNC is most significant for LP5 and LP6. Overall, the feeder ECOST and the electric utility's ERNC reduced by approximately 34% respectively (Table 6.8).

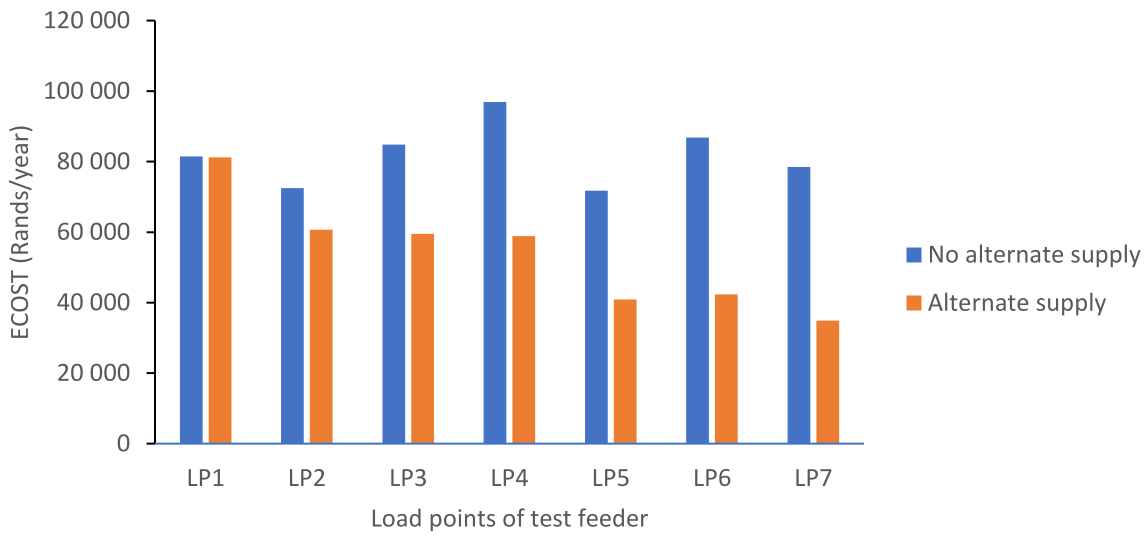

Figure 6.7: Mean ECOST of test feeder load points when the feeder has an alternate supply and when it does not.

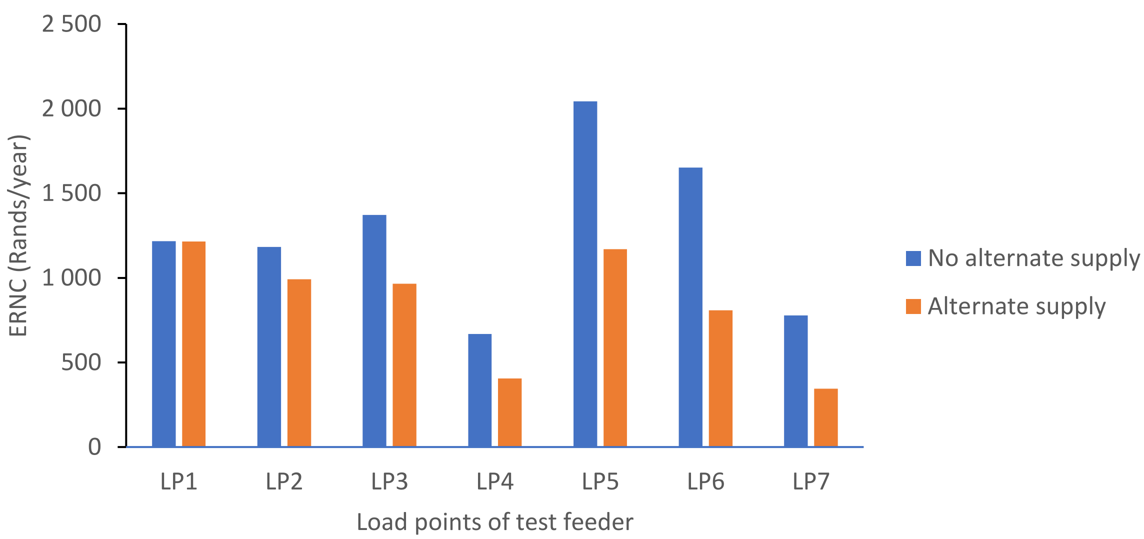

Figure 6.8: Mean ERNC of test feeder load points when the feeder has an alternate supply and when it does not.

Table 6.8: Improvement in test feeder reliability worth indices gained by including alternate supply

	No alternate supply	Alternate supply	Percentage reduction
ERNC (Rands/year)	8 911.20	5 899.55	34%
ECOST (Rands/year)	57 2644.82	37 8428.88	34%

6.7.3 Case 3: Optimal location of switches *(TVPIC model used)*

For the feeder of figure 6.2, there are $2^6 = 64$ possible switch configurations, thus an exhaustive search routine was used for the determining the optimal of placement of 3 switches that minimizes the feeder ECOST. The routine is outlined below:

1. Index switch configurations with positive integers, $i = 0, 1, 2, \ldots, 63$.
2. For each switch configuration i, obtain a corresponding 1 x 6 binary vector S_i indicating the presence or absence of a switch on feeder line sections L1, L3, L5, L6, L7, L9, L11.
3. For each S_i satisfying $sum(S_i) \leq 3$, evaluate the corresponding mean feeder ECOST using the TS-MCS algorithm in section 6.5.
4. Determine the switch configuration with the minimum mean feeder ECOST.

For the case where there is no alternate supply, the optimal locations of the 3 switches that the electric utility can afford to install are feeder line sections L1, L3, L7 (Figure 6.2). The feeder's mean ECOST and ERNC for this case are approximately R 603 649.67 and R 9615.26 respectively. For the case where there is an alternate supply, the optimal locations of the 3 switches are line sections L3, L5, L11. The feeder's ECOST and ERNC for this case are approximately R 444 863.38 and R 6917.84 respectively. The presence of an alternate source of supply results in a reduction of the feeder's mean ECOST and ERNC. A comparison of the load points' ECOST and ERNC with optimal placement of the 3 switches, with switches on all feeder main sections and with no switch at all is depicted in Figures 6.9 and 6.10 respectively for the scenario without alternate supply. Optimal placement of the 3 switches which the budget-constrained electric utility in this case study can afford achieves similar reduction in the load points' mean ECOST and ERNC as placement of switches on all feeder sections.

The ECOST at LP7 is approximately equal across all three scenarios. It is at the farthest end of the feeder, thus the placement of switches on the feeder only causes marginal improvement in its reliability. The ECOST of LP4 is quite similar to that of LP5 and LP6 (Figure 6.9), but its ERNC is smaller than those of the duo (Figure 6.10). This is because of the business customer mix at the load points (Table 6.4). LP4 has only trade and 'other commercial services' sectors that have high CICs (Table 5.4), but low average monthly electricity bills (Table 6.6).

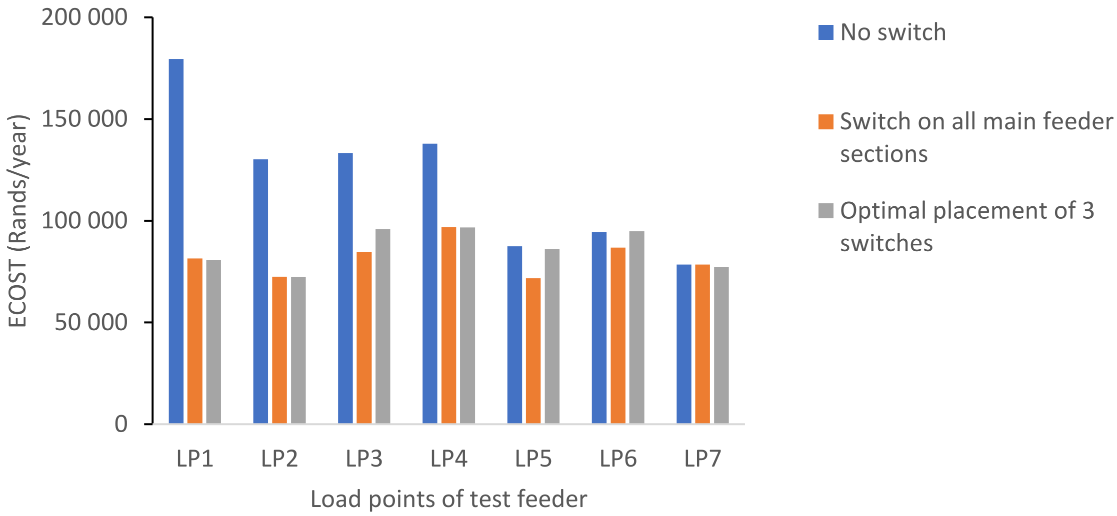

Figure 6.9: Comparison of the load points' ECOST with optimal placement of the 3 switches, with switches on all feeder main sections and with no switch at all for the scenario without alternate supply.

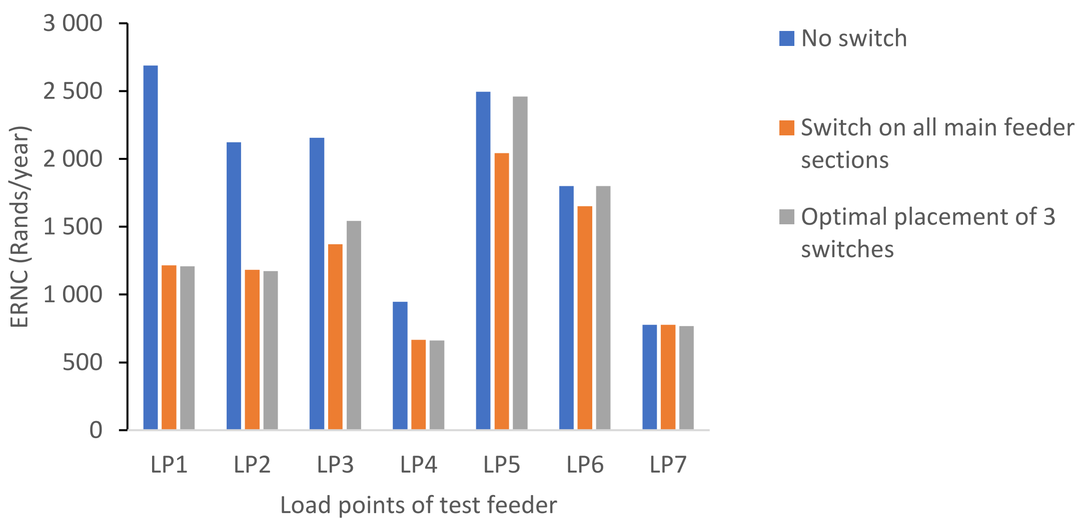

Figure 6.10: Comparison of the load points' mean expected revenue not collected (ERNC) with optimal placement of the 3 switches, with switches on all feeder main sections and with no switch at all for the scenario without alternate supply.

6.8 Summary

In this chapter, a case study distribution system (Feeder 2 of bus 6 of the RBTS) was adopted to demonstrate the practical application of the CIC data analyzed in the previous chapter in power system reliability planning. The reliability parameters of the test feeder components, as well as CIC and load models developed in this study were used in a time-sequential Monte-Carlo simulation framework to evaluate reliability worth indices for the test feeder under different scenarios. The results obtained show that a probabilistic description of CIC is more robust and effective for power system decision making. Also, a constrained optimization problem of optimal switch placement was solved to demonstrate that electric utilities can still make optimal and effective decisions even under budget constraint using reliability worth indices. The next chapter discusses the investigative procedures and results of an exploratory macroeconomic analysis done to assess the potential economy-wide cost of a hypothetical nation-wide blackout which may be precipitated by a sporadic event.

7 Economy-Wide Cost of Electricity Interruptions: An Exploratory Case Study

This chapter discusses the application of publicly available macroeconomic data and a suitable economy-wide model to assess the economic cost of a potential nation-wide blackout in South Africa. The chapter ends with a summary of key findings from the macroeconomic analysis.

7.1 Model selection and case study description

A region or nation-wide sporadic electricity interruption in South Africa can disrupt inter-sector and inter-region economic flows causing significant economic costs. The CDFs and CIC models presented in chapters 5 and 6 of this dissertation mainly capture the direct financial cost of electricity disruptions to individual business customers or sectors. The potential cost of economic chain disruptions which may be caused by a sporadic electricity interruption can be assessed using any of the three economy-wide models presented in section 2.4. However, publicly available macroeconomic data largely determines which model may be readily adopted.

There is considerable difference in the effectiveness of the data collation practices of various economies and the usability of the available data. In line with the United Nation's system of national accounts (SNA), Statistics South Africa (Stats SA) compiles an IO table (IOT) from an SU table for a reference year and makes it publicly available. IOTs may be compiled as product-by-product tables or as industry-by-industry tables [136]. Stats SA prioritizes the publication of the industry-by-industry IOT, because of its analytical advantages including its suitability for the analysis of economic impacts that may be precipitated by various shocks to economic sectors [137]. The IOT shows the interaction between these sectors in a matrix format. Supplying sectors are placed on the table's rows, while purchasing sectors are placed on the table's columns [129].

The latest publication of SA's IOT at the time of this research was the 2014 IOT. It consists of 50 industries representing industrial sectors at the 2-digit level of the 5th edition of SA's SIC. Inter-industry transactions are indicated in million Rands.

Examining the 50-sector 2014 IOT, it was observed that the electricity sector was lumped with the gas and water sector, thus a logical approach was required for its separation. This separation was necessary in order to assess the unique effects that shocks to the electricity sector could have on other sectors and the broad economy. For this separation, a 2013 summary report on the lumped electricity, gas and water sector [138] was used[29]. The averages of the percentage contribution of the split sectors to sales and expenditure of the lumped sector i.e. 83.7% for the electricity sector and 16.3% for the water and gas sector (combined) were used to weight the rows and columns of the lumped electricity, gas and water sector in the IOT. A revised 50-sector table with the electricity sector separated from the water and gas sector was derived. The revised table retains the key features of the base table i.e. equality of gross outputs and gross outlays. An aggregated version of the IOT (at the 1-digit level of SA SIC) is shown in Appendix C5 for illustrative purposes.

The availability of an IOT allows for the performance of economic analyses such as impact analysis, extraction analysis or a multiplier production matrix (MPM) analyses [139]. The effect of a policy change on individual sectors or a broad economy may be assessed via an IO-based impact analysis. Economic evolutions over time may be studied using the MPM analysis. A special method of the extraction analysis termed *hypothetical extraction method (HEM)* may be used to assess the importance of a sector in an economy based on its output and linkages with other sectors. The sector is hypothetically removed from interactions with the rest of the economy and consequent impact on other sectors and the broad economy is evaluated. Hence, the IO-based HEM was adopted for an assessment of the potential economy-wide impact of a hypothetical blackout to SA.

[29] The 2013 summary statistics for the electricity, gas and water sector was the latest available at the time of this study.

7.2 Hypothetical extraction method

The HEM evaluates the backward linkage (demand-side) and forward linkage (supply-side) impacts due to a hypothetical removal of the electricity sector from inter-sectoral interactions. This gives an indication of the economic importance of the electricity sector in monetary terms. The modelling approach adopted in this study assumes that the other sectors still interact somewhat without the electricity sector albeit with reduced output. This is a very optimistic scenario. It is possible that round-by-round non-interaction of other sectors might occur if their activities are 100% dependent on electricity. For instance, a complete blackout lasting several days might also lead to a non-interaction of the manufacturing sector with the rest of the economy. This non-interaction of the manufacturing sector has its own unique forward and backward linkages impacts on the economy. Thus, the analysis presented here applies to a case where a blackout is not as extended as to cause the precipitation of such round-by-round non-interactions of other sectors (e.g. a blackout of only a few hours to a day).

The evaluation of backward and forward linkages was based on mathematical formulations used in reference [140]. The Leontief inverse matrix was used to compute the reduction in sectoral outputs due to backward linkage impact (Equation 7.1). The Ghoshian inverse matrix was used to compute the reduction in sectoral outputs due to forward linkage impacts (Equation 7.2). The economic impact to the removed sector in both cases is called the feedback effect.

$$x - \bar{x} = \begin{pmatrix} x^1 & - & \bar{x}^1 \\ x^R & - & \bar{x}^R \end{pmatrix} = \begin{bmatrix} L^{11} & L^{1R} \\ L^{R1} & L^{RR} \end{bmatrix} - \begin{bmatrix} (1 - A^{11})^{-1} & 0 \\ 0 & (1 - A^{RR})^{-1} \end{bmatrix} \begin{pmatrix} f^1 \\ f^R \end{pmatrix} \tag{7.1}$$

$$(x - \bar{x}') = \left(v^{1'} v^{R'}\right) \left\{ \begin{bmatrix} G^{11} & G^{1R} \\ G^{R1} & G^{RR} \end{bmatrix} - \begin{bmatrix} (1 - B^{11})^{-1} & 0 \\ 0 & (1 - B^{RR})^{-1} \end{bmatrix} \right\} \tag{7.2}$$

Where *x, A, L, f,* represent the vector of sector outputs, matrix of direct requirements (technical coefficients), Leontief inverse matrix, and final demand vector respectively; *v* is the primary input vector, *G* is the Ghoshian inverse and *B* is the direct sales (or output allocation) matrix.

Superscripts *'1'* and *'R'* represent the removed sector/region and the rest of the economic system respectively.

Equations (7.1) and (7.2) are based on the following assumptions:

- In the backward linkage model (Equation 7.1), the ratio of a sector's production requirements is fixed i.e. a 10% reduction in the output of a given sector due to electricity interruption would lead to a 10% reduction in all of its intermediate demands on other sectors.
- In the forward linkage model (Equation 7.2), the function of production inputs for each sector is fixed, hence a 10% reduction in the output of a given sector would lead to a 10% reduction in the sector's sale to all other sectors.

The HEM was implemented using *PYIO* – an IO modeling software developed at the Regional Economics Applications Laboratory at the University of Illinois [139].

7.3 HEM results

The backward and forward linkages impact due to the hypothetical removal of the electricity sector was computed for the 50-sectors in SA's 2014 IOT. The results were aggregated to the 10-sector level at 1-digit level of SA's SIC (Table 7.2 and Figure 7.1). The results for the 50 sectors are in Appendix C5 – Table C5.1. The estimates in both tables are annual estimates, because they are based on annual figures in the IOT. The forward linkage impact is higher than the backward linkage impact for most sectors (Table 7.3 and Figure 7.1). This indicates that electricity interruptions significantly affects the distribution of sectoral outputs across the economy. The forward linkage impact is expected to be more critical when there is pervasive use of *'just-in-time'* technologies to save on inventory cost. Besides the feedback effect to the removed electricity sector, the manufacturing sector has the highest forward and backward linkages impact. This is due to its large economic size and high dependence on electricity for its activities.

Table 7.1: Backward and forward linkages impacts due to hypothetical extraction of the electricity sector

Industrial Sectors*	Backward Linkage (R Millions)	Forward Linkage (R Millions)
I1-Agriculture	690	8 593
I2-Mining and quarrying	30 532	33 665
I3-Manufacturing	40 665	101 844
I4-Electricity	114 434	64 498
I5-Gas and water supply	4 739	4 669
I6-Construction	367	11 766
I7-Trade	10 258	18 360
I8-Transp & Comm.	14 689	13 724
I9-Finance	17 351	25 311
I10-Other services	5 829	24 144
Total	**239 554**	**306 574**

**Results shown at 10 -sector level i.e. 1 – digit of SA SIC.*

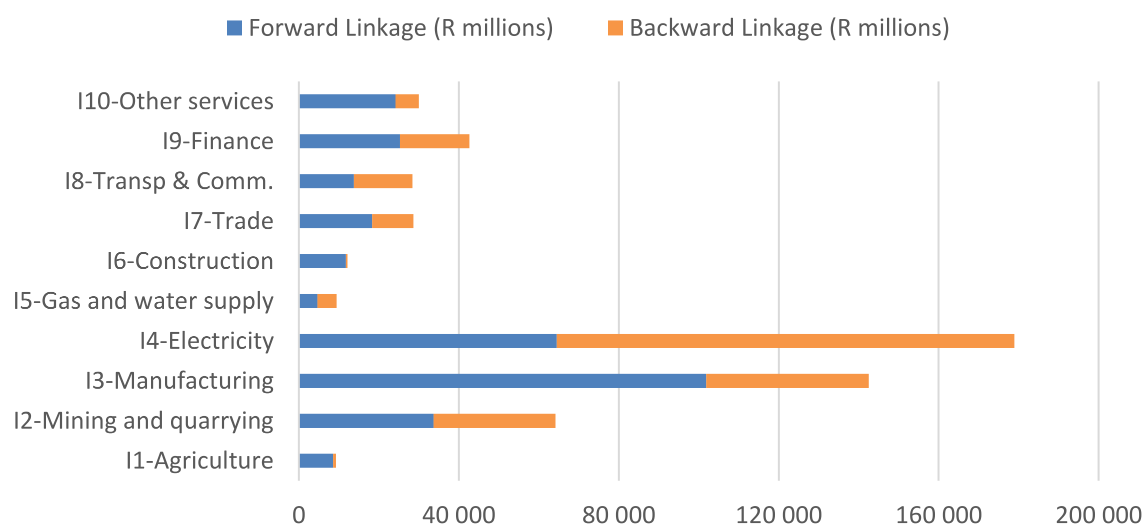

Figure 7.1: Backward and forward linkage impacts due to hypothetical extraction of the electricity sector (10 -sector level)

To suit the proper application context of the results as described in section 7.2, the aggregated impact estimates in Table 7.2 can be scaled down to daily estimates based on the following steps:

1. Assume even dispersion of economic activity in each quarter of the year.
2. Use the proportion of GVA generated per quarter to scale down annual impact estimates to

obtain quarterly impact estimates. Stats SA makes available data of sectoral GVA generated per quarter at the 1-digit level of SA's SIC.

3. Divide the quarterly impact estimates by the number of days in each quarter (Q) of a 365-day year i.e. 90 in Q1 (January – March), 91 in Q2 (April – June), 92 in Q3 (July – September) and Q4 (October – December).

Performing the steps above yields potential daily backward linkage and forward linkage for each sector in each quarter of the year (Table 7.3). Thus, there is a differentiation of the potential daily indirect economic loss of each sector across seasons of the year. The daily impact is highest in the Q4, because the proportion of GVA generated in Q4 is fairly larger than that in each of Q1 – Q3. Overall, the total daily backward and forward linkages impact for all sectors does not vary much across the quarters (Figure 7.2). This is because the proportion of GVA generated per quarter does not vary much across the quarters (Appendix C5 – Table C5.2).

Table 7.2: Sectoral daily backward and forward linkage impacts in each quarter

Sector Label*	**Estimate of daily impact in each quarter (R million)**							
	Q1		**Q2**		**Q3**		**Q4**	
	BI_D**	**FI_D****	**BI_D**	**FI_D**	**BI_D**	**FI_D**	**BI_D**	**FI_D**
I1	2	20	3	34	2	25	1	15
I2	81	89	84	93	82	91	88	97
I3	108	270	110	276	112	279	116	290
I4	302	170	311	175	319	180	321	181
I5	13	12	13	13	13	13	13	13
I6	1	32	1	32	1	32	1	33
I7	27	48	27	48	27	49	32	57
I8	39	36	40	37	41	38	42	39
I9	48	70	47	69	47	69	48	69
I10	16	67	16	67	16	66	16	66
Total	**635**	**815**	**652**	**843**	**661**	**842**	**677**	**859**

Sector labels have similar connotations as in Table 7.2.
***BI_D – daily backward linkage impact. FI_D – daily forward linkage impact.*

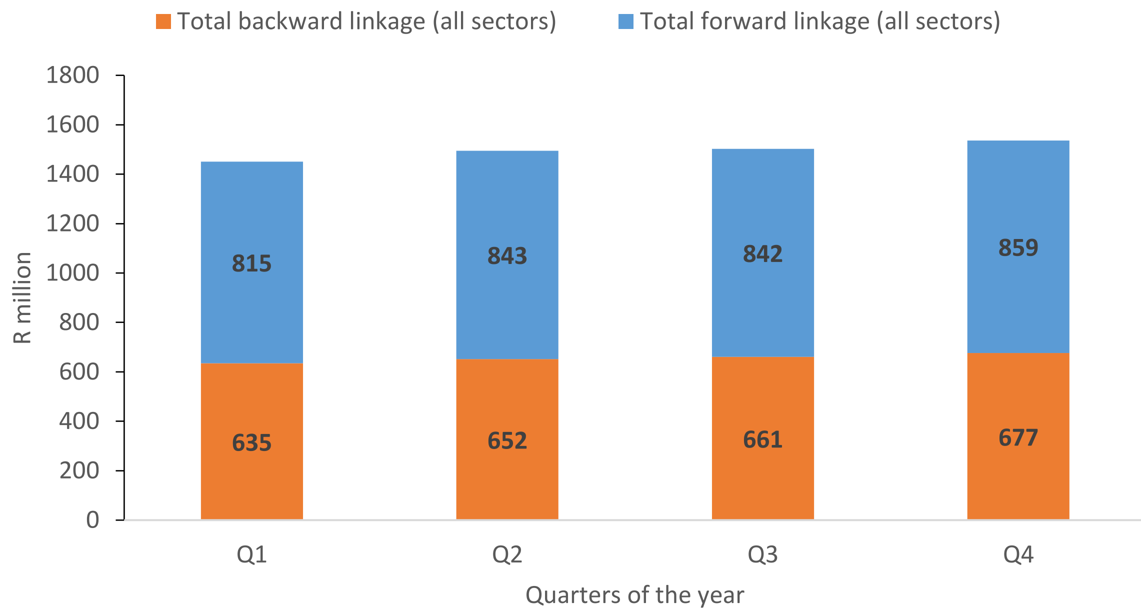

Figure 7.2: Total daily backward and forward linkage for all sectors in the different quarters of the year

GVA impacts

The results of the HEM indicate the reduced gross outputs due to disruption in normal inter-sectoral interactions (i.e. both sales and consumption of intermediate goods and services). The potential sectoral daily GVA impacts were computed based on these results. For each sector, the GVA impacts include impacts to its capacity to cover its operational expenses (e.g. labour compensation), make savings/investment and pay indirect taxes. The daily GVA impact for each sector was computed using the following steps:

1. Compute total daily reduced gross-output for the sector by summing up its daily backward and forward linkage impacts in Table 7.3.
2. Compute its GVA – gross output ratio from the IOT.
3. Multiply the results in steps 2 and 3.

The computed daily GVA impacts at the 1-digit SIC level are shown in Table 7.3.

Table 7.3: Sectoral daily gross value added (GVA) impacts in each quarter (R million)

Sector index	**Daily gross value added (GVA) impacts**			
	Q1	**Q2**	**Q3**	**Q4**
I1	8	15	11	6
12	90	94	92	98
I3	90	92	93	97
14	266	274	281	282
I5	14	14	15	15
I6	10	10	10	10
I7	39	39	40	46
I8	37	37	39	39
I9	61	60	60	60
I10	51	51	51	50
Total	**666**	**686**	**690**	**705**

7.4 Comparison of HEM results with past estimates of the economic impact of load shedding in South Africa

NERSA estimated the cost of 23 days of load shedding in 2008 to be approximately R50 billion i.e. R2.17 billion per day [18, 20]. This estimate was based on a CoUE of R75/kWh at the time. Also, Chris Yelland, an energy expert estimated the economic cost of the 2015 load shedding events to be R20 billion, R40 billion, and R80 billion per month for stage 1, 2, 3 load shedding respectively, based on the following assumptions: CoUE of R100/kWh, 10 hours of blackout per day and 20 days per month. This resulted in daily estimates of R1 billion, R2 billion and R4 billion per day for stage 1, 2, and 3 load shedding respectively. NERSA and Yelland's estimate are not contained in peer-reviewed academic studies and the methods used to obtain their estimates were not clearly described. Nonetheless, they provide a basis for comparing the estimates in this study. Since the analysis in this study was based on a 2014 IOT, the equivalent value of NERSA's estimate in 2014 Rands was obtained using GDP deflators as approximately R2.4 billion per day.

The difference in GDP deflators for 2014 and 2015 is marginal, hence there was no need to deflate Yelland's estimates.

In this study, the average daily total linkage impact for the economy across all quarters is approximately R1.5 billion. Adding this to the average daily GVA impact for the economy across all quarters yields a potential daily economy-wide impact of R2.2 billion. This is very comparable with the estimates of NERSA and Yelland, considering the large variability that can exist in estimates of the economic cost of electricity interruptions. To put the comparisons above in appropriate perspective, it is worth restating that the economic impact estimates in this study were based on a modeling approach that assumes that the other sectors still interact somewhat without the electricity sector albeit with reduced output. Thus, the estimates from the exploratory analysis done in this chapter are very optimistic.

7.5 Assessing the relationship between the firm-level survey and the analytical macroeconomic approaches to electricity interruption cost assessment

In this dissertation, the assessment of the cost of electricity interruptions to commercial and industrial end-users has been done using two approaches: a firm – level survey (chapter 3 – 6) and a macroeconomic IO model - HEM (chapter 7). The two approaches differ primarily in their data collection, modelling assumptions and modelling framework. To compare the relative magnitude of impact of electricity interruption as measured by the two different approaches, both were applied to estimate the weekly cost of load shedding to the trade and manufacturing sectors in South Africa, as the description of these sectors is largely consistent in both approaches.

Load shedding cost estimation using firm-level survey results

The following assumptions were the basis of the estimations.

1. During a stage 1 load shedding, an individual customer will experience load shedding 3 times for 2 hours each over a 4-day period [30]. For stages 2, 3, and 4, the frequency increases to 6, 9, and 12 times respectively.

2. From 1, in a 168-hour week, electricity supply to a customer in each sector will be interrupted for approximately 6%, 13%, 19%, and 25% of the time for stage 1, 2, 3, and 4 load shedding respectively. Thus, it is assumed that 6%, 13%, 19%, and 25% of the electricity customers in each sector experience electricity interruption during each stage 1, 2, 3, and 4 load shedding event, respectively.

3. There are 24 possible hours of load shedding in a day. Thus, in each time interval of a given row of the season-time activity weight matrix for a sector (Appendix C1), there are 3 load shedding events.

4. The reference season is January – March (first row of the season-time activity weight matrix). Past load shedding events in SA have occurred in this period.

5. Businesses do not use backup power supply.

The time-varying probabilistic interruption cost model presented in section 6.3 was extended and applied for the estimations (Equation 7.3).

$$TIC_i^d = N_e^d \times CIC_{nb}^{*(i)}\left(\tau_{ref}, d\right) \times W_i(\tau) \times E_i \times P_i(\tau) \tag{7.3}$$

TIC_i^d is the total interruption cost sector i, due to electricity interruption events of duration d, occurring over a given period; in this case, a week. N_e^d is the number of electricity interruption events of duration d in the considered period. $CIC_{nb}^{*(i)}\left(\tau_{ref}, d\right)$ is the probabilistic normalized CIC estimate for an electricity interruption event of duration d in a reference season – time-of-day interval τ_{ref}. $CIC_{nb}^{*(i)}\left(\tau_{ref}, d\right)$ is obtained using the parameters of the beta distribution of the normalized CIC data for electricity customers without backup power supply. E_i is average monthly electricity bill (in Rands). $P_i(\tau)$ is the proportion of electricity customers affected by an

[30] http://loadshedding.eskom.co.za/LoadShedding/ScheduleInterpretation *(Accessed 01 April 2019)*

electricity interruption event in season – time-of-day interval τ. $W_i(\tau)$ is the season – time-of-day activity weight corresponding to τ.

The normalized 2 - hour CIC estimates for the two sectors were described using parameters of their beta probability distribution (section 5.2). For comparison purposes, the estimation for the trade sector was done using both the normalized 2-hour CIC data from the 2018 survey in this study and that reported by Dzobo [70] from a 2009 CIC survey of commercial and industrial electricity customers in Cape Town. Normalized 2-hour CIC data for the manufacturing sector were not specifically reported in [70]. In extrapolating the normalized CIC estimates from the firm-level surveys to estimate weekly sectoral load shedding cost at the national level, average monthly electricity bill of the sectors at the national level was taken as: annual sectoral electricity purchases ÷12.

The estimates obtained for the trade sector using the 2018 CIC data in this study were significantly higher than those obtained using the 2009 CIC data [70] (Table 7.4). The observed differences were much greater with higher percentile values of the beta distributions of the normalized 2-hour CICs. Also, the 50th percentile weekly cost for the trade sector in this study was significantly higher than that of the manufacturing sector which has a higher electrical size (Tables 7.4 and 7.5). This indicates a potential overestimation of CIC by trade sector respondents in this study. The effect of the higher electrical size of the manufacturing sector respondents on the estimation only becomes evident when higher percentile values of the CIC data were used. Therefore, the 80th and 90th percentile estimated weekly cost for the manufacturing sector was higher than that of the trade sector.

To determine whether the trade sector respondents in the 2018 survey largely overestimated their CICs, a further comparison was made with Goldberg's estimate of the cost of load shedding to the retail trade sector in 2015 [141]. Goldberg [141] used the CIC data from a 2015 survey conducted for the SA's retail trade sector in Pretoria and an estimation procedure quite different from the one in this study. The cost of 99 days of load shedding between January – June 2015 was estimated to be R13.72 billion. In this period, the implemented load shedding stages were mainly between stage 1 – 3, but the estimate was not differentiated across load shedding stages.

Adjusting Goldberg's 2015 estimate to 2017 values using available GDP deflators [142] results in an average of R0.57 billion per week over the 6-month period or R1 billion per week of continuous load shedding. The latter figure lies in the range of the 50th percentile weekly cost of stage 1 – 3 load shedding estimated using the 2009 CIC data [70], thus there is considerable cross validation for the estimates in these studies. However, it is significantly smaller than the estimates for all load shedding stages using the 2018 CIC data e.g. it is approximately 2 times smaller than the 50th percentile weekly cost of stage 1 load shedding. Accordingly, there is a potential overestimation of CIC by the trade sector respondents in the 2018 survey.

Table 7.4: Weekly cost of load shedding to the trade sector using different percentile values of the beta distribution of its normalized 2 – hour CIC from firm – level surveys.

Load shedding Stage	**Survey year**	**Weekly cost (R millions)**		
		50th percentile	**80th percentile**	**90th percentile**
1	2018	1 886	11 935	19 523
	2009[a]	378	2 213	3 941
2	2018	3 771	23 869	39 047
	2009	756	4 426	7 882
3	2018	5 657	35 804	58 570
	2009	1 134	6 639	11 822
4	2018	7 542	47 738	78 093
	2009	1 511	8 852	15 763

[a] Estimates based on 2009 survey data [70] were adjusted to 2017 values using available GDP deflators.

Table 7.5: Weekly cost of load shedding to the manufacturing sector using different percentile values of the beta distribution of its normalized 2 – hour CIC from firm – level surveys.

Load shedding Stage	**Weekly cost (R millions)**		
	50th percentile	**80th percentile**	**90th percentile**
1	1 447	26 459	49 234
2	2 893	52 918	98 468
3	4 340	79 377	147 702
4	5 787	105 836	196 936

Load shedding cost estimation using macroeconomic HEM results

Total macroeconomic impact was considered as the sum of backward linkage, forward linkage, and GVA impacts. The estimates of the weekly cost of load shedding were obtained by scaling the daily estimates in section 7.3 using the proportion of electricity customers affected during each load shedding event, the duration of a load shedding event, and the total number of events experienced in a week. Influence of time-of-day was not considered, as the macroeconomic data are just averages.

The weekly load shedding cost estimate for the manufacturing sector is significantly higher than that of the trade sector at all load shedding stages (Table 7.6). This is quite expected as the manufacturing sector has a higher electrical size than the trade sector.

Table 7.6: Weekly cost of load shedding to the trade and manufacturing sectors using the macroeconomic HEM

	Weekly cost for each load shedding stage (R millions)			
Sector	**Stage 1**	**Stage 2**	**Stage 3**	**Stage 4**
Trade	58	125	182	240
Manufacturing	239	519	758	998

Comparison of load shedding cost estimates using firm-level survey and macroeconomic HEM

The weekly cost estimates using firm-level survey data and extrapolations are considerably higher than those using macroeconomic IO data and the HEM. For instance, the estimated weekly cost of stage 4 load shedding to the trade sector using the 50th percentile of its normalized 2 – hour CIC data from the 2009 [70] and 2018 surveys are approximately 6 and 31 times greater than that using the HEM, respectively. The estimated weekly cost of stage 4 load shedding to the manufacturing sector using the 50th percentile of its normalized 2 – hour CIC data from the 2018 survey is approximately 6 times greater than that using the HEM. This observation appears counterintuitive, as one might expect the macroeconomic cost estimates to be higher. Although a plausible explanation might be that survey respondents are more inclined to estimate very high CIC values when directly asked for monetary figures, a conclusion should not be drawn too quickly as the observation seems to align with an argument in [47]:*"While the impact of sporadic electricity interruptions would be negligibly small, the effects of chronic electricity interruptions* *can be significant."* Thus, it is worthwhile to reconsider some underlying factors that might further explain the observation above.

- *Composite economic resilience to electricity interruptions (i.e. at regional or national levels) differs significantly from individual business customer or sector resilience.* During sporadic electricity interruptions, economic systems might experience only a relatively small shock[31] and then tend to recover. Spoilage (during processing/manufacturing) might be no greater than those experienced with the economy as usual. Few sales are lost in manufacturing. Lost sales might be more in the retail sector. However, during times of chronic electricity interruptions, the ability to recover is reduced significantly [70]. Sales might be lost to other regions or countries, both materials and labour wastage are high, backup energy is expensive, etc. If the condition is perceived to likely continue, business customers will act to reduce the costs, especially by energy diversity (which might be difficult [143-145]) or backup generators. Business customers who cannot afford backup generators continue to incur high costs. Those with backup generators incur lower cost during electricity interruptions, but experience significant increase in operating cost.

- *The firm-level survey considers the direct financial cost of individual business customer interruptions. This differs among business customers due to their electrical size and nature of use of electrical energy.* For instance, energy storage as in water heating or water pumping to storage might incur no cost as it can be made up – this saves no energy but shifts demand. The direct financial cost estimates can distinguish between such business customers, because disaggregated information are also retrieved in the survey. This distinction is not possible with the IO model.

- *The IO model does not consider individual business customer interruptions. It averages production over the whole economy and for long periods – a quarter or a whole year.* The costs incurred by a manufacturer in installing and operating a backup generator are seen

[31] This is with regard to the electricity interruption itself - sporadic electricity interruptions caused by events originating within the power system are good examples. In other cases, catastrophic hazards might have initiated the sporadic electricity interruption (e.g. a hurricane) and cause other major physical and environmental damages.

as positive production in the sectors supplying those systems. IO models do not account for the cost of stock damages, they only account for the economic flows from stock. An argument supporting this approach is that stock damages are embedded in flow losses, as the true value of a stock is determined by the flows it generates, thus counting both flow and stock damages in the modelling of disaster impacts might be tantamount to double-counting [49]. The IO approach only sees load shedding as a cost if it reduces the whole economic output of the country or region. This might be the case if the load shedding is very extensive or during prolonged regional or national blackouts where ability to make up lost sales or production is significantly diminished.

Despite the aforementioned major contrast between both approaches, results from some of the analyses of the firm-level survey data corroborate some assumptions in the IO model. The results in section 4.7 show that survey respondents (especially in the commercial sector) deem that lost sales and production are the main components of their CIC. This somewhat validates the assessment of the cost of electricity interruption to economic sectors in terms of reduced flows (sales and production) in the IO model. From the survey results of section 4.6, the average of percentage of business activities dependent on electricity was greater than 90% in both commercial and manufacturing sectors. This indicates a very high need for availability of supply. Accordingly, the substitutability of electricity as a factor of production is very low. This is in line with another fundamental feature of the IO model that assumes zero input substitution (Section 2.4.1).

7.6 Summary

This chapter presented the data structure, methods and results of an exploratory macroeconomic analysis done to assess the potential economy-wide costs of a hypothetical nation-wide blackout. Optimistic estimates of the potential annual and daily economic cost were compared with estimates of the economic costs of past load shedding events in South Africa and were found to be reasonably comparable within the bounds of the assumptions applied in this study. Also, the relationship between the firm-level survey and macroeconomic IO approaches to estimating the cost of electricity interruptions was assessed via a case study of the weekly cost of stage 4 load shedding to SA's trade and manufacturing sectors. The ensuing discussions show that caution must be exercised in quoting blanket figures of the cost of load shedding to the South African economy without appropriate description of the basis for estimation. The next chapter consolidates the overall findings in this dissertation.

8 Conclusions and Recommendation

This chapter summarizes the research findings in this dissertation and validates the research hypothesis. The research questions posed at the beginning of the study are reiterated and concisely answered based on findings from a critical literature review and from results of the qualitative and quantitative analysis undertaken in the study. The limitations of the study are presented and recommendations for further research are put forward.

8.1 Summary of research findings and validation of research hypothesis

The research undertaken for this dissertation was based on the following hypothesis:

A time-based probabilistic model of the cost of electricity interruptions to business customers which can be applied for effective power system management can be developed through appropriate data collection and analysis that incorporates key parameters of the interruption, characteristics of business customers and the uncertainty in their interruption cost estimates.

The central investigation carried out to validate the research hypothesis was a micro-level assessment of the direct financial cost of electricity interruptions to suit value-based reliability planning and power system operations management. CIC assessment was done from the business customer's viewpoint via a firm-level survey in Cape Town. The data retrieved from the survey provided significant qualitative and quantitative indication of the financial and economic risk posed by electricity interruptions to business customers. The validity of the research hypothesis was proven through the statistical analyses done on the survey data in chapters 4 – 6.

Statistical hypothesis tests on the survey data showed that commercial and manufacturing sector respondents differed mainly in their electrical and labor size. There was little variation in electricity interruption frequency across the surveyed respondents, and most respondents in both sectors were either satisfied or very satisfied with their electricity supply reliability in the two years preceding the survey period. Also, there was little variation in the perceived level of dependence on electricity for business activities in both sectors. The average percentage of business activities dependent on electricity was greater than 90%. The differences between the commercial and manufacturing population based on frequency of electricity interruptions experienced, satisfaction level with reliability of supply, and perceived dependence on electricity for business activities were not statistically significant at the 5% significance level. The primary influencers of CIC in both sectors were respondents' economic activity, activity level profile across time-of-day, day-of-week and season, electrical size (proxied by their average monthly electricity bill[32]), electricity interruption duration, and ownership of backup power supply.

Three CIC models were developed for the surveyed business sectors from an analysis of the survey data viz. *a time-invariant average interruption cost (TIAIC) model, a time-varying average interruption cost (TVAIC) model, and a time-varying probabilistic interruption cost (TVPIC) model.* All three models were applied in an assessment of reliability cost/worth indices for a case study distribution system to demonstrate the practical application of the cost data. The results showed that the TVPIC model is more effective for describing CIC as it accounts for the time-dependencies and uncertainty in CIC estimates. The TVPIC allows for an evaluation of the impact of different confidence levels in decision-making. Reliability worth indices like ECOST derived based on the TVPIC can be expressed as Rands@Risk in different season – time windows. This allows for optimal implementation of contingency measures like load shedding or reliability improvement programs like switch/disconnect placement on distribution feeders.

An exploratory macroeconomic analysis was also done using an input-output model that allowed the investigation of the effect of the removal of the electricity sector from intersectoral interactions in South Africa's economy. Based on the model's framework and assumptions, approximately R2.2 billion was estimated as the potential economy-wide cost of a day-long blackout. However, compared to estimates of the economic cost of past load shedding events, this figure seemed to be a very optimistic estimate and a potential lower bound of a day-long blackout in South Africa.

[32] It is important to reemphasize that respondents' average monthly electricity bill was used as a proxy of their electrical size because of the absence of information about their electrical loads (in kW or kWh).

8.2 Answers to research questions

The findings in this research provided some extra insights to some research questions that were partly answered from the literature review at the beginning of the research. These are summarized below.

- ***What is the nature of the various electric service interruption business customers are subjected to and how do they respond?***

The findings in section 4.9 of this study showed that chronic electricity interruptions prod businesses to implement mitigative measures to reduce their electricity interruption impact. However, since the marginal cost of backup power supply is often higher than the cost of the electric utility's supply (section 5.3), business customers who own such backup power supply often remain connected to the grid. Over time, the impact of chronic electricity interruptions may change economic relationships at the national, regional and sectoral levels. Businesses who own backup power supply may gain brand and customer goodwill improvement because of their ability to provide continued service during electricity interruptions. This ultimately improves their competitive advantage and may extend a domino effect by prodding their competitors to also purchase backup power supply. This situation is evident in Nigeria and other emerging economies with unreliable power systems.

In sporadic events, especially extensive ones, business customers do not immediately enter a process of adaptation. Extremely sensitive business customers might have mitigation strategies. The electricity interruptions reflected on national risk registers (e.g. electricity interruption caused by space weather or terrorism) guide strategic responses mainly at national/regional levels to the perceived risks to the economy, and mitigation like investing in space weather forecasting or bolstering regional security.

- ***What is the best approach to assessing the cost of electricity interruptions to businesses and an economy?***

This study showed that a dual-level approach consisting of a *micro- and macro-level* assessment of the cost can provide significant insight that suit different power system decision-making needs.

For value-based reliability planning and power system operation management (especially at the distribution functional zone), effective load shedding scheme design, short-term customer-centric financial costs are needed. These are best collected via customer surveys using a direct costing approach. Depending on the pervasion of backup generator usage, CIC may be assessed as the marginal cost of using backup generators and the direct unmitigated loss due to partial facility coverage by the backup generator. Macroeconomic cost of electricity interruptions at regional/national levels (specifically, the impact on sectoral cross-linkages) may be ascertained using economy-wide models like the IO model used in chapter 7. These are more applicable to long - term strategic planning contexts like grid resilience planning, integrated electricity plan development or energy policy designs.

- ***What is the best way for describing the CIC of business customers?***
    - *What quantitative and qualitative insights does a probabilistic representation of their interruption cost provide over averaged or aggregated interruption cost?*

A probabilistic description of cost seems a more superior approach especially for risk-based decision making. A probabilistic description of cost accounts for the uncertainty in cost estimates and captures possibility of extremely low/high CIC values (section 5.2.2). In addition, a time-based differentiation of probabilistic CIC according to the activity profile of business customers is vital for implementing contingency measure like load shedding effectively. The impact of different confidence levels in decision-making can be assessed based on Rands@Risk (section 6.7.1).

- ***How do the results of past SA studies on the cost of electricity interruption compare with the results of this research? Do they corroborate each other? What factors explain the difference?***

The normalized CIC estimates for the trade sector in this study were over 350% higher than those in a similar 2010 study. The difference between the CIC estimates for the hospitality (hotel and restaurants) sector in both studies was less than 50%. The large difference observed could be due to using the mean as a comparison metric instead of the median[33]. Also, the time the surveys were conducted dictates prevailing conditions and respondents' state of mind. The survey for the 2010 study was conducted in 2009 – quite close to the 2008 – load shedding events, thus the respondents then might have been more poised to leverage on recent electricity interruption experience when estimating their CIC. The results for the exploratory macroeconomic analysis are quite comparable with estimates reported for the 2007/2008 and 2014/2015 load shedding events, within the bounds of the associated assumptions.

8.3 Recommendations

1. With respect to the research in this dissertation, It was observed that for a given business sector and a given electricity interruption duration, several respondents with relatively low average monthly electricity bill reported higher CIC than those with higher electricity bill. This had significant effect on the leverage of the linear fit in the linear regression analyses on CIC and average monthly electricity bill. High levels of correlation between CIC and average monthly electricity bill were only obtained using a robust linear regression approach. The positive correlation between CIC and average monthly electricity bill was the basis for normalizing CIC estimates in this study with average monthly electricity bill. While the need for using an electricity related-factor for normalizing CIC data to allow their ease of use in power system application has been emphasized and taken into consideration in this study, it might be necessary to give further thought to the position of Targosz and Manson [114] regarding the normalization of CIC estimates. They posit that the appropriate normalization factor for the CIC of large industries is their annual turnover. The authors argue that annual turnover has a more prominent effect on CIC than electricity consumption, because the annual turnover for such large industries is significantly higher than their annual electrical energy consumption. This position of Targosz and Manson [114] may also apply to small to medium business whose turnover – electricity consumption ratio is significantly high. Where

[33] The reason for comparison based on the means of the normalized interruption cost estimates in both studies was explained in section 5.2.4; the medians of the normalized interruption cost estimates in the 2010 study were not reported.

there is sufficient data to allow for multidimensional business segmentation as proposed in [85], normalization based on just an electrical size parameter will suffice, as the economic sizes of the business segments formed from such segmentation will be more homogenous. Where such volume of data are not available, a hybrid normalization factor that incorporates both an electrical and economic size parameter of the respondents in the CIC study may be imperative. A hybrid normalization factor based on average monthly electricity bill and average monthly turnover could be explored, as both parameters can be represented in monetary value. When comparing different items with multiple properties that have different numeric ranges, the geometric mean of the numeric values of each item's properties is an effective comparison metric. Thus, for each business segment in a CIC study, a hybrid CIC normalization factor for a respondent may be determined as the *geometric mean of its average monthly electricity bill and average monthly turnover.* The development and application of hybrid CIC normalization factors could be further investigated in future CIC researches for business customers.

2. In the case of chronic electricity interruptions in South Africa, Sub-Saharan Africa and elsewhere, the conduction of representative customer surveys by electric utilities across the country or region will allow for the development of a meta-database that will allow for accurate assessment of the cost of chronic electricity interruptions at regional and national levels. Collaboration between electric utilities and academic researchers involved in research on the cost of electricity interruptions will enhance the data collection process, as electric utilities can share ancillary customer data that will significantly improve the quality of study. For instance, a comprehensive customer data base of an electric utility can be used as sampling frame. This allows for employing a stratified random sampling technique to get a representative study sample. Furthermore, the ancillary data from the electric utility will reduce the length of the survey questionnaire as questions pertaining to respondents' electrical size and economic activity may be omitted. For such region-wide or nation-wide customer surveys, it is necessary to maintain consistency in the survey design and execution

protocol.

3. The availability of such meta-database described in (2) above will allow for the evaluation of more robust and accurate risk-based reliability worth indices expressed in Rands@Risk using the procedures presented in this chapters 5 and 6 of this dissertation. Such indices are more effective for value-based decision making, thus electric utilities and regulators should prime their use over average non-financial indices. The application of the CIC models in this study for designing effective electric utility regulation schemes is an area open for further research. For instance, regulators may apply risk-based CIC estimates to determine compensations for a business customer under different electricity interruption scenarios.

4. SA is not immune to HILF risks, neither is it prepared for region-wide blackouts that might ensue should any of these risks occur and cause significant damage to the nation's electricity infrastructure. National or regional impact of sporadic electricity interruptions may be obtained on smaller temporal resolutions (e.g. hourly or daily intervals) by studying the dynamic inoperability of economic sectors during a long duration blackout [120]. In this regard, it is necessary to account for the resilience of economic sectors in the modelling framework, as different sectors have different adaptive mechanisms and may exhibit different recovery profiles. The investigation of the resilience of SA's economic sectors vis-à-vis sporadic electricity interruptions is an area requiring extensive research.

5. Also, as innovations in technology prod towards a smarter grid, there are concerns on cyber-attacks on the grid. Furthermore, policy initiatives are fostering the advancement of the renewable energy independent power procurement programme (REIPPP). Renewables are expected to contribute approximately 18.5% to SA's total generation mix by 2027 [22, 141]. This percentage is expected to grow in the long-term. If the stochasticity of renewable energy sources is not properly managed, it could impair grid security. There is a need for commitment to long-term investment to improve not just grid reliability, but grid resilience. This is because *a highly reliable power system is not necessarily a resilient power system.* The

research on power system resilient is still incipient and significant research gaps exist on:

- Defining grid resilience;
- Developing an effective grid resilience evaluation framework;
- Appropriate metrics for quantifying grid resilience;
- Assessing critical infrastructure interdependencies with a special focus on the electricity sector;
- Decision-making frameworks for optimal investments to improve grid resilience.

Accordingly, there is a need for creative and practically relevant research on power system resilience assessment and power system resilience improvement program development.

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APPENDIX A

The Beta Distribution

Random variables that lie in the interval (0, 1) can be effectively described using the Beta probability distribution function (PDF). The Beta PDF's shape parameters are denoted by α and β. The Beta PDF may be applied to characterize random variables with a finite range outside the interval (0, 1) by the application of a scaling factor *C*. Equations A.1 and A.2 can be used to compute the shape parameters of Beta PDF for a given data from the mean μ, standard deviation σ, and a suitable scaling factor *C* of the data.

$$\alpha = \mu\left(\frac{C\mu - \mu^2 - \sigma^2}{C\sigma^2}\right) \quad \text{(A.1)}$$

$$\sigma = \frac{(C-\mu)(C\mu-\mu^2-\sigma^2)}{C\sigma^2} \quad \text{(A.2)}$$

The Beta PDF is described mathematically as:

$$\mathrm{f}(x) = \frac{x^{\alpha-1}(1-x)^{\beta-1}}{B(\alpha\beta)} \forall x \in [0,1]; \alpha > 0 \text{ and } \beta > 0 \quad \text{(A. 3)}$$

The Beta function $\mathrm{B}(\alpha\beta)$ is evaluated as in equation A.4

$$\mathrm{B}(\alpha\beta) = \int_0^1 A^{\alpha\,-\,1}(1-A)^{\beta\,-\,1}\,\mathrm{du} \quad \text{(A. 4)}$$

The Beta PDF can take on assortment of shapes and characterize data of varying skewness as depicted in Figure A.1. For α = β, the Beta distribution is the same as the normal distribution for a given data.

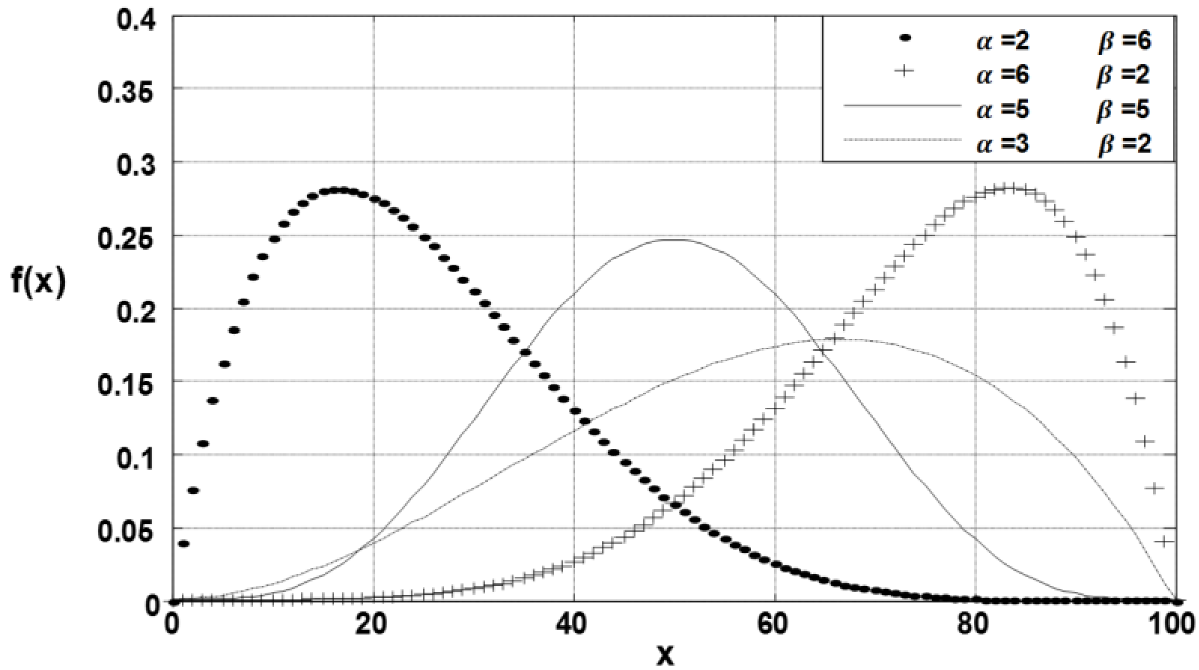

Figure A.1:Different Shapes exhibited by the Beta PDF for different shape parameters
Adapted from [28]

APPENDIX B

Additional survey information

B1 Sample of comprehensive questionnaire

2018 ELECTRICITY INTERRUPTION SURVEY OF COMMERCIAL AND INDUSTRIAL CUSTOMERS.

South Africa's electric power system is still vulnerable to events that can cause unplanned electric power outages or load shedding - with significant financial and non-financial effects on electricity customers.

This survey is designed to collect data on outage cost from commercial and industrial customers.

By participating in this survey, you can help to develop better, more cost-effective electricity supply systems. Your participation is voluntary. There will be no negative consequence for not participating, and you can withdraw whenever you choose to.

Estimated time to complete the survey is 10 minutes.

N.B.: There are no wrong answers; your best estimate is the right response.

This survey has ethics clearance from the Faculty Ethics Committee. All responses will be strictly confidential. We will never identify individuals or businesses when reporting our results.

Researcher Kingsley Akpeji (MScEng Student)

Supervisors Prof. Komla Folly
Mrs Kehinde Awodele

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A_SN:

SECTION A – BUSINESS' EXPERIENCE WITH POWER OUTAGES

A power outage refers to a *COMPLETE INTERRUPTION OF YOUR UTILITY'S ELECTRICITY SUPPLY.*

1. How many times has your organization experienced power outages at its present location in the last ***2 years***? *Best estimate:* ________; *Can't Say* ☐

2. How satisfied are you with the reliability of electricity supply from your utility?
   Very satisfied ☐ Satisfied ☐ Dissatisfied ☐ Very dissatisfied ☐ Not applicable ☐

3. Is your organization connected to a backup/parallel electricity supply ?
   Yes ☐ *PLEASE CONTINUE WITH SECTION B* No ☐ *PLEASE SKIP TO SECTION C*

SECTION B – BACKUP/PARALLEL ELECTRICITY SUPPLY INFORMATION

4. How much of your organization's facilities are powered by your backup/parallel supply?
   [%]

5. Is this backup/parallel supply equipment owned by your organization or is it provided as a service?
   Owned ☐ *SKIP TO Q. 7* Provided as a service ☐ *ANSWER Q.6*

6. What is the monthly service charge (Rands) of the backup/parallel electricity supply to your organization?
   [**R**] → *SKIP TO SECTION B*

7. Which of these does your organization own?
   Diesel/petrol generator ☐ Uninterruptible power supply (UPS) / Inverter-battery system ☐
   Solar power system ☐ Other (Please specify): ________________

8. When was your backup/parallel supply installed? *Tick applicable box.*
   Before 2008 ☐ 2008 - 2010 ☐ 2011 - 2013 ☐ 2014 - 2016 ☐ 2017 - 2018 ☐ Don't know ☐

9. Kindly provide the following information about your backup/parallel electricity supply equipment.

Size (kW/kVA)	
Purchase and Installation Cost (Rands)	
Monthly Maintenance Cost (Rands)	
Running cost (Rands/hour)	

SECTION C – POWER OUTAGE COST

Often, the cost of a power outage to a business depends on the nature of the outage and characteristics of the business, and may vary across time, day, and season depending on business conditions.

10. Please, **on a scale of 0 – 5**, indicate your organization's **business activity level at different time-of-day and seasons of the year**. ***0 means 'no activity at all'; 5 means 'Most busy'***

Time of day	*12am – 6am*	*6am – 12noon*	*12noon – 6pm*	*6pm – 12am*
WEEKDAY business activity level				
WEEKEND business activity level				

Season	*Jan - Mar*	*Apr - Jun*	*Jul - Sep*	*Oct - Dec*
Business activity level				

11. **Suppose** an **unplanned power outage** lasting **2 hours** occurs at your organization's **busiest time-of-day and season.**
    Besides fuel cost (if any), what will be the **highest or worst-case total cost** of this **2-hour power outage** to your organization?

2 – hour highest total outage cost	**R**

12. What percentages do the following factors contribute to your **2 – hour highest total outage cost** above?

Lost sales or production	Stock or material damages	Extra labour, restarts, operational difficulties	**Total**
%	%	%	**100%**

13. What **percentage of the 2 – hour total outage cost** will your organization experience if the unplanned outage lasted only **30 minutes**:

% Not applicable ☐

14. Suppose the **2 - hour** power outage occurred in the **morning,** please **Indicate the amount of lost sales/production your organization can make up** when power is restored.

None ☐ Up to 20 % ☐ 20 – 40 % ☐ 40 – 60 % ☐ 60 – 80 % ☐ 80 – 100 % ☐ Not applicable ☐

SECTION D – SOME BACKGROUND INFORMATION

Please, help us put your answers in context by answering the following questions.

15. What is the size of your organization's electrical load?

Maximum demand:	**kW**
Average monthly electricity consumption:	**kWh**
OR Average monthly electricity bill.:	**R**

16. On a scale of 1 – 10, how dependent are your organization's activities on electricity ? ☐

17. Which of the following best describes your organization? ***Please tick just one.***

Commercial		**Manufacturing**	
Restaurants and Hotels		Bakeries, Food processing industries	
Food / grocery retail trade		Chemical industries	
Other retail trade		Clothing, textile, furniture and leather industries	
Wholesale trade		Foundries, smelting, glass, ceramic industries	
Other (specify):		Other (specify):	

18. What is the location of your organization? ☐

19. How many employees are employed by your organization at this location? ☐

20. Are you willing to be contacted to acknowledge receipt, for limited queries, a short telephone interview, **for us to send you a report on our results, or to participate in another year?** (There will be no other contact and the details will not be shared outside the survey group.) If so, please give contact details:

Name: ______________________________

Tel. No.: ____________ and/or **E-mail:** ____________________

THANK YOU FOR YOUR PARTICIPATION!!!

Please, return this questionnaire to:
Department of Electrical Engineering,
University of Cape Town,
Private Bag 7701,
Rondebosch.

OR Photograph with a cell phone and send by WhatsApp to *+27731416067*

OR Scan pages 2 – 4 and e-mail to akpkin001@myuct.ac.za

B2 Ethics in research clearance

UNIVERSITY OF CAPE TOWN
DEPARTMENT OF
ELECTRICAL ENGINEERING

Application for Approval of Ethics in Research (EiR) Projects
Faculty of Engineering and the Built Environment, University of Cape Town

APPLICATION FORM

Please Note:
Any person planning to undertake research in the Faculty of Engineering and the Built Environment (EBE) at the University of Cape Town is required to complete this form **before** collecting or analysing data. The objective of submitting this application *prior* to embarking on research is to ensure that the highest ethical standards in research, conducted under the auspices of the EBE Faculty, are met. Please ensure that you have read, and understood the **EBE Ethics in Research Handbook** (available from the UCT EBE, Research Ethics website) prior to completing this application form: http://www.ebe.uct.ac.za/ebe/research/ethics1

APPLICANT'S DETAILS		
Name of principal researcher, student or external applicant		Kingsley Oladipo Akpeji
Department		Electrical Engineering
Preferred email address of applicant:		kingsleyakpeji@gmail.com
If Student	Your Degree: e.g., MSc, PhD, etc.	MSc
	Credit Value of Research: e.g., 60/120/180/360 etc.	180
	Name of Supervisor (if supervised):	Prof. K. A. Folly
If this is a researchcontract, indicate the source of funding/sponsorship		Click here to enter text.
Project Title		Cost of electricity supply disruptions to commercial and industrial customers

I hereby undertake to carry out my research in such a way that:

- there is no apparent legal objection to the nature or the method of research; and
- the research will not compromise staff or students or the other responsibilities of the University;
- the stated objective will be achieved, and the findings will have a high degree of validity;
- limitations and alternative interpretations will be considered;
- the findings could be subject to peer review and publicly available; and
- I will comply with the conventions of copyright and avoid any practice that would constitute plagiarism.

SIGNED BY	Full name	Signature	Date
Principal Researcher/ Student/External applicant	Kingsley Oladipo Akpeji		03 Jul 2018

APPLICATION APPROVED BY	Full name	Signature	Date
Supervisor (where applicable)	Prof. K. A. Folly	Folly	03 Jul 2018
HOD (or delegated nominee) Final authority for all applicants who have answered NO to all questions in Section1; and for all Undergraduateresearch (Including Honours).	Prof O. E. Falowo Click here to enter text.		27/07/18 Click here to enter a date.
Chair : Faculty EIR Committee For applicants other than undergraduate students who have answered YES to any of the above questions.			

UNIVERSITY OF CAPE TOWN
DEPARTMENT OF
ELECTRICAL ENGINEERING

Page 1 of 1

B3 Letter of introduction

UNIVERSITY OF CAPE TOWN

DEPARTMENT OF ELECTRICAL ENGINEERING

University Private Bag, Rondebosch 7701
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Faculty URL: http://www.ebe.uct.ac.za
UCT URL: http://www.uct.ac.za

30/08/2018

TO WHOM IT MAY CONCERN

Dear Sir/ Madame,

This letter serves to introduce Mr. Kingsley Akpeji, a postgraduate student in the Department of Electrical Engineering, University of Cape Town who is doing research on "electricity supply reliability and the costs of customer interruption" under the supervision of myself and my colleagues in the Department of Electrical Engineering. This research is very relevant for developing a more cost-effective and reliable electricity supply systems for the customers.

For this research to be successful, Kingsley will need some inputs from you, the customer. He will be contacting you with some few interview questions. I would appreciate it if you could please assist him.

Should you have any questions regarding this interview, please feel free to contact me on 0216502795 or the Department Secretary on 0216502795.

Yours sincerely,

Komla A. Folly, Ph. D.
Professor,
Department of Electrical Engineering
University of Cape Town

UNIVERSITY OF CAPE TOWN
DEPARTMENT OF
ELECTRICAL ENGINEERING

"OUR MISSION is to be an outstanding teaching and research university, educating for life and addressing the challenges facing our society."

B4 Breakdown of survey participation request and response rate

- *174* businesses were contacted via *telephone calls.*
    - *20.1%* resulted in scheduling *face-to-face interviews.*
    - *76.4%* yielded *emails* of potential respondents to whom web-survey links could be sent.
    - *3.4%* were *telephone interviews.*
- *177 emails* were *sent* to request participation in the *web-based survey.*
    - *4.5%* responded after *3 reminders*.
- *96 hard copy forms* were dropped off for retrieval/return
    - *12.5% retrieved* via in-person collection
    - *3.1% returned* via means indicated on the form
- *155 responses* were gotten through *direct requests for face-to-face interviews* at business sites across Cape Town.

B5 Data coding for categorical variables in CQ

Table B5.1: Coding for satisfaction with electricity reliability

Satisfaction level (Q2)	**Coding of responses**				
	Very satisfied	Satisfied	Dissatisfied	Very dissatisfied	N/A
	4	3	2	1	0

Table B5. 2: Coding for backup power supply information

Backup power supply availability (Q3)	Coding of responses	
	Yes	No
	1	2

Percentage of facilities powered by backup/parallel supply (Q4)	Coding of responses				
	0 - 20%	20 - 40%	40 - 60%	60 - 80%	80 - 100%
	1	2	3	4	5

Backup power ownership (Q5)	Coding of responses		
	Owned	Provided as service	None
	1	2	3

Backup power supply type (Q7)	Coding of responses			
	Diesel/petrol generator	UPS / inverter-battery	Solar power system	other
	1	2	3	4

	Coding of responses					
Backup power supply installation period (Q8)	Before 2008	2008-2010	2011-2013	2014-2016	2017-2018	Do not know
	1	2	3	4	5	6

Table B5. 3: Coding for ability to make up lost production

Lost sales or production that can be made up after a power outage (Q14)	Coding of responses					
	None	< 20%	20-40%	40-60%	60-80%	80-100%
	1	2	3	4	5	6

Table B5. 4: Coding for respondents' economic sectors

Economic sector	**Coding of responses**
Commercial	
Restaurants and Hotels	1
Food / grocery retail trade	2
Other retail trade	3
Wholesale trade	4
Other commercial	5
Manufacturing	
Bakeries, Food processing industries	6
Chemical industries	7
Clothing, textile, furniture and leather industries	8
Foundries, smelting, glass, ceramic industries	9
Other manufacturing	10

APPENDIX C

Additional results

C1 Sectoral season-time activity weights

Table C1.1: Season-time activity weight matrix for the trade sector (retail – food and non-food – and wholesale)

Seasons	**Season - Weekday**				**Season - Weekend**			
	00:00 - 6:00	**06:00 - 12:00**	**12:00 - 18:00**	**18:00 - 00:00**	**00:00 - 6:00**	**06:00 - 12:00**	**12:00 - 18:00**	**18:00 - 00:00**
Jan - Mar	0.073	0.603	0.756	0.164	0.046	0.572	0.530	0.156
Apr - Jun	0.074	0.611	0.766	0.166	0.047	0.580	0.537	0.158
Jul - Aug	0.080	0.662	0.829	0.180	0.050	0.628	0.582	0.171
Oct - Dec	0.097	0.798	1.000	0.217	0.061	0.757	0.702	0.207

Table C1.2: Season-time activity weight matrix for the hospitality sector (hotel and restaurants)

Season	**Season - Weekday**				**Season - Weekend**			
	00:00 - 6:00	**06:00 - 12:00**	**12:00 - 18:00**	**18:00 - 00:00**	**00:00 - 6:00**	**06:00 - 12:00**	**12:00 - 18:00**	**18:00 - 00:00**
Jan-Mar	0.097	0.700	0.872	0.468	0.099	0.546	0.623	0.491
Apr-Jun	0.087	0.627	0.782	0.420	0.089	0.489	0.559	0.440
Jul-Aug	0.091	0.657	0.819	0.440	0.093	0.513	0.585	0.461
Oct-Dec	0.111	0.802	1.000	0.537	0.114	0.626	0.715	0.563

Table C1.3: Season-time activity weight matrix for the garage sector

Season	**Season - Weekday**				**Season – Weekend**			
	00:00 - 6:00	**06:00 - 12:00**	**12:00 - 18:00**	**18:00 - 00:00**	**00:00 - 6:00**	**06:00 - 12:00**	**12:00 - 18:00**	**18:00 - 00:00**
Jan-Mar	0.265	0.909	0.898	0.403	0.265	0.725	0.529	0.368
Apr-Jun	0.268	0.922	0.910	0.409	0.268	0.735	0.537	0.373
Jul-Aug	0.272	0.935	0.923	0.414	0.272	0.746	0.544	0.379
Oct-Dec	0.291	1.000	0.987	0.443	0.291	0.797	0.582	0.405

Table C1.4: Season-time activity weight matrix for other commercial sectors

Season	Season - Weekday				Season – Weekend			
	00:00 - 6:00	06:00 - 12:00	12:00 - 18:00	18:00 - 00:00	00:00 - 6:00	06:00 - 12:00	12:00 - 18:00	18:00 - 00:00
Jan-Mar	0.024	0.821	0.909	0.152	0.000	0.647	0.489	0.116
Apr-Jun	0.026	0.895	0.991	0.165	0.000	0.705	0.533	0.127
Jul-Aug	0.026	0.904	1.000	0.167	0.000	0.712	0.538	0.128
Oct-Dec	0.026	0.879	0.973	0.162	0.000	0.692	0.524	0.124

Table C1.5: Season-time activity weight matrix for all commercial sectors combined

Season	Season - Weekday				Season - Weekend			
	00:00 - 6:00	06:00 - 12:00	12:00 - 18:00	18:00 - 00:00	00:00 - 6:00	06:00 - 12:00	12:00 - 18:00	18:00 - 00:00
Jan-Mar	0.091	0.690	0.825	0.253	0.073	0.604	0.555	0.245
Apr-Jun	0.091	0.690	0.825	0.253	0.073	0.604	0.555	0.245
Jul-Aug	0.096	0.725	0.866	0.266	0.077	0.635	0.583	0.257
Oct-Dec	0.111	0.837	1.000	0.306	0.089	0.732	0.673	0.297

Table C1.6: Season-time activity weight matrix for the manufacturing sector

Season	Season - Weekday				Season - Weekend			
	00:00 - 6:00	06:00 - 12:00	12:00 - 18:00	18:00 - 00:00	00:00 - 6:00	06:00 - 12:00	12:00 - 18:00	18:00 - 00:00
Jan-Mar	0.255	0.842	0.845	0.343	0.196	0.498	0.318	0.214
Apr-Jun	0.256	0.846	0.850	0.345	0.197	0.501	0.319	0.215
Jul-Aug	0.268	0.885	0.888	0.361	0.206	0.524	0.334	0.225
Oct-Dec	0.301	0.996	1.000	0.406	0.231	0.590	0.376	0.253

C2 Plots of regression on customer interruption cost and average monthly electricity bill.

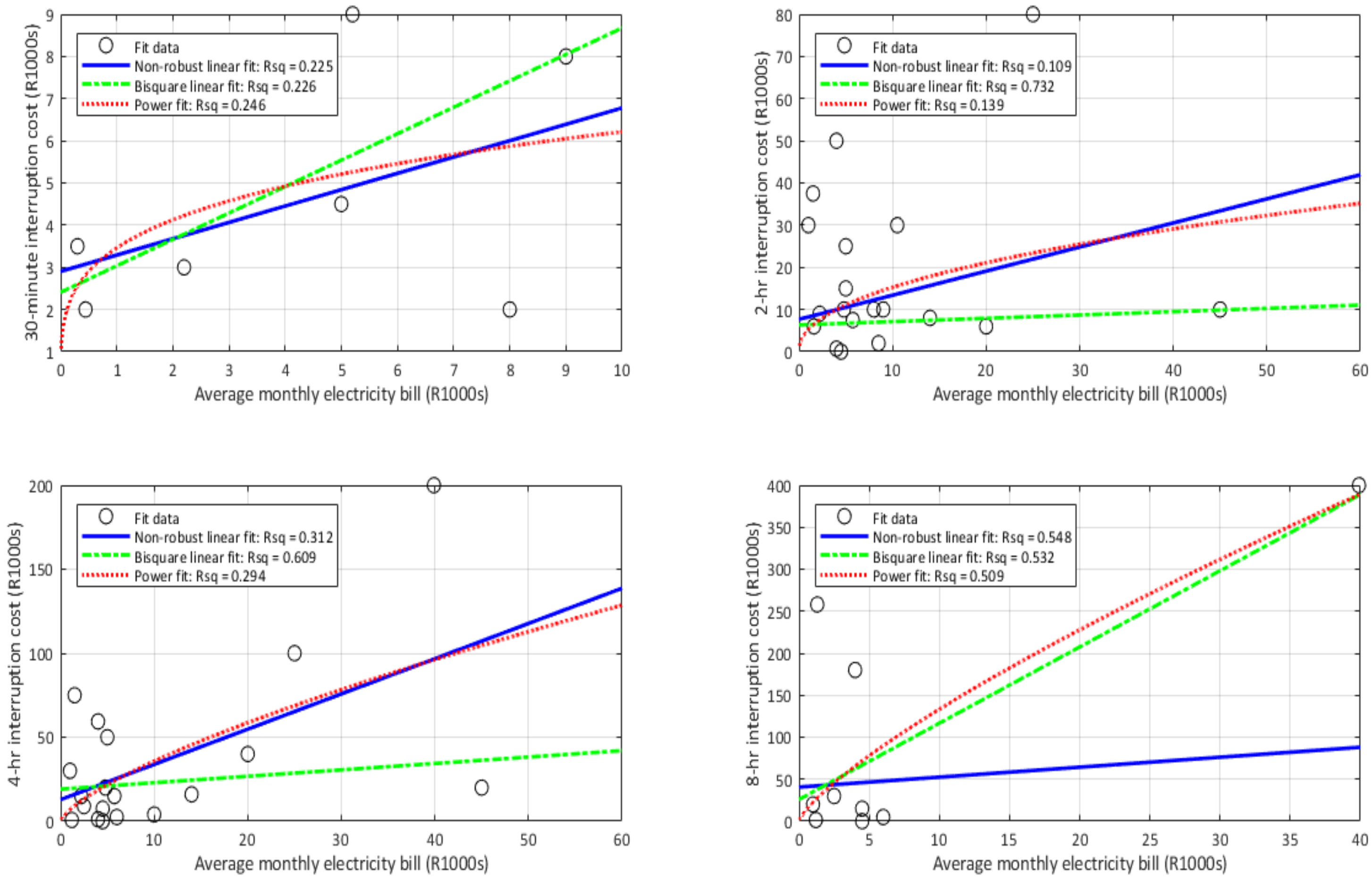

Figure C2.1: Relationship between average monthly electricity bill and interruption cost for respondents in the trade sector

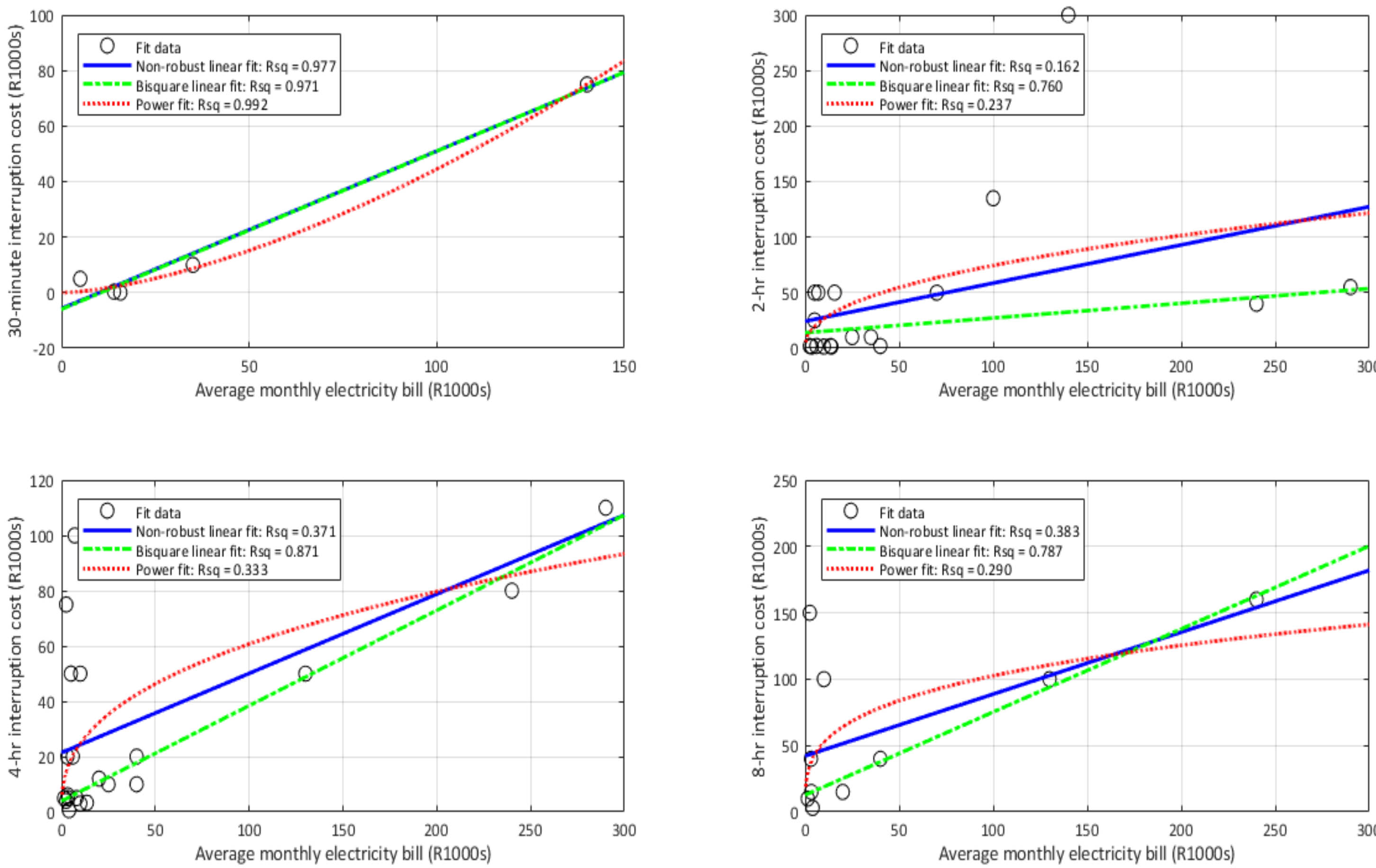

Figure C2.2: Relationship between average monthly electricity bill and interruption cost for respondents in the manufacturing sector

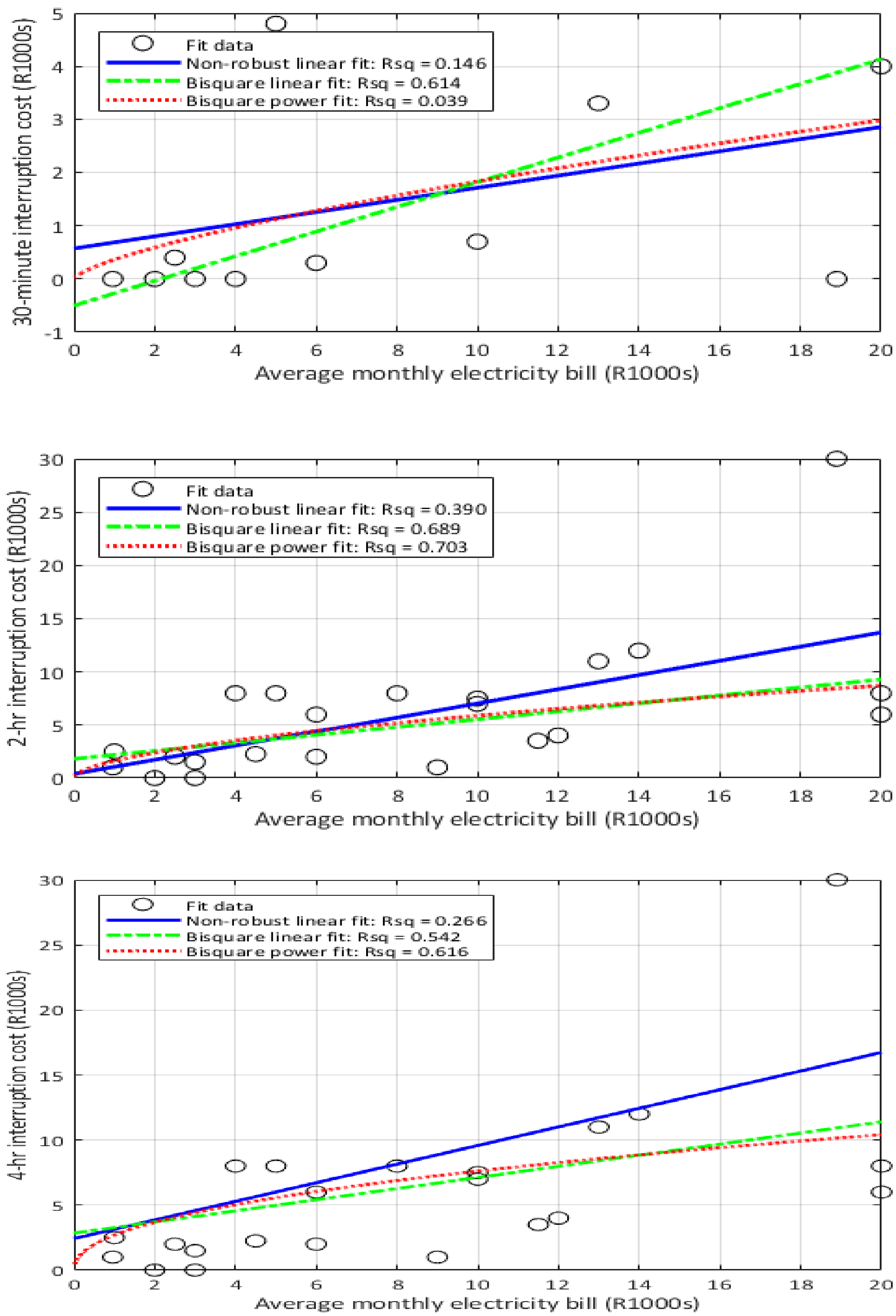

Figure C2.3: Relationship between average monthly electricity bill and interruption cost for respondents in the hospitality sector

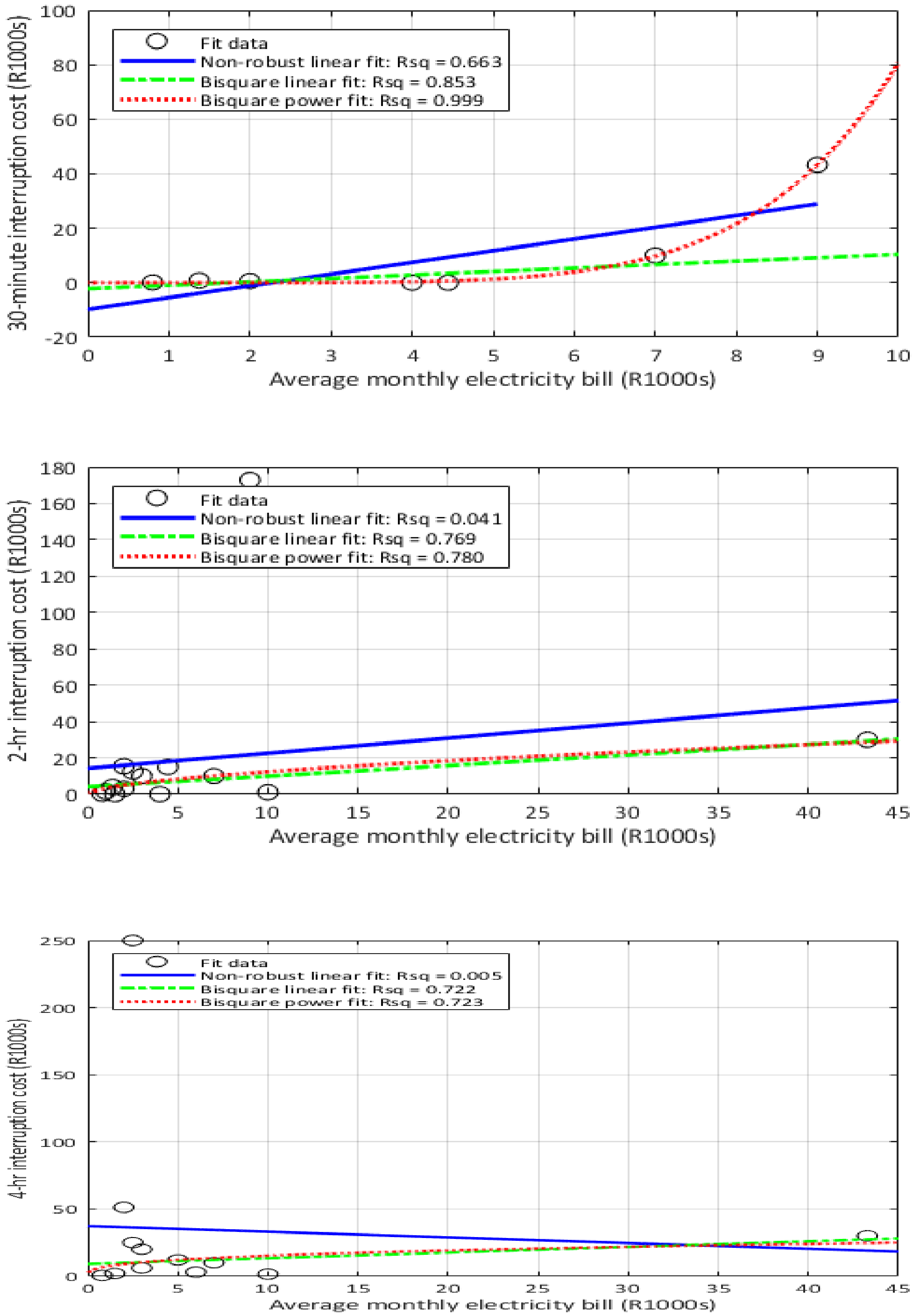

Figure C2.4: Relationship between average monthly electricity bill and interruption cost for respondents in 'other commercial services' sector

C3 CDFs for the hospitality and other commercial services sectors

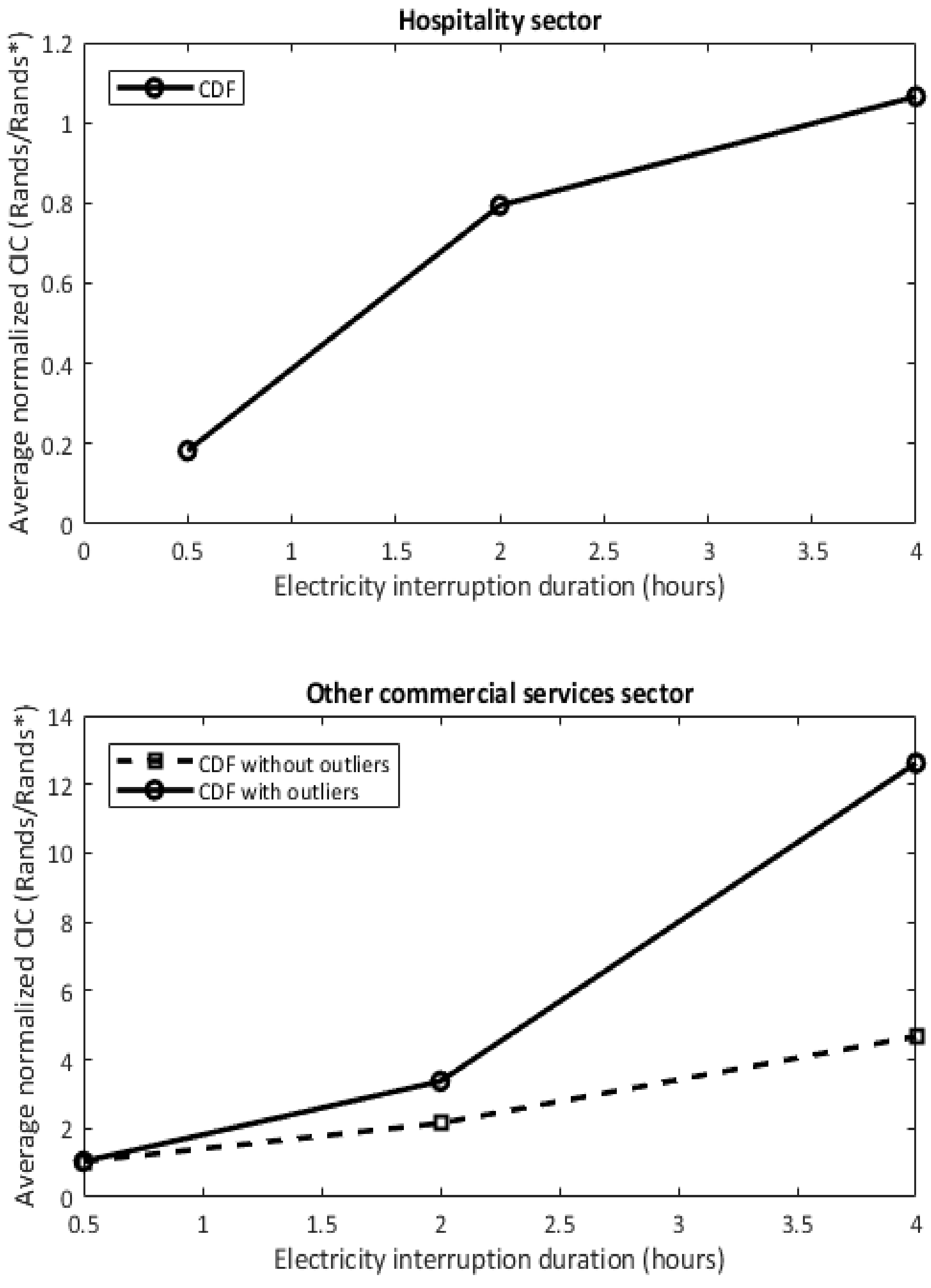

Figure C3.1: CDFs for the hospitality and 'other commercial services' sectors
**Rands per Rands of average monthly electricity bill*

C4 Extra results on backup generator cost analysis.

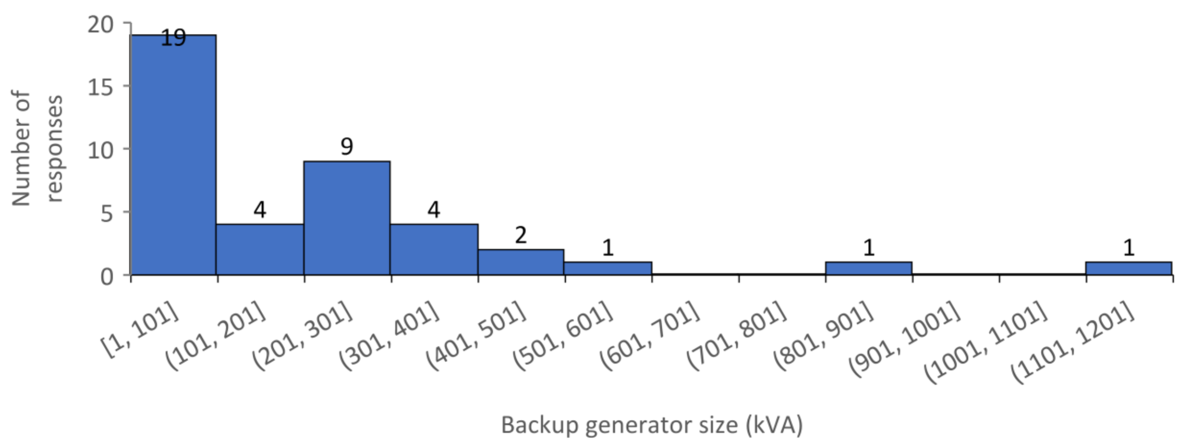

Figure C4.1: Distribution of backup generator sizes

Table C4.1: Backup generator cost summary statistics by generator size ranges

Size	**Description**	**Rands per kVA**					
		No. of responses	Mean	Std	Min	Med	Max
1 - 10kVA	Purchase and installation cost	11	2421.66	1448.86	1117.73	2000.00	6225.66
	Monthly maintenance cost	6	0.00	0.00	0.00	0.00	0.00
	Running cost per hour	10	5.09	3.78	2.73	3.64	15.00
>10 - <100kVA	Purchase and installation cost	4	3206.78	2446.67	894.18	3229.16	5474.60
	Monthly maintenance cost	6	12.36	10.29	0.00	10.36	30.00
	Running cost per hour	5	1.36	0.48	0.82	1.25	1.90
100 - 300kVA	Purchase and installation cost	14	4729.34	2439.46	1117.73	4909.18	8047.66
	Monthly maintenance cost	9	4.91	3.76	0.00	4.17	12.50
	Running cost per hour	5	1.89	1.28	0.63	1.50	4.00
>300kVA	Purchase and installation cost	6	4693.97	2450.69	2076.53	4049.10	8819.68
	Monthly maintenance cost	5	4.14	2.75	1.04	3.57	8.33
	Running cost per hour	6	3.48	1.05	1.83	3.42	5.00

Table C4.2: No of respondents who reported non-zero unmitigated loss as well as relevant backup power supply information and electricity bill to support interruption cost modelling of customers with backup power supply

Sector	Number of respondents per interruption scenario			
	30 mins	2 hours	4 hours	8 hours
Trade	1	3	4	1
Hospitality	0	0	0	0
Other commercial services	0	1	2	1
Manufacturing	1	3	6	4

Table C4.2 shows that data on unmitigated loss for customers with backup is too small to allow comprehensive modelling of the interruption cost of this type of customers for the interruption scenarios considered.

Table C4.3: Data of selected respondents for generator cost and electricity bill comparison

Respondents	Average monthly electricity bill	Generator details				Estimated average monthly operating hours
		Size (kVA)	Purchase and Installation cost (R)	Monthly maintenance cost (R)	Running cost per hour (R/hr)	
C_1	R 14 000.00	45.00	149 227.09	500.00	46.50	540
C_2	R 15 238.00	70.00	224 474.45	865.04	95.26	624
C_3	R 2 000.00	5.50	10 000.00	0.00	28.00	240
M_1	R 450 000.00	600.00	3 400 000.00	5 000.00	3000.00	360
M_2	R 331 777.00	1 200.00	5 632 761.28	1 250.00	3840.00	624
M_3	R 10 509.94	250.00	250 000.00	0.00	472.92	312

Values in shaded cells estimated using relevant average cost estimates in Table B5.2; *as actual estimates were no provided by these respondents*

Excerpt of email from a facility Manager on the cost of installing backup power supply

Below is an excerpt from an email exchange with a facility manager that buttresses these points. Minor grammatical corrections were made.

"XXX[34] *is like a small town. Our maximum demand at one stage was more than 13.7MVA and we (on Landlord side) have more than 40 x UPS's, ranging from 600VA to 10KVA for specific equipment where we only need a maximum of about 2hrs for either backup, evacuation, CCTV cameras, etc… Our tenants, about 400, will have a number of UPS's, and we do not have any idea*

[34] Dummy identifier for business facility

what the number is!!! Also, you need to understand that in a shopping centre the Landlord only controls about 15% of the actual electricity consumption; their own offices and common areas…but the bulk of it is with the tenants and here we only know what we meter".

XXX does not have generator supply enough for trading, therefore the centre is to be evacuated if a confirmed power failure will last for more than 2.5hrs. In order for us to go on full generator supply, we'll need 36 x 500KVA generators…which does not make sense. These generators need to be run and serviced on a regular basis, even though they are not being used. I know of a number of shopping centres who opted to install full generator supply at double digit Rm[35] *and they have not run for a power failure, for more than 6hours during the past 8years!!*

We opted to save energy and committed this to Cape City Council. XXX have saved, and this can be verified by Council metered billing, more than 32% on consumption (kWh) and about 22% on Maximum Demand compared to 2007 which NERSA use as baseline year… this even though our gross leasable area (GLA) increased by about 23% since 2007."

[35] Million Rands

C5 South Africa's 2014 input-output table and results from the economy-wide cost assessment

Table C5.1: South Africa's 10-sector 2014 IOT (all values in million Rands)

			Purchasing industries											
			I1	**I2**	**I3**	**I4**	**I5**	**I6**	**I7**	**I8**	**I9**	**I10**	Final demand	Total output
Supplying industries	**I1**	Agriculture, forestry and fishing	4 835	19	103 912	26	5	6	543	12	196	5 101	96 289	210 943
	I2	Mining and quarrying	3 136	4 475	205 721	23 767	4628	12 953	61	1 441	0	10 136	271 466	537 785
	I3	Manufacturing	57 680	89 279	628 058	15 201	2960	145 967	117 651	120 484	90 832	177 055	425 274	1 870 441
	I4	Electricity	4148	26136	32799	21882	4261	701	7910	3828	14467	6686	62689	185507
	I5	Gas and water supply	808	5090	6387	4261	830	137	1540	745	2817	1302	12208	36126
	I6	Construction	116	989	2781	100	20	4874	388	3421	4245	1471	369089	387493
	I7	Wholesale, retail, motor trade, catering & accommodation	14 962	18 124	157 539	3766	733	41 151	39 400	36 905	36 724	46 579	374 780	770 663
	I8	Transport, storage, and communication	19 742	59 365	84 148	4620	899	20 831	60 969	41 335	56 248	70 438	238 100	656 695
	I9	Finance, real estate, and business services	10 415	27 050	66 398	5887	1146	34 891	119 641	87 985	331 846	142 558	452 485	1 280 303
	I10	Other services	8 240	15 087	110 709	716	139	3 811	5 573	26 460	78 120	113 117	1 221 286	1 583 260
	Total intermediate demand		124 081	245 615	1 398 453	80227	15623	265 322	353 677	322 615	615 495	574 443	3 523 666	7 519 216
	Net taxes on products		4 190	5 802	25 182	941	183	4 800	12 200	14 528	7 254	30 681	283 855	389 616
	GVA		82 672	286 368	446 806	104338	20319	117 371	404 787	319 552	657 555	978 136	0	3 417 904
	Total output		210 943	537 785	1 870 441	185507	36126	387 493	770 663	656 695	1 280 303	1 583 260	3 807 521	**11 326 738**

Table C5.2: Sectoral backward and forward linkage impacts due to hypothetical extraction of the electricity sector (50 – sector level)

Sector index	Description	Backward linkage (R millions)	Forward linkage (R millions)	Total linkage (R millions)
I1	Agriculture	456	7700	8 156
I2	Forestry	210	791	1 002
I3	Fishing	24	102	125
I4	Coal and lignite	24 659	3294	27 953
I5	Metal ores	2 376	27077	29 454
I6	Other mining	3 498	3294	6 791
I7	Food	732	9484	10 216
I8	Beverages and tobacco	324	3274	3 598
I9	Spinning and textiles	259	1651	1 909
I10	Knitted fabrics, fur	114	935	1 048
I11	Leather and luggage	74	247	321
I12	Footwear	54	332	385
I13	Wood	843	1483	2 326
I14	Paper	1 020	3776	4 796
I15	Publishing	579	1321	1 900
I16	Coke oven manufacture	4 881	5731	10 612
I17	Nuclear fuel	3 424	14116	17 541
I18	Other chemicals	2 552	9166	11 718
I19	Rubber	660	1275	1 935
I20	Plastic	599	2067	2 665
I21	Glass	230	828	1 058
I22	Non-metallic minerals	364	2114	2 478
I23	Furniture	61	760	822
I24	Recycling and NEC	644	1451	2 096
I25	Basic iron and steel	4 016	14172	18 188
I26	Precious metals	2 354	5214	7 568
I27	Structural metal	2 870	5005	7 876
I28	General machinery	3 311	3930	7 241

I29	Electrical machinery	7 029	2783	9 811
I30	Electronic valves	1 395	569	1 964
I31	Medical appliances	132	308	440
I32	Motor vehicles	2 145	9856	12 000
I33	Electricity	114 434	64498	178 933
I34	Gas and water	4 739	4669	9 408
I35	Construction	367	11766	12 132
I36	Trade	9 656	16393	26 049
I37	Hotels and restaurants	602	1966	2 569
I38	Transport	12 313	9574	21 888
I39	Telecommunications	2 376	4150	6 526
I40	Financial intermediation	4 383	1675	6 058
I41	Insurance and pensions	1 450	717	2 167
I42	Auxiliary financial	3 103	176	3 279
I43	Real estate activities	1 688	11502	13 189
I44	Renting of machinery	427	499	926
I45	Research	5	166	170
I46	Computer activities	6 296	10577	16 873
I47	Other community activities	74	9247	9 321
I48	Education	1 015	2424	3 438
I49	Health and social work	589	4801	5 390
I50	Other services nec	4 151	7673	11 824
Total		**239 555**	**306575**	**546 130**

Estimates based on 2014 annual IOT

Table C5.3: Proportion of annual GDP generated per quarter in 2014 (for aggregated sector at 1 - digit level of SA's SIC

Sector	**Quarter**			
	1	**2**	**3**	**4**
Agriculture, forestry and fishing	0.208	0.364	0.271	0.158
Mining and quarrying	0.238	0.250	0.248	0.264
Manufacturing	0.239	0.247	0.252	0.262
Electricity, gas and water	0.238	0.248	0.257	0.258
Construction	0.248	0.247	0.247	0.257
Wholesale, retail, motor trade and accommodation	0.236	0.236	0.244	0.284
Transport, storage and communication	0.238	0.245	0.257	0.260
Finance, real estate and business services	0.249	0.249	0.250	0.253
Other services - govt., comm., pers., soc	0.248	0.251	0.251	0.250
Total value added at basic prices	0.242	0.250	0.251	0.257

APPENDIX D

MATLAB simulation codes for reliability cost/worth case study

Main Code

```
%RELIABILITY COST-WORTH ANALYSIS FOR DISTRIBUTION SYSTEM WITH RADIAL
%FEEDERS.
%%
%~Kingsley Akpeji
%MSc in Electrical  Engineering candidate.
%University of Cape Town
%January 2019.
%%
clear

%Request Network structure to simulate
prompt_Rmod = strcat('To simulate network without alternate feed, enter
1;\n',...
'To simulate network with alternate feed, enter 2. \n');

Rmod = input(prompt_Rmod);

if ~isa(Rmod, 'double') || Rmod < 0
error('Please, enter 1 or 2 without signs or space')
end

%Request Interruption cost model to simulate
prompt_Cmod = strcat('For non-time varying average cost model, enter
1;\n',...
'For time varying average cost model, enter 2;\n',...
'For time varying  probabilistic cost model, enter 3; \n');

Cmod = input(prompt_Cmod);

if ~isa(Cmod, 'double')||Cmod < 0
error('Please, enter 1, or 2, or 3 without signs or space')
end

%Request simulated period (in years) to run
n = input('Please, enter the number of years you want to simulate\n');

%Request number of simulations to run
N = input('Please, enter the number of simulations you want to run\n');


SwCase = input(strcat('Enter switch configuration you want to simulate',...
        ' for', '\nPress 0 for no switch at all;',...
        '\nPress 1 for switch on all feeder sections',...
```

```
        '\nOr press 2 to find optimal switch configuration\n'));

SwCaseCheck = SwCase == 0 || SwCase == 1 || SwCase == 2;

while ~SwCaseCheck
    disp('Please, enter 0, 1, 2 to select a switch configuration\n')
    SwCase = input(strcat('Enter switch configuration you want to
simulate',...
        ' for', '\nPress 0 for no switch at all;',...
        '\nPress 1 for switch on all feeder sections',...
        '\nOr press 2 to find optimal switch configuration\n'));
    SwCaseCheck = SwCase == 0 || SwCase == 1 || SwCase == 2;
end

%%
%No. of switches/disconnects positions
nSw = 6;

%No. of switches/disconnects configuration
if SwCase == 0
    SwConfig = zeros(1, nSw);
elseif SwCase == 1
     SwConfig = ones(1, nSw);
else
    %Request numeber of switches whose optimal locations should be found
    nSwOpt = input('Enter number of switches to be optimally placed \n');
    if nSwOpt > nSw || nSwOpt < 0
        error(strcat('No. of switch to be optimally placed ', ...
            'cannot be greater than the available switch positions ',...
        'on the test feeder\n', 'Rerun program\n'));
    end
    %Binary string of switch postions with max equivalent decimal
    maxB = [de2bi(2^nSwOpt - 1, 'left-msb'), zeros(1, nSw - nSwOpt)];

    %max decimal corresponding to maxB
    maxD = bi2de(maxB, 'left-msb');

    %Initialize placeholder for possible switch configurations
    SwConfigH = nan(2^nSw, nSw);

    %Evaluate possible switch configurations for the no. of switches to be
    %optimally placed
    for isw = 0:maxD
        A = de2bi(isw, nSw, 'left-msb');
        if sum(A) > nSwOpt
            continue
        else
            SwConfigH(isw+1,:) = A;
        end
    end
    %Matrix of possible switch configs
    SwConfig = rmmissing(SwConfigH);

    %Intialize vectors of ECOST and ERNC to store result for each config
    ECOST_Sw = zeros(size(SwConfig, 1), 1);
```

```
    ERNC_Sw = zeros(size(SwConfig, 1), 1);
    Res3 = cell(size(SwConfig, 1), 1);
end

%%
%Load required supplementary dataset into struct S for cost evaluation
Svar = load('CIC_SumStat.mat');

%%
%Define network data for Main feeder and laterals.
%-------------------------------------------------
%Number of laterals per feeder section
nLF = [1 1 1 1 1 1 1];

%Cumulative number of laterals at ith feeder section
LC = cumsum(nLF);

%Total no. of laterals (load points)
nl = LC(end);

%Number of customers per customer category at each load point(ncl)
%N.B.: Rows of ncl --> customer category; Columns of ncl --> load pt.
ncl = Svar.ncl; %Random gen. of no. of cust. per sec. per load pt.

%Total number of customers at each load point
nc = sum(ncl, 1);

%Ave. annual failure rates of main feeder components
%(N.B.: 1st component - CB)
FrF = [0.006 0.039 0.04875 0.039 0.039 0.052 0.04875 0.039];

FrFn = FrF./8760;%hourly values for FrF

%Ave. annual failure rates of lateral components
%Row 1 - distributors; Row 2 - transformers.
FrL = [0.04875 0.052 0.052 0.039 0.04875 0.039 0.04875;
       0.015*ones(1,7)];

FrLn = FrL./8760;%hourly values for FrL

%Number of main feeder components
nf = numel(FrF);

%Number of components on lateral with maximum no. of components
k = size(FrL,1);

%Feeder components' repair and switching times
%Repair. Structure: Fdr- [CB, lines]; Lateral - [distr; Trx]
TrF_mean = [4 5];
TrF_sd = [0.4 1];
%Switching
TsF_mean = [1 1];
TsF_sd = [0.4 0.4];
```

```
%Parameters for lognormal distribution of feeder components' repair and
%switching time
TrF_mu = log(((TrF_mean).^2)./sqrt(TrF_sd.^2 + TrF_mean.^2));
TrF_sig = sqrt(log((TrF_sd.^2)./(TrF_mean.^2)+1));

TsF_mu = log(((TsF_mean).^2)./sqrt(TsF_sd.^2 + TsF_mean.^2));
TsF_sig = sqrt(log((TsF_sd.^2)./(TsF_mean.^2)+1));

%Lateral components' repair times
%Repair
TrL_mean = [5; 10];
TrL_sd = [1; 1];

%Parameters for lognormal distribution of lateral components' repair time
TrL_mu = log(((TrL_mean).^2)./sqrt(TrL_sd.^2 + TrL_mean.^2));
TrL_sig = sqrt(log((TrL_sd.^2)./(TrL_mean.^2)+1));


%%
%Loop over switch configuration
for sn = 1:size(SwConfig,1)

%Determine switch positions
S = SwConfig(sn,:);

%%
%Start stopwatch
tic;

%Set up no. of simulation loop
for i = 1:N

%Initialize simulation variables
%No. of failures (i.e. Nff), downtime(i.e. Df)
%Customer int. cost (i.e. Cf), Utility lost revenue ( i.e. Rf)

Nf = zeros(1,nl); Df = zeros(1,nl);
Cf = zeros(1,nl); Rf = zeros(1,nl);

%Set random number generator seed
rng;
%%
%Set up loop for simulation period
for j = 1:n
%Generate Time-to-failure (TTF) for components in running year
    TF = (-1./FrFn).*reallog(rand(1,nf));
    TL = (-1./FrLn).*reallog(rand(k,nl));

%Initialize failure chronology tracker
    t = min(min(TF), min(min(TL,[],'omitnan')));
%%
%Set up hour-based sequential failure loop
    while t < 8760
    %Obtain indices of component with min. TTF in feeder and laterals
```

```matlab
        %Feeder
        [mnTf, iTf] = min(TF);

        %Lateral
        mnTl = min(min(TL, [], 'omitnan'));
        [r_mnTl, c_mnTl] = find(TL == mnTl); iTl = [r_mnTl, c_mnTl];
%%
        %Feeder component failure
        if mnTf <= mnTl
            %Select no alt. feed or alt. feed based on Rmod
            switch Rmod
                case 1 %No alt. feed
                    %Breaker section failure
                    if iTf <= 2
                        iLPo = 1:LC(end);
                        iLPs = [];

                    %Switch at failed sec after CB, check affected load pts:
                    elseif iTf > 2 && S(iTf - 2) == 1
                        %Load pts fully out
                        iLPo = LC(iTf - 2) + 1 : LC(end);

                        %Load pts to switch
                        iLPs = 1 : LC(iTf - 2);

                    %No switch at 1st sec after CB: check affected load pts
                    elseif iTf == 3 && S(iTf - 2) == 0
                        iLPo = 1:LC(end);
                        iLPs = [];

                    %No switch at other secs further from CB:
                    elseif iTf > 3 && S(iTf - 2) == 0

                    %Obtain indices of nearest switch to left of failed sec
                        iLs = find(S(1 : iTf - 3) == 1, 1, 'last' );

                        if ~isempty(iLs)
                            %Load pts fully out
                            iLPo = LC(iLs) + 1 : LC(end);

                            %Load pts to switch
                            iLPs = 1 : LC(iLs);
                        else
                            iLPo = 1:LC(end);
                            iLPs = [];
                        end
                    end

                case 2 %With alt. supply
                    if iTf <= 2
                    %Breaker section

                    %Determine nearest RHS with switch
                        iRs = find(S(1 : end) == 1, 1 );
                        if ~isempty(iRs)
```

```
            iLPo = 1:LC(iRs);
            iLPs = LC(iRs) + 1 : LC(end);
        else
            iLPo = 1:LC(end);
            iLPs = [];
        end

    elseif iTf > 2 && iTf < nf && S(iTf - 2) == 1
        %Switch at failed section (before feeder end) and
immediate RHS

        %Determine nearest RHS with switch
        iRs = find(S(iTf - 1 : end) == 1, 1 ) + (iTf - 2);

        %Determine switchable & fully out load points
        if ~isempty(iRs)
            iLPs = [1:LC(iTf - 2), LC(iRs) + 1 : LC(end)];
            iLPo = LC(iTf - 2) + 1 : LC(iRs);
        else
            iLPs = 1:LC(iTf - 2);
            iLPo = LC(iTf - 2) + 1 : LC(end);
        end

    elseif iTf > 2 && iTf == nf && S(iTf - 2) == 1
    %Switch at end section of feeder

    %Determine switchable & fully out load points
        iLPo = LC(iTf - 2) + 1 : LC(iTf - 1);
        iLPs = 1:LC(iTf - 2);

    %No switch at failed section:

    %%Special case of 1st section after breaker section
    elseif iTf == 3 && S(iTf - 2) == 0

        %Find nearest RHS switch
        iRs = find(S(iTf - 1 : end) == 1, 1 ) + (iTf - 2);

        %Determine switchable & fully out load points
        if ~isempty(iRs)
            iLPs = LC(iRs) + 1 : LC(end);
            iLPo = 1 : LC(iRs);
        else
            iLPs = [];
            iLPo = 1:LC(end);
        end

    %Failure after first section but not at end of feeder
    elseif iTf > 3 && iTf < nf && S(iTf - 2) == 0


        %Find nearest LHS switch
        iLs = find(S(1 : iTf - 3) == 1, 1, 'last' );
```

```
            %Find nearest RHS switch
            iRs = find(S(iTf - 1 : end) == 1, 1 ) + (iTf - 2);

            %Determine switchable & fully out load points
            if ~isempty(iLs) && ~isempty(iRs)
                iLPs = [1 : LC(iLs), LC(iRs) + 1 : LC(end)];
                iLPo = LC(iLs) + 1 : LC(iRs);

            elseif ~isempty(iLs) && isempty(iRs)
                iLPs = 1:LC(iLs);
                iLPo = LC(iLs) + 1 : LC(end);

            elseif isempty(iLs) && ~isempty(iRs)
                iLPs = LC(iRs) + 1 : LC(end);
                iLPo = 1:LC(iRs);
            else
                iLPs = [];
                iLPo = 1:LC(end);
            end

        %End of feeder
        elseif iTf == nf && S(iTf - 2) == 0


            %Find nearest LHS switch
            iLs = find(S(1 : iTf - 3) == 1, 1, 'last' );

            %Determine switchable & fully out load points
            if ~isempty(iLs)
                iLPs = 1 : LC(iLs);
                iLPo = LC(iLs) + 1 : LC(end);
            else
                iLPs = [];
                iLPo = 1:LC(end);
            end
        else
            print(strcat('unexpected condition reached for',...
                'switching in feeder with alt. supply\n'))
            pause
        end
end

%Evaluate TTR and TTS for failed feeder comppponent
if iTf == 1
    %Failed component is breaker
    Tr = lognrnd(TrF_mu(1), TrF_sig(1));
    Ts = lognrnd(TsF_mu(1), TsF_sig(1));
else
    %Failed component is feeder line section
    Tr = lognrnd(TrF_mu(2), TrF_sig(2));
    Ts = lognrnd(TsF_mu(2), TsF_sig(2));
end

%Evaluate next time when repaired feeder component fails
TF(iTf) = t + Tr + (-1./FrFn(iTf)).*reallog(rand);
```

```
            %Evaluate no. of failure (Nf) and downtime (Df) of load
            % pts due to failed component

            %Fully out load pts
            Nf(iLPo) = Nf(iLPo) + 1;
            Df(iLPo) = Df(iLPo) + Tr;

            %Switched load pts
            if ~isempty(iLPs)
                Nf(iLPs) = Nf(iLPs) + 1;
                Df(iLPs) = Df(iLPs) + Ts;
            end

            %Evaluate CIC and Utility revenue not collected
            [C, R] = CostFunc(Svar, nl, ncl, iLPs, iLPo, Tr, Ts, t, Cmod);
            Cf = Cf + C;
            Rf = Rf + R;
        else
%%
        %Lateral component failure
        %--------------------------
        %Determine switchable & fully out load points
            iLPo = iTl(2);
            iLPs = [];

        %Evaluate TTR for failed lateral component
            Tr = lognrnd(TrL_mu(iTl(1)), TrL_sig(iTl(1)));
            Ts = 0;

        %Evaluate next time when repaired lateral component fails
            TL(iTl(1),iTl(2)) = t + Tr + ...
                (-1./FrLn(iTl(1),iTl(2))).*reallog(rand);

        %Evaluate no. of failure (Nf) and downtime (Df) of load
        % pt due to failed lateral component:

            %Fully out load pt
            Nf(iLPo) = Nf(iLPo) + 1;
            Df(iLPo) = Df(iLPo) + Tr;

            %Evaluate CIC and Utility revenue not collected
            [C, R] = CostFunc(Svar, nl, ncl, iLPs, iLPo, Tr, Ts, t, Cmod);
            Cf = Cf + C;
            Rf = Rf + R;
        end
        %Set hour in running year to new minimum TTF
        t = min(min(TF), min(min(TL,[],'omitnan')));
    end %Loop for annual failure chronology ends here.

end %Loop for no. of cost/worth simulated period ends here.
%%
%Evaluate basic load pt. reliability indices
%---------------------------------------------
```

```
%Load point failure rate
FrLP = Nf./(n - Df./8760);

%Load pt. average downtime
rLP = Df./Nf;

%Load pt. average annual unavailabiility
ULP = FrLP.*rLP;

%%

%Evaluate system reliability indices for current simulation run
Res.SAIFI(i) = sum(FrLP.*nc)/sum(nc);

Res.SAIDI(i) = sum(ULP.*nc)/sum(nc);

Res.CAIDI(i) = Res.SAIDI(i)./Res.SAIFI(i);

Res.ERNC(i, 1:nl) = (sum(Rf,1) + sum(Rf,1))./n;

Res.ERNC(i, nl+1) = sum(sum(Rf,1) + sum(Rf,1))./n;

Res.ECOST(i, 1:nl) = (sum(Cf,1) + sum(Cf,1))./n;

Res.ECOST(i, nl+1) = sum(sum(Cf,1) + sum(Cf,1))./n;

Res.IEAR(i,1:nl) = Res.ECOST(i,1:nl)./Res.ERNC(i,1:nl);

Res.IEAR(i, nl+1) = Res.ECOST(i, nl+1)./Res.ERNC(i, nl+1);
end %Loop for cost/worth simulations ends here

%%
%Store results for current switch configuration

%Base case: No switch on feeder
if SwCase == 0
    Res1 = Res;
    break
end

%Switch on all feeder sections.
if SwCase == 1
    Res2 = Res;
    break
end

%Switch configuraion with minimum ECOST
if SwCase == 2
    ECOST_Sw(sn) = mean(Res.ECOST(:,nl+1));
    ERNC_Sw(sn) = mean(Res.ERNC(:,nl+1));
    Res3[24] = Res;
end
```

```
end %End of switch configuration loop


%%
%Determine elapsed smulation time
toc;

disp('COLLATING AND STORING SIMULATION RESULTS IN EXCEL...')

%%
%Collate simulation results and statistics on results and write to Excel

%Excel sheet names to store results in
sheet = {'Rel_CW_IndSummary_S0_C1', 'Rel_CW_LdPtEcost_S0_C1',...
    'Rel_CW_LdPtErnc_S0_C1'; 'Rel_CW_IndSummary_S0_C2',...
    'Rel_CW_LdPtEcost_S0_C2', 'Rel_CW_LdPtErnc_S0_C2';
    'Rel_CW_IndSummary_S0_C3', 'Rel_CW_LdPtEcost_S0_C3',...
    'Rel_CW_LdPtErnc_S0_C3';
    'Rel_CW_IndSummary_Sall_Alt0','Rel_CW_LdPtEcost_Sall_Alt0',...
    'Rel_CW_LdPtErnc_Sall_Alt0';
    'Rel_CW_IndSummary_Sall_Alt1','Rel_CW_LdPtEcost_Sall_Alt1',...
    'Rel_CW_LdPtErnc_Sall_Alt1';
    'Rel_CW_IndSummary_Sopt_Alt0','Rel_CW_LdPtEcost_Sopt_Alt0',...
    'Rel_CW_LdPtErnc_Sopt_Alt0';
    'Rel_CW_IndSummary_Sopt_Alt1','Rel_CW_LdPtEcost_Sopt_Alt1',...
    'Rel_CW_LdPtErnc_Sopt_Alt1'};



%%
%Call to function  'WrCWResFunc' evaluate statistics and write results

%Effect of cost model: results statistics evaluation and storage
if Rmod == 1 && SwCase == 0 && Cmod == 1 %Time invariant ave. cost model
    WrCWResFunc(Res1, sheet(1,:));
elseif Rmod == 1 && SwCase == 0 && Cmod == 2%Time-varying ave. cost model
    WrCWResFunc(Res1, sheet(2,:));
elseif Rmod == 1 && SwCase == 0 && Cmod == 3%Time-varying prob. ave cost
model
    WrCWResFunc(Res1, sheet(3,:));
else
end


%Effect of alt. supply and switch: results statistics evaluation and storage
if Rmod == 1 && Cmod == 3 %No Alt supply

    if SwCase == 1
        %for switch on all feeder sections
        WrCWResFunc(Res2, sheet(4,:));
    end

    if SwCase == 2
        %optimal switch configuration with minimum ECOST
        SwOpt_Alt0 = SwConfig(ECOST_Sw == min(ECOST_Sw),:);
```

```
        mnECOST_SwOpt_Alt0 = min(ECOST_Sw);
        Res_SwAlt0 = Res3{ECOST_Sw == min(ECOST_Sw)};
        save('CIC_SumStat.mat', 'SwOpt_Alt0', '-append');
        save('CIC_SumStat.mat', 'mnECOST_SwOpt_Alt0', '-append');

        %Write results for optimal switch config
        WrCWResFunc(Res_SwAlt0, sheet(6,:));
    end

elseif Rmod == 2 && Cmod == 3 %Alt supply

    if SwCase == 1
        %for switch on all feeder sections
        WrCWResFunc(Res2, sheet(5,:));
    end

    if SwCase == 2
        %optimal switch configuration with minimum ECOST
        SwOpt_Alt1 = SwConfig(ECOST_Sw == min(ECOST_Sw),:);
        mnECOST_SwOpt_Alt1 = min(ECOST_Sw);
        Res_SwAlt1 = Res3{ECOST_Sw == min(ECOST_Sw)};
        save('CIC_SumStat.mat', 'SwOpt_Alt1', '-append');
        save('CIC_SumStat.mat', 'mnECOST_SwOpt_Alt1', '-append');

        %Write results for optimal switch config
        WrCWResFunc(Res_SwAlt1, sheet(7,:));
    end
else
end

disp('SIMULATION RESULT COLLATION AND STORAGE IN EXCEL DONE!')
```

Subroutine 1 – Function to evaluate CIC and RNC

```
function [C, R] = CostFunc(S, nl, ncl, iLPs,iLPo, Tr, Ts, t, mod)
%Evaluates the cost to customers and utility due to load point downtime
%caused by failed distribution network components

%INPUTS:
%S: Supplementary variables for cost evaluation
%ncl: No. of customers per customer category at each load point
%nl: No. of load points on radial feeder
%iLPs: Load points that can be switched in event of component failure
%iLPo: Load points that would be fully out
%Tr: Repair duration of failed component
%Ts: Switching time for isolating failed component
%t: Simulation time instant i.e. hour within running simulated year
%mod: Customer interruption cost model to evaluate

%OUTPUTS:
%C: Customer interruption cost for different load points affected  by
%failed compopnent
%R: Utility revenue not collected at the load points affected by failed
%component
```

```
%%

%%

%Define CDF function
CDF = @(x)[S.TrCDF(x) S.HosCDF(x) S.OcmCDF(x) S.ManCDF(x)];

nc = size(ncl, 1); %number of customer categories

nlo = numel(iLPo); %Number of non-switachable load points

nls = numel(iLPs); %Number of switchable load points

%Initialize cost vector and other needed variables
C = zeros(1, nl); R = zeros(1, nl);

to = ones(1, nlo).*Tr; %Downtime vector for non-switchable load points
ts = ones(1, nls).*Ts; %Downtime vector for switchable load points

if mod == 1 || mod == 2
%Evaluate CDF (Co) & total base case customer cost (TCo) for unswitchable
load pts
    Co = CDF(to);
    Co = reshape(Co, nc, nlo);

    TCo = ncl(:,iLPo).*Co.*(S.Em *  ones(1, nlo));

%Evaluate CDF (Cs) & total base case customer cost (TCs) for switchable load
pts
    if ~isempty(iLPs)
        Cs = CDF(ts);
        Cs = reshape(Cs, nc, nls);

        TCs = ncl(:,iLPs).*Cs.*(S.Em*ones(1, nls));
    end
end

%%
%Evaluate time-varying business activity level weights
%Assumptions: 12-month year; 30-day month; 7-day week; 24-hour day
Dt = floor(rem(t, 24)) + 1; %time-of-day indicator
Wt = floor(rem(t, 168)/24) + 1; %Day-of-week indicator
St = floor(t/720) + 1; %Month-of-year indicator

%Extract activity level weight corresponding to Dt, Wt, and St
if 1 <= Dt && Dt <= 6   %1am - 6am
    id = 1;
elseif 7 <= Dt && Dt <= 12 %7am - 12noon
    id = 2;
elseif 13 <= Dt && Dt <= 18 %1pm - 6pm
    id = 3;
else                        %7pm - midnight
    id = 4;
```

```
end

if 1 <= Wt && Wt <= 5 %Weekday
    iw = 1;
else                  %Weekend
    iw = 2;
end

if 1 <= St && St <= 3 %Jan - Mar
    is = 1;
elseif 4 <= St && St <= 6 %Apr - Jun
    is = 2;
elseif 7 <= St && St <= 9 %Jul - Sep
    is = 3;
else                      %Oct - Dec
    is = 4;
end

%Collate time weight for sectors (Twt_x) in a vector and expand to
%size of load pts
Twt_x = zeros(nc, 1);

%Ave. activity level weight across all time-of-day intervals in the season
Twt_x_ave = zeros(nc, 1);

for i = 1 : nc
    Twt_x(i) = S.Twt{i, iw}(is, id);
    Twt_x_ave(i) = mean(S.Twt{i, iw}(is,:));%ave. of time wts across season
end

Twt_o = Twt_x * ones(1, nlo);
Twt_o_ave = Twt_x_ave * ones(1, nlo);

Twt_s = Twt_x * ones(1, nls);
Twt_s_ave = Twt_x_ave * ones(1, nls);


%%
%customer interruption cost at each load pt based on choice model
if mod == 1
%Cost model 1: Non-time varying average cost model
    C(iLPo) = sum(TCo, 1);

    if ~isempty(iLPs) %Switched load points
        C(iLPs) = sum(TCs, 1);
    end
end

if mod == 2
%Cost model 2: Time-varying average cost model based
    C(iLPo) = sum(TCo .* Twt_o, 1);

    if ~isempty(iLPs) %Switched load points
        C(iLPs) = sum(TCs .* Twt_s, 1);
```

```
    end
end

if mod == 3
%Cost model 3: Time-varying probabilistic cost model
bdur = [4; 4; 4; 8]; %Chosen worst-case cost base duration.

    %Generate beta random normalized cost
    Cbeta = betarnd(S.CbetaP(:,1), S.CbetaP(:,2));

    %Rescale normalized cost
    Co = (Cbeta * ones(1, nlo)) .* (S.CbetaP(:,3) * ones(1, nlo));

    TCo = ncl(:,iLPo).* Twt_o .* Co .* (Tr./bdur) .* (S.Em * ones(1, nlo));

    C(iLPo) = sum(TCo, 1);

    if ~isempty(iLPs) %Switched load points
        Cs = (Cbeta * ones(1, nls)) .* (S.CbetaP(:,3) * ones(1, nls));

        TCs = ncl(:,iLPs) .* Twt_s .* Cs .* (Ts./bdur) .* (S.Em * ones(1,
nls));

        C(iLPs) = sum(TCs, 1);
    end

end

%%
%Evaluate estimate of utility revenue not collected (based on median
%monthly electricity bill per sector

%180 hours per unique 6-hour time block with identical business activity
%level weight.

Eo = ncl(:,iLPo).*((S.Em/180) * ones(1, nlo)).*(Twt_o./Twt_o_ave) .* Tr;

R(iLPo) = sum(Eo, 1);

if ~isempty(iLPs) %Switched load points
    Es = ncl(:,iLPs).*((S.Em/180) * ones(1, nls)).*(Twt_s./Twt_s_ave) .* Ts;

    R(iLPs) = sum(Es, 1);
end

end
```

Subroutine 2 – Function to evaluate summary statistics of results and store them in Excel.

```
function [] = WrCWResFunc(Res, sheet)
%WrCWResFunc(Res, sheet) evaluates summary statistics of reliability
%cost/worth & writes the result of the cost/worth simulation to excel files
%   Inputs: Res - Result to write; sheet - sheet to write to.
```

```
stat = @(x)[mean(x) std(x) min(x) median(x) max(x)];

%Collate system indices
sysInd = [Res.SAIDI' Res.SAIFI' Res.CAIDI' Res.ERNC(:,end)
Res.ECOST(:,end)...
    Res.IEAR(:,end)];

sysIndStat = zeros(size(sysInd, 2), 5);

for l = 1 : size(sysInd, 2)
sysIndStat(l,:) = stat(sysInd(:,l));
end

tvars = {'Mean', 'Std', 'Min', 'Med', 'Max'};
indnam = {'SAIDI', 'SAIFI', 'CAIDI', 'ERNC', 'ECOST', 'IEAR'};

sysIndTab = array2table(sysInd, 'VariableNames', indnam);

sysIndStatTab = array2table(sysIndStat, 'VariableNames', tvars,...
'RowNames', indnam);
%%
%Collate load point cost result
nl = size(Res.ECOST(:,1:end-1),2);

LP_ECOST = Res.ECOST(:,1:nl); LP_ERNC = Res.ERNC(:,1:nl);

LP_ECOSTstat = zeros(nl, 5); LP_ERNCstat = zeros(nl, 5);

LPnam = cell(1,nl);

for m = 1 : nl
    LP_ECOSTstat(m,:) = stat(LP_ECOST(:,m));
    LP_ERNCstat(m,:) = stat(LP_ERNC(:,m));
    LPnam{m} = strcat('LP', num2str(m));
end

LP_ECOSTstatTab = array2table(LP_ECOSTstat, 'VariableNames', tvars,...
'RowNames', LPnam);

LP_ERNCstatTab = array2table(LP_ERNCstat, 'VariableNames', tvars,...
'RowNames', LPnam);
%%
filename = 'MSc_Rel_Cost_Worth_Results.xlsx';

writetable(sysIndTab, filename, 'Sheet', sheet{1}, 'Range', 'A2');

writetable(sysIndStatTab, filename, 'Sheet', sheet{1}, 'Range', 'J2');

writetable(LP_ECOSTstatTab, filename, 'Sheet', sheet{1}, 'Range', 'R2');

writetable(LP_ERNCstatTab, filename, 'Sheet', sheet{1}, 'Range', 'Z2');
```

```
xlswrite(filename,LP_ECOST, sheet{2}, 'A3');

xlswrite(filename, LP_ERNC, sheet{3}, 'A3');

end
```