The Economic Losses of Power Quality Disturbance: different perspectives of cost models

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By

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Declaration of Author's Right

This thesis is the result of the author's original research. It has been composed by the author and has not been previously submitted for examination which has led to the award of a degree.

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C_{si}	Log and recoded short interruption unit cost
C_{si}^{*}	Log and recoded positive short interruption unit cost
t	The duration that PQ disturbed
con	Average monthly consumptions of customer
r	Competitor indicator, =1 when there are other rivals, otherwise =0
β_i	The Tobit parameters, coefficients of short interruption impact factors
wf	The weighting factor in voltage sag cost calculation
C_{vs}	Voltage sag unit cost
D_{losses}	Total energy loss cost due to harmonic
D_a	Total aging cost due to harmonic
k_i	Average number of harmonics per year
$p(t)$	The probability of harmonics with THD above 5% for durations less or equal to t
λ_i	The time varying coefficient
λ_k	The adjustment factor, the proportion of individual load demand in total load demand

Glossary of Terms

PQ	*Power Quality*	
	The ability of normally operation of equipment without affecting others	

PQ — *Power Quality*
The ability of normally operation of equipment without affecting others

CDF — *Customer Damage Function*
A function to describe the relationship between economic losses of customers and associated impact factors

LBNL — *Lawrence Berkley National Laboratory*
A laboratory that provides reports on power quality economic losses

THD — *Total Harmonic Distortion*
A measurement of harmonic distortion based on fundamental frequency

TDD — *Total Demand Distortion*
A replacement of THD regarding current harmonic standards

NOK — *Norwegian Krone*
A currency symbol for the Norwegian Krone

OLS — *Ordinary Least Squares*
A minimizing regression process to realize the minimum error terms

MLE — *Maximum Likelihood Estimation*
A regression process to find a set of parameters that maximizing the probability of observed data

SAS — *Statistical Analysis System*
A commercial analytics software

QLF — *Quality Loss Function*
A function to to describe the relationship between deviations of quality characters and associated economic losses in a numeric way

PCC — *Power Control Centre*
A connection point between power network and consumers

Abstract

An assessment of the economic impact of power quality disturbances can be performed from the perspective of either electricity customers or power grid owners, depending on the consequences considered by either side. Examples of economic losses due to power quality issues for power grid owners may include compensation and loss of customer royalties, while for electricity customers, the losses may come from damaged products, disrupted industrial process and loss of revenue. In this thesis, the economic losses due to power quality issues are mainly discussed from the customer-oriented perspective.

To assess the customer-oriented economic losses of a power system, a cost model is required to describe the characteristics of economic losses in mathematical terms. Some cost models for power quality disturbances are already in existence. Many of these models represent economic losses due to a single factor. However, in this thesis, the following two additional points are included: (a) Power quality disturbances always have a short term economic impact on customers, which is not covered in most cost models; (b) Economic losses due to power quality disturbances are actually determined by multiple factors rather than a single factor. The cost models developed in this thesis take the effects of multiple factors into account.

This thesis has developed a set of new cost models to evaluate the multiple-factor-dependent potential economic losses due to power quality disturbances. These proposed cost models are specifically designed to calculate short term economic losses while considering customer and time varying impact factors.

A time varying coefficient to quantify the effects of time of occurrence for different types of power quality disturbance is also proposed. With the use of the time varying coefficient, the differences in economic losses at different times of occurrence can be accurately represented.

In this thesis, all of the proposed cost models are demonstrated individually in different power quality disturbance scenarios and a simple distribution system is used

to illustrate the applications of these proposed cost models in a system. The results show the valid applications as well as the advantages of the proposed short term cost models.

Chapter 1 Introduction

1.1 Background

1.1.1 Power Quality and Power Quality Cost

With the development of modern technologies, an increasing number of highly sensitive electronic devices are being brought into electrical power systems. In addition, a large amount of wind power equipment is being installed for the purposes of renewable power energy utilization. All of these have brought new challenges to supply quality. Now, electricity customers are concerned not only with the level of the power supply but also with its quality. The Power Quality (PQ) has therefore become the main issue in modern power systems. According to the definition in the IEEE Standard Dictionary of Electrical and Electronics Terms [1], Power Quality (PQ) is "the concept of powering and grounding sensitive electronic equipment in a manner that is suitable to the operation of that equipment." For different types of equipment, the requirements of suitable operations vary. Hence, for different types of electricity customers, the power quality requirements are dissimilar. Higher levels of power supply quality can be obtained by increased investment and maintenance costs. However, despite the fact that the greater the investment and maintenance costs the higher the power supply quality, the money paid for the surplus level of power quality is believed to be wasted. From the electricity customers' points of view, finding the optimal level of power quality to suit individual requirement becomes of the utmost importance. In order to achieve this, it is important to balance the investment for providing the required PQ level with the potential economic losses related to PQ disturbances. Thus, the optimal level of power quality is deemed to be when investments are just equal to the potential economic losses. In this case, the estimation of the potential economic losses due to PQ disturbances becomes essential. From the electricity regulators' and providers' points of view, for the purpose of providing required and reliable power supply quality with proper regulation schemes, it is also of great importance to gain knowledge of the PQ potential losses.

The potential economic losses due to PQ disturbances could be called the PQ cost, which can be described as the summation of the potential financial losses due to disturbances which affect the power supply quality or result in interruptions of power supply. Such disturbances normally include short interruptions, voltage sags, harmonics, flickers, transients, etc. However, due to the relative difficulty in assessing the financial losses, in addition to the relatively small economic losses, in comparison to those caused by other types of PQ disturbances, the economic losses caused by flickers, transients and other slight disturbances will not be discussed in this thesis. This means that the short interruptions, voltage sags and harmonics are the main components of PQ cost in this thesis.

Studies on PQ cost [2] [3] [4] indicate that the PQ cost is affected by several factors. Firstly, PQ cost will vary with the types of customers. For example, a voltage sag disturbance may only result in dips in illumination for residential customers. However, for industrial customers without appropriate protection systems, the same voltage sag disturbance may lead to defective production, which means raw materials wasted, production reduced and other economic damage. Even for industrial customers, the same scales of PQ disturbances may lead to completely different economic losses. According to the survey results of [4], continuous process industrial customers generally have more severe losses than non-continuous process industrial customers with the same type of PQ disturbance.

Secondly, the PQ cost is also impacted by the duration; generally, the longer the duration, the larger the economic losses. However, totally speaking, the relationship between cost and duration is non-linear and customers may experience different variations of the PQ cost over time, depending on the types of customer. Taking the short interruption as an example, some customers may suffer from severe economic losses at the beginning of interruption, and very few economic losses after a long period of time, or even decreased losses. Others may experience a contrary variation.

Thirdly, the time of occurrence also has a great influence on the PQ cost. Normally, the PQ variations during peak hours, while most industries are operating, may result in massive financial losses. In contrast, if the PQ variations occur during off-peak hours, when most industries are off-work, the losses may be minor. Without doubt, the off-peak economic losses will be much smaller than during peak hours.

In addition to these factors, there are other factors such as fault location, market environment, etc. which also affect PQ cost, though not as greatly as mentioned above. For example, the economic losses may be higher for customers in very competitive markets, as the disturbed production could become a competitors' advantage. In this way, additional competition losses will need to be added into total economic losses.

1.1.2 Power Quality Cost Models

Commonly, the PQ cost data are collected by surveys on electricity customers, whereby customers are asked to estimate and assess their economic losses due to PQ disturbances based on hypothetical or experienced scenarios. The PQ cost models can thus be derived according to the collected data,. These cost models are then used for assessing potential economic losses due to a given type of PQ disturbance. Hence, in order to estimate the potential economic losses due to PQ disturbances, the modelling of associated cost is essential. There are several existing modelling methods for each type of PQ disturbance.

- **Short Interruption Cost Model**

As one of the mostly studied PQ costs, the short interruption cost could be expressed through various models. As one of the earliest and simplest models, the energy dependent model [5-8] provides short interruption cost information in terms of energy unit cost upon representative discrete duration of interruption. Thereafter, due to the introduction of the Customer Damage Function (CDF) [9-12], the short interruption cost can be represented continuously by the duration of interruption. After consideration of the bias of respondents in interruption cost surveys, Billinton, Chan and Wacker [13] have improved the accuracy of the short interruption cost model by modelling the probability distribution of the survey results. By adding cost weighting factors, several literatures [14-17] have designed further improved cost models which consider "time of occurrence". Due to the lack of consideration of the other factors besides "duration" and "time of occurrence" in the above models, in [18], the

Lawrence Berkley National Laboratory (LBNL) has introduced multiple effects into one interruption cost model using the Tobit regression model.

- **Voltage Sag Cost Model**

In the early studies, the voltage sag cost is studied as a long term rather than a short term disturbance and the frequency dependent model is widely used [19] [20]. Based on the average voltage sag cost derived from surveys, the long term voltage sag cost is then estimated according to the total expected number of voltage sags. Having considered the impact of both the magnitude and duration of voltage sags, in [21] and [22], Milanovic and Gupta have proposed a more accurate model based on the trip probabilities of devices in the power systems. The effects of voltage sag magnitude could be introduced in other ways, such as the weighting factor cost model that is proposed in [23] [24], which is based on the relationship between short interruption and voltage sag. Moreover, in order to provide continuous estimation of voltage sag magnitude, [25] proposes an approach that uses the Quality Loss Function and the Signal-to-Noise Ratio to estimate voltage sag cost based on the magnitude of voltage sags and specified maximum economic losses for representative durations. Furthermore, in [26], based on the disturbed stages in process, a time varying voltage sag cost model is also introduced.

- **Harmonic Cost Model**

Generally, the harmonic cost is calculated from two aspects: energy loss and aging costs. Existing literature concerned with harmonic cost estimation is scarce [27-29], and uses average constant energy unit cost to evaluate the energy loss cost, while using the estimated useful life-time of equipment and purchasing price to estimate the aging cost in the long term.

1.2 Objectives

Based on the recent PQ cost models, the PQ cost could be estimated approximately, although most of these do not take into consideration PQ disturbances of less than one minute, which are of great importance for online monitoring and regulation. In addition, there are no models which are capable of quantifying the multiple impact factors on PQ cost. Therefore, this thesis will mainly study the short term PQ cost model. The purpose of this study is to develop a methodology taking into consideration the multiple factors for PQ cost according to the different types of customers, which can be obtained from the following aspects:

- Structures of PQ Cost Studies

Normally, a PQ cost could be examined from both direct and indirect aspects of economic losses. In order to describe a realistic and reliable cost model, studies of the main contributors to the PQ cost are important. Therefore, it is necessary to clarify which aspects are included in the PQ cost calculation. The components of both direct and indirect economic losses need to be determined, based on the analysis of PQ cost reports.

- Classification of Customer Types

For each type of customer, the PQ requirement as well as the potential economic losses may vary. In this case, the classification of customers in power systems becomes necessary. It is important to classify customers into different types according to their PQ requirements.

- Existing Cost Model Reviews

In order to develop new models, it is necessary to review the existing cost models for each type of PQ disturbance, mainly short interruption, voltage sag and harmonics in this thesis. The advantages and disadvantages of each existing model need to be discussed in order to find suitable models for each component of PQ disturbances.

- New Short Interruption Cost Model

Though the interruption cost model introduced in [18] seems likely a good cost model to evaluate the interruption cost, it has been built for evaluating the long term interruption cost. Due to the characteristics of the Tobit regression model, it is impossible to fully consider every point of time of occurrence factor for each type of customer in the same model. For example, the interruption cost model in [18] is not able to reveal the impact of short interruption occurring in the afternoon for agriculture customers. Hence, based on the original Tobit interruption cost model, it is possible to adjust the definition of the Tobit parameters in the cost model and make it suitable for short term interruption cost calculation, with more precise description of impact factors. Hence, in this thesis, according to the classification of customer types, each type of customer requires an individual cost model for PQ cost calculation. In the meantime, the effects of time of occurrence need to be extracted from the Tobit cost model and represented as an independent coefficient rather than a Tobit coefficient. Moreover, the effect of market environment also needs to be considered. In this case, the purpose of the short interruption cost studied is to build a multiple impact factor dependent cost model with full consideration of time of occurrence for different types of customers.

- New Voltage Sag Cost Model

Though the voltage sag cost has already been estimated as a time varying cost in [26], it depends too much on individual data, such as individual industrial process, that make the estimation process complicated. Furthermore, none of these voltage sag cost models is capable of quantifying the multiple impact factors, such as time of occurrence and market environment. Therefore, based on the financial relationship between short interruption and voltage sag, it is possible to take the Tobit short interruption cost model as a maximum voltage sag cost, and utilize the Quality Loss Function to estimate the weighting factors. Taken together, a more practical voltage sag cost model could be designed in terms of duration and magnitude of voltage sag as well as other impact factors, such as customer consumption and market environment.

- New Harmonic Cost Model

Based on the existing harmonic cost models, it is impossible to estimate the short term harmonic cost, especially the aging cost. For example, it is impossible to estimate the economic losses of a harmonic variation lasting 1ms on a Monday morning with the existing harmonic cost models, as they are not able to provide cost information for a single harmonic variation. Therefore, the objective of the harmonic cost model is to estimate the short term harmonic cost in terms of single harmonic variations.

- The Time Varying Coefficient

As mentioned above, the effect of time of occurrence needs to be represented as an individual coefficient that varies with time. By adding the time varying coefficient into each PQ cost model, i.e. short interruption, voltage sag and harmonic cost models, these PQ cost models then become time varying cost models. Hence, the objective of the time varying coefficient is to be able to reflect the economic variations with time.

- Practical Analysis

In order to demonstrate the utilization of the PQ cost models proposed in this thesis, i.e. short interruption, voltage sag and harmonic cost models, it is necessary to apply them to designed PQ disturbances.

1.3 The Original Contributions

According to the aforementioned objectives, this research has made the following contributions:

1. A detailed discussion of the nature and characteristics of power quality and associated economic losses. Accordingly, electricity customers have been classified into different categories based on different economic losses due to PQ disturbances. The existing cost models for PQ disturbance have been reviewed, and the advantages and disadvantages of existing models are summarized. These have provided the basic information for further PQ and PQ cost research.

2. Based on the existing short interruption cost models, a modified Tobit short interruption cost model has been proposed. It has overcome inaccuracies caused by the original cost model, and is capable of quantifying the effects of disturbance duration and customer consumption in the same model. In addition, the effects of market environment have also been considered.

3. Based on the relationship between short interruption and voltage sag, the Tobit short interruption cost model and Quality Loss Function are combined to represent a new voltage sag cost model. In this combined cost model, both the effects of

voltage sag duration and magnitude can be estimated continuously. The effects of customer consumption as well as market environment have been quantified.

4. Rather than a constant energy unit cost in harmonic energy loss cost calculation, the Tobit cost model has been introduced into the energy unit cost calculation. Therefore, the energy unit cost is capable of reflecting varying impact factors.

5. For the calculation of aging cost due to harmonics, a new short term estimation method has been proposed. Based on the long term aging cost, the expected number of harmonics that may result in aging issues is estimated according to the probability of occurrence with similar characteristics of harmonics. Thereafter, the average aging cost for a given harmonic variation can be estimated for the short term. Together with factor varying energy loss cost due to harmonics, the short term harmonic cost can be evaluated.

6. A new time varying coefficient has been proposed to quantify the effect of the time of occurrence. With the time varying coefficient, all of the proposed PQ cost models, i.e. the Tobit short interruption, combined voltage sag and short term harmonic cost models can be estimated properly while taking the time of occurrence into account.

1.4 Thesis Outlines

This thesis is made up of seven chapters which are organized as follows:

Chapter 1 presents an introduction to power quality, associated economic losses, their importance in electricity regulation and what has already been done to the cost models. Then, the objectives and assumptions of this research are discussed, followed by the main contributions of this research.

Chapter 2 provides an overview of the component of power quality and associated economic losses. Then, methodologies to collect cost data are presented and the main impact factors of the PQ cost are discussed. This chapter also explores the classification of customer types.

Chapter 3 discusses the advantages and disadvantages of existing short interruption cost models. Based on the discussion, the improved Tobit short interruption cost model is proposed. After being compared with the original long term Tobit interruption cost model, the reasons for the adjustment of the new model are presented. Through case studies of industrial customers, utilization of the new model is demonstrated.

After giving an overview of the existing cost models for voltage sag cost, Chapter 4 presents a mathematical model to evaluate the effects of voltage sag magnitude, i.e. Quality Loss Function. Then, based on the discussion of the financial relationship between short interruption and voltage sag, the combined cost model is introduced. According to the case study, the characteristics of continuous estimation on voltage sag magnitude of this combined cost model are demonstrated.

Chapter 5 analyzes two aspects of the harmonic cost:, energy loss and aging cost. The energy loss cost is calculated based on the total energy losses due to harmonic and a constant energy unit cost. Accordingly, the methodology to evaluate the total harmonic energy losses is introduced based on the discussion of the harmonic energy loss calculation of individual devices. Then, rather than constant energy unit costs, a flexible energy unit cost is proposed according to the calculations of the Tobit cost model under different conditions. Together with the total harmonic energy losses, a factor varying total energy loss cost is evaluated. For aging cost, the existing long term cost calculation is discussed. Thereafter, the new short term aging cost model is proposed based on the Weibull probability distribution. In this chapter, case studies are used to demonstrate the process of this new short term aging cost model.

In Chapter 6, after introduction of the load curve that represents the variation of load demand at different times, the relationship between load demand and PQ cost is discussed. Based on the above discussion, a new time varying coefficient is derived. Then, a simple case study on a daily load curve demonstrates the variation of the time varying coefficient. Accordingly, the time varying PQ cost models are studied based on a simple distribution system.

Chapter 7 concludes this thesis, and discusses possible further work.

1.5 Publications

According to the research work that has been done in this thesis, the following publications have been published or submitted for review:

Zhemin Lin; Gengyin Li; Ming Zhou; Lo, K.L.; , "Economic evaluation of real-time power quality cost," *Universities Power Engineering Conference (UPEC), 2010 45th International* , vol., no., pp.1-5, Aug. 31 2010-Sept. 3 2010

Zhemin Lin; Gengyin Li; Ming Zhou; Lo, K.L.; , "Economic cost evaluation of time varying voltage dips," *Electrical Power Quality and Utilisation (EPQU), 2011 11th International Conference on* , vol., no., pp.1-6, 17-19 Oct. 2011

Zhemin Lin and Prof.K.Lo; “Time varying short term harmonic cost evaluation”, Under preparation for journal submission.

Chapter 2 Power Quality and Power Quality Cost

2.1 Introduction

There are no general agreements on what power quality is. However, the literature concerned with power quality does agree that power quality has become an important aspect in modern power networks. This does not necessarily mean power quality was not important in the past. On the contrary, for decades, utilities providers have been dedicated to improving power quality. However, with the penetration of power electronic based highly automatic and sensitive devices and controllers, as well as deregulation of electricity markets and the introduction of renewable energy such as wind energy, stricter demands on the quality of power delivered to customers lie ahead for power providers [30][31][32].

Understanding of Power Quality (PQ) may vary according to different viewpoints. Power providers may consider PQ from a system reliability point of view. They may claim that their systems are 99.9% reliable, which represents a good quality of power. For equipment manufacturers, the PQ may be treated as the level of power supply that enables the proper operation of equipment. Meanwhile, from the customers' point of view, the PQ could be considered as ensuring the continuous power supply to maintain industrial processes, business activities and normal operations [33].

Due to deregulated electricity markets, multiple suppliers provide different choices for customers. As a result, customers can easily switch to new providers, driven by the quality of power supply and their demand for higher service quality. Due to the natural characteristics of electricity customers, power suppliers have to provide high quality power services in order to retain their competitive edge in markets and attract more customers. For those power providers who seek to maximize their profits while retaining the best level of power quality, the risk-benefit analysis becomes important.

The essential key element in this kind of analysis is the potential economic loss due to power quality problems, which refers to the cost of power quality. As it is impossible to completely avoid PQ disturbances in a system, under predefined requirements, both the power suppliers and consumers are responsible for maintaining the power network operation normally under a certain level of PQ disturbance. If the suppliers fail to meet the requirement, the power quality costs may be used as reference for compensation to consumers. On the other hand, if the consumers fail to meet the requirement, the power quality costs measure the potential economic losses to consumers themselves.

In this chapter, a background on power quality and related cost will be presented. A brief discussion on the concept of power quality will be introduced in Section 2.2, followed by an introduction to the main components in power quality problems in Section 2.3. Then Section 2.4 provides definitions and relative information on power quality cost. Finally, the main aspects related to this thesis will be outlined in Section 2.5.

2.2 Conception of Power Quality

2.2.1 Power Quality Definition

Back in the 70s, the term ‘power quality’ was first coined by electrical power suppliers to include limits on voltage and frequency fluctuations, voltage unbalance, transient voltage, voltage harmonics and interruptions. The purpose of introducing this term was more about ‘safety’, ‘reliable service’, and ‘low initial and operating costs’ [34].

In 1983, Meynaud [35] claimed that there were two factors which could be used to describe the quality of electricity: the continuity of supply and quality of voltage. In his paper, after presenting the causes and effects of voltage disturbances, he discussed the characteristics of rapid voltage variation, asymmetry, transient overvoltage, and harmonics in terms of parameters and consequences.

Today, there is still no consensus on use of the term ‘power quality’ to define the phenomena mentioned above. The main argument against its use is that, unlike traditional goods, ‘quality’ cannot be used to describe a physical phenomenon like electrical power. In the electricity industry, engineers and researchers have tried different terminologies to define these phenomena.

Voltage quality is more concerned with deviations of voltage from a technical perspective. It refers to short interruption, voltage fluctuation/flicker, asymmetrical voltage and voltage harmonics [36] [37]. Obviously, the voltage is not the only component of the phenomenon, as there is also ‘current’. Therefore, the term ‘voltage quality’ is limited by only covering technical and voltage aspects.

Current quality is a complementary term to voltage quality and is concerned with the deviations of current. As such, this term has rarely been seen in published papers [38] [39]. Compared to voltage quality, which is related to what the utilities providers deliver to customers, current quality mainly focuses on what the customers take from the utilities. As with voltage quality, this term only defines one part of the phenomenon.

Quality of supply includes both technical and non-technical aspects of power supply [40] [41]. In this term, ‘quality’ means more than the technical quality of voltage; it also indicates the ‘quality of service’, which may refer to the commercial quality and reliability of supply. The commercial quality is concerned with the agreements between customers and suppliers, such as responsibility for problems, conditions for newly connected customers, equipment installation etc., while the reliability of supply is the measurement of the capability of the network to continuously deliver power to customers. The word ‘supply’ clearly indicates that this term relates directly to power suppliers, excluding the activities of customers.

Electromagnetic compatibility (EMC) has been used by IEC (International Electro-technical Committee) standards. It is defined as “the ability of a device, equipment or system to function satisfactorily in its electromagnetic environment without introducing intolerable electromagnetic disturbances to anything in that environment" [42]. It covers two aspects: (1) a device, piece of equipment or system should have the ability to perform normally in its environment, and (2) it should not produce too much pollution of its environment. The first aspect refers to the voltage quality at the power 'delivering end', while the second refers to the current quality at the power 'receiving end'.

Power Quality (PQ) is a combination of voltage and current quality. It reflects voltage and/or current deviations from the ideals and, although it is still not a perfect description of the phenomenon, it is currently the most widely accepted and suitable term. Consequently, PQ is also used to represent the phenomenon in this thesis. The definition of PQ given by IEEE (Institute of Electrical and Electronic Engineers) dictionary [1] is "the concept of powering and grounding sensitive equipment in a matter that is suitable to the operation of that equipment and compatible with the premise wiring system and other connected equipment." More simply, PQ can be understood as the ability of equipment to operate normally without affecting others.

When under the effect of good PQ, the devices and equipment will run efficiently and correctly. The condition of the power system will be satisfactory, and the running cost will be minimized, while for poor PQ, the efficiency of devices and equipment will be reduced, and in extreme cases, they may be disconnected from the system and some may also experience lifetime shortening. The operation of the power system will definitely be affected, which appears as interruptions, un-balanced loading, etc. and the running cost will be extremely high if there is no proper protection. [43]

2.2.2 Power Quality Disturbance

From the previous section, it can be seen that PQ is concerned with the deviations of voltage or current from the ideal waveform, magnitude or frequency. Such deviations are called "Power quality disturbance" (PQ disturbance) [44]. In practice, it is almost impossible to maintain exactly the same values as nominal or desired voltage (or current), as there are almost always deviations in the system. According to the different characteristics of deviations, PQ disturbance could be further divided into two groups:

- **Events**: Sometimes, sudden and dramatic deviations from nominal or ideal values appear in the voltage or current; these kinds of deviations are called “power quality events” (PQ events). Examples of these include when the magnitude of voltage suddenly drops to zero due to the opening of a circuit breaker, or a rapid overcurrent caused by a lightning strike on transmission lines. Normally, PQ events can be recorded by a triggering mechanism starting from the moment the pre-defined threshold is exceeded.
- **Variations**: The small and slow deviations from ideal values are called “voltage variation” or “current variation”. One important attribute of any variation is that the actual value will vary from time to time. For example, the frequency will never be precisely equal to 50Hz or 60 Hz; the waveform will never be exactly the same as the ideal. Therefore, this kind of slow deviation needs continuously monitoring.

2.3 Overview of Power Quality Phenomena

2.3.1 Short Interruption

As one of the best known PQ events, an interruption of power supply voltage is known as “voltage interruption” [1], “supply interruption” [45] or just “interruption” [46]. Interruption here does not necessarily mean complete loss of voltage. In EN 50160 [45], interruption is defined as “lower than 1% of the declared voltage”. While in IEEE Standard 1159 [46], it is defined as “lower than 10%”. When these extreme variations of voltage magnitude occur within a very short time, such short time events are called “short interruption”. Again, there are different definitions on ‘short’. IEC introduces ‘short’ as events of up to 3 minutes, while IEEE defines ‘short’ as no longer than 1 minute. Considering the interruptions of current, the short interruption in this thesis is defined according to IEEE standards as "the complete loss of voltage or current (<0.1 p.u.) on one or more phases for a period of time greater than 0.5 cycles but not exceeding 1 min." [1]

A further distinction can be made within short interruptions based on their duration. They are momentary and temporary interruptions [1]:

- **Momentary**: interruptions lasting from 0.5 cycles to 3 seconds. Normally, this kind of event is more problematic for industrial customers whose processes are continuous and more vulnerable to short interruptions.
- **Temporary**: interruptions lasting from 3 seconds to 1 minute. With greater duration, these events may bring more losses to customers than momentary interruptions do and are typically reported by customers whose processes are dispersed, which will be discussed in later sections.

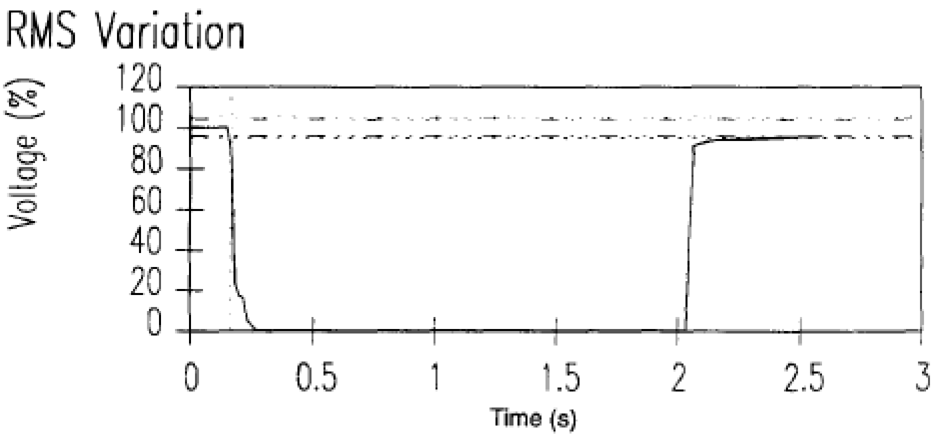


Figure-2.1 Short Interruption Variation [1]

Fig-2.1 is a typical short interruption with a complete loss of voltage [1]. The y-axis is the value of voltage variation as a percentage, while the x-axis is the duration in seconds. It shows that this short interruption lasts around 2.3 seconds, which could be classified as a momentary interruption. It should be noted that the magnitude of voltage would not drop to zero immediately, and it takes around 0.1 second to become a complete loss of voltage. In addition, the magnitude would not recover to 100% as soon as the fault has been cleared.

There are many possible sources of short interruptions. One of the main sources is system faults such as short circuits in electrical lines which trigger the protection system, disconnecting the equipment. Sometimes, the protection systems may also operate when there are no faults in the system, which is called protection malfunction. This is another major possible cause of short interruption: parts of a generator may stop working, transformers may break down, a re-closer may not work properly, or a control signal may have no response, etc.; these may also cause short interruptions in in the system.

The effects of short interruption can be divided into two types: immediate effects and extent effects. Once a short interruption has occurred, it will cause immediate disconnection from a power network to customers who experience it, while for industrial customers the process of industry or manufacturing will be interrupted. This will certainly directly affect the business activities or production of customers. These immediate and direct losses are the immediate effects of short interruption. With the increasing duration of interruption, customers could suffer additional losses incurred by prolonging the industrial process, wasting time etc. All of these are called extent effects, which come after immediate effects.

Short interruptions can be unpredictable. Therefore it is necessary when short interruptions occur to reduce their impact. There are several solutions, such as stand-by generators, uninterruptable power supply (UPS) devices, multiple electrical independent feeders, etc., all of which will act as back-up power suppliers to continuously provide the power required when there are short interruptions.

Although short interruptions are inevitable in power systems, there does exist a distinction between what is ‘good’ and ‘bad’ performance regarding short interruptions. This is called “minimum standards” [36]. A minimum standard indicates the minimum acceptable range to achieve a certain level of performance. It sets up quantitative targets to achieve. The effects and definitions of short interruptions may differ among various areas and countries so it is difficult to find a common standard to distinguish short interruptions. However, most standards suggest that short interruptions are characterized by duration and frequency of occurrence. Duration is used to make a distinction between short interruption and long interruption, while frequency presents an average number of short interruption events. Therefore, the minimum standards of short interruption could be introduced by setting a cap on the number of short interruptions for a certain duration.

2.3.2 Long Interruption

As a complementary definition to short interruption, long interruption is described as any interruption which lasts longer than a short interruption. As with short interruptions, the definitions of 'long' are different. IEC considers it as "longer than 3 minutes" [45], while IEEE recognizes an interruption "longer than 1 minute" as "sustained interruption", which is a long interruption according to IEEE standards [1]. In line with the definition of a short interruption, a long interruption in this thesis is defined as interruptions longer than 1 minute. Normally, long interruptions are permanent in nature, and restoration of power requires manual intervention.

2.3.3 Voltage Sag (Dip)

There are always voltage deviations in power systems; however, as long as these deviations stay within acceptable ranges, electronic devices can function properly. However, some deviations may exceed limits and lead to PQ problems. One of the most common and significant PQ events challenging industrial customers is voltage sag (also known as voltage dip). This is a short duration under-voltage. The term 'voltage sag' is preferred by the IEEE, and used by many papers on power quality, while 'voltage dip' is used by the IEC. The 'voltage sag' by IEEE is referred to as "A decrease to between 0.1 and 0.9 p.u. in rms voltage at the power frequency for durations of 0.5 cycle to 1 min" [1], and the definition of 'voltage dip' is "a sudden reduction of the supply voltage to a value between 90% and 1% of the declared voltage, followed by a voltage recovery after a short period of time" [45], where the "short period of time" is "10 ms to 1 minute". In accordance with this definition of 'short interruption', in this thesis, the term 'voltage sag' is used to describe the phenomenon of voltage magnitude reduction, which refers to the voltage drops to between 10% and 90% of nominal value with duration lasting from 0.5 cycles to 1 minute. It should be noted that the range of voltage sag duration is the same as that for short interruption. According to this definition, it is evident that the short interruption is an extreme case of the voltage sag, in which voltage magnitudes drop to below 10% of nominal value.

To eliminate confusions on the terminology, according to [1], it should be clear that the usage of “a sag to 20%” means the magnitude of voltage is reduced down to 20% of its nominal value, not reduced by 20%.

As with short interruptions, voltage sags can be further divided into momentary and temporary ones. However, the duration is not the only factor that decides the effects of voltage sags; the effects also depend on the depth of sags. Therefore, to make distinctions in voltage sags, both the duration and depth of sags need to be considered. As the IEEE does not specify the depth of sags while classifying voltage sags, a good example is from EN 50160 [45]. The IEC roughly divides voltage dips into four groups:

- Short and Shallow Dips: voltage dips with a magnitude of more than 0.4 p.u. and duration of less than a few seconds
- Short and Deep Dips: voltage dips with a magnitude of less than 0.4 p.u. and duration of less than a few seconds
- Long and Shallow Dips: voltage dips with a magnitude of more than 0.4 p.u. and a duration of more than a few seconds
- Long and Deep Dips: voltage dips with a magnitude of less than 0.4 p.u. and a duration of more than a few seconds.

Fig-2.2 shows a voltage sag event associated with a single line-to-ground fault [1]. This voltage sags to around 20% of nominal value and lasts approximately 100ms. As with the short interruption, the magnitude of voltage does not drop to 20% of nominal voltage immediately after the fault occurs but declines at various rates within 50ms. Furthermore, the recovery of voltage accounts for the rest of the event duration. The magnitude of voltage does not return to 100% immediately after the fault has been cleared; rather, it is usual for the fault clearing time for voltage sag to range from 3 to 30 cycles, depending on the fault type and the sensitivity of protection equipment [1].

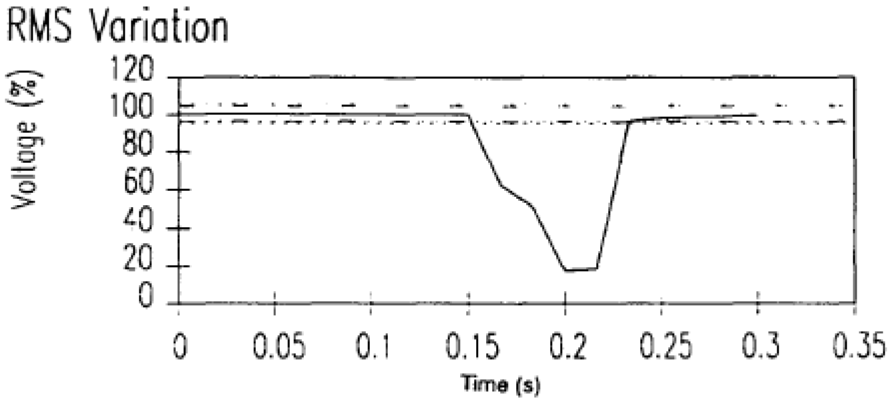


Figure- 2.2 Voltage Sag Variation [1]

Most of the time, voltage sags are associated with short circuit faults in transmission lines, while a fault on a parallel line will also lead to a voltage sag event via the reduction of voltage on associated buses. In addition, starting a large motor and connecting a heavy load are the other main sources of voltage sag. During the starting of an induction motor, several times its full load current are produced, and this causes a significant voltage drop across the system.

For different purposes, devices and equipment are designed to sustain a certain level of sag. A voltage sag event within sustained levels may cause very little or no damage. However, in modern electricity networks, numbers of electronic devices utilized are extremely sensitive to voltage quality, such as variable speed drive controls, programmable logic controllers, etc. Once the sag of voltage exceeds the sustained level, the cost of downtime is extremely expensive. Based on the definition of short interruption and voltage sag, the short interruption could be treated as an extreme case of the voltage sag. The severity of PQ disturbances is usually measured in terms of affected activities. If, under extreme circumstances, a short interruption causes a whole industrial process to shut down, then a voltage sag with similar characteristics except voltage magnitude would only have a partial impact on industrial process. Thus, the economic evaluation of PQ disturbances is usually derived from the affected processes, and the economic losses due to voltage sags are a proportion of short interruption cost.

There are many solutions to reduce the impact of voltage sags. The least expensive solution is to increase the tolerance to voltage sags by purchasing control devices and other electronic equipment designed with greater thresholds. Another efficient and inexpensive way is to reduce the power consumed by the heavy load based on soft starters, which are known for their ability to temporarily reduce the load current during startup. A Dynamic Voltage Restorer (DVR) can be used to generate the missing part of the supply where heavy load or deep sags are concerned. If the voltage of a load sags to 75%, then the DVR generates the missing 25%. Normally, a DVR is expected to work only during a short period of time. Other solutions such as on-line and off-line UPS or reliable back-up sources provide quick-acting voltage regulators [47] [48].

As with short interruptions, common minimum standards are hard to reach due to the various definitions and sustained levels of voltage sags. The acceptable levels of voltage sag depend on the structures and characteristics of systems, devices and equipment. To make a measurement of the level of a voltage sag, [36] suggests that a minimum standard could be introduced to limit the number of voltage sags per period for different types, which are classified based on duration and magnitude.

2.3.4 Transient

A voltage (or current) deviation with an extremely short duration, typically one cycle of power system frequency or less, is referred to as “transient”, “transient (over) voltage (or current)”, or “voltage (current) transient” [44]. However, the word ‘transient’ is not a precise description for this PQ phenomenon. ‘Transient’ refers more to a temporary state between two steady states. Thus, the term is applicable in events caused by switching actions, but not in cases caused by lightning strikes. However, due to the similarity in time period and possible results, both of these are considered as ‘transient’.

According to [1], generally, the waveform variation of a transient could be a unidirectional impulse or damped oscillatory. Based on their different wave shapes, transients can be divided into two groups: impulsive and oscillatory.

An *impulsive transient* is a sudden change in a steady-state condition of voltage or current, and the polarity is unidirectional (either all variations within the positive side or within the negative side). Normally, an impulsive transient is characterized by the rise and decay time. For example, a 1.2/50 us 2000V impulsive voltage transient means this transient voltage reaches its peak value 2000V within 1.2 us, then decays to half its peak values in the next 50us [1]. Fig-2.3 shows a typical impulsive current transient caused by lightning. In the first few microseconds, the current increases extremely quickly in the negative side, then decays slowly with a few variations. It takes much more time to recover than to reach its peak.

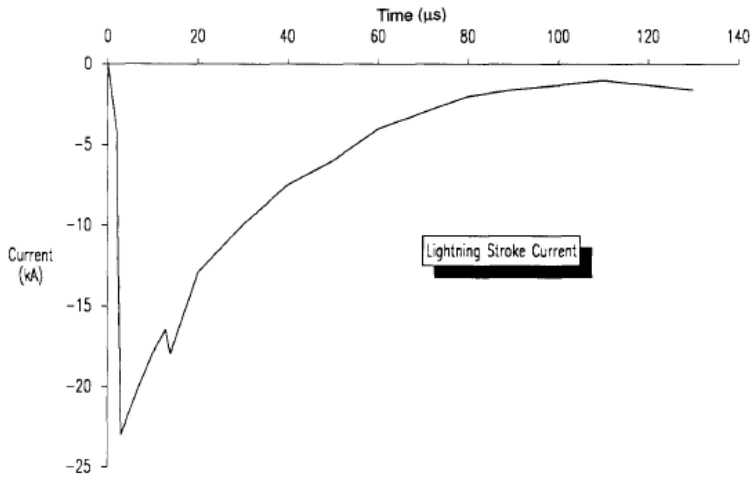


Figure- 2.3 Impulsive Transient Current [1]

An *oscillatory transient* is the instantaneous value of rapid voltage or current change in polarities. It is described by predominant frequency, duration and magnitude. Fig-2.4 shows an oscillatory current transient caused by capacitor switching. The polarity of the current changes rapidly all the time, while the magnitude reduces.

The sources of transients are normally from two aspects as discussed above, lightning and switching. Lightning causes impulsive transients, while switching actions are the main causes of oscillatory transients.

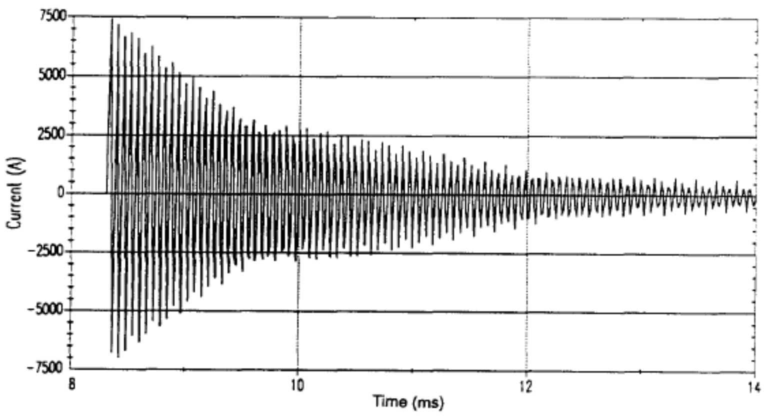


Figure- 2.4 Oscillatory Transient Current [1]

Transients have voltages or currents significantly larger in magnitude than expected, and can lead to serious damage to installations and connected equipment. Earthing and shielding are efficient and simple methods to protect installations and equipment. By providing a low impedance path, earthing and shielding lead transients into the ground or other protection devices or lines without damaging protected targets. Surge protectors are another solution to limit the amplitude of transient voltage or current. In practical terms, levels of thresholds, response time and methods of installation determine how many reductions in transient voltage or current can be achieved by surge protectors.

2.3.5 Harmonic

An ideal voltage waveform is exactly sinusoidal at a fairly constant single fundamental frequency. However, the ideal voltage (or current) would not exist in practical scenarios. Loads, especially non-linear ones, produce currents at frequencies which are multiples of fundamental ones. These currents then lead to distorted voltages or currents in systems. This phenomenon is called “harmonic distortion” or “harmonic”. Both the IEEE and IEC define “harmonic” in the same way: “Harmonics are sinusoidal voltages or currents having frequencies that are integer multiples of the frequency at which the supply system is designed to operate” [1] [42]. Harmonics are combined with fundamental frequency and individual elements of harmonic distortion, the individual ones are named after their multiples, such as in a 50Hz system, where the 2nd harmonic is referred to as two times the fundamental frequency, which is 2*50Hz, ie. 100Hz.

Based on the multiples of each individual frequency, the harmonics can be divided into two groups: odd and even harmonics. Each of them has a different effect on the shape of the waveform. An ideal sinusoidal current sin (θ) is shown in Fig- 2.5 (a).

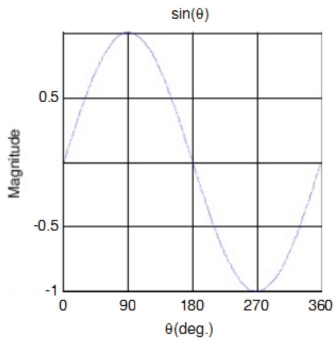


Fig-2.5 (a)

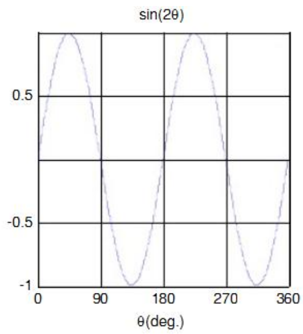


Fig-2.5 (b)

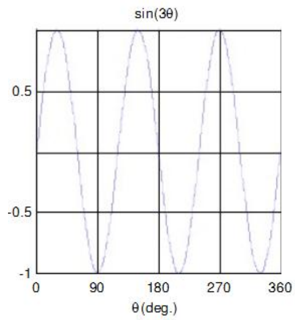


Fig-2.5 (c)

Figure-2.5 Current Waveforms

The y-axis is the magnitude of the current, while the x-axis is the phase degree. In Fig-2.5 (b), sin (2θ) is the 2nd harmonic of sin (θ), which is an even multiplier. This can be called an even harmonic. In contrast, in Fig-2.5(c), sin (3θ) is the 3rd harmonic of sin (θ), which is an odd multiplier, and is thus referred to as an odd harmonic. Fig-2.6 (a) and (b) illustrate the differences between even and odd harmonic distortions. Harmonics are dominated by even harmonics, such as in Fig-2.6 (a) and always appear as an asymmetrical waveform, while harmonics dominated by odd harmonics, such as in Fig-2.6 (b), are represented by a symmetrical waveform. Symmetry is essential to the performance of AC systems, and asymmetry leads to various problems to system operation, such as DC offset. Direct current in AC systems brings additional stresses on insulation and has other adverse impacts. In this case, even harmonics are more harmful than odd harmonics to system operation. Fortunately, most non-linear loads in power systems produce odd harmonics. The numbers of even harmonics presented are limited or even absent in AC systems. [49]

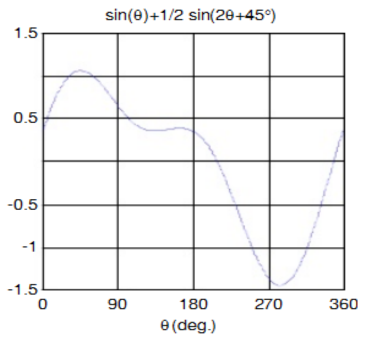


Fig-2.6 (a)

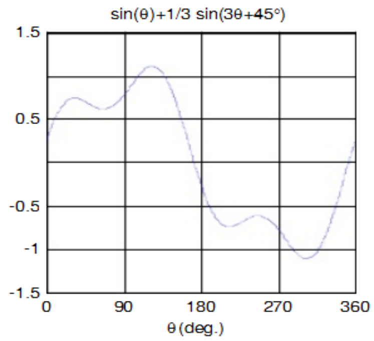


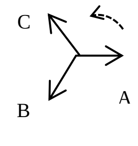
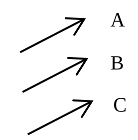
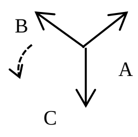
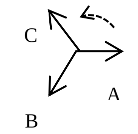
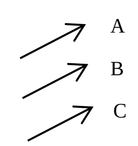
Fig-2.6 (b)

Figure-2.6 Harmonic Current Waveforms

There are various components in harmonic distortions. It is a complex task to analyze harmonics. In order to make it easier, an important concept called "sequence" is introduced. There are three types of sequences: 'zero sequence', 'positive sequence' and 'negative sequence'. As shown in Table-2.1, in AC systems, the fundamental three phase currents (or voltages) are magnitude equal and 120° phase-shifted, which places A, B and C in order when phasor A is used as a reference. According to these calculations, harmonic orders such as 3rd and 9th become 0° phase-shifted to each other, which means phasors A, B and C are equal in the phase and there is no relative phase 'rotation' between these three. This is called "zero sequence". For orders such as the 5th, the phasors are still 120° phase-shifted. However, the three phasor placement becomes C-B-A, where the phase rotation is opposite to the fundamental one. This opposite rotation is called "negative sequence". When it comes to orders like the 7th, the phasors are shifted 120°, and placed in the same order as fundamental ones, and have the same rotation as the fundamental ones. This positive rotation is called "positive sequence".

Sequences are particularly important when dealing with motors, as the rotation of rotors depends on the torque produced by sequential ‘rotation’ of 3-phase power.

Table-2.1 Three Phase Rotation of Each Order

Harmonic Orders	**Phase A**	**Phase B**	**Phase C**	**A-B-C Position**
Fundamental	0°	120°	240°	
3th	0°	3*120° (360°=0°)	3*240° (720°=2*360°=0°)	
5th	0°	5*120° (600°=360°+240°=240°)	5*240° (1200°=3*360°+120°=120°)	
7th	0°	7*120° (840°=2*360°+120°=120°)	7*240° (1680°=4*360°+240°=240°)	
9th	0°	9*120° (1080°=3*360°=0°)	9*240° (2160°=6*360°=0°)	

Positive sequence (7th, 13th, 19th, etc.) helps to push the rotor in the proper direction just as the fundamental one does.

Negative sequence (5th, 11th, 17th, etc.) produces torque in the opposite direction to the rotor rotation.

Zero sequence (3rd, 9th, 15th, etc. which is triple harmonic orders) does nothing to torque. It neither drives nor pushes against the rotation [50]. However, zero sequence is responsible for problems such as high neutral current, high neutral to ground voltage, increasing system losses etc. [51].

Normally, there are three contributions to harmonic distortions [44]:

1) From the generation side, in practical scenarios, even the generated voltages with the best quality consist of small deviations from the ideal voltages. Although these deviations are small enough to be ignored, they are part of harmonic sources.
2) In terms of transmission, the electrical energy transported from generators to loads is never completely linear. A typical example is a power transformer, where the nonlinearity is introduced by a magnetic flux saturation of iron core. Though the initial deviations are slight, there is a potential risk that deviations can be amplified by other power electronics in systems.
3) The main contributions of harmonics in power systems are the non-linear loads themselves. The classic non-linear loads in systems include rectifiers, adjustable speed drives, arc furnace, etc. Loads such as rectifiers and adjustable speed drivers only generate odd harmonics, while loads such as arc furnace generate even harmonics. Compared with even harmonics, odd harmonics are more common in systems. However, in certain conditions, such as failures, odd harmonics sources also produce even harmonics.

The effects of harmonics can be divided into two types: long term and short term [52].

- **Short term effects**: In protection systems, harmonics may lead to a malfunction of protection devices, mainly on those tripped by thermals. For low current systems, such as remote control, telecommunications, hi-fi systems, etc. harmonics induce noises, abnormal signals, even disturbances. In addition, harmonics increase the energy losses of operating equipment due to thermal issues, which might be big problems for large power equipment such as transformers.
- **Long term effects**: The main long term effect of harmonics is the aging issue. If equipment is exposed to harmonics that approach or exceed its sustaining ability too often, in the long term, this will shorten its life significantly.

The possible solutions to harmonic issues come from the following methods [48]. Passive harmonic filters lead harmonic currents flowing into filters instead of systems by providing a low impedance path. These filters can be designed for filtering either single order harmonics or various wide band orders. Alternatively, active harmonic filters (or active harmonic conditioners) are an efficient way to reduce harmonics. The concept is simple, using power electronics to compensate for harmonic currents required by non-linear loads; thereafter, the supply resources are only required to provide fundamental current. There are another ways to overcome the effects of harmonics, such as oversizing equipment and cables, which improve the system tolerance of harmonics. In this way, the thermal impacts of harmonics are reduced.

Normally, the levels of harmonics are characterized by Total Harmonic Distortion (THD). Within the IEEE standards [53], the term "Total Demand Distortion" (TDD) is used to replace the total harmonic distortion regarding current harmonic standards.
THD is a measurement of harmonic distortion based on fundamental frequency, defined as the ratio of the root-sum-square magnitudes of higher frequency current or voltage to the fundamental ones. For voltage signal, THD is presented as Equation-2.1.

$$\mathrm{THD} = \frac{\sqrt{{V_2}^2+{V_3}^2+{V_4}^2+\cdots+{V_n}^2}}{V_1} \tag{2.1}$$

where, V_1 is the fundamental voltage, while V_2, $V_3 \ldots V_n$ represent the higher frequency of harmonic voltages.
TDD has the same meaning as THD, the total root-sum-square harmonic current distortion, as a percentage of the maximum demand load current, which can be presented as Equation-2.2,

$$\mathrm{TDD} = \frac{\sqrt{{I_2}^2+{I_3}^2+{I_4}^2+\cdots+{I_n}^2}}{I_L} \tag{2.2}$$

where, I_L is the maximum demand load current, and I_2, $I_3 \ldots I_n$ are the higher frequency harmonic currents.

While considering the 'worst cases' for normal operations, the IEEE has set up various standards of harmonics for different levels of power systems. Table-2.2 is an example of current distortion limits for general sub-transmission systems (69kV~161kV) taken directly from [53]. In this case, based on the effects of each individual harmonic, the IEEE has divided harmonics into different groups: less than 11^{th} harmonics, harmonics orders between 11^{th} and 17^{th}, larger than 35^{th}, etc. The ratio of maximum short-circuit current (I_{SC}) to maximum demand load current (I_L) at the point of common coupling (PCC: the interface between sources and loads on an electrical system), as a percentage of maximum demand load current, suggests different limits of maximum harmonic current distortion and TDD for each group.

Table-2.2 Current Distortion Limits for 69 kV~161kV Systems [53]

Maximum Harmonic Current Distortion in Percent of I_L						
Individual Harmonic Order (Odd Harmonics)						
I_{sc}/I_L	<11	$11 \le h < 17$	$17 \le h < 23$	$23 \le h < 35$	$35 \le h$	TDD
<20*	2.0	1.0	0.75	0.3	0.15	2.5
20<50	3.5	1.75	1.25	0.5	0.25	4.0
50<100	5.0	2.25	2.0	0.75	0.35	6.0
100<1000	6.0	2.75	2.5	1.0	0.5	7.5
>1000	7.5	3.5	3.0	1.25	0.7	10.0

Table-2.3 is another example of the limits regarding voltage distortion suggested by IEEE. They have defined the limits of individual and total voltage distortion according to different voltage levels.

Table-2.3 Voltage Distortion Limits [53]

Bus Voltage at PCC	Individual Voltage Distortion (%)	Total Voltage Distortion THD (%)
69 kV and below	3.0	5.0
69.001 kV through 161 kV	1.5	2.5
161.001 kV and above	1.0	1.5

Any distortion beyond these limits will be treated as ‘unacceptable’ harmonics, and harmful to devices and power systems.

2.3.6 Others

Besides events like short interruptions, voltage sags and transients, and variations such as harmonics, there are many other PQ phenomena in power systems, such as:

Flicker: a PQ variation refers to visual changes in the luminance caused by rapid voltage changes which may include load connection, switching, etc. Flicker mainly affects people rather than equipment as it may be inconvenient and annoying to low voltage level customers.

Long term voltage variation: Any voltage variations lasting longer than 1 minute, or even several seconds according to some standards, will be defined as either overvoltage or undervoltage. These long term voltage variations are not the result of system faults; normally, theses variations are caused by load variations, voltage regulations, etc. They may be problems for some voltage sensitive equipment, such as controlled equipment driven by voltage values.

Unbalance: When the rms values of voltage (or current) or the phase angles are not equal in a three phase system, this phenomenon is called unbalance. Unbalances usually come from unbalanced loads, or large single phase load such as an arc furnace, and lead to issues like increased heat, reduced efficiency, etc.

2.4 Power Quality Cost

2.4.1 Definition of PQ Cost

From the power suppliers' points of view, when considering investments into power quality, it is important to balance the cost of improving power quality to a desired level against the cost of potential losses due to PQ disturbances that could be avoided by upgrading. For power customers, when determining which PQ level is required, it is a priority for customers to understand the amounts of economic losses due to PQ disturbances. For both power providers and customers, the financial damages due to PQ disturbances are key aspects when making financial decisions. These financial damages can be evaluated in term of customers' costs due to PQ disturbance [54] [55]; these costs are called Power Quality Cost. Irrespective of the purpose of PQ cost studies, the meaning of PQ cost itself does not change. It means neither the investment for a certain level of supply quality, nor the amount customers are willing to pay for a required level of supply quality; rather it implies the potential financial losses associated with PQ disturbances.

However, the applications of cost data can vary and can normally, be directly or indirectly related to the following aspects.

- **Regulations**: PQ cost data are used as guidelines for formulating regulation schemes such as penalty schemes under PQ contracts.
- **Policies and Standards**: References for evaluating charges of guaranteed supply quality levels, or determining levels of quality required.
- **Monitoring**: Difference between actual levels and standards
- **Planning**: Justification of investments
- **Operation and Maintenance**: Cost-benefit analysis of PQ improvement, preventive maintenance, etc.

From a socio-economic perspective, as shown in Fig-2.7, the total cost comes from two parts: private customer cost and spill-over cost (cost to others). Both consist of non-momentary and momentary costs, which can be further sub-divided into direct and indirect costs respectively [56].

Direct Costs: Associated with costs occurring directly due to PQ disturbances in a short time period. A typical example could be damaged equipment or loss of production, etc.

Indirect Costs: Costs that not can immediately be seen after PQ disturbances have occurred, and do not have a clear connection with a single PQ disturbance. An example could be higher stock keeping due to inability to maintain industrial processes.

Momentary Costs: can be measured right after power quality disturbances, such as re-start cost, delay or lost deliveries.

Non-momentary Costs: Typically associated with household customers. Costs normally are related to ‘annoyance’ and ‘inconvenience’, which are hard to evaluate as it is impossible to value human feelings; however, they do exist.

Private Customer Costs: Costs directly incurred by customers who experience power quality disturbances. These could be momentary or non-momentary costs.

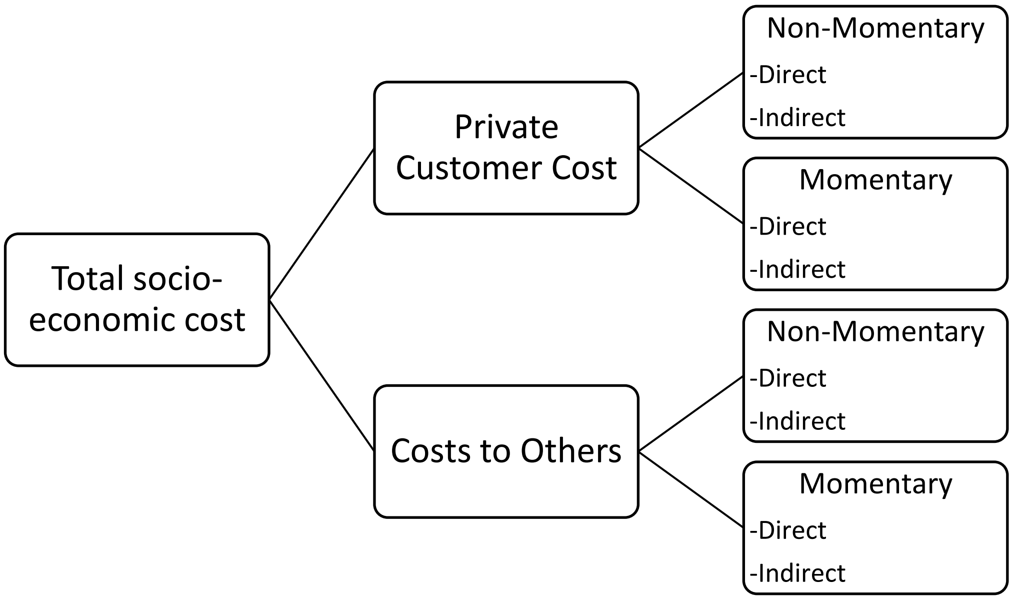


Figure-2.7 Structure of Total Socio-economic Cost

Costs to Others: Spill-over costs to others who are affected by connection to private customers impacted by power quality disturbances. An example could be a client who does not receive a desired product in time due to the manufacturer being impacted by PQ disturbances. However, these costs may become benefits to rivals. Alternatively, rivals could increase their sales when production is reduced due to PQ disturbances.

Total Socio-economic Costs: The sum of the above costs becomes the total socio-economic cost. The total costs reveal the financial impact on the whole of society.

Based on the applications of PQ cost data, most research is concerned with individual financial losses, rather than the total socio-economic analysis. Similarly, in this thesis, the economic losses of individual customers will be mainly discussed. Therefore, the concept of PQ costs here is in relation to private customer economic losses.

2.4.2 Main Aspects of PQ Cost

The total PQ costs of private customers can be derived from many aspects. For industrial and commercial customers, the main PQ cost elements may include direct costs such as [2]:

- **Field service costs**: Undetected disturbances may result in no verifiable faults. To clear these kinds of faults, inspections in the field are required. These inspections are done by extra labourers for fault analysis and clearance. The field service costs may include the cost of parts replacement, cost of labour, etc. Either the equipment manufacturer or customers themselves have to bear the cost of field services.
- **Manufacturing costs**: When certain parts of manufacturing systems are impacted by PQ disturbances, it may cause the whole systems to fail to meet the standard operation requirements. The quality, rates or volume of production will be affected. In order to avoid these, it may be necessary for manufacturers to invest in back-up systems. The cost of back-up systems then becomes part of the PQ costs for manufacturing. Manufacturers with back-up systems will definitely have lower costs per unit service or product loss than those without proper back-up or protection systems.
- **Productivity costs**: Usually refers to costs associated with product activities, such as idle labourers during interruptions, clean-up activities in order to maintain industrial processes, or using alternative resources, which effectively decrease productivity and increase costs.
- **Product damage**: Occasionally, PQ disturbances in industrial processes may result in damaged products. Most of these damaged products can be easily observed, then either discarded or recycled. The number and value of these products are the main factors in determining the total PQ cost.
- **Wasted energy**: Any interruptions in manufacturing processes require restart processes to recover. The energy consumed during these restart processes is wasted energy due to PQ interruptions. Furthermore, in the case of product

damage occurring due to PQ disturbances, the energy consumed for these damaged products is also wasted.

- **Loss of revenue**: For any industrial or commercial customers, most of their revenue comes from production sales. Once the manufacturing processes have been affected by PQ disturbances, which leads to a delay in or interruption of sales, the revenue flow is severely impacted. Generally, the economic losses of revenue are not hard to observe when calculating PQ cost.

In addition to direct costs, there are also indirect costs, such as

- **Decreased equipment life**: Both the detected and un-detected PQ disturbances may result in decreased equipment lifetime in some way. High energy and fast rise time transients may even cause equipment to break down in the short term and cause degradation in the long term. Harmonics are the main sources of equipment life curtailment.
- **Lost opportunity**: The effects of PQ disturbances from a business point of view are not only loss of revenue, but also loss of opportunities. In particular, for companies whose products are cutting edge, the impacted manufacturing or service processes also mean loss of opportunity to sell the products in time.
- **Decreased competiveness**: When PQ disturbances occur in manufacturing processes, they lead to poor production quality and delayed or even missed production delivery for the company affected. Accordingly, this results in customer dissatisfaction and customers may choose to take their business to other companies with similar products, which will certainly decrease the competitiveness of the company affected by PQ disturbances.

For customers whose main concerns after PQ disturbances are ‘inconvenience’, such as households, the PQ costs are considered from the perspectives of both leisure time lost and goods lost [57]. The loss of leisure time is normally evaluated as time of disruption, and the loss of goods is calculated as the value of goods consumed or wasted during PQ disturbances, such as defrosting due to freezers losing power, wood burnt for warmth during cold weather, etc. However, as it is hard to evaluate and collect data for this kind of economic loss, few surveys include customers such as households.

2.4.3 Methods of Accessing Cost Data

Most of the cost estimation studies on PQ disturbances are based on survey data, which are normally provided by customers who have experienced or may experience PQ disturbances. There are several existing approaches for acquiring these data:

1) Direct Worth Method

This is the most common method to estimate momentary cost. By distributed surveys, customers are asked to estimate the direct economic losses due to hypothetical or experienced PQ disturbances. Meanwhile, customers are also required to give specific estimations for several different scenarios. The cost data can be based on either absolute or relative cost [56]. The absolute cost estimation means customers have to state a specific estimation for each of the given scenarios independently. An example of a survey associated with absolute cost may look like that in Table-2.4.

Table-2.4 Absolute Cost Estimation of Direct Worth Method

Assuming an electricity interruption occurs with the following characteristics, what would be the costs for your company? Duration: 1 min Time of day: 10am Day of week: Monday Month: December Warning: No advance warning	
A	Lost production: £
B	Costs for making up production (overtime, etc.): £
C	Costs for delayed delivery (fines, etc.): £
D	Damage to raw materials and finished products: £
E	Damage to equipment: £
Sum of all cost: £	

Accordingly, the relative cost estimation is based on a reference scenario. The customers are given the options for the relative changes depending on the reference scenario. They then have to choose one for each scenario. An example of this is presented in Table-2.5

Table-2.5 Relative Cost Estimation of Direct Worth Method

<table>
<tr><td colspan="10">Assuming an electricity interruption occurs at 1pm on Monday in May without any advance warning, lasting for 1 minute, estimate the cost from the following categories</td></tr>
<tr><td>A</td><td colspan="9">Lost production: £</td></tr>
<tr><td>B</td><td colspan="9">Costs for making up production (overtime, etc.): £</td></tr>
<tr><td>C</td><td colspan="9">Costs for delayed delivery (fines, etc.): £</td></tr>
<tr><td>D</td><td colspan="9">Damage to raw materials and finished products: £</td></tr>
<tr><td>E</td><td colspan="9">Damage to equipment: £</td></tr>
<tr><td colspan="10">Sum of all cost: £</td></tr>
<tr><td colspan="10">If the same interruption occurs at another time rather than 1pm, what would be the relative change of total cost?</td></tr>
<tr><td></td><td colspan="4">Lower Costs</td><td></td><td colspan="4">Higher Costs</td></tr>
<tr><td></td><td>-100%</td><td>-75%</td><td>-50%</td><td>-25%</td><td>0%</td><td>25%</td><td>50%</td><td>75%</td><td>100%</td></tr>
<tr><td>6 am</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>12 am</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>6 pm</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>12 pm</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
</table>

The direct worth method is more suitable for collecting data from commercial and industrial customers, as they understand their economic losses well and the main components of their PQ cost are momentary cost, which can be easily and directly evaluated.

2) Contingent Valuation

In this survey, customers are presented with more detailed hypothetical or experienced PQ disturbance scenarios, and are then asked to make decisions on how much they would be ‘willing to pay’ to avoid this PQ disturbance or be ‘willing to accept' as compensation if they experienced this disturbance. Examples of this method are shown in Table-2.6 and Table-2.7 respectively.

Table-2.6 Example of Willing to Pay

Assuming a reserve power supply is available which could fill the electricity supply gap during interruption, and could only be purchased actually in use, how much would you be willing to pay for this service to maintain power supply? The interruption has the following characteristics: Duration: 1 minute Time of day: 2 pm Day of week: working day Month: February Warning: No advance Warning
Willing to pay for the service: £

Table-2.7 Example of Willing to Accept

Assuming you have been informed of an up-coming interruption (with no time for preventative action), you have the option to either accept the interruption and then receive compensation, or continue to use power without being cut-off, what is minimum compensation you could accept for an interruption with the following characteristics: Duration: 3 minutes Time of day: 12 am Day of week: Weekend Month: February Warning: No advance Warning
Willing to accept as compensation: £

This method may include willingness, which may lead to biased estimation on cost. Moreover 'willing to pay or accept' data are hardly true PQ costs and are only a reflection of customers' willingness. Therefore, in most surveys, this method is only adopted as providing reference data.

3) Conjoint Analysis

Instead of asking amounts of potential or existing economic losses, customers are asked to select the preferred one from pairs of hypothetical scenarios, or alternatively, they are required to rate or rank different hypothetical scenarios. These hypothetical scenarios consist of various attributes. Customers are then presented with these designed scenarios one by one, where the attributes differ slightly in each scenario. In this way, the effects of each attribute could be further examined. Based on customers' choices, the costs are then derived from econometric models. A hypothetical scenario in Conjoint Analysis method may look like that in Table-2.8.

Table-2.8 Example of scenario in Conjoint Analysis

Single Outage: Series A, card 1	
Duration of outage	3 minutes
Time of day	In the afternoon (12 pm till 6 pm)
Day of week	Friday
Season	Summer
Warning	No advance warning
Change in electricity bill	5% discount
Rating mark:	

This is a complex method as many econometric models are required. Normally, this method is used to gather cost data that are inefficient to acquire directly, such as the economic losses of households.

4) Preparatory Action Method

In this method, customers are still offered a list of hypothetical actions which help to reduce the impact of PQ disturbances and each of these actions comes with a given cost. Customers are asked to choose one or more preferred actions. According to their choices, the cost data are then estimated. Possible samples of these actions for households may be as shown in Table-2.9.

The accuracy of this method mainly depends on the design of the action list. A good action list needs to cover a wide range of actions. However, it still has a great chance to miss some important and unexpected actions. Therefore, this method is not generally used in cost estimation. Nevertheless, it could complement other methods well.

Table-2.9 List of Possible Preparatory Actions

List of possible preparatory actions for households during power outage
• Candles used for lighting (£0.5) • Ice to keep food cool in fridge (£2) • Drive to relative or friend's home (£ 10) • Battery backup system for running PCs (£30) • Go to restaurant for one meal (£40)

5) Preventative Cost Method

Unlike the preparatory action method, which focuses on the costs of actions customers are prepared to take, preventative cost method is concerned with the costs of actions which have already occurred, such as back-up systems installed to prevent interruption, as well as paid insurances. The data derived from this method is actually treated as the amount of PQ disturbance costs that customers incur in seeking to prevent disturbance. Questions asked in this method may be as presented in Table-2.10.

Table-2.10 Possible Questions in Preventative Cost Method

What is the investment cost for your backup system: £
What is the operation cost of your backup system: £

Although cost data in this method are easily collected and truly reflect market behaviors (not hypothetical scenarios), it is still difficult to estimate the actual economic losses due to PQ disturbances, since data provided by this method seem to reveal investment cost rather than potential economic losses. However, it is a good reference for other methods, such as contingent valuation.

6) Case Study Method

Generally, the case study method can be performed in two different ways. First, investigations are made into customers who have just experienced PQ disturbances. According to post disturbance analysis, it is possible to derive actual and relatively accurate cost data. This is the most important advantage of this method. However, as these cases have occurred at particular times and in particular regions, they are not necessarily representative of other similar types of PQ disturbance, unless the disturbances themselves are very representative, such as large area blackouts, which happen under extreme conditions.

Another method is to perform intensive analysis on one or more cases in the survey results. These cases are normally typical customers who can represent a large number of customers, or special customers who suffer complex consequences that vary on a case-to-case basis. Based on both realistic and hypothetical scenarios, the cost is then estimated. In fact, the second case study method is commonly recommended by most research groups [3].

2.4.4 The Nature of PQ Cost

Around the world, based on the above methods, various surveys on PQ cost have been initiated by many research institutes. Most of these surveys have focused on interruption, especially long interruption costs, while only a few of them have considered the economic impact of other PQ elements, such as voltage sags, harmonics, etc. However, the results of these surveys do reveal a few characteristics of PQ costs in some way.

1) Customer variation

Surveys on different types of customers have depicted one of the most important characteristics of PQ cost, which is that, for different types of customers, the economic effects of PQ disturbance may vary widely. An obvious example is presented in Fig-2.8.

Fig-2.8 illustrates part of the survey results taken by the Leonardo Power Quality Initiative Team (LPQI) [4]. This is a long-term survey which aims to analyze the financial losses due to PQ disturbances in Europe. The LPQI team has interviewed various types of customers about their PQ economic losses. Then, based on the survey results, the structures of PQ costs for each customer type are shown in Fig-2.8. The y-axis is the percentage of each PQ component, and the x-axis is the type of customer.

Based on this diagram, it can be said that the economic effects of the same PQ disturbance may differ greatly among different customers. For voltage sensitive customers, such as industrial customers and manufacturers, voltage sags may have a great impact on their products. Consequently, the voltage sag cost represents a large part of the total PQ cost, while, for non-industrial customers like design companies, who are much less sensitive to voltage variation, there may be no voltage sag losses.

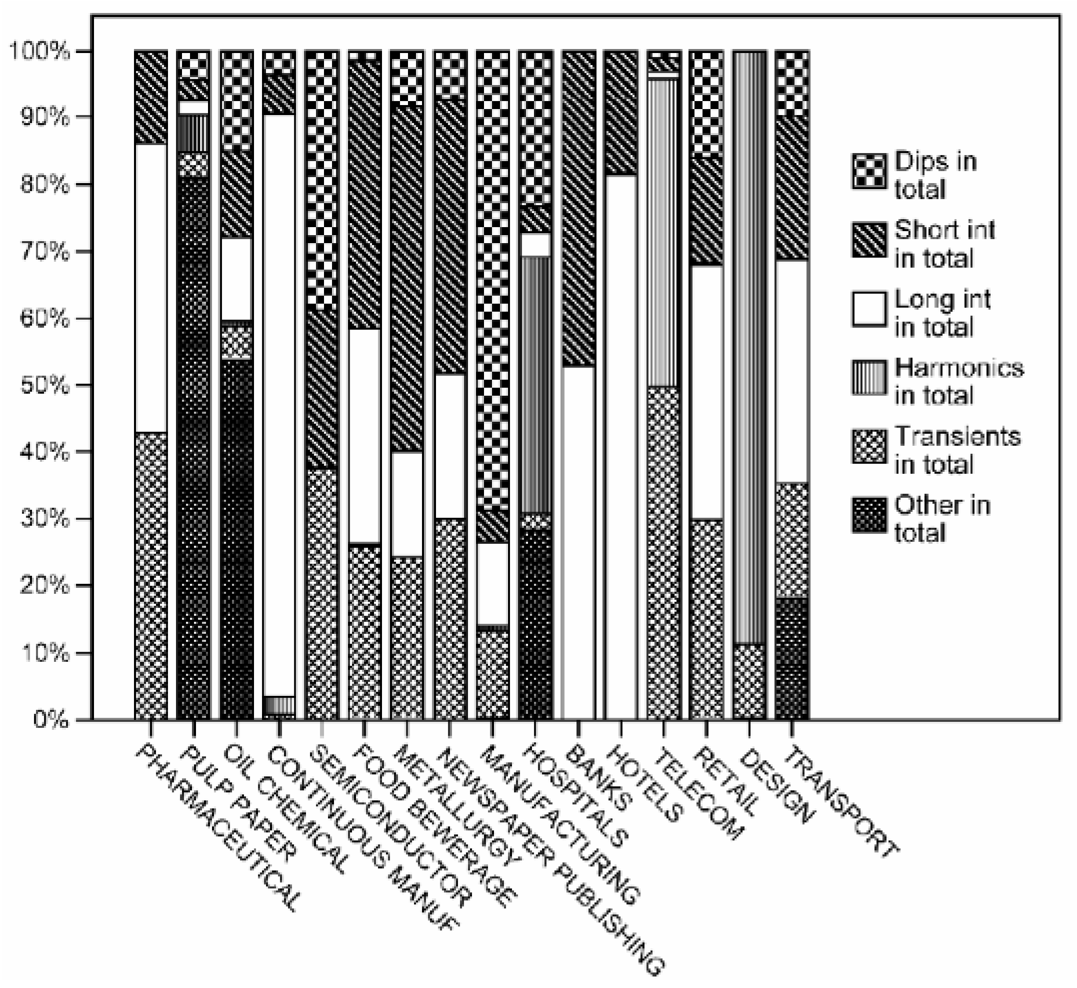


Figure-2.8 Structures of PQ Cost for Different Customers [4]

However, even for two similar manufacturing customers, different industrial processes play different roles in determining the structure of the PQ cost. For continuous manufacturers, who have continuous processes in production, once power interruption has occurred, all the products in the working line will be affected and it will take a long time to recover. Hence, in Fig-2.8, the total PQ cost of continuous manufacturing largely depends on interruptions. In contrast, for non-continuous processes such as manufacturing, where the products can be made intermittently, the interruptions would not be a big issue, whereas voltage sags could be.

2) Time variation

There are two meanings of the term ‘time’ here: disturbance duration and time of occurrence. Both play important roles in estimation of PQ cost. Indeed, research from Lawrence Berkley National Laboratory (LBNL) clearly shows how PQ costs are affected [18]. They have built cost models upon their survey results, and investigated how PQ costs change while varying different attributes. While studying the effects of time on outage cost for large commercial and industrial customers, they have demonstrated the following results (Fig-2.9).

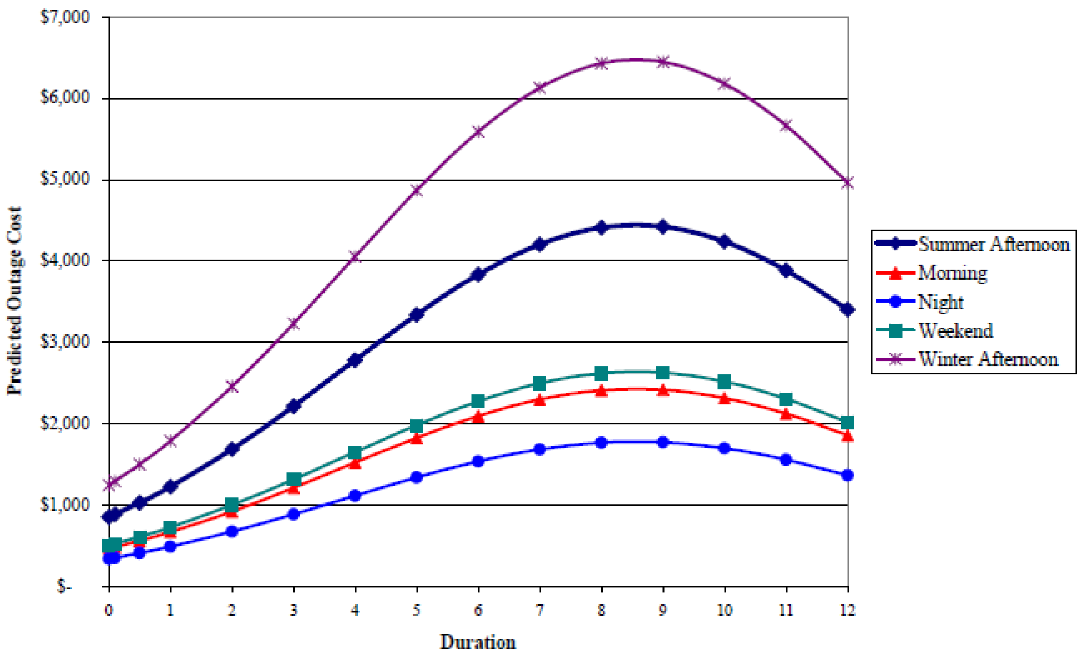


Figure-2.9 Outage Cost Prediction for Large Commercial and Industrial Customers [18]

In their surveys, the LBNL is more interested in long term outages rather than short interruptions. Therefore, the durations are measured in hours. In this model, they suggest that the relationship between outage cost and duration is non-linear. All the curves in Fig-2.9 depict almost the same trends; the outage costs increase slowly in the first few hours and accelerate in the next a couple of hours until they reach a maximum value; thereafter, they begin to decline. This can be explained in terms of the nature of outages and customer reactions. At the beginning of outage events, the economic losses increase slowly as the impact of outages is only limited to within a small ranges of where the outage occurred. At this stage, the economic losses may include some of the direct costs which occur in a short time, such as damaged products, idle labourers, wasted raw materials, etc. However, as the outage duration increases, it has a snowball effect, the impact of the outages grows quickly and leads to more extensive consequences. These consequences may incur costs such as wasted energy, loss of revenue, replacement of damaged equipment etc. In addition to some costs incurred in the first stage, the costs increase much faster. When a longer outage duration occurs, customers may begin to take action to avoid further economic losses, such as sending employees home, and if outages extend for a long time, most productive activities may need to be stopped. Therefore, the costs start to decrease at this point. This non-linear relationship can be applied to all kinds of customers, not only industrial and commercial customers.

However, the different curves in Fig-2.9 also indicate the effects of time of occurrence. Firstly, according to different times of occurrence, the predicted outage costs are classified as outages occurring in the morning, afternoon, or night during working days, and a special curve represents the cost variation during the weekend. The curves show that the outages during the afternoon cause the highest economic loss compared to the other four. This is a result of the busy working schedule of most industrial and commercial customers during the afternoon. Outages during the weekend lead to higher losses than outages during the morning or night because of the overtime working schedule of some industrial and commercial customers during the weekend. Furthermore, most electricity consumers shut down during the night until the late morning. Seasonal factors also need to be considered. Comparing outages during winter afternoons with those during summer afternoons, it can be concluded that the economic losses due to outages in winter are larger than those of summer.

This makes sense as more energy is required for warmth during winter. The effects of time of occurrence are more remarkable among industrial and commercial customers, who have specific time schedules.

3) Consumption variation

A report from the Electric Power Research Institute (EPRI) in 2001 describes another interesting characteristic of PQ cost [58]. Based on surveys of U.S. businesses, the EPRI states that, besides customer types and time, the PQ cost is also associated with another customer characteristic: annual consumption. Fig-2.10 indicates this relationship.

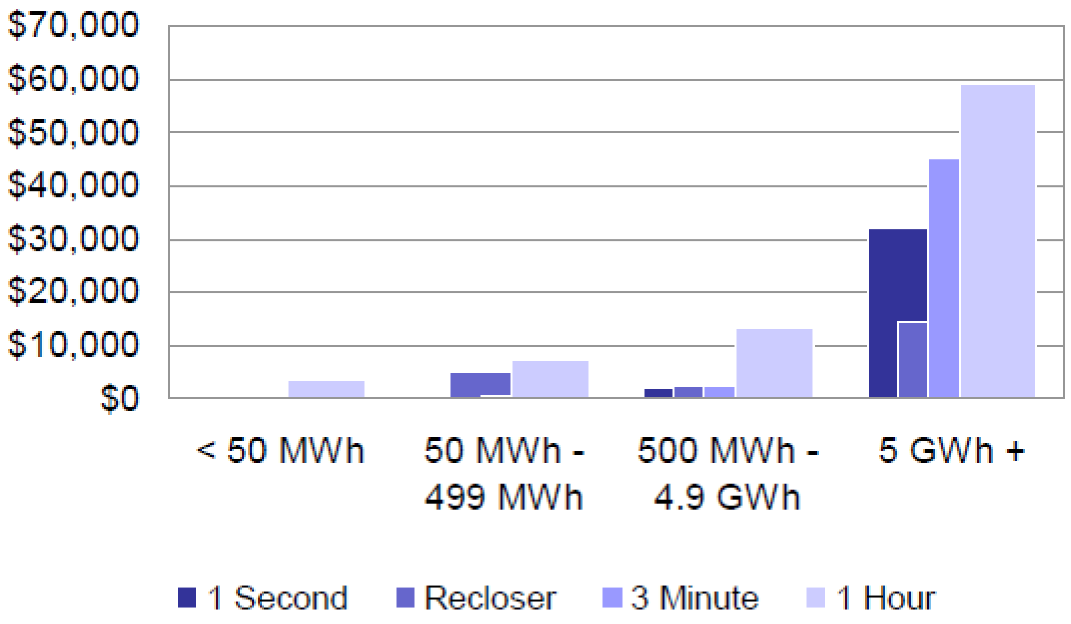


Figure-2.10 Average Cost per Outage by Annual kWh Consumption [58]

Firstly, considering the effects of different durations, the EPRI divided outage events into four groups, which are 1 Second, Re-closer, 3 Minute and 1 Hour in order of duration. Re-closer refers to several seconds but less than 1 minute. Then they break the average outage cost data into different groups according to the consumption of customers, rather than types of customer. Clearly, the patterns in Fig-2.10 show how consumption affects PQ cost. In terms of consumption, larger scales of businesses will suffer greater economic losses due to PQ disturbances. This makes sense when considering that greater power consumption is required to make a larger number of products. Normally, a larger number of products indicates the necessity for more raw materials, and in this case, once PQ disturbances occur, more materials will be wasted. In addition, due to the fact that the production costs of most large consumption customers are greater than those of small ones, the economic losses of large consumption customers are greater than small consumption customers.

4) Others

In addition to the above, PQ cost may also depend on other factors, such as in competitive markets, where losses to one participant mean opportunities for others. Hence, the effects of competitors may also need to be considered under competitive markets.

2.5 Summary

2.5.1 Involved Components of PQ Cost

Generally speaking, the studies on PQ cost mentioned above are mainly concerned with the economic losses of customers rather than energy suppliers. Hence, similarly, the PQ cost in this thesis is investigated from the customers' point of view, and could be interpreted into the following main components,

1) Interruption Cost

The interruption costs are the financial losses caused by either short or long interruptions. Unlike other PQ disturbances, interruptions require restart processes, which may cause extra economic losses. Therefore, besides the general direct and indirect costs mentioned above, interruption costs also consist of restart costs [59]. The direct costs of interruptions may include the cost of wasted raw material, loss of energy, idle labour, etc. The restart costs normally refer to the financial losses during the recovery period, which may include costs due to replacement or repair of damaged equipment, labour, extra working time payments, cost of energy wasted etc. Moreover, the indirect costs of interruptions are usually the results of loss of opportunities and competitiveness.

Though the long interruption is a kind of PQ phenomenon, in the terms of financial losses, most studies prefer to classify long interruption cost as part of security costs rather than PQ costs due to the fact that long interruptions mostly originate from the power supplier sector. As this research is concerned with short term PQ cost variation, the interruption cost here is actually only concerned with short interruption cost.

2) Voltage Sag Cost

The voltage sag cost is associated with economic losses due to voltage sags. The financial components of voltage sags are almost the same as short interruption costs except that most voltage sags may not require restart processes, i.e. no restart costs. In addition, as the economic losses of voltage sags are normally a proportion of short interruption costs, the voltage sag costs are actually estimated based on the economic losses of short interruptions with the same duration. However, voltage sag costs also depend on the magnitude of voltage sags rather than duration. This is the reason most voltage sag costs are calculated in different groups of magnitude.

3) Harmonic Cost

Harmonic cost is the financial losses caused by harmonic distortions. Due to the effects of harmonics, harmonic costs come from two sources, energy loss costs and aging costs. The energy loss costs are calculated according to the differences between the fundamental energy absorbed from the network and the total energy consumed by customers, whereas the aging costs are normally the long term economic losses which involve incremental investment costs.

As for the cost of other PQ events such as transients, these occur in such a short time that it is almost impossible to investigate the variation of cost. Other PQ variation costs such as flickers are normally associated with the values of human activities. It is hard to evaluate precise data of activity economic losses. Furthermore, the economic losses caused by other PQ phenomena such as unbalances, long term voltage variations, etc. are small enough to be excluded from total PQ costs.

2.5.2 Classification of Customers

As mentioned in the previous section, the components of PQ cost may vary among different types of customers. However, according to similar economic effects, various customers could be generally classified into the following categories:

- Non-continuous Process Industry

In this category, these non-continuous industries may refer to both heavy and light industries and manufacturing, of which industrial processes could be dispersed. These special industrial processes make it possible to introduce a short pause without additional economic losses due to PQ disturbances. Therefore, compared with momentary interruptions, temporary interruptions are more important to non-continuous industries. Examples could be manufacturing (general, machinery, automotive parts, etc.), food and beverage production, etc. The major components of PQ cost for non-continuous industries in this thesis may include temporary short interruption and voltage sag cost.

- Continuous Process Industry

In contrast to the previous category, continuous industrial processes are more vulnerable to PQ disturbances. As these processes are usually long term, lasting hours or even days, and operating parameters have strict tolerances, any interruption or variation from the steady state conditions may result in defective products. Another possible drawback, particularly for chemical processes where manufacturing flows may be stopped or interrupted in mid-cycle, is the fact that a complete system ‘clean-up’ is necessary before the process can be continued. These consequences can be very costly. For continuous process industries, even a momentary disturbance may have the same economic effect as disturbances of longer duration. That is why momentary interruptions need additional attention for industries like these. Classic examples may include metallurgy, semiconductors, etc. PQ costs of continuous process industries in this thesis mainly consist of momentary short interruptions and voltage sag costs.

- Commercial and Public Business

In modern commercial and public business, data processing and communications are the core elements and are essential to a successful commercial business. Customers in this category usually include banks, transport, hospitals, telecoms, etc. Many of them rely on nation-wide links for sharing information and distribution; any interruptions that cause downtime in such systems result in minutes or hours of business lost. Hence, these business sectors normally implement back-up systems to prevent losses during interruptions. Consequently, interruptions have much less effect on these business sectors; instead, voltage sags and harmonic costs become the main economic losses in respect of PQ.

- Domestic users

Household PQ problems are usually flickers and short interruptions, like VCR flashing or loss of heating during cold weather. It is extremely hard to calculate the cost of human activities due to loss of power supply, in addition to the fact that short interruptions have very little financial impact on households. As a result, in this thesis, domestic PQ cost will not be discussed.

2.5.3 Conclusions

As a conclusion, the PQ cost study is a complex financial losses analysis, due to the fact that the cost itself depends on various factors, as well as the methods of accessing data available. In terms of components, all in all, the total PQ costs in this thesis come from three main aspects: short interruption costs, voltage sag costs and harmonic costs. These three may not necessarily occur at the same time; the total PQ costs are not simply the sum of these three costs. Instead, they depend on the types of disturbance. On some occasions, harmonic costs may even be found when equipment functions well under acceptable levels.

From the customer types point of view, the PQ costs need to be investigated separately according to different types, i.e. non-continuous and continuous process industrial customers, commercial and public service customers and domestic customers. In this thesis, due to the main components of their PQ cost, industrial and commercial customers will be mainly discussed.

As for time factors, many surveys have proved that the relationship between duration and PQ cost is non-linear, as well as the fact that the PQ cost depends on the time of occurrence. The effects of both duration and time of occurrence are considered in the cost models in the following chapters.

In addition to the above factors, the consumption of customers and market elements will also be discussed in cost models.

Chapter 3 Short Interruption Cost Model

3.1 Introduction

As a part of PQ cost, costs associated with short interruptions are the most common and expensive economic losses for most customers. During the last 20 years, suppliers and researchers have shown increasing interest in interruption costs [5] [60] [10]. However, with the number of long term interruptions limited by improvements in control and protection systems, they have begun to realize the importance and value of collecting and analyzing short interruption costs. Meanwhile, the raw cost data obtained by any of the survey approaches mentioned in the previous chapter are only straightforward reflections of economic losses in particular scenarios for customers who experienced them or were surveyed. In order to represent other customers in the same sectors and provide predictions for further similar PQ disturbances, ‘interpreters’ are required to transfer the raw data into usable and normalized cost data. The ‘interpreters’ in PQ cost contexts are referred to as ‘cost models’.

The continuous investigations into the momentary financial impacts of power interruptions have derived diverse short interruption cost models, ranging from duration dependent dispersed simple unit cost to continuous distributed cost considering multiple impact factors. Though most of these models take duration into account, few of them have considered the effects of the time of occurrence, not to mention customer characteristics such as consumption and competition factors.

Therefore, further developments are needed to address the short interruption cost models while considering two main aspects, time and customer characteristics, at the same time. ‘Time’ is interpreted as disturbance duration and time of occurrence, while ‘customer characteristics’ refers to customer types, customer consumption and competition factors.

In this chapter, a developed short interruption cost model considering interruption duration and customer characters is introduced. However, the impact of time of occurrence will be added to this model in a later chapter. Together, it is possible to predict short interruption cost according to various impact factors in different scenarios. An overview of existing interruption cost models will be given in Section 3.2, after which a regression model is introduced as the basic theory for the new short interruption cost model in Section 3.3 Section 3.4 discusses how this regression model has already been used in cost models and how to make improvements. Through case studies in Section 3.5, how the new cost model works is demonstrated. Thereafter, summaries and discussions are concluded in the last section.

3.2 Existing Models for Interruption Cost

The purpose of interruption cost models is to predict potential financial losses for a random interruption event, which may require further cost-benefit analysis. For years, interruption costs have been studied from different angles. Irrespective of whether the interruptions are short or lone, they share the same interruption cost model as long as they possess the same dependent factors. Many diverse attempts have been made to model interruption costs according to different dependent factors, and the general models are summarized in the following sections.

3.2.1 Energy Dependent Model

Ever since cost models were introduced into electric power analysis, the energy dependent model has been used to describe the relationship between cost and energy. As one of the earliest and simplest models, it has appeared in much literature from the time it was introduced till now [5-8]. Normally, from surveys, interruption cost data are reported as specific costs associated with specified energy aspects such as energy not supplied, peak load, annual consumption, etc. Based on these specific cost data, the average cost of energy not supplied is derived and presented as £/kWh upon representative discrete time. This is called data normalization, which is to make data usable and more comparable for various scenarios. This expression is the earliest energy dependent model [60]. An improved expression of this model is believed to be a more accurate description [6]. For long term interruptions, as in the old model, energy not supplied in kWh is used as unit, while for short term interruptions, interrupted power in kW is preferred. A paper regarding a Norwegian interruption cost survey is a good example of this improved model, the results of which are listed in Table-3.1 [6].

Table-3.1 Norwegian Customer Interruption Cost [6]

Interruption Duration	1 Min. NOK/kW	1 Hr. NOK/kWh	4 Hrs. NOK/kWh	24 Hrs. NOK/kWh
Industry	38.4	123.0	107.3	65.3
Commercial	34.6	201.5	166.5	98.9
Large ind.	8.2	23.8	20.7	7.4
Public	1.4	19.9	25.6	15.3
Agriculture	4.5	16.6	13.8	12.3
Residential	-	11.5	12.7	11.1

As shown in Table-3.1, though the model does show the non-linear relationship between interruption cost and duration, the energy dependent model has an obvious and critical drawback. The costs are approximate and based on average value, which is represented according to cross-sectional time, such as 1 minute, 1 hour, 4 hours and 24 hours respectively in Table-3.1. These data only indicate the average cost in the given period; e.g. for the industry customer, the average cost for a 1 minute interruption is 38.4 NOK per kW. For interruptions with durations not given, such as 20 minutes or 2 hours in Table-3.1, the costs are unknown. Hence, the energy dependent models are limited by discrete estimation on duration, as well as disregarding any other impact factors, such as time of occurrence, etc. However, despite this approach is a single element dependent cost model, this is a simple and visual representation of interruption cost data.

3.2.2 Duration Dependent Model

From the customers' points of view, compared with energy not received or load disconnected during interruptions and associated costs, they are more interested in economic losses associated with disrupted activities due to interruptions [60]. Duration is the main measuring pole regarding disrupted activities. These interests have contributed to the formulation of Customer Damage Function (CDF) [9]. In CDF, the interruption costs are described as a function of duration. This is an improvement on the energy dependent model, which enables continuous cost estimation on duration. The principle of CDF formulation is rather simple: based on duration discrete average cost data from surveys, the approximate cost data for intermediate durations missing from surveys is estimated by linear interpolation. Normally, this model appears in research that is concerned with the effect of duration [6] [10-12].

According to [61], there are two ways to formulate CDF distinguished by data normalization: the average process and the aggregating process. The average process begins with data normalizing, whereby the raw data of customer cost from surveys are transformed into normalized cost data; thereafter the average values of normalized cost are derived to formulate CDF for each customer sector. In the aggregating process, summarizing the cost of customers for each sector occurs in the first place. Then the summarized costs are normalized by the sum of normalizing factors such as energy not supplied, interrupted power etc. In this way, the cost data are then transformed into average normalized cost. Based on these results, the CDFs for each customer sector are then derived. However, studies show that the two different procedures will not provide the same CDFs [62].

An advanced CDF may be used to represent the total interruption costs of a region or service area consisting of different customer sectors; this advanced function is called Composite Customer Damage Function (CCDF) [9] [10] [63] [65]. All the customer sectors within the same region or service area are summed together according to various multipliers to form the CCDF, where the individual CDFs of each customer sector are featured by the multipliers. A classical CCDF expression is presented as Equation-3.1:

$$\mathrm{CCDF} = \sum CDF_i * w_i \tag{3.1}$$

where the CDF_i is the customer damage function of individual customer sector i, and w_i is the associated multiplier of each customer sector; normally, these multipliers are weighted by the customer sector's fraction of total annual consumption in its region. Unlike the CDF, the CCDF is concerned with the total interruption cost of a region or service area, it is a system dependent function rather than customer dependent.

A typical Customer Damage Function can be shown as Table-3.2 [11].

Table-3.2 Norwegian Customer Damage Function (NOK/kW) [11]

Sector	**Cost function (r durations)**	
	r = 0-4 hours	r> 4 hours
Industry	55.6 r + 17	18.4 r +166
Commercial	97.5 r + 20	33.1 r + 280
Public	14.6 r + 1	4.1 r + 44
Large Industry	7.7 r + 6	3.1 r + 23

Still the results in Table-3.2 are derived from Norwegian power quality surveys taken from 2001-2003. The linear CDFs of different customer sectors have been divided into two sections based on duration of interruptions, less than 4 hours and longer than 4 hours. Each section has its own expression. Obviously, these functions possess the possibility of continuous cost estimation via duration. In these models, interruption costs are estimated under the assumption that interruption cost varies linearly with event duration. If studies are concerned with the tendency of interruption cost via duration, rather than actual cost variation, then this linear relationship assumption is acceptable. However, the fact is that many surveys suggest the variation of interruption cost is not constant over time. It varies with different times of occurrence and load characteristics for the same interrupted period [18] [64]. Hence, although the duration dependent model is capable of providing continuous cost estimation on duration, the estimated values of cost according to the inserted durations are biased and not applicable.

3.2.3 Probability Distribution Model

Many studies on interruption cost surveys indicate that the distributions of surveyed interruption costs for each customer sector are not normally distributed, but are very 'skewed' [66] [67]. A classic example of this kind of 'skewed' distribution is shown in Fig-3.1 [6] [66].

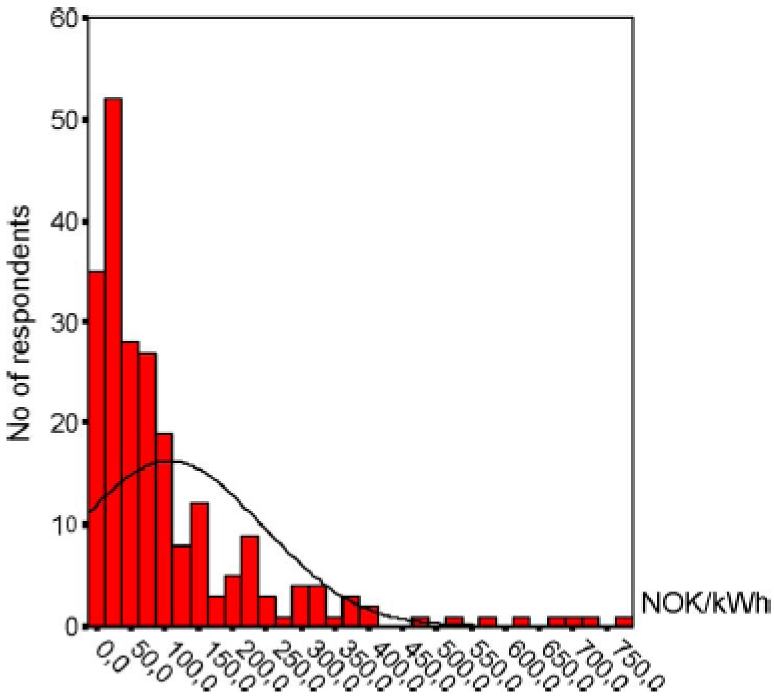


Figure-3.1 Example of Distribution of Normalized Interruption Cost for 4h Duration for Industrial sector [6] [66]

It can be seen in Fig-3.1 that the x-axis is the normalized interruption cost from surveys for 4 hours in duration in NOK/kWh, while the y-axis is the number of respondents in the surveys, which means how many times the normalized costs within given ranges are returned from surveys. Due to the relatively high number of respondents to surveys, the normalized interruption cost data are centralized around 100 NOK/kWh, which will be mainly used as the basic data to formulate cost models. Obviously, due to lack of consideration of higher values, for the cost models that use average values derived from skewed distribution raw cost data, such as the duration dependent model, the interruption costs are believed to be underestimated [13] [68] [69].

In this case, many probability distribution approaches have been developed to compensate for the biased estimation. The most representative probability distribution model is introduced in [13]. The process of surveyed duration is simple as the probability distribution of original cost data can be derived from non-zero data, while for the intermediate durations not covered by surveys, this is not the case. Therefore, the model introduced by [13] firstly transforms the raw surveyed cost data into normal probability distribution. Then, based on these normal probability distributions, the distribution parameters are interpolated at the intermediate duration by regression analysis. In the end, the estimated interruption costs for intermediate durations are obtained after inversed transformations with the interpolated parameters.

Utilizing the regression analysis and the probability distribution does lessen the effects of lack of response in surveys and thus improves the accuracy of interruption cost estimation. However, this probability distribution model is still not capable of providing analysis of other impact factors apart from duration.

3.2.4 Frequency Dependent Model

A further use for the cost models mentioned above is to investigate the long term cost, such as annual cost, with a frequency dependent model. Frequency here means the number of interruptions. The theoretical basis of the frequency dependent model is extremely straightforward and simple [70-72]. Unlike the probability dependent model, the frequency dependent model is concerned with the number of interruption events rather than responses to surveys. The total annual interruption cost of customer sector *C* for example, is represented in Equation-3.2:

$$\mathrm{C} = \sum C_i(t) * P_i * f_i \tag{3.2}$$

where, i represents the type of interruption, which may be classified according to duration in this case, $C_i(t)$ is the interruption cost per kW for duration t, P_i is the load impacted by interruption, and f_i is the average number of type *i* interruption events per year based on historical data. According to this equation, the total customer annual interruption cost is expressed as a function of interruption frequency and the cost estimation will rely on experienced reliability levels; if the interruption frequency rises above the historical level, the annual cost will increase accordingly.

The frequency dependent model offers an overview of long term cost estimation. However, as argued in [70], in a system with reasonable reliability, the interruption cost may be assumed to be independent of interruption frequency with a predefined frequency of once a month. Obviously, this model only works for long term cost estimation; for short term interruption cost, which is mainly concerned with prediction of events which have already occurred, this is not the case.

3.2.5 Time of Occurrence Dependent Model

With the development of cost models, researchers have begun to realize the importance of time variation in cost models. Therefore, several published works have devised improved cost models that take time of occurrence into account [14-17]. There are two approaches to introduce time of occurrence factors into cost models.

In the first approach [14] [15], the consideration of time of occurrence starts from the survey phases. Customers are specifically asked to estimate the degree of financial damage in terms of variations associated with hourly, daily, or monthly values based on their reference interruption costs stated. Then, based on these time varying values, the maximum damage level of interruptions in relation to observed time of occurrence is then set as the reference cost weight factor. Thereafter, the ratios of interruption costs at time *i* on the interruption costs associated with the maximum damage level are derived; these are called ‘cost weight factors’ and are expressed in Equation-3.3

$$WF_i = \frac{Interruption\ Cost\ at\ time\ i}{Maximum\ Interruption\ Costs} \tag{3.3}$$

where, WF_i equals 1 when interruptions are investigated at the time of maximum damage level. Therefore, knowing the cost weight factor WF_i at time i, and the average interruption cost, the actual time varying interruption cost at time i for a period of t could be predicted according to Equation-3.4.

$$Actual\ Interruption\ Cost\ at\ time\ i = C(t) * WF_i \tag{3.4}$$

where, $C(t)$ is the interruption cost for duration t.

The other approach is taken from the failure rate's point of view [16] [17]. According to historical data, the effects of time of occurrence could be represented by time varying failure rate, which is shown as Equation-3.5,

$$\lambda_{h,d,m} = \frac{\lambda_h}{\lambda_{av}} * \frac{\lambda_d}{\lambda_{av}} * \frac{\lambda_m}{\lambda_{av}} \tag{3.5}$$

where, $\lambda_h, \lambda_d, \lambda_m$ is the number of failures occurring at a particular hour, on a particular day and in a particular month respectively, and λ_{av} is the average annual failures. Then, the total expected annual interruption cost in terms of particular time can be estimated in Equation 3.6.

$$C_{h,d,m} = \sum C_{h,d,m}(t) * P_{h,d,m} * t_{h,d,m} * \lambda_{h,d,m} \tag{3.6}$$

where, $C_{h,d,m}(t)$ is the interruption cost for duration t, $P_{h,d,m}$ is the loss of load due to interruption, $t_{h,d,m}$ is the expected duration.

Obviously, the first approach is practicable for both short and long term analysis, while the second approach appears to be more suitable to long term analysis. For the short term, although the first time of occurrence dependent cost model provides reasonable cost estimations, it relies on customer estimation of time variation instead of realistic time varying data. Correspondingly, estimation biases may arise due to customer mis-estimation, as well as from the fact that a large amount of data needs to be collected and transformed.

3.2.6 Summary and Discussion

All the cost models mentioned above can be summarized in Table-3.3

Table-3.3 Summary of Interruption Cost Models

Model	Descriptions	Advantages	Disadvantages
Energy Dependent Model	- One of the first interruption cost models - Represented as £/kWh or £/kW	Simple and direct measurement	Does not consider the other impact factors
Duration Dependent Model	- Formulate CDFs as a function of interruption duration - Based on average cost data, estimates the cost for intermediate durations.	Continuous distribution of cost while varying duration	- Ignores the effect of time of occurrence - Cannot reflect the dispersed nature of interruption cost
Probability Dependent Model	- For surveyed durations, probability distribution could be approximated - For non-survey duration, data are estimated according to regression analysis	- Captures the dispersed nature of interruption cost -provides more precise estimation	Still does not consider time of occurrence
Frequency Dependent Model	- Based on historical data, the mean values of frequency of interruptions are calculated - Together with average cost per interruption to predict cost	Easy to understand	- Roughly estimated - Cost may be assumed to be independent of frequency - Long term estimation
Time of Occurrence Dependent Model	- Time-varying cost weight factors are estimated based on specified customers surveys or failure rate - Multiplied by customer damage function	The impact of time of occurrence on interruption cost is considered	- Needs additional information in surveys - Requires large amount of collected data - Long term estimation

As the purpose of this research is to propose an interruption cost model for analysis of economic losses variation with multiple factors in the short term, though some of the models mentioned above are suitable for short term analysis, none of them is capable of considering the multiple impact factors, such as customer characteristics and duration of short interruption at the same time. Hence, a different cost model is required to investigate the various effects on short interruption cost.

3.3 Tobit Regression Model

3.3.1 Linear Regression Model

The major purpose of most statistical analysis is to predict one or more variables in terms of associated impact factors. Therefore, there are studies on prediction of salary in terms of personal specialties such as education, gender, occupation, etc., potential sales of a new product in terms of its price and advertising on TV, child's height in terms of parents' heights, and so on. In terms of statistical expression, these relationships can be included into different statistical models represented as equations. Back in the 19^{th} century, the term 'regression' was first used by Francis Galton to describe these kinds of statistical models. Thereafter, the regression models are termed as the statistical relationship between predicted variables and their associated factors [73].

There are two types of regression models: the single element regression model and multiple elements regression model.

1) Single element regression model

   This is a basic regression model to investigate the relationship between two variables, y and x, both representing some interested populations. To explain y in terms of x, a simple linear model is used as Equation-3.7 shows:

$$y = \beta_0 + \beta_1 x + \mu \tag{3.7}$$

   where, y is the dependent variable (explained variable) and x is named as the independent variable (explanatory variable), while β is the regression coefficients representing how y varies with x. μ is called the error term, representing factors other than x that also affect y. Due to the expression of the single element regression model, it is also known as a simple linear regression model.

A classic example illustrates how a simple linear regression model works. Assuming an employee's income from a company is investigated according to their educations, which measured by years of study, a small group of data are gathered and plotted in Fig-3.2, and each point indicates an individual sample, where the I-axis represents the individual's income in £/year, and the E-axis represents the related education years.

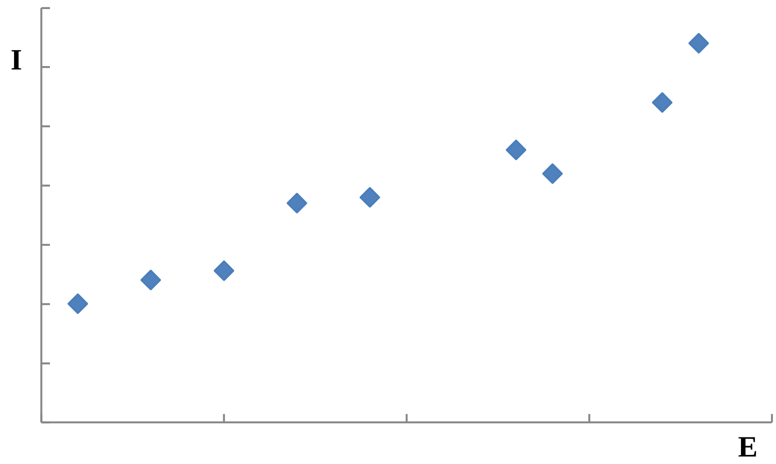


Figure-3.2 Incomes with associated Educations

Fig-3.2 suggests that the higher value of E (education) will yield higher I (income); furthermore, the best guess of this relationship appears to be linear, which means each additional year of study will add approximately the same amount of income. Hence, the most suitable estimated model is a simple linear regression model, which can be written according to Equation-3.7

$$I = \beta_0 + \beta_1 E + \mu \tag{3.8}$$

In Equation-3.8, E and I are already known from the data set; the coefficients β_0, β_1 and error term μ are unknown data, which need to be derived from the regression process. The β_0 is the 'intercept' term, which refers to the income of an employee without education. The β_1 represents how the income changes when education varies. To better understand how the regression process works, by ignoring error term μ, the equation $I = \beta_0 + \beta_1 E$ is actually an expression of a line with an 'intercept' of β_0 on the vertical axis and a 'slope' of β_1. This highlights the purpose of regression: to find where the line expressed as $I = \beta_0 + \beta_1 E$ is, i.e. the values of β_0 and β_1. To approximate the relationship between E and I, there might be several linear equations available depending on the values of the error term μ, meaning the locations of these lines depend on μ. The error term in the diagram is defined as the vertical distance from the original income in dataset to the derived incomes along the line $I = \beta_0 + \beta_1 E$, which can be illustrated in Fig-3.3. In order to locate the most precise line, compared with other lines, the mean values of error term in this line should be smallest and approach zero. To assure the smallest mean values of error terms, the regression process minimizes the value of summation of squared errors. This minimizing regression process is named Ordinary Least Squares (OLS) [74, 75].

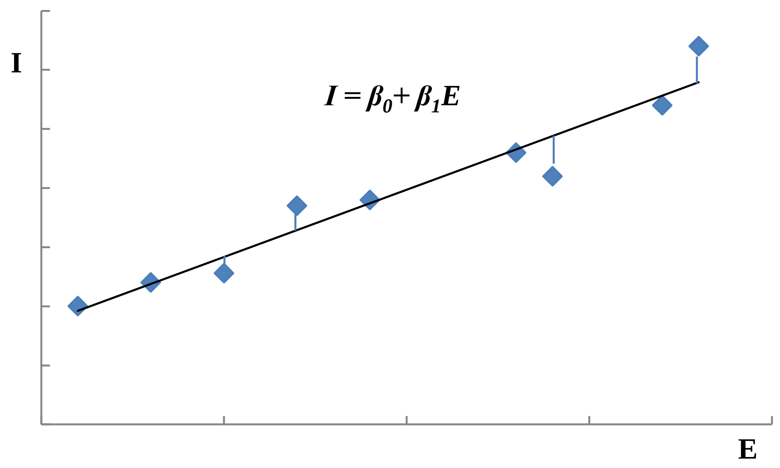


Figure-3.3 Meanings of Error Terms

2) Multiple elements regression model

In many cases, the observed objective is hardly affected by only one element. Normally, it depends on multiple elements. A simple linear regression model is not capable of quantifying the effects of multiple elements anymore. Correspondingly, the multiple elements regression model is introduced. It enables additional factors to be estimated in analysis and provides a better model for predicting observed dependent variables. To illustrate this, income is again used as an example. However, this time, an additional factor, experience, is considered in the regression model. Therefore, the multiple elements regression model becomes:

$$I = \beta_0 + \beta_1 E + \beta_2 X + \mu \tag{3.9}$$

where, X represents experience in terms of years of work. The β_0 is the income of individuals with no education or experience. The β_1 indicates the effect of education on income when experience is a constant. Similarly, the β_2 reflects the impact of experience on incomes when holding education constant.

In the context of theory, the purpose of estimating coefficient β_i in a multiple elements regression model is the same as that of the simple linear regression model. However, instead of looking for a line in a two-dimensional diagram, for models like Equation-3.9, the multiple elements regression model seeks a proper plane so that the sum of squared errors is minimized in a three-dimensional diagram with an additional X-axis. In this case, the error term μ becomes the vertical distance between original incomes I and the estimated plane. The intercept of this plane on the I-axis is the value of β_0, and the slope in the E-axis indicates the β_1; accordingly, the slope in the X-axis represents the β_2.

The more independent variables observed, and the more dimensions involved, the more complex the shape of the desired figure (such as lines, planes, hyper-plane, etc.) will be. Normally, the equation of a multiple elements regression model can be written as:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \mu \tag{3.10}$$

The multiple elements regression model is capable of dealing with a large number of independent variables. Essentially, this model is still a linear regression model.

Both models are written in the form of linear equations. The linear expression is chosen, even without knowing the relationship between dependent variables and independent variables, because the ‘linear’ regression here has a different meaning than usual. As mentioned in [75], the key is that the regression models are linear in the coefficients β_i rather than the usual relationship between y and x. Therefore, in a multiple elements regression model, there may be expressions such as $y = \beta_0 + \beta_1 x_1 + \beta_2 x_2^2$. Normally, when there are clear relationships between observed dependent variable y and parameters β_i, the linear regression models are the most suitable. Besides the definition of 'linear', there are other reasons that a linear regression equation is of special interest:

a) Linear equations are the most basic and simplest mathematical tools. Their statistical properties are better known than others; they will provide more convenience for further mathematical treatment.
b) Except in complicated regression models, linear regression equations are able to suggest good approximations of most realistic data variations.

Normally, in the context of economic analysis, optimizing analysis behaviors exclude some values when they are below or above given thresholds. In many cases, the excluded values are expressed as certain constant values. In addition, in some surveys, the results may also return as zero. For instance, for a given period, families' spends on alcohol are surveyed. However, some families may not buy alcohol at all. As a result, the survey results may contain data distributed over a wide range of positive values, but include piled up zeros as well. Such a dataset will be treated as limited response data. To make a prediction on limited data, as claimed in [76], both the probability of limited response and the size of non-limited response need to be considered. Obviously, the normal linear regression model does not possess the capability of considering probability and size. Utilizing the normal linear model for limited dataset prediction provides a great chance to have either negative or positive deviations on expected values, which may lead to biased predicted data. For data such as families' spending on alcohol, it is definitely not possible to have negative values. Therefore, the Tobit regression model becomes the perfect tool to deal with limited data like these [75].

3.3.2 Tobit Regression Model

Such limited data as mentioned above are called ‘Censoring’. The censoring occurs when the +values of observation variables are only partially known or available, while for the unavailable or unknown observation variables, the values of associated variables still exist [77, 78]. Surveys on employees’ incomes are an example; for many reasons, certain high income employees may not be willing to share their income information. Despite unknown incomes, their other information such as education background, gender, etc. are still part of any surveys. Therefore, this kind of survey results lead to censoring data. The regression models applied to deal with censoring data are called ‘censored regression models’. However, as the previous example of spending on alcohol shows, for some families, their spending on alcohol is zero. For this reason, while the raw data of dependent variables (i.e. spending on alcohol) are continuously distributed over positive values, there are also pile-up zero values. This is a special case of censoring data and regression models applied to a dataset like this are called ‘corner solution models’. As one of these models, the Tobit regression model is proposed especially to deal with this zero containing dataset [75].

The Tobit model was first proposed by James Tobin [76], and mainly used in economics and statistical analysis. As a mathematical model, it demonstrates how the impact factors (expressed as independent variables x_i) affect the observed value (represented as non-negative dependent variable y). The dependent variable y of this model continuously covers strictly positive values with several zeros as well. Apart from the dependent variable, there is a latent variable y^* representing all the positive values. Due to the absence of zero, the latent variable y^* possesses the same contents as non-censoring dependent variables in classical linear regression models, and can be represented as a normal linear regression model as well. Therefore, the Tobit model can be written as:

$$y^* = \beta_0 + \boldsymbol{x\beta} + u, u|x \sim Normal(0, \sigma^2) \tag{3.11}$$

$$y = \begin{cases} y^* & if\ y^* > 0 \\ 0 & if\ y^* \leq 0 \end{cases}$$

where

$$\boldsymbol{x\beta} = \sum_{i=1}^{n} x_i\, \beta_i \tag{3.12}$$

Equation-3.11 shows that the dependent variable y is a normal linear regression model when $y^* > 0$, equals to 0 when $y^* \le 0$, while the error term u is assumed to be normally N $(0,\sigma^2)$ distributed. To estimate the parameters β_i and u, the Maximum Likelihood Estimation (MLE) is used.

As mentioned above, the OLS method is a method to seek the most suitable hyper-plane with the smallest deviations of original observed values. However, due to the existence of piled-up zeros, it is not possible for the Tobit regression model to estimate regression coefficients by the OLS method, as the ordinary linear regression model does. Utilizing the OLS method in the Tobit regression model only reflects positive values without considering the probability of zero values. Therefore, to avoid the biased estimation, the MLE is suggested for the Tobit regression model. Instead of finding a specific line or plane, etc., the MLE looks for the greatest probability density functions by varying parameters of regression models, namely finding a set of parameters that maximize the probability of observed data. Based on Equation-3.11 and 3.12, the joint probability density function of y given $x_i\beta_i$ can be represented as below:

$$f(y|x) = f(y = 0|x_i\,\beta_i) * f(y > 0|x_i\beta_i) \qquad (3.13)$$

where $f(y = 0|x_i\beta_i)$ is the probability density function of y = 0, and the $f(y > 0|x_i\beta_i)$ is the probability density function of y > 0. It should be mentioned that both functions will be expressed by $x_i\beta_i$ and for the joint probability density function, y depends on independent variables x_i by coefficients β_i. As in Tobit regression models, the independent variables x_i are already known. To derive coefficients β_i, accordingly, it is possible to take β_i as variables in joint probability density functions. Normally, for the purpose of calculation, the functions are written in log-form, which can be called log-likelihood:

$$\begin{aligned}\mathcal{L}(\beta_i) &= log[f(y = 0|x_i\,\beta_i) * f(y > 0|x_i\beta_i)] \\ &= log[f(y = 0|x_i\,\beta_i)] + \log[f(y > 0|x_i\,\beta_i)] \qquad (3.14)\end{aligned}$$

where the β_i are the unknown variables in Equation-3.14. Based on Equation-3.14, by maximizing the $\mathcal{L}(\beta_i)$, the values of Tobit coefficients are then derived. As a result, knowing the probability of y =0 ($y^* \leq 0$) and $y = y^*$ ($y^* > 0$), it is possible to estimate coefficients of the Tobit regression model according to MLE [75]. Unlike the normal linear regression model, β_i in the Tobit regression model are no longer interpreted as the effects of x_i on y. Instead, β_i are the changes in positive dependent variable y^* in terms of probability.

3.4 Tobit Short Interruption Cost Model

3.4.1 Why Choose the Tobit Model?

As mentioned in the previous chapter, much PQ literature shows interruption cost data gathered from surveys. However, in several scenarios, even for large industry customers, the cost may return as zero (as there may be no economic losses as a result of some minor power disturbances). When the survey samples are large enough, interruption cost data will appear as continuously distributed in positive values, and contain dozens of zeros in the meantime. This is the type of data with which the 'corner solution model' is familiar. Using a normal linear regression model to describe such a dataset will definitely cause biased estimation as discussed above. To overcome these errors, the Tobit regression model is applied to formulate an interruption cost model in this thesis. In other words, the Tobit regression model possesses the ability to provide a relatively accurate estimation of interruption cost.

However, the type of interruption cost dataset is not the only reason to choose the Tobit regression model. Compared with the traditional interruption cost models reviewed at the beginning of this chapter, the most important advantage of the Tobit regression model is its capability to quantify the multiple effects on interruption cost at the same time, as shown in [79]. In this paper, the author studies the differences of family incomes between black and white people. In addition to the effect of race, the author believes that other factors, such as age, education, children, etc. may affect family incomes. The Tobit regression model satisfies the author's need to quantify the multiple effects on family incomes. As the author asserts that the results are relatively reliable. As discussed in the previous chapter, besides duration, the interruption cost as well as other PQ costs, depend on many other factors, such as time of occurrence, system loading conditions and competition within the power market, etc. Other traditional cost models may be able to quantify duration, but not the other factors. However, with the Tobit model, it is possible to take these multiple factors into account while considering duration.

3.4.2 Tobit Model in Electric Power Economic Analysis

This thesis is not the first piece of literature to propose the utilization of the Tobit model for interruption cost calculation. The Tobit regression model has already been used to analyse long term interruption cost in [18]. In that paper, based on survey results, the Lawrence Berkley National Laboratory (LBNL) attempts to evaluate long term interruption cost while taking various impact factors into account in one cost model according to the Tobit regression model. The impact factors considered in the Tobit model include duration, customer types, customer annual consumption, time of occurrence etc. Two interruption cost models are derived from this, and shown in Table-3.4.

where the S.E. is the standard error, and Pr> ChiSq is used to determine a statistically significant estimated parameter, which will be discussed in detail in a later section.

Model One is the interruption cost model without considering the types of customers, while the types of customers are included in Model Two. Although these two models do provide relatively sensible prediction, there are several drawbacks that make it almost impossible to build a short interruption cost model according to these cost models.

Table-3.4 Tobit Regression Model for Predicting Interruption Cost [18]

	Model One			Model Two		
Predictor	Parameter	S.E.	Pr>ChiSq	Parameter	S.E.	Pr>ChiSq
Intercept	7.7954	0.1377	<.0001	7.6941	0.1542	<.0001
Duration (hours)	0.5753	0.0376	<.0001	0.5771	0.0357	<.0001
Duration Squared	-0.0338	0.0035	<.0001	-0.0331	0.0032	<.0001
Number of Employees	0.0007	0.0001	<.0001	0.0006	0.0001	<.0001
Annual kWh	2.52E-08	0.004	<.0001	2.25E-08	0.0036	<.0001
Interaction Duration and kWh	-1.80E-09	0.001	0.0703	-1.30E-09	0.0009	0.1282
Morning	-0.5624	0.1308	<.0001	-0.4319	0.1144	0.0002
Night	-1.3857	0.1841	<.0001	-1.4464	0.1739	<.0001
Weekend	-0.7149	0.1485	<.0001	-0.6482	0.1441	<.0001
Winter	0.8992	0.0996	<.0001	0.8376	0.0901	<.0001
Manufacturing				0.5292	0.1166	<.0001
Mining				1.1378	0.2484	<.0001
Construction				0.9168	0.808	0.2565
Transportation/Utilities				-0.193	0.1585	0.2233
Finance/Insurance/Real Est.				0.3252	0.2841	0.2522
Services				-0.4661	0.1363	0.0006
Public				0.0253	0.2431	0.917
Number of Observations		3198			2542	
Zero Response		718			427	
Log Likelihood		-6904			-5087	

1) Model Two takes the type of customer into account, represented as switch variables with only ‘1’ and ‘0’ values. For example, when the independent variable x_m representing ‘Mining’ is equal to ‘1’, this means the ‘Mining’ customer sector is considered in this interruption cost model. Otherwise, it equals ‘0’. Therefore, for the purpose of illustration, assuming only survey data of ‘Mining’, ‘Construction’ and ‘Finance’ are gathered, and every customer sector surveyed is considered in the same Tobit model, then the data of independent variables for customer types will become:

Table-3.5 Values of Independent Variables for Customer Types

	Mining (x_m)	Construction (x_c)	Finance(x_f)
Inputs of Mining	1	0	0
Inputs of Construction	0	1	0
Inputs of Finance	0	0	1

As shown in Table-3.5, β_m, β_c and β_f are the effect coefficients of customer type ‘Mining’, ‘Construction’ and ‘Finance’ respectively. Note that the terms of customer type effects, i.e. $x_m\beta_m$, $x_c\beta_c$ and $x_f\beta_f$ in this case, actually represent constant values either independently existing or absent from the given customer type, e.g. $x_m\beta_m$, will only exist when mining customers are considered and are absent while the other two types of customers are considered. Then, for the starting point of cost estimation, which refers to the instant economic losses due to interruption, the instant cost of mining customers is $c_m=\beta_0+\beta_m$, the instant cost of construction customers is $c_c=\beta_0+\beta_c$, and the instant cost of the finance customers is $c_f=\beta_0+\beta_f$, where β_0 is the intercept term. It should be mentioned that the effect coefficients of customer type represented in the instant costs are actually the variations of β_0 for each type of customer. Hence, the β_0 is the average instant cost, which is derived from $(c_m+c_c+c_f)/3$; consequently, the relationship shown as Equation-3.15 can be derived.

$$\frac{c_m + c_c + c_f}{3} = \frac{(\beta_0 + \beta_m) + (\beta_0 + \beta_c) + \left(\beta_0 + \beta_f\right)}{3} = \beta_0$$
$$\xrightarrow{yields} \beta_m + \beta_c + \beta_f = 0 \tag{3.15}$$

With this linear relationship between coefficients, it is actually hard to evaluate the actual value of certain coefficients for most Tobit regression estimation programmes. Most of them randomly assume one of the Tobit coefficients to be '0' or an uncertain value instead of the actual estimated value. For example, SAS (i.e. Statistical Analysis System, which will be introduced in detail in a later section) will return the following messages instead of estimated values and associated results for one of the estimated coefficients [81],

```
NOTE: The following parameters have been set to 0 (or feasible values), since the variables are
a linear combination of other variables as shown.
```

As the message shows, the programme recognizes the parameter as strictly linear and dependent on other parameters. As a result, the programme will not provide individual estimated information on this coefficient, which may be used to check the statistical significance of results. Therefore, to ensure every estimated coefficient comes with available information, as Model Two in Table-3.4, the LBNL actually breaks down the linear relationship of coefficients by considering parts of individual customer types and two customer categories only (Services and Public), instead of considering every customer sector in the Tobit cost model. This partial estimation is definitely not able to provide full prediction for every customer type. The coefficients of customer types are actually not the directly quantified effects of customer types. Instead, they are only the reflections of variations from the average starting point of cost estimation.

2) The same reason may be applied to the time of occurrence effects as well. In Table-3.4, the time of occurrence is only considered as morning and night as well as weekend and winter in both models. Undoubtedly, there are various differences from time to time. The interruption cost for any specified time needs to be represented.
3) From the observed predictors shown in Table-3.4, there are no marketing competition considerations in either model. As previously discussed, the competition of customers plays an essential role in marketing, and affects the economic losses of customers during interruptions as well.
4) The Tobit interruption cost models derived by the LBNL need to deal with all sorts of information during the regression process, which makes a heavy calculation, and may amplify minor errors.

Generally speaking, to predict short term interruption cost using the Tobit regression model, a new and reformed Tobit cost model is required to overcome some of the disadvantages mentioned above.

3.4.3 Tobit Short Interruption Cost Model

In traditional interruption cost studies, short interruption cost is normally represented as the total cost per event. However, in this expression, it is hard to distinguish the customers' capability of sustaining short interruption, e.g. the case that two customers may have the same total economic losses with different load impact. In order to study the differences, the average unit variation of cost is used as the dependent variable in this model. The one with a higher average unit cost is more vulnerable to short interruptions. Hence, the purpose of the short interruption cost model in this thesis is to explain the unit cost with its relevant impact factors. Based on this purpose and Equations-3.11 and 3.12, the Tobit model can be expressed as:

$$Cost^* = \beta_0 + \textstyle\sum_{i=1}^{n} x_i\beta_i + u$$
$$Cost = \begin{cases} Cost^* & if\ Cost^* > 0 \\ 0 & if\ Cost^* \leq 0 \end{cases} \tag{3.16}$$

Due to the fact that the data of cost cannot be negative, the Tobit short interruption cost model can be rewritten as:

$$Cost^* = \beta_0 + \sum_{i=1}^{n} x_i\beta_i + u$$
$$Cost = \begin{cases} Cost^* & if\ Cost^* > 0 \\ 0 & otherwise \end{cases} \tag{3.17}$$

where $Cost^*$ is the positive dependent variable, referred to as interruption cost, and represents the average unit cost of loads affected by short interruption, in the form of £/kW.

Cost is the total dependent variable as short interruption cost which contains dozens of ‘zeros’.

The term β_0 is the intercept term which indicates the starting point of short interruption cost estimation. The numeric meaning of this term is the instant unit economic loss once a short interruption occurs.

The x_i are the independent variables representing the impact factors of short interruption cost, such as duration, consumption, etc. while the β_i are the associated regression coefficients of each impact factor. To some extent, these coefficients β_i indicate how the impact factors affect the positive short interruption cost.

u is the error term of normal distribution.

As in other Tobit regression models, this Tobit interruption cost model is built based on datasets of dependent and independent variables which are acquired from interruption cost surveys, and the values of parameters and error terms (β_i and u) are estimated by Tobit regression processes.

As discussed above, this will result in limited estimation of short interruption costs when taking types of customers into account in the Tobit regression model. For this reason, in this thesis, the different types of customers will have individual cost models based on customer types classified in the previous chapter, namely a non-continuous process industry cost model, continuous process industry cost model, commercial and public business cost model, and domestic users cost model. Each model is investigated according to the aspects of time, customer characteristics and marketing factors, which will be the inputs of x_i in the Tobit model. However, just as with types of customers, considering time of occurrence in the Tobit model provides only limited estimation. Therefore, the time effect only refers to the duration of interruption, and the effect of time occurrence is excluded from the cost model and will be introduced into and discussed in the cost model in a later chapter.

Inevitably, in addition to piled-up ‘zeros’, the overall interruption cost data also have some extreme values which are distributed in positive parts 100 or 1000 times higher than other ordinary values. Normally, these extreme values are the result of extreme interruption cases or misunderstanding of the questionnaires during surveys. After the survey data are acquired, a lot of attention is needed to confirm these data under extreme cases or exclude them if they appear to be inappropriate (such as misunderstanding, calculation errors, etc.). However, even when the inappropriate data are excluded, the rest of the confirmed extreme data will show severe tails in the shape of the distribution of interruption cost. Apparently, these abnormal appearances of shape of distribution do not result in normal distribution of error terms in Tobit regression models, which is one of the most important assumptions of Tobit regression, as shown in Equation-3.11. As a result, biased estimations will be provided due to these abnormal data. To reduce the influence of extreme data on error terms, a transformation is applied to shape the cost data distribution [18] [80].

The transformation is made only by converting original cost data into their log-forms, and leaving the associated impact factors as normal. With log-forms, the gaps between extreme and ordinary values are reduced. In this way, the shape of cost data distribution becomes milder and closer to normal distribution. Correspondingly, this transformation helps to improve the accuracy of Tobit regression estimation.

Meanwhile, it is still possible to investigate the relationship between cost associated impact factors and reformed cost.

However, due to the introduction of log transformation, the meaning of dependent variable has been changed. The dependent variables in the Tobit regression cost model could not be directly interpreted as interruption costs. They become the logged interruption cost. To obtain the actual predicted cost, an anti-log transformation is required in the end. Theoretically, the anti-log transformation introduces an exponential relationship between the actual cost and duration. While observing this exponential relationship in a graph, the curve of the actual cost appears to be a non-linear rise with increasing duration. The increment of the actual cost is slight at the start, and becomes dramatic thereafter. The variations of cost after an anti-log transformation are similar to realistic changes of cost upon durations. Therefore, under logarithmic transformation, the relationship between cost and duration is described more realistically.

Under the transformation of log-forms, the zero economic losses will be meaningless as ln (0) has an indeterminate value and hence its meaning cannot be interpreted. To make these zero values meaningful, a further recoding of original cost data is required, which is done by adding the value of 1 to all the original data. Accordingly, a log form cost model can be rewritten as ln (cost+1). Hence, cost data are valid at value zero as ln (0+1) = 0.

Finally, the expression of the Tobit interruption cost model becomes:

$$\ln(Cost^* + 1) = \beta_0 + \sum_{i=1}^{n} x_i\beta_i + u$$

$$\ln(Cost + 1) = \begin{cases} \ln(Cost^* + 1) & if\ Cost^* > 0 \\ 0 & otherwise \end{cases} \tag{3.18}$$

It can be seen from Equation-3.18 that the transformation is only taken against cost data rather than associated effects. The expressions on the right side of the equation remain the same as in the previous Tobit model. However, in this transformed Tobit cost model, the meanings of each Tobit regression coefficient are no longer directly associated with interruption cost. Instead, they are now associated with log-formed interruption cost.

As a result of anti-log, the actual predicted cost can be derived from Equation-3.19,

$$Cost_{actual} = e^{\beta_0 + \sum_{i=1}^{n} x_i \beta_i + u} - 1 \tag{3.19}$$

3.4.4 Process of Tobit Cost Model

The total process of Tobit cost model estimation is shown in the following flowchart:

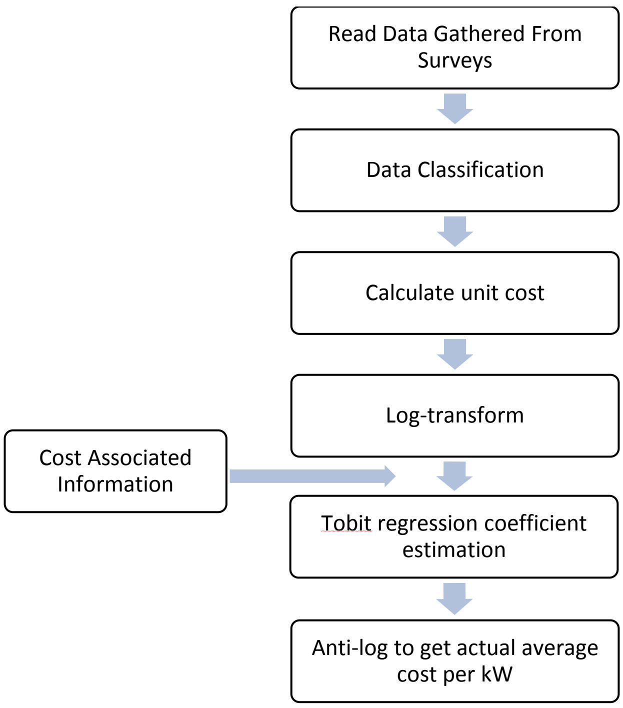


Figure-3.4 Process of Tobit Cost Model

1) The first step in the process of estimating the Tobit cost model is to gather data from surveys which could be composed by survey methods mentioned in the previous chapter, such as direct worth method, contingent valuation, etc. The surveys can combine two or more of these methods. To estimate Tobit coefficients,

the information required may include duration, load impact, either monthly or annual consumption, daily load curves and marketing relativities, etc.

2) As each type of customer needs their own cost model, after data gathering, the classification of survey data according to customer types is a critical step to ensure the accuracy of Tobit parameter estimation.
3) As the purpose of this cost model is to investigate the unit variation of cost, the original data from surveys normally show total cost for each event. Therefore, the unit interruption cost is calculated based on surveyed interruption cost over load impacted for each interruption event.
4) After applying the log-transformation to those unit cost data, the reformed cost data are used as inputs of dependent variables in the Tobit cost model. Together with event information such as duration, consumption, etc. as inputs of independent variables, the Tobit regression parameters are derived.
5) With the Tobit regression parameters, the Tobit cost model is formulated. However, at this stage, the outputs of predicted dependent variables in the Tobit cost model are transformed cost data. To obtain the actual unit cost, anti-log and anti-recoding are required in the end.

3.5 Case Study

To illustrate how the Tobit cost model works, a case study is given in this section. As the industrial customers are the main victims of short interruptions, the example will be based on industrial sectors. As discussed in previous the chapter, industrial customers are divided into two groups according to their industrial procedures. They are continuous process industrial customers and non-continuous process industrial customers. For the former groups of customers, most attention is paid to momentary interruptions which last less than 3 seconds. For the latter group of customers, the temporary interruptions last less than 60 seconds.

3.5.1 Main Factors

For a Tobit short interruption cost model of industrial customers in this thesis, the effects on cost are considered from the following perspectives: duration, customer consumption and competitors in the system, where the meanings of each Tobit variable are listed in Table-3.6.

Table-3.6 Definition of Tobit Variables

Original Variables	Expressions in Cost Model	Descriptions
y	C_{si}	Log and recoded short interruption unit cost
y^*	C_{si}^*	Log and recoded positive short interruption unit cost
x_1	t	The duration of short interruption
x_2	t^2	Duration squared
x_3	con	Average monthly consumption of customer
x_4	r	=1 when there are rivals in the same area, otherwise =0

In the Tobit short interruption cost model, the dependent variable y is the log-formed and recoded short interruption unit cost, which may include zero values and be expressed as C_{si} in the Tobit cost model. For the positive values of short interruption unit cost, the latent dependent variable y^* is represented as $C_{si}{}^*$ in the Tobit cost model.

The first effect, i.e. independent variable in the Tobit model, on short interruption is duration, which is represented as t in the Tobit short interruption cost model. To investigate the non-linear relationship between interruption cost and duration, both the first and second order of duration are considered. On account of the relatively tiny impact of other higher orders of duration (e.g. t^3, t^4 etc.), only the second order of duration is considered and represented as t^2 in the Tobit cost model. As discussed in the previous section, the linear regression model of Tobit refers to the linear relationship of parameters rather than independent and dependent variables. Therefore, the introduction of squared duration has no impact on the linear regression character of the Tobit model.

As introduced in the previous chapter, the interruption cost is not only a time varying cost, but also a consumption varying cost. The average customer consumption is also important to interruption cost valuations. In this Tobit cost model, rather than annual consumption of customers, the monthly consumption is used and expressed as *con*, i.e. another independent variable. Using monthly consumption means it is possible to reveal the monthly variation of customer consumption compared with annual consumption. Correspondingly, in terms of monthly consumption, the effects of time of occurrence in the month are introduced according to the various predicted monthly cost.

The last concerned impact factor is from a market competition perspective. In open markets, competition is an important factor to participants. Assuming that in an economic area, the products of industrial customers are consumed within the same location and the demands of local production are fixed, the loss of productions due to power interruption for industrial customers may become an opportunity to increase production for other competitors in the same production category. Therefore, the economic interruption losses may be further extended by competitors in the same area. Though the actual economic losses may depend on the competitive strength of other competitors, it is difficult to encompass this kind of market information in surveys. Hence, in this cost model, a logical value is introduced as the market factors, and is expressed as r. When there are other competitors for observed customers in the same economic area, r equals 1. In contrast, if there are no competitors in the area, r is 0. According to this logical variable, the effects of market competition are investigated roughly, i.e. competitors will lead to more economic losses than no competition.

Hence, according to Equation-3.18, the Tobit short interruption cost model can be written as:

$$C_{si}^{*} = \beta_0 + \beta_1 t + \beta_2 t^2 + \beta_3 con + \beta_4 r + u$$
$$C_{si} = \begin{cases} C_{si}^{*} & if\ Cost^{*} > 0 \\ 0 & otherwise \end{cases} \tag{3.20}$$

3.5.2 Data source

Typically, no matter what types of cost models are applied, various studies [4] [18] [6] on interruption cost suggest that a large number of cost and associated data are required to build relatively accurate cost models and the Tobit cost model is no exception. To predict short term interruption cost variations, the short term data are essential to cost models. However, in most of the published interruption cost data, there are few short term data available from different surveys. Obviously, the shortage of data means it is impossible to deduce a cost model. This also leads to more difficulty in accessing data as an individual researcher as it is almost impossible to access the private data of industrial and commercial customers on interruption cost, not to mention that many of these customers are unwilling to share their information with individuals.

Under these restrictions, in order to demonstrate how the Tobit cost model is used for predicting short term interruption cost, the raw input cost data are then composed manually based on derived results in published surveys and some reasonable assumptions are made:

1) Due to an inability to obtain original survey data, it is hard to compose data of load impact during each interruption event. However, unit cost data are available from some survey reports [6]. Hence, the primary raw data on composed interruption costs are assumed to be the unit cost of interrupted power.

2) To manually compose as many datasets as possible, a reference cost dataset is first required. The reference cost data are derived from realistic cost data in [6]. Based on the normalized unit costs of interruptions in [6], one minute interruptions for industry customers will lead to an average 38.4 NOK/kW, with a standard deviation of 56.4. Accordingly, the normal one minute interruption cost will be

less than 94.8NOK/kW, which can be converted into pounds Sterling thus: £10.43/kW. Taking the extreme values into account, which are deliberately set to be up to 70% higher than normal interruption costs, the reference cost data are defined as these maximum interruption costs in extreme cases. Correspondingly, it is assumed that for temporary interruptions which last around one minute, the reference unit economic losses are 10.43*(1+70%) ≈£17/kW.

3) As continuous process industrial customers are more vulnerable to interruptions than non-continuous process industrial customers, i.e. continuous process industrial customers will incur larger economic losses during interruptions, in this case study, as mentioned in the previous chapter, the short interruptions of continuous process industrial customers are mainly momentary interruptions which range from 0.01 second to 3 seconds, while for the non-continuous process industrial customers, the main short interruptions are temporary interruptions which are less than one minute. Considering the impact of duration, the reference unit economic losses of 3 seconds momentary interruptions for continuous process industrial customers are half of those of the one minute temporary interruptions, at £8.5/kW.

4) As stated in the previous chapter, the interruption cost is a type of consumption varying economic loss. For the same types of customers, the ones with larger monthly consumption will be always exposed to more unit interruption economic losses. Compared with smaller consumption customers, a longer recovery period and larger amount of energy are normally required during the restart period by larger consumption customers, which will lead to higher unit economic losses during interruptions.

5) Assuming in this case study, all the industrial customers involved are in the same economic area, and all of their production is consumed within this area, the customers with competitors in this area will incur additional economic losses due to competition. Conversely, the ones with no competitors will have less economic losses.

Based on the above assumptions and reference to initial cost data for 3 second momentary interruptions and 1 minute temporary interruptions, the reference dataset of short interruption cost are manually composed and listed in Table-3.7 and Table-3.8 respectively.

Table-3.7 Composed Reference Interruption Cost for Non-continuous Industrial Customers

N	**Unit interruption cost (£/kW)** C_{si}^{*}	**Duration (second)** t	**Squared Duration** t^2	**Monthly Consumption (MW)** *Con*	**Competitors or not** r
1	1.50	0.01	0.0001	3.10	1
2	0.70	1.0	1.00	3.30	0
3	1.70	2.0	4.00	3.40	1
4	0.80	3.0	9.00	3.50	0
5	1.80	4.0	16.00	3.60	1
6	1.80	5.0	25.00	2.60	1
7	1.90	6.0	36.00	2.70	1
8	1.10	7.0	49.00	2.80	0
9	2.20	8.0	64.00	2.90	1
10	2.30	9.0	81.00	3.00	1
11	1.40	10.0	100.00	3.10	0
12	2.70	11.0	121.00	3.20	1
13	3.00	12.0	144.00	3.30	1
14	3.30	13.0	169.00	3.40	1
15	3.60	14.0	196.00	3.50	1
16	2.90	15.0	225.00	3.60	0
17	4.00	16.0	256.00	2.60	1
18	4.40	17.0	289.00	2.70	1
19	4.60	18.0	324.00	2.80	1
20	5.00	19.0	361.00	2.90	1
21	5.40	20.0	400.00	3.00	1
22	5.80	21.0	441.00	3.10	1

N	**Unit interruption cost (£/kW)** C^*_{si}	**Duration (second)** t	**Squared Duration** t^2	**Monthly Consumption (MW)** *Con*	**Competitors or not** r
23	6.20	22.0	484.00	3.20	1
24	6.60	23.0	529.00	3.30	1
25	6.90	24.0	576.00	3.40	1
26	4.90	25.0	625.00	3.50	0
27	7.49	26.0	676.00	3.60	1
28	7.50	27.0	729.00	2.60	1
29	7.80	28.0	784.00	2.70	1
30	8.10	29.0	841.00	2.80	1
31	8.40	30.0	900.00	2.90	1
32	8.70	31.0	961.00	3.00	1
33	9.00	32.0	1024.00	3.10	1
34	6.80	33.0	1089.00	3.20	0
35	9.60	34.0	1156.00	3.30	1
36	9.90	35.0	1225.00	3.40	1
37	10.20	36.0	1296.00	3.50	1
38	10.55	37.0	1369.00	3.60	1
39	10.60	38.0	1444.00	2.60	1
40	10.90	39.0	1521.00	2.70	1
41	11.20	40.0	1600.00	2.80	1
42	11.50	41.0	1681.00	2.90	1
43	9.50	42.0	1764.00	3.00	0
44	12.10	43.0	1849.00	3.10	1
45	12.40	44.0	1936.00	3.20	1
46	12.70	45.0	2025.00	3.30	1
47	13.00	46.0	2116.00	3.40	1
48	13.30	47.0	2209.00	3.50	1
49	13.60	48.0	2304.00	3.60	1
50	13.95	49.0	2401.00	3.70	1

N	**Unit interruption cost (£/kW)** C_{si}^{*}	**Duration (second)** t	**Squared Duration** t^2	**Monthly Consumption (MW)** *Con*	**Competitors or not** r
51	14.00	50.0	2500.00	2.70	1
52	14.30	51.0	2601.00	2.80	1
53	14.60	52.0	2704.00	2.90	1
54	13.00	53.0	2809.00	3.00	0
55	15.20	54.0	2916.00	3.10	1
56	15.50	55.0	3025.00	3.20	1
57	15.80	56.0	3136.00	3.30	1
58	16.10	57.0	3249.00	3.40	1
59	16.40	58.0	3364.00	3.50	1
60	16.70	59.0	3481.00	3.60	1
61	17.00	60.0	3600.00	3.70	1

Table-3.8 Composed Reference Interruption Cost for Continuous Process Industrial Customers

N	**Unit interruption cost (£/kW)** C_{si}^{*}	**Duration (second)** t	**Squared Duration** t^2	**Monthly Consumption (MW)** *Con*	**Competitors or not** r
1	3.90	0.01	0.0001	3.50	1
2	4.05	0.05	0.0025	3.60	1
3	3.20	0.10	0.0100	2.60	0
4	4.30	0.20	0.0400	2.70	1
5	3.50	0.25	0.0625	2.80	0
6	4.50	0.30	0.0900	2.90	1
7	4.70	0.40	0.1600	3.00	1
8	4.80	0.45	0.2025	3.10	1
9	4.90	0.50	0.2500	3.20	1

N	Unit interruption cost (£/kW) C^*_{si}	Duration (second) t	Squared Duration t^2	Monthly Consumption (MW) Con	Competitors or not r
10	5.00	0.55	0.3025	3.30	1
11	5.10	0.60	0.3600	3.40	1
12	5.30	0.70	0.4900	3.50	1
13	5.40	0.75	0.5625	3.60	1
14	5.55	0.80	0.6400	3.70	1
15	5.70	0.90	0.8100	2.70	1
16	4.90	0.95	0.9025	2.80	0
17	5.90	1.00	1.0000	2.90	1
18	6.20	1.15	1.3225	3.00	1
19	6.30	1.20	1.4400	3.10	1
20	5.60	1.30	1.6900	3.20	0
21	6.60	1.35	1.8225	3.30	1
22	5.80	1.40	1.9600	3.40	0
23	6.90	1.50	2.2500	3.50	1
24	7.15	1.60	2.5600	3.60	1
25	7.25	1.70	2.8900	3.70	1
26	7.30	1.80	3.2400	2.70	1
27	7.40	1.90	3.6100	2.80	1
28	6.65	2.00	4.0000	2.90	0
29	7.65	2.10	4.4100	3.00	1
30	7.70	2.15	4.6225	3.10	1
31	7.75	2.20	4.8400	3.20	1
32	7.80	2.25	5.0625	3.30	1
33	6.95	2.30	5.2900	3.40	0
34	7.90	2.35	5.5225	3.50	1
35	7.95	2.40	5.7600	3.60	1
36	8.00	2.45	6.0025	3.70	1
37	8.00	2.50	6.2500	2.70	1

N	**Unit interruption cost (£/kW) C^*_{si}**	**Duration (second) *t***	**Squared Duration t^2**	**Monthly Consumption (MW) *Con***	**Competitors or not *r***
38	8.05	2.55	6.5025	2.80	1
39	8.10	2.60	6.7600	2.90	1
40	8.15	2.65	7.0225	3.00	1
41	8.20	2.70	7.2900	3.10	1
42	7.35	2.75	7.5625	3.20	0
43	8.30	2.80	7.8400	3.30	1
44	8.40	2.90	8.4100	3.40	1
45	8.45	2.95	8.7025	3.50	1
46	8.50	3.00	9.0000	3.60	1

where in these two tables, 'N' represents the number of composed data. Costs are the unit cost of short interruptions with associated duration, squared duration, monthly consumption and competitor information. The cost data increase gradually with duration. However, due to the existence of consumption variations, the non-linear relationships between cost and duration are then ensured.

Obviously, the reference datasets are not enough to simulate realistic survey results. In order to generate sufficient and continuous data for Tobit regression, a series of datasets is fabricated and inserted into the gaps between durations based on these composed reference data.

The inserted data are composed by introducing random variations into reference datasets. Assuming a random variable rv is a standard normal distribution, i.e. $rv \sim N(0, 1)$, it may cause the random variable rv to appear as both positive and negative variations. These two directional variations generate random inserted data with values above as well as below reference data, and thus simulate the variations in realistic survey data well. Then, for the number nth unit reference cost $C^*_{si_n}$, the inserted random unit cost $C^*_{si_r}$, random duration t_r and random monthly consumption con_r are calculated as follow:

$$C^*_{si_r} = C^*_{si_n} + d_{cost} * rv \quad (3.21)$$

$$t_r = t_n + d_t * rv \quad (3.22)$$

$$con_r = con_n + d_{con} * rv \quad (3.23)$$

where the variable d is the range of normal random deviations of unit cost, duration and monthly consumption respectively. Based on the reference dataset, the d are calculated as,

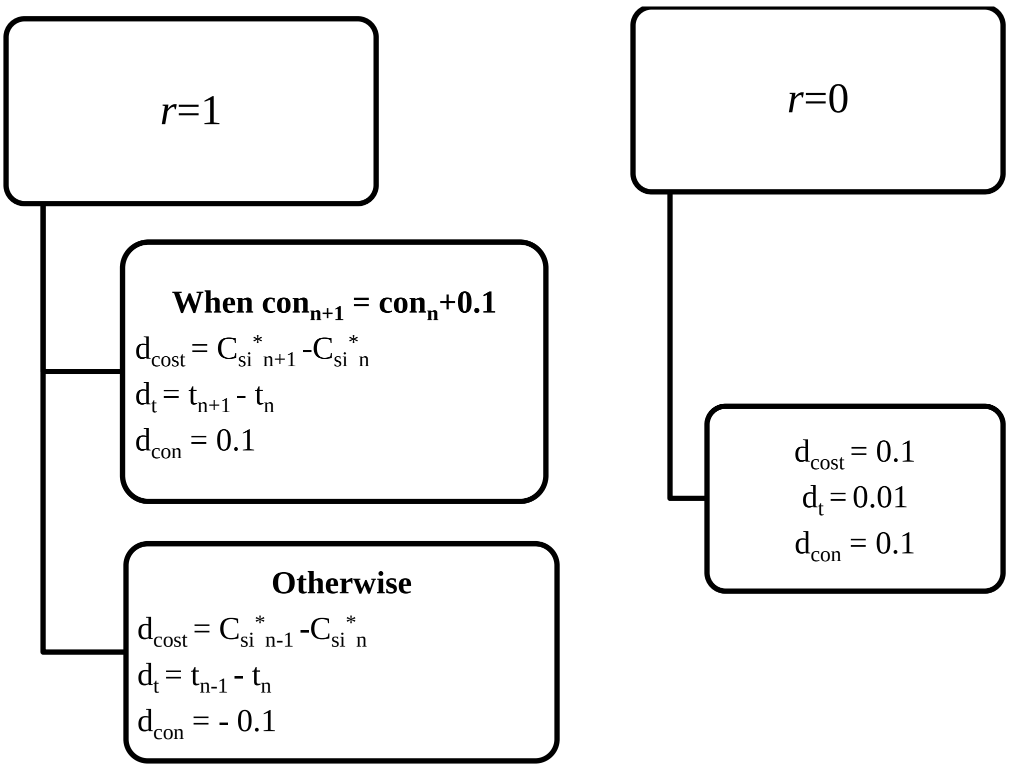


Figure-3.5 Calculations of *d* for Different Types of Data

1) For customers with competitors, i.e. r =1,

For the *nth* observed unit cost data, when $con_{n+1} = con_n+0.1$, i.e. composed monthly consumption increases every 0.1 MW for each number of unit cost data and the 'n+1' represents the next available data of unit cost with r=1. Then, the deviation ranges used to generate random unit costs depend on the differences between the observed data and the next available data, and the differences between associated durations become the ranges of duration deviation. In the cases of $con_{n+1} \neq con_n+0.1$, the increments of monthly consumption are no longer 0.1 MW, for instance, the 5th and 6th cost data in Table-3.7. Then, instead of the next data, the differences between the observed data and the previous available data are used to determine the ranges. Accordingly, the deviations of consumptions become – 0.1 MW.

2) For customer without competitors, i.e. r =0,

In modern markets, there may not be so many customers without competitors. Therefore, the data of this type of customer are not continuously distributed. In this case, relatively small deviations are added to generate potential data around composed data, which are shown in Fig-3.5. For the unit cost, the normal deviation ranges are set to be 0.1 £/kW and the ranges of duration deviations are 0.01 second. In terms of consumption, the ranges are 0.1MW.

By generating numbers of random data rv, it is possible to insert various reasonable datasets based on reference data and different deviations d for each cost data. Meanwhile, to present zero economic losses in realistic cost data, 5% of these are inserted unit costs equal to zero during generating random data. This can be done by setting up a cruise variable c which is continuously uniformly distributed on the interval [0, 1]. The reason for uniform distribution is to ensure the probability of each value of generated cruise variable to be equal. This cruise variable keeps step with generated random data rv, i.e. when generating one random data rv, another value of cruise variable will be generated at the same time. Thereafter, when this cruise variable is less than 0.05, the unit cost will be deliberately equal to zero. In this way, 5% of these random generated unit cost data are zero. An example is the data inserted between the 6th and 7th unit cost in Table-3.9 which is the unit cost for non-continuous process industrial customers.

In this thesis, the data are generated by commercial analytics software SAS (Statistical Analysis System) provided by the SAS Institute Inc. [81]. Assuming 100 data will be generated, the program is shown below:

```
data random6;  -----------{create database called 'random6' for generated
                          data of 6th unit cost data}
do i=1 to 100; ----------{do 100 times of the following steps}
```

```
   rv = rannor(12345); --- {generate a random value from a standard normal
                            distributed dataset, where (12345)gives an
                            expression for this generated dataset to
                            ensure that getting the same dataset while
                            running the program another time}
   c=ranuni(12345); ------{generate a random value from a standard uniform
                             distribution as cruise variable}
   tr= 5.0 + 1*rv;  -------{according to the reference duration 5 second,
                            and deviation of 1 second, a random duration
                            is generated}
   tsr=tr*tr;       -------{square duration}
   conr=2.60+0.1*rv; -----{according to the reference consumption 2.6MW,
                            and deviation of 0.1MMW, a random consumption
                            is generated}

  if c<0.05 then csir=0; ---{letting 5% of unit cost equal to zero}
  else csir=1.8 + 0.1*rv;-- {rest of the unit cost equal to reference cost
                            adds up with random deviation}
 output;
 end;
```

Table-3.9 Number 6th and 7th Unit Cost Data

N	Unit interruption cost (£/kW) C^*_{si}	Duration (second) t	Squared Duration t^2	Monthly Consumption (MW) *Con*	Competitors or not r
6	1.80	5.0	25.00	2.60	1
7	1.90	6.0	36.00	2.70	1

Based on the reference dataset and programs as shown above, it is possible to generate thousands of short interruption cost databases for each type of customer, which is sufficient for Tobit regression estimation. Based on these composed data, two Tobit cost models are then derived to verify the accuracy of Tobit cost model prediction.

3.5.3 Results and Discussion

Again, the SAS is used to estimate the Tobit regression coefficients. The Statistical Analysis System is a complex piece of software that is capable of providing software analytics solutions to commercial problems. As a result, most statistical models and their estimation progresses are already integrated into SAS's procedures, including the Tobit regression model. Basically, both the QLIM (qualitative and limited dependent variable model) and LIFEREG Procedure in SAS are capable of dealing with censoring data. QLIM is specialized in multivariate limited dependent variables where the dependent variables could be discrete or observed in a limited range of values. The LIFEREG Procedure estimates the parameters by maximum likelihood with a Newton-Raphson algorithm [81]. However, the LIFEREG Procedure is preferred for Tobit short interruption cost model calculation. The reason is associated with the statistical hypothesis test, which is used to decide whether the calculated coefficients of independent variables significantly affect the predicted dependent variable or not, i.e. whether the estimated coefficient is statistically reliable. The one used in the QLIM procedure is a t-test, which is more accurate for small samples of less than 30 [82]. Normally, cost data from PQ surveys number in the hundreds, and thus have far too many samples for a t-test to handle. Hence, the LIFEREG procedure, of which the statistical hypothesis test is the chi-square test, is used due to being relatively more accurate in handling a large number of samples [83]. The chi-square is named after the ratio between squared residuals (i.e. the differences between observed dependent variable y and its predicted dependent value under a null hypothesis) and the squared variation of the error term σ (as the error term u of Tobit is $N(0, \sigma^2)$ distributed), i.e. $(\text{residuals})^2/\sigma^2$, which are used in the hypothesis test [84].

According to Fig-3.4, after obtaining the original data, classification and normalization of the original data are required. However, the composed data are already the unit costs of each observed customer type. Then the unit composed data need to be transformed and recoded as discussed in previous sections for further Tobit calculations.

With the transformed and recoded unit cost data, using the generated datasets as inputs of Tobit regression estimations in SAS, and with the help of the LIFEREG procedure, the outputs of Tobit coefficient estimations by SAS are shown in the following Table-3.10 and 3.11

Table-3.10 Tobit Cost Model Coefficient Estimations for Non-continuous Process Industrial Customer

Predictor	DF	Estimate	Standard Error	95% Confidence Limits		Pr > ChiSq
Intercept	1	0.2049	0.0825	0.0431	0.3666	0.0130
t	1	0.0604	0.0015	0.0574	0.0635	<0.0001
t^2	1	- 0.0004	0.0001	-0.0005	-0.0004	<0.0001
con	1	0.0699	0.0238	0.0233	0.1165	0.0033
r	1	0.4021	0.0222	0.3586	0.4457	<0.0001
σ	1	0.0546	0.0048	0.0459	0.0649	-

Table-3.11 Tobit Cost Model Coefficient Estimations for Continuous Process Industrial Customer

Predictor	DF	Estimate	Standard Error	95% Confidence Limits		Pr > ChiSq
Intercept	1	1.3197	0.0422	1.2370	1.4023	<0.0001
t	1	0.4601	0.0173	0.4261	0.4940	<0.0001
t^2	1	- 0.0773	0.0056	-0.0883	-0.0663	<0.0001
con	1	0.0288	0.0136	0.0022	0.0553	0.0336
r	1	0.1347	0.0109	0.1134	0.1560	<0.0001
σ	1	0.0793	0.0028	0.0739	0.0850	-

Tables-3.10 and 3.11 represent the results of Tobit coefficient estimations for continuous and non-continuous process short interruption cost models respectively. According to that which is expressed in Table-3.6 and Equation-3.20, the '*intercept*' in Tables 3.10 and 3.11 indicates the row associated with the intercept term β_0 of each model; '*t*' and 't^2' refer to the rows associated with the Tobit coefficient β_1 and β_2

respectively; '*con*' represents the row associated with the Tobit coefficient of average monthly consumption β_3, while '*r*' expresses the row associated with a coefficient of 'competitor or not' in the Tobit model, i.e. β_4. The estimated values of each coefficient are expressed in column 'Estimate'. The error term in the Tobit model μ is assumed to be N $(0, \sigma^2)$ distributed, and the value of σ for each model is also given by SAS.

In these tables, DF is the degree of freedom associated with each coefficient. The value of DF indicates that the number of values in statistical estimation results is 'free to vary' [85]. According to DF values shown in Tables-3.10 and 3.11, '1' indicates that there is only one choice of Tobit coefficient for this variable, i.e. the values of coefficients are stable.

Standard error is the standard deviation of estimation in this case. It can be further used to calculate the 95% confidence limits.

Based on standard errors of estimated coefficients, 95% confidence limits are the Confidence Interval (CI) with lower and upper critical limits, which indicates the reliability of the estimated results. The CI suggests a range with a 95% chance that the 'true' value of estimated coefficients may lie in [86]. As shown in the above Tables-3.10 and 3.11, all the coefficients are expressed as their estimated values with associated 95% confidence intervals, which provide general ideas about the ranges of estimated coefficients.

The value of 'Pr > ChiSq' determines whether the estimated coefficients are statistically significant or not. Normally, a 5% significance level is chosen [87], which means there is a 5% chance of obtaining the observed data when the null hypothesis is true [88]. In the linear Tobit regression model, the null hypothesis is often referred to as a coefficient which equals zero, which means there is no significant linear relationship [89]. Hence, a 5% significance level in cost models means there is a 5% chance of obtaining the observed re-formed unit cost when the estimated coefficient equals zero. Accordingly, when the chance drops to less than 5%, the null hypothesis is rejected, i.e. the coefficient, significantly, is not equal to zero, i.e. the linear relationship of the Tobit regression model is confirmed. In other words, if the value of

'Pr > ChiSq' is less than 5%, the estimated parameter will be defined as significant. Based on the values given in Tables-3.10 and 3.11, it can be concluded that all estimated parameters are statistically significant, and capable of providing predictions in the cost model. It should be mentioned that, if the value of 'Pr>ChiSq' of an estimated coefficient is much larger than 5%, it may imply that the impact factor associated with this estimated coefficient is unconnected to the predicted dependent variable; accordingly, this impact factor could be excluded from the Tobit model.

After checking the results in SAS, according to Equation-3.20, the expressions referring to the positive re-formed cost for each Tobit cost model could be represented as:

$$C_{sin}^{*} = 0.2049 + 0.0604t - 0.0004t^{2} + 0.0699con + 0.4021r + u, u \sim N(0, 0.0546^{2}) \quad (3.24)$$

$$C_{sic}^{*} = 1.3197 + 0.4601t - 0.0773t^{2} + 0.0288con + 0.1347r + u, u \sim N(0, 0.0793^{2}) \quad (3.25)$$

where Equation-3.24 is the expression for non-continuous process industrial customers, while Equation-3.25 is for continuous process industrial customers. Based on these equations and the meanings of each C_{si}^{*}, in order to predict the final unit interruption cost, anti-transformations are required. Based on Equation-3.19, the actual predicted values of unit interruption cost then become:

$$C_{n} = Exp(0.2049 + 0.0604t - 0.0004t^{2} + 0.0699con + 0.4021r + u) - 1, u \sim N(0, 0.0546^{2}) \quad (3.26)$$

$$C_{c} = Exp(1.3197 + 0.4601t - 0.0773t^{2} + 0.0288con + 0.1347r + u) - 1, u \sim N(0, 0.0793^{2}) \quad (3.27)$$

where the C_n and C_c represent the actual predicted unit interruption cost for non-continuous process industrial customers and continuous process industrial customers respectively.

To observe the deviations from actual data, the same reference cost associated factors in Tables-3.7 and 3.8 are put into Equations-3.26 and 3.27 without considering error term *u* (as the impact of the error terms on final results is relatively small according to the small value of σ). Accordingly, the results of predicted unit interruption costs are shown in the following Tables-3.12 and 3.13.

Table-3.12 Error Deviations of Predicted Values for Non-continuous Process Industrial Customers

N	Reference Unit Interruption Cost (£/kW)	Predicted Unit Interruption Cost (£/kW)	Error Deviation
1	1.50	1.28	-14.67%
2	0.70	0.64	-8.57%
3	1.70	1.62	-4.71%
4	0.80	0.87	8.75%
5	1.80	1.99	10.56%
6	1.80	1.95	8.33%
7	1.90	2.14	12.63%
8	1.10	1.23	11.82%
9	2.20	2.55	15.91%
10	2.30	2.77	20.43%
11	1.40	1.68	20.00%
12	2.70	3.25	20.37%
13	3.00	3.50	16.67%
14	3.30	3.77	14.24%
15	3.60	4.05	12.50%
16	2.90	2.57	-11.38%
17	4.00	4.22	5.50%
18	4.40	4.51	2.50%
19	4.60	4.81	4.57%
20	5.00	5.13	2.60%
21	5.40	5.45	0.93%
22	5.80	5.79	-0.17%
23	6.20	6.14	-0.97%
24	6.60	6.50	-1.52%

N	Reference Unit Interruption Cost (£/kW)	Predicted Unit Interruption Cost (£/kW)	Error Deviation
25	6.90	6.88	-0.29%
26	4.90	4.53	-7.55%
27	7.49	7.66	2.27%
28	7.50	7.40	-1.33%
29	7.80	7.79	-0.13%
30	8.10	8.19	1.11%
31	8.40	8.60	2.38%
32	8.70	9.02	3.68%
33	9.00	9.45	5.00%
34	6.80	6.29	-7.50%
35	9.60	10.35	7.81%
36	9.90	10.81	9.19%
37	10.20	11.28	10.59%
38	10.55	11.75	11.37%
39	10.60	11.26	6.23%
40	10.90	11.72	7.52%
41	11.20	12.18	8.75%
42	11.50	12.65	10.00%
43	9.50	8.45	-11.05%
44	12.10	13.60	12.40%
45	12.40	14.09	13.63%
46	12.70	14.58	14.80%
47	13.00	15.07	15.92%
48	13.30	15.56	16.99%
49	13.60	16.05	18.01%
50	13.95	16.55	18.64%
51	14.00	15.71	12.21%
52	14.30	16.16	13.01%
53	14.60	16.62	13.84%

N	Reference Unit Interruption Cost (£/kW)	Predicted Unit Interruption Cost (£/kW)	Error Deviation
54	13.00	11.09	-14.69%
55	15.20	17.52	15.26%
56	15.50	17.97	15.94%
57	15.80	18.41	16.52%
58	16.10	18.84	17.02%
59	16.40	19.27	17.50%
60	16.70	19.69	17.90%
61	17.00	20.11	18.29%

Table-3.13 Error Deviations of Predicted Values for Continuous Process Industrial Customers

N	Unit interruption cost (£/kW) C_{si}^{*}	Predicted Unit Interruption Cost (£/kW)	Error Deviation
1	3.90	3.76	-3.65%
2	4.05	3.86	-4.71%
3	3.20	3.22	0.62%
4	4.30	4.06	-5.61%
5	3.50	3.53	0.83%
6	4.50	4.31	-4.29%
7	4.70	4.54	-3.35%
8	4.80	4.67	-2.72%
9	4.90	4.80	-2.11%
10	5.00	4.92	-1.51%
11	5.10	5.05	-0.92%
12	5.30	5.29	-0.14%
13	5.40	5.42	0.40%
14	5.55	5.55	0.01%

N	Reference Unit Interruption Cost (£/kW)	Predicted Unit Interruption Cost (£/kW)	Error Deviation
15	5.70	5.58	-2.15%
16	4.90	4.86	-0.87%
17	5.90	5.83	-1.26%
18	6.20	6.15	-0.74%
19	6.30	6.28	-0.39%
20	5.60	5.55	-0.91%
21	6.60	6.61	0.18%
22	5.80	5.75	-0.78%
23	6.90	6.94	0.52%
24	7.15	7.14	-0.19%
25	7.25	7.33	1.09%
26	7.30	7.25	-0.72%
27	7.40	7.42	0.22%
28	6.65	6.49	-2.33%
29	7.65	7.72	0.97%
30	7.70	7.81	1.39%
31	7.75	7.89	1.77%
32	7.80	7.97	2.12%
33	6.95	6.90	-0.71%
34	7.90	8.11	2.68%
35	7.95	8.18	2.90%
36	8.00	8.25	3.08%
37	8.00	8.02	0.23%
38	8.05	8.08	0.33%
39	8.10	8.13	0.38%
40	8.15	8.18	0.39%
41	8.20	8.23	0.36%
42	7.35	7.11	-3.33%
43	8.30	8.32	0.19%

N	Reference Unit Interruption Cost (£/kW)	Predicted Unit Interruption Cost (£/kW)	Error Deviation
44	8.40	8.36	-0.47%
45	8.45	8.39	-0.69%
46	8.50	8.42	-0.96%

In Tables-3.12 and 3.13, the error deviations of both non-continuous process industrial customer cost and continuous process industrial customer cost models are calculated according to:

$$\mathrm{ED} = \frac{Predicted\ Unit\ Cost - Reference\ Unit\ Cost}{Reference\ Unit\ Cost} * 100\% \qquad (3.28)$$

The variations of errors for each model are then illustrated in the following figure,

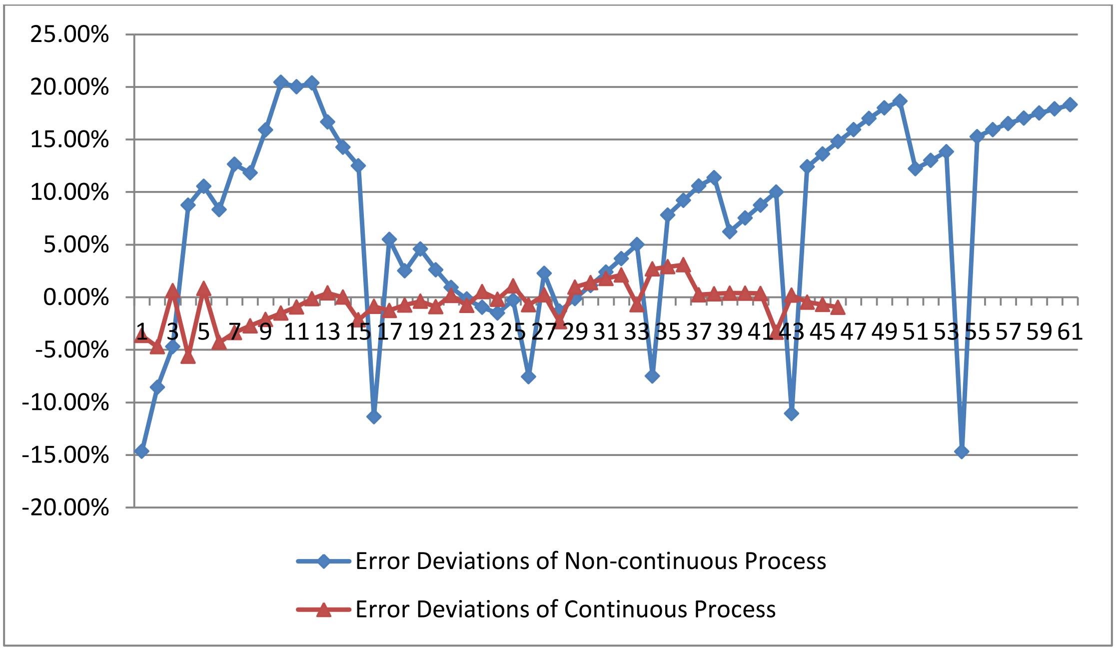
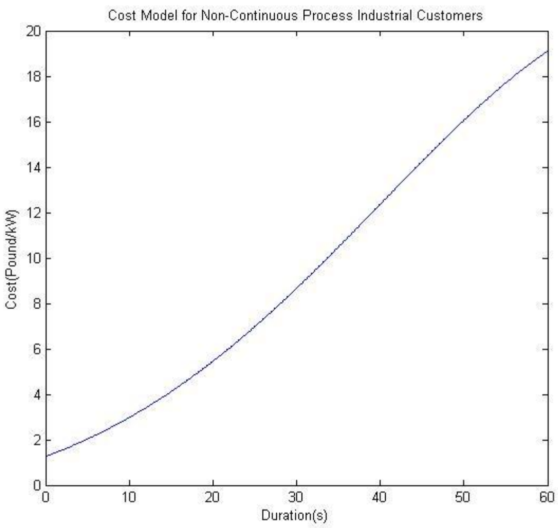


Figure-3.6 Error Deviations of Both Cost Models

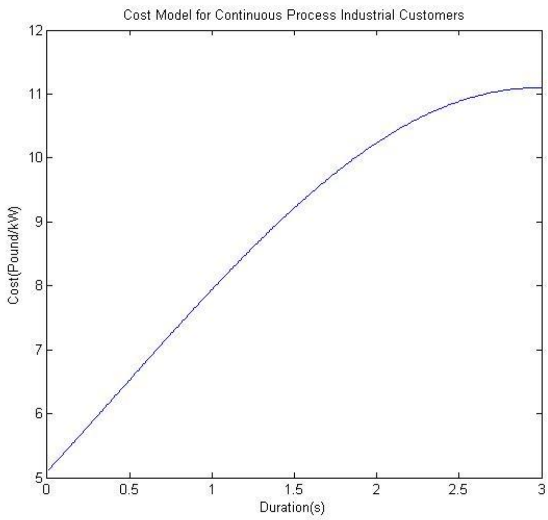
In Fig-3.6, the x-axis represents the number of unit costs in each model, while the y-axis shows the percentage of deviations. For the non-continuous process industrial customer cost model, the error deviations vary within a range of 20%, and appear to increase with the unit costs in later numbers of unit cost. Compared with the non-continuous process industrial customer cost model, the error deviations of the continuous process cost model are smaller. In this case, this model is capable of providing more accurate predictions. The different appearance of error deviations may arise from the data composing procedures, and the relationship between unit cost and associated cost information of non-continuous process cost models may be composed with relatively less significance for the Tobit model to describe. However, it also should be noted that, when the original input data for Tobit models vary widely, the predicted results may return as relatively large error deviations.

Based on these Tobit cost models, it is also possible to observe the relationship between cost and associated impact factors by holding the other impact factors as constants.

1) Relationship between duration and unit cost
   To investigate this relationship, it is necessary to imagine the average monthly consumption as *con*=3.0 MW, and that there are other competitors around, i.e. *r* =1, then to vary the durations within the short interruption periods of each model, for example 1 minute for non-continuous process industrial customers and 3 seconds for continuous process industrial customers.



(a)



(b)

Figure-3.7 Unit Cost Variations with Durations for Non-continuous and Continuous Process Industrial Customers

In Fig-3.7, the y-axis is the unit cost in £/kW and the x-axis is the duration in seconds. Accordingly, the relationship between unit cost and duration for non-continuous process industrial customers is shown in (a), while the relationship for continuous process customers is represented in (b). Both of these show non-linear relationships between unit cost and duration, in accordance with realistic circumstances. The relationship in (a) describes a more realistic variation at the beginning, i.e. the cost slowly rises in the first few seconds, rising dramatically thereafter. Compared with the cost variations shown in (a), the variations for continuous process industrial customers in (b) are relatively constant from the beginning. However, as duration increases, the increment of unit cost becomes steady. This would occur when the economic losses of short interruption reach maximum values.

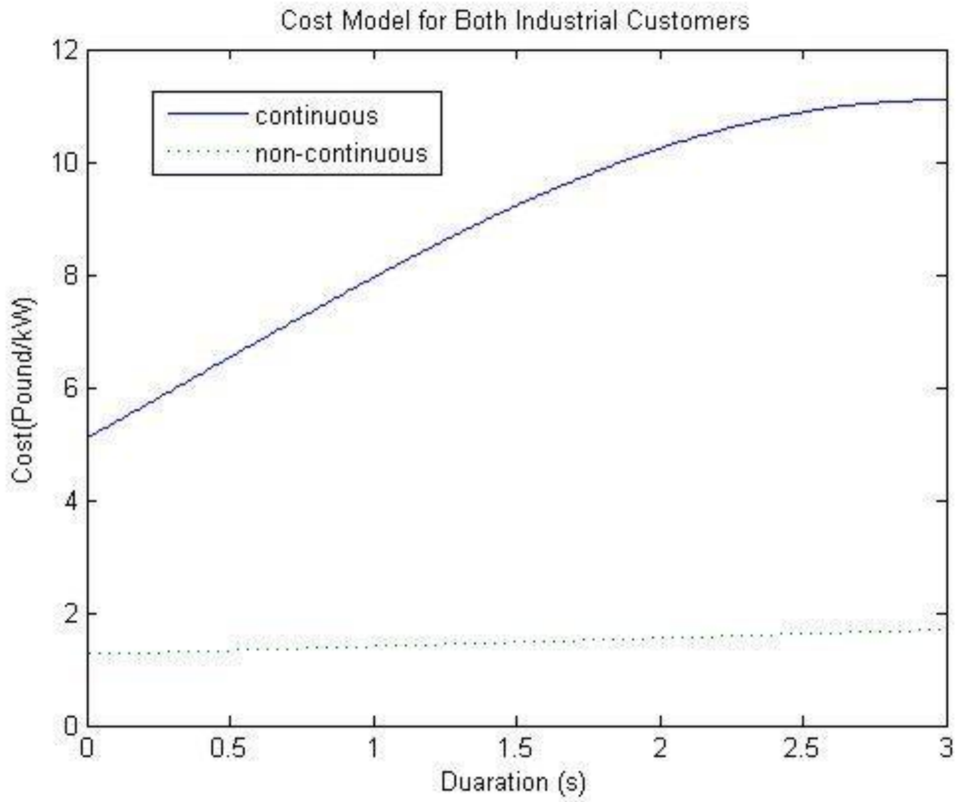
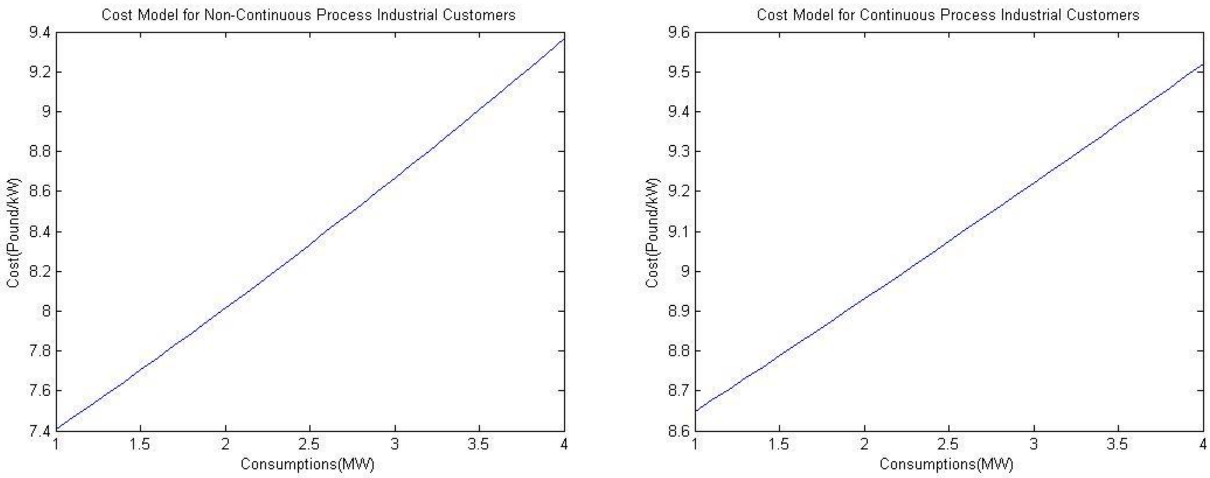


Figure-3.8 Comparing Unit Cost Variation with Durations of Both Industrial Customers

A comparison of unit cost variation of both industrial customers is plotted in Fig-3.8. The solid line represents the variation of cost for continuous process industrial customers, while the dotted line represents the variation of cost for non-continuous process industrial customers. Fig-3.8 reveals one of the assumptions at the beginning of this section, i.e. that the continuous process industrial customers have more economic losses than non-continuous process industrial customers within the same period of interruptions.

2) Relationship between consumption and unit cost

   To reveal this relationship, the duration for non-continuous process industrial customers is set as t = 30s, and t=1.5s for continuous process industrial customers, and competitors r =1. It is assumed that the consumptions vary between 1.0MW and 4.0MW for both models.



(a) (b)

Figure-3.9 Unit Cost Variations with Consumptions for Non-Continuous and Continuous Process Industrial Customers

In Fig-3.9, the relationship between consumption and unit cost for non-continuous process industrial customers is represented in (a) with the x-axis referring to consumption. For continuous process industrial customers, it is shown in (b). Both indicate that the unit costs increase almost linearly with consumption in spite of the fact that this might not be the case in reality. The reason for a linear relationship may be due to the composed data; the data with relatively slight variations in consumption could result in underestimation of consumption impact. In reality, the larger the consumption impact, the greater the cost increment of greater consumption.

Fig-3.10 indicates that consumption has fewer effects on unit cost for continuous process industrial customers than non-continuous process customers, based on composed data. There is a greater increment of unit cost for non-continuous process customers. The contrasting results may be de

rived in another case, as it is hard to determine which type of customer is affected more by consumption on unit cost without original databases.

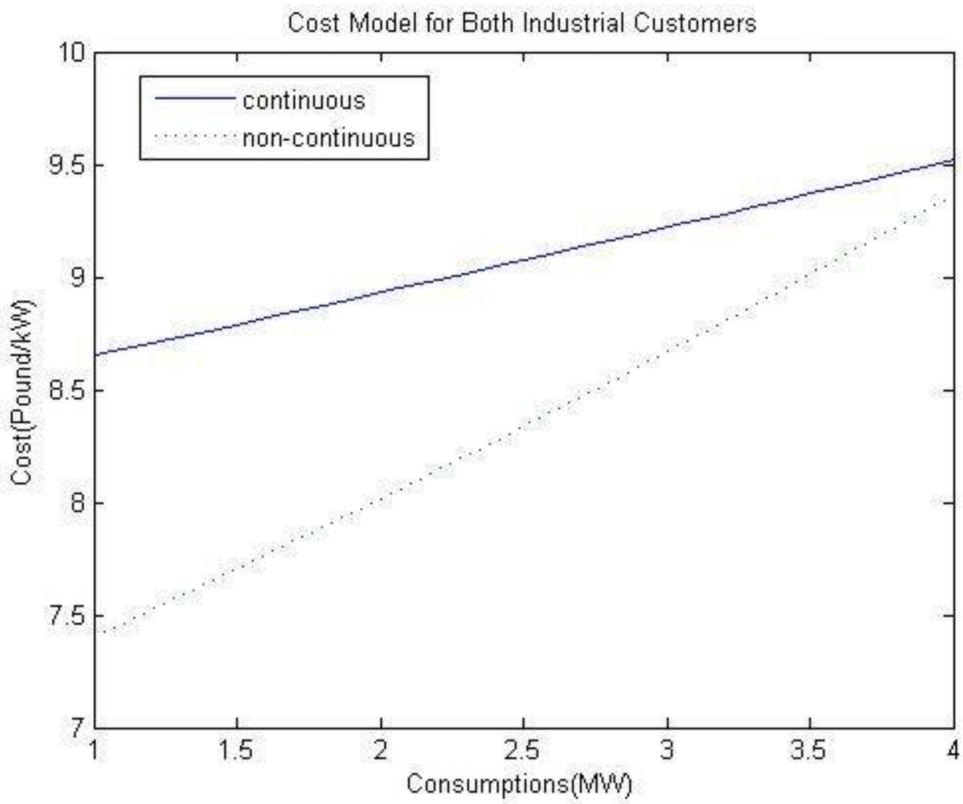


Figure-3.10 Comparing Unit Cost Variation with Consumptions of Both Industrial Customers

According to what is shown in Fig-3.10, continuous increases in consumption, sooner or later may lead to the unit cost of non-continuous process industrial customers becoming larger than continuous process industrial customers. This might be true under extreme circumstances, though it will be in contradiction to the assumptions that continuous process industrial customers have larger unit economic losses than non-continuous process industrial customers. However, it should be noted that these extreme circumstances occur outside the ranges of consumption that are provided by the composed data (the maximum value of consumption in composed data is around

3.8 MW), which indicates that, if the original data were fully adequate, there would not be such circumstances as in predictions.

3.6 Summary

In this chapter, after reviewing existing cost models for short interruptions, it has been found that existing methods are not available that are capable of predicting short interruption cost while considering multiple impact factors. It is possible to introduce the Tobit regression model for predicting short interruption cost, though it has already been used in long interruption cost predictions. However, it is not possible to utilize the existing Tobit cost model directly due to its inability to cover all components of impact factors and consider the effects of competitive markets. Hence, it is necessary to propose a new Tobit cost model with full consideration of multiple impact factors.

The attributes of the new Tobit cost model are:

1) Each type of customer has its own cost model rather than being considered as coefficients in one Tobit model. It is not possible to derive a relatively accurate cost model while considering type of customers as Tobit regression coefficients, especially when calculations are made based on the various cost data of different types of customers.

2) Considering the effects of duration, customer consumption and market factors, the effects of time of occurrence are excluded from the Tobit cost model. Due to the inability to fully consider time of occurrence in the Tobit model, the time of occurrence will be introduced in a later chapter as an individual complementary coefficient to the Tobit cost model.

3) The Tobit cost model is capable of observing the relationship between cost and associated impact factors. In the Tobit cost model, varying the observed impact factor within its limits, while keeping the other impact factors as constants, the relationship between cost and observed impact factors can be investigated.

4) The accuracy of prediction by the Tobit cost model depends on the raw data input. The more ample the input data, the more accurate and significant the predictions are.

5) Due to the anti-log and reforming at the end of cost model calculations, the error terms of Tobit regressions are actually amplified, though they are still relatively small and can be neglected in the above case study. Attention should be paid when dealing with error terms that are close to estimated coefficients in other cases.

Although the case studies are based on composed data, predictions by Tobit cost models provide relatively acceptable results, which validate the utilization of the new Tobit cost model.

Chapter 4 Voltage Sag Cost Model

4.1 Introduction

As one of the most common PQ variations in power systems, the economic losses of voltage sags exist in every PQ cost report and vary significantly from zero to massive amounts. To a certain extent, the interruptions are recognized as extreme cases of voltage sags, which are those of less than 0.1 p.u.. Similar to interruptions, the economic losses of voltage sag depend on many aspects, e.g. event duration, time of occurrence, type of customer, consumption, market environment, etc. From the discussion in the previous chapter, it is clear that the economic impact of voltage sags is a proportion of short that for interruptions; it is thus possible to evaluate voltage sag cost based on the short interruption cost model. However, unlike interruptions, the severity of voltage sags depends not only on duration but also the magnitude of sags. Although the Tobit short interruption cost model may be applied to consider the effects of the magnitude of voltage sags as well, there exists a more accurate model to quantify the effects of magnitude.

Voltage sag costs have not been specifically studied as sufficiently as interruption costs in the past. There are few models available from different points of view. Some of the literature evaluates the economic impact of voltage sag according to trip probability in the manufacturing process, while others may analyse the percentage of product completion during manufacturing processes to predict the voltage sag cost. Some literature suggests weighting factor methods according to engineering experiences to quantify the differences between the economic impact of short interruptions and voltage sags, while other research may estimate weighting factors based on mathematical functions. However, none of them is capable of quantifying customer characteristics, e.g. consumption and market environment, in voltage sag cost models. The necessity for multiple effects to be considered in cost models makes the Tobit regression model again the most suitable cost model to describe voltage sag cost. Meanwhile, to better quantify the effects of voltage sag magnitude and reduce the deviations of the Tobit cost model, a combined cost model is required.

In this chapter, the existing voltage sag cost models will be discussed in Section 4.2, followed by introduction of a mathematical method to evaluate the effects of voltage sag magnitudes in Section 4.3. Together with the Tobit cost model, in Section 4.4, the combined voltage sag cost model is introduced based on the financial relationship between short interruption and voltage sag. In Section 4.5, a simple case study is introduced to demonstrate how the new cost model works. In the end, the features of this new model will be summarized.

4.2 Existing Models for Voltage Sag Cost

Due to almost the same calculating characteristics as short interruption cost, there are only a few cost models particularly concerned with voltage sag cost, although it is one of the main PQ costs in power systems. Generally, the existing voltage sag cost models can be classified into the following categories:

4.2.1 Frequency Dependent Model

Just as with short interruption cost, in early studies of voltage sag cost, most cost models were mainly concerned with long term voltage sag cost, e.g. annual voltage sag cost, rather than short term variations of voltage sag cost. One of the most straight-forward cost estimations is the frequency dependent cost model [19] [20]. It is designed so that the long term cost is estimated based on expected average cost per event, in combination with the expected number of events. The expression could be:

$$Cost_{long} = C * N * f \tag{4.1}$$

where C is the expected average cost per voltage sag. As mentioned in [19] and [20], the average cost is estimated directly and approximately from different customer economic loss surveys in terms of customer types. N is the number of customers involved for each observed type, and f is the frequency of estimated annual sags for observed types of customers.

The estimation of the frequency is the key issue in this model. Based on the surveyed network reliability data, and taking the fault position along the lines into account, the average voltage sags are estimated. Thereafter, the authors in [19] and [20] believe that all faults reported in surveys are permanent faults, and that there are other faults that are cleared by time-delayed or high-speed auto-reclosing which may also result in voltage sags; the percentage of these potential faults needs to be considered. Meanwhile, in [19] and [20], it is suggested that the type of fault, such as single or two phase short circuit, may lead to different effects of voltage sags. In addition, with permanent or potential faults, the types of fault need to be taken into account. According to the different percentages of the potential and different types of faults in reported permanent faults, a new set of average number of voltage sags is derived in terms of voltage magnitude, and based on these average number of voltage sags, the frequency of annual voltage sags is then estimated.

This frequency dependent cost model provides long term voltage sag cost estimation based on detailed fault classification. However, lots of information such as shares of other faults and types of faults are actually difficult to gather, particularly with regard to the inordinate amount of time required to deal with this kind of information. Furthermore, although the effects of magnitude are considered according to different types of voltage sag, this cost model fails to consider the effects of voltage sag durations.

4.2.2 Probability Dependent Model

A more precise description of expected voltage sag frequency is believed to be associated with the number of the disrupted industrial or commercial processes in systems in terms of equipment sensitivity [21] [22]. This sensitivity is usually quantified as the accumulative trip probability of the equipment in observed processes. Hence, this cost model is probability dependent. Due to the fact that the process may be disrupted by the tripping of individual or numerous pieces of equipment depending on the interconnection of process, as stated in [21] and [22], the process configuration is essential for the assessment of financial losses due to voltage sags.

According to [21] and [22], by knowing the sensitivity of individual pieces of equipment, their tripping probability can be derived in terms of voltage sag duration and magnitude. Then, taking into account the connection of individual pieces of equipment which are connected in a series in the process, any equipment trips will lead to the whole process being disrupted. For processes in which the equipment is connected in parallel, the whole process will only be affected if trips occur in more than one piece of equipment. Hence, the total tripping probability of a process can be derived from Equation-4.2:

$$p_{trip} = 1 - [\prod_{i=1}^{m}(1 - \prod_{j=1}^{n} p_{i,j})] \tag{4.2}$$

where m is the total number of serially connected equipment/groups of equipment in the process, while n is the total number of parallel connected equipment in the ith equipment group. $p_{i,j}$ is the tripping probability of the jth equipment in the ith equipment group. Accordingly, the total expected number of process trips is then estimated and is based on:

$$Total\ Process\ Trips = \sum(p_{trip} * N) \tag{4.3}$$

where the p_{trip} is the probability of process trips for specified types of voltage sags in terms of duration and magnitude, while N is the expect number of voltage sags for associated voltage sag types. Then, instead of an expected number of voltage sags, the number of total process trips is used to estimate the long term voltage sag cost.

Though the probability dependent model is capable of providing relatively reasonable estimations of long term voltage sag cost, it requires comprehensive information such as individual equipment sensitivity, equipment connections, etc. which may make the cost calculation complex and lead to potential estimation errors. In addition, this model is not a direct reflection of the effects of voltage magnitude and duration and it fails to consider the effects of other voltage sag factors in this model, such as consumption, time of occurrence, etc. all of which make it less likely to predict the actual economic losses in relation to the severity of voltage sags.

4.2.3 Cost of Downtime (COD) Model

The economic losses of voltage sags could be more complex and sophisticated with time varying factors. A simple solution for time varying factor consideration is to build a cost model consisting of detailed analysis of each individual time frame. As stated in [26], the cost of downtime (COD) due to voltage sags is estimated in this manner.

The authors in [26] believe that the cost of downtime due to voltage sags can be estimated according to three main aspects:

$$COD = DC + RC + HC \tag{4.4}$$

where *DC* is the 'direct cost', which may include costs associated with raw materials, energy, labor, etc., while *RC* is the 'restart cost', which may include costs associated with repairs, replacements, etc., and *HC* is the 'hidden cost', which may refer to decreased competitiveness, customer dissatisfaction, etc. All of these are then carefully investigated according to real time cost data or historical failure scenarios.

In addition to the above factors, more importantly, the time varying effects of voltage sags with regard to time of day, time of week and time of year are taken into consideration. To introduce the time varying factors, firstly, the direct cost is represented in the form of average value of a complete process activity. Production nears completion as it progresses along the production line. For instance, a whole manufacturing process may be divided into 5 sub-stages, namely P_1, P_2, … , P_5, and the percentage of product completion will vary from 0% in P_1 to 100% in P_5. Thereafter, due to the fact that direct economic losses in manufacturing processes depend on which stages of the process are disrupted, the percentage of product completion can be used to distinguish the direct costs at different stages. Then, the reformed direct cost DC_p will depend on the stages of process activity:

$$DC_p = DC * p_i \tag{4.5}$$

where the p_i is the percentage of product completion in the *i*th process activity. Based on Equation-4.4, the COD due to voltage sags then depends on process activities as well. It should be noted that the process activity consideration is based on the fact that the percentage of product completion at each sub-stage should be constant and not affected by other factors. Therefore, the authors in [26] suggest that the time varying process activity should be further subdivided into smaller new process activities with constant percentages of product completion. In this way, the time varying factors can be introduced and analyzed.

This COD cost model provides time varying cost estimation according to constant product completion percentages in process sub-stages. The authors in [26] state, the economic losses due to voltage sags can be assessed not only in the long term, but also immediately after events have occurred. However, every manufacturing customer conducts its own process activity, which is different from that of other customers, even within the same type of manufacturing. Therefore, if there were only tens of customers observed, the COD cost model would be suitable. However, when hundreds or even thousands of customers are observed, innumerable process activities need to be analyzed and associated COD models need to be built. Obviously, it is impossible to investigate the process activities one by one for such a large number of customers.

4.2.4 Weighting Factor Dependent Model

A convenient approach to evaluate voltage sag cost is based on the relationship between voltage sag and short interruption. As discussed previously, the economic impact of voltage sag are always a proportion of that of short interruption due to the fact that the economic losses will typically depend on the severity of the power quality disturbance. The proportions could be estimated based on historical data, and quantified as weighting factors. Taking short interruption cost as a basic value and associated weighting factors as multipliers, the economic losses of voltage sags are then evaluated [23][24]. Accordingly, the weighting factor dependent cost model becomes

$$C_{vs} = C_{si} * \omega_i \tag{4.6}$$

where C_{vs} is the voltage sag cost model, C_{si} is the short interruption cost model with similar duration, customer characteristics (consumption, type, competitors, etc.) and other relative cost effect coefficients. ω_i is the weighting factor associated with the magnitude of the voltage sag. Obviously, the weighting factor cost model mainly depends on the short interruption cost model. Normally, the weighting factors vary with the ranges of voltage sags in magnitude, e.g. the weighting factor will be 0.4 for all voltage sags from 0.5 p.u. to 0.7 p.u..

This weighting factor dependent model can be applied directly and simply by knowing the magnitude of voltage sags. However, its disadvantages are also obvious. The weighting factors are rough estimations of the relationship between short interruption and voltage sag; accordingly, the results based on the weighting factor dependent cost model are a poor reflection of actual voltage sag cost. Furthermore, the weighting factors are discrete from the magnitude of voltage sags, and make no distinctions between different voltage sags within the same range.

4.2.5 Summary

All the voltage sag cost models mentioned above are summarized in Table-4.1.

As with the short interruption cost model, the purpose of proposing a voltage sag cost model in this thesis is to investigate the short term variation of voltage sag cost regarding associated effects. As discussed in Table-4.1, the above cost models are either too complex or are not suitable for short term estimation. Considering the multiple impact factors of voltage sag cost and their relative simplicity in terms of utilization, the Tobit short interruption cost model discussed in the previous chapter can identify the basic cost of voltage sags and represents the most severe economic losses due to extreme voltage sags, i.e. short interruptions. Then a new set of weighting factors will be introduced to formulate a newly combined voltage sag cost model.

Table-4.1 Summary of Voltage Sag Cost Models

Model	Descriptions	Advantages	Disadvantages
Frequency Dependent Model	- Considering fault types and characteristics - Based on the frequency of voltage sags to predict long term cost	- Detailed faults consideration - The magnitude of voltage sags considered	- Lots of fault information needed - Lack of considering voltage sag duration
Probability Dependent Model	- Estimating the trip probability of manufacturing processes - Multiplied with associated damage cost	- Reasonable estimation of cost - Analyses the trip probability of the whole process	- Requires complex process analysis - Lack of consideration of multiple effects
COD Model	- Detailed cost component analysis - voltage sag cost is estimated based on product completion in manufacturing process,	- Considers time varying effects - Instantly estimates economic losses	- Definition of constant percentage of product completion not clear - cost models too complex and enormous
Weighting Factor Dependent Model	- Basic relationship between short interruption and voltage sag - Estimated according to historical data	Simply applied	- Roughly estimated - Discrete estimation based on voltage magnitude

4.3 Quality Loss Function

Besides the other multiple impact factors, the key issues in voltage sag cost models are the magnitude and duration of voltage sags. To better quantify the relationship between short interruption and voltage sag, the effect of magnitude can be evaluated separately rather than considered as a Tobit coefficient. As short interruptions could be treated as extreme cases of voltage sags, in addition to the characteristics of the Tobit model, the effects of duration and other multiple factors of voltage sag cost can be quantified in the Tobit short interruption cost model. Therefore, the target is to convert the Tobit short interruption cost model into a voltage sag cost model in terms of voltage magnitude. This can be achieved by Quality Loss Function (QLF).

4.3.1 Introduction of Quality Loss Function

From a single small product to a wide range of services provided, there always exist standards to measure the quality of products or services. The quality itself depends on how closely the products or services match their quality standard requirements. Any deviations of quality associated characteristics will result in additional actions, such as a remanufacturing process, after-sales services, etc. From an economic point of view, this means additional financial losses, i.e. quality loss cost. It could be imagined that further deviations of quality characteristics would lead to larger losses. To evaluate the quality loss cost in terms of quality characteristics, the Quality Loss Function (QLF) is introduced by G. Taguchi [90].

The QLF is proposed to describe the relationship between deviations of quality characteristics and associated economic losses in a numerical way. Generally, it can be represented as:

$$L(x) = k * f(x - T) \tag{4.7}$$

where k is a cost-related constant value when the quality characteristics deviate from standard requirements or target values; x represents the observed quality characteristic; T is the target value, i.e. standard requirement in most cases; x-T refers to the deviation of quality characteristics from the standard requirement; $f(x\text{-}T)$ quantifies the relationship between deviation of the quality characteristics and associated quality economic losses.

Normally, the relationships between deviations of quality characteristics and associated quality losses could be investigated from three perspectives: smaller-the-better, nominal-the-better and larger-the-better [90].

1) Smaller-The-Better (STB)

Figure-4.1 The Smaller-the-better Relationship between Deviation of Quality Characteristics and Associated Quality Loss

In Fig-4.1, the horizontal axis is the deviation of quality characteristics, while the vertical axis is the associated quality losses. It should be mentioned, for the purpose of demonstration, the quality characteristic discussed here varies in positive values as only very few quality characteristics will be negative. Obviously, in this kind of relationship, the target value T in Equation-4.7 equals zero, i.e. the best quality occurs when quality characteristics equal zero as well. Due to the fact that T=0, the value of quality characteristics directly indicates their deviation. As shown in Fig-4.1, the smaller the value of the quality characteristics, the better the quality, and quality losses increase with the values of quality characteristics. Such a relationship, for instance, may be carbon dioxide emissions from driving: the faster the driving speed, the more emissions are produced, and, consequently, the higher the environmental cost. The most environment friendly situation occurs when the car is not in use.

2) Larger-The-Better (LTB)

Figure-4.2 The Larger-the-better Relationship between Deviation of Quality Characteristics and Associated Quality Loss

As shown in Fig-4.2, in this relationship, the target value *T* becomes infinity or a maximum target value within limits. The larger the value of the quality characteristics, the better is the quality. Meanwhile, with less quality loss, the quality losses decline with the quality characteristics. Such examples may include maximizing production for a manufacturing process. With more production, less social cost is incurred. By maximizing production, the social costs are reduced to a minimum.

3) Nominal-The-Better (NTB)

Instead of zero or infinity, as shown in Fig-4.3, the target value *T* in the nominal-the-better relationship is a certain constant, which may be derived from lower and upper limits of quality characteristics. The closer to *T* the quality characteristic, the better the quality, and correspondingly the smaller be the associated quality loss will be. Examples may be evaluation of equipment damage: the longer equipment must be sustained in abnormal conditions which deviate from set values, the more potential losses will occur.

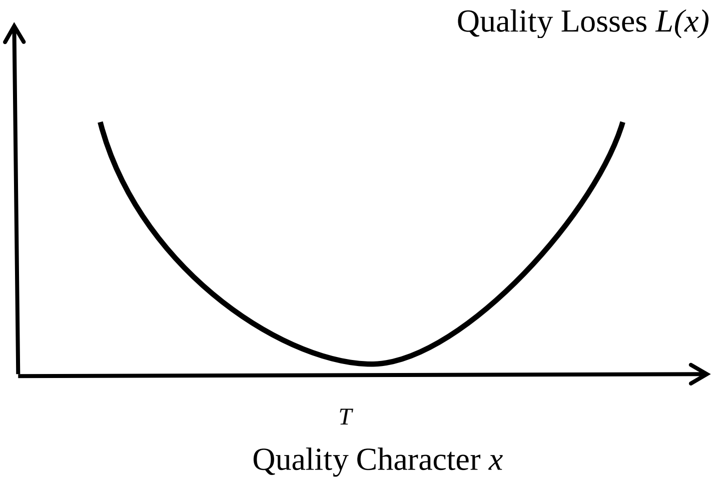


Figure-4.3 The Nominal-the-better Relationship between Deviation of Quality Characteristics and Associated Quality Loss

4.3.2 Typical Expressions

Typically, there are several expressions which could be utilized to quantify the three relationships mentioned above, i.e. STB, LTB and NTB. Back in 1986, when Taguchi first proposed a general quadratic quality loss function [90] [91], it was represented as follows, based on Equation-4.7:

$$L(x) = k * (x - T)^2 \tag{4.8}$$

where x is the quality characteristic, k is a cost-related constant value, and T is the target value.

In Equation-4.8, *f(x-T)* is represented in quadratic form. Therefore, the quality loss in this equation is also called a squared error loss. Obviously, the expression indicates an NTB relationship between losses and quality deviation, as the evaluation of losses is eventually associated with a nominal value *T*.

Correspondingly, when *T*=0, the loss function in Equation-4.8 becomes:

$$L(x) = k * x^2 \tag{4.9}$$

In terms of quality and associated loss relationships shown in Equation-4.9, the smallest loss *L(x)* appears when quality characteristic x equals zero. Undoubtedly, this expresses the STB relationship as shown in Fig-4.1.

In terms of the LTB relationship, the target value is infinity and it is impossible to set T = ∞ in Equation-4.8. However, if the relationship between x and *L(x)* complies with the STB, *1/x* and *L(x)* will be the LTB relationship. Hence, the LTB relationship can be represented as Equation-4.10:

$$L(x) = k/x^2 \tag{4.10}$$

From Equations-4.8 to 4.10, it can be said that the STB and LTB relationships of observed quality characteristics and associated losses are actually special cases of the NTB. Accordingly, all of them could be represented as the quadratic loss function in one way or another.

Although the quadratic loss function provides a reasonable estimation of the relationship between losses and quality characteristics; it has been criticized by many researchers [92] [93] [94] due to the fact that the quadratic loss function is not capable of quantifying the maximum losses due to quality deviations. Without doubt, there will be maximum values for quality losses; the quality losses would not be infinite. As is shown in the quadratic loss function, there is no clue as to where the boundaries of losses lie, as $(x\text{-}T)^2$ may result in any value. As a result, the quality losses could even be infinite in terms of quadratic loss function expression.

Regarding the shape of the curve shown in Fig-4.3 for an NTB relationship, if a maximum value of quality losses L(x) is considered, the shape of the curve may become

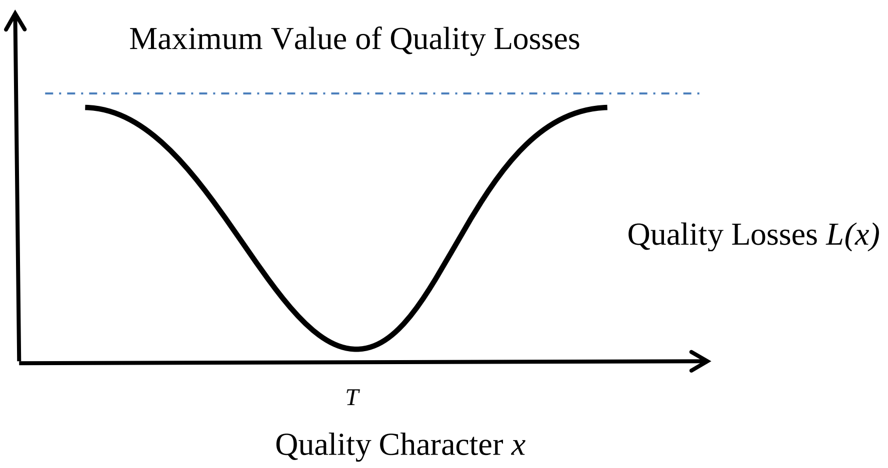


Figure-4.4 The Nominal-the-better Relationship between Deviation of Quality Characteristics and Associated Quality Loss with Maximum Value

From Fig-4.4, it is evident that the shape of the quality losses curve in terms of quality characteristics is similar to the upside-down curve of a normal probability density function. Hence, in [94] and [95], Spiring has proposed an Inverted Normal Loss Function (INLF), and the general expression of this kind of loss function is:

$$L(x) = K(1 - \frac{\pi(x)}{m}) \tag{4.11}$$

where K is the maximum quality losses, $\pi(x)$ is the probability density function of quality character x, and m is the ratio of inversion from a normal probability density function to a component of quality loss function. It is equal to the maximum value of $\pi(x)$ according to Spiring. The normal probability density function of random variable x is written as:

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \tag{4.12}$$

where the $f(x)$ has a maximum value of $x = \mu$ with a standard deviation of σ. For quality loss evaluation, due to the reversed curve, the minimum losses occur at μ, which refers to target value *T*. Hence, the quality characteristic probability density function *π(x)* in Equation-4.11 can be expressed as:

$$\pi(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-T)^2}{2\sigma^2}} \tag{4.13}$$

Obviously, the $e^{-\frac{(x-T)^2}{2\sigma^2}}$ part of *π(x)* will never be larger than 1; accordingly, the maximum value of *π(x)*, i.e. inversion ratio *m* is $\frac{1}{\sigma\sqrt{2\pi}}$. Hence, the INLF can be rewritten as

$$L(x) = K[1 - e^{-\frac{(x-T)^2}{2\sigma^2}}] \tag{4.14}$$

where the σ can also be called a shape parameter [94], as the shape of *L(x)* depends on this parameter, as shown in Fig-4.5. In the new expression, the quality losses *L(x)* will be zero when the quality characteristic x = T, i.e. target value. Furthermore, the quality losses will increase with |*x*-*T*| becoming larger; i.e. the larger the deviation of quality characteristics, the larger the quality loss. Moreover, the maximum value of *L(x)* is K due to the fact that the value of $[1 - e^{-\frac{(x-T)^2}{2\sigma^2}}]$ is not larger than 1 and at a certain point will approach or be equal to 1.

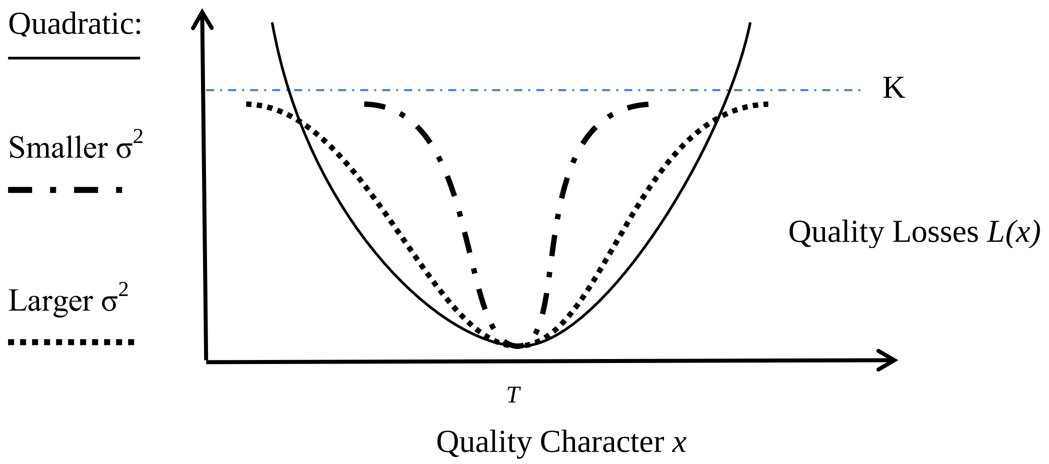


Figure-4.5 Quadratic Loss Function and INLF with Different Shape Parameter σ

Fig-4.5 also shows the difference between Quadratic Loss Function and INLF. Obviously, the INLF does not only provide a maximum value of quality losses as K, but also a flexible description of quality losses varying with quality characteristics due to the alterable shape parameter σ. Hence, compared with Quadratic Loss Function, the INLF is a more reasonable and precise function to illustrate the relationship between quality characteristics and quality loss.

4.4 Voltage Sag Cost Model

To evaluate the financial losses in terms of voltage variation, it is possible to apply a quality loss function, as discussed above. When the voltage quality is investigated in terms of magnitude, the ideal voltage will always be of constant magnitude maintained at the designed level, i.e. standard value. Any deviations of voltage magnitude will cause quality losses which are the result of maintaining magnitude constant at the required level. The further the deviations are from the voltage magnitude, the more quality loss there will be. The deviations of voltage magnitude could be larger or smaller than the standard value; the NTB relationship of quality characteristics (voltage magnitude here) and quality losses could be utilized to evaluate the voltage variation by INFL.

4.4.1 Existing Voltage Quality Loss Function

Normally, the magnitudes of voltage variations are observed in p.u.. If the ideal voltage magnitude is the desired target value, then the target value T i in Equation-4.14 will equal 1 p.u. According to [25], the voltage quality loss function could be represented as:

$$L(x) = \sum_{i=1}^{4} \omega_i \, K_i \{1 - \exp\left[- \frac{(x-1)^2}{2\sigma_i^2}\right]\} \quad (4.15)$$

In paper [92], the voltage sags are divided into four groups, which are:

Table-4.2 Types of Voltage Sags in [25]

Number (*i*)	**Sag Type**	**Duration (s)**	**Magnitude (p.u.)**
1	Instantaneous Sag	0.01~0.5	0.1~0.9
2	Momentary Sag	0.5~3	0.1~0.9
3	Temporary Sag	3~60	0.1~0.9
4	Short-term Sag	>60	0.1~0.9

As shown in Table-4.2, the classification of voltage sags in [25] is based on the different durations of voltage sag. Accordingly, Equation-4.15 refers to the multivariate voltage quality loss function, where ω_i is the calculation index of type-i voltage sag, which is used to differentiate the type of voltage sag; K_i is the maximum economic losses of type-i voltage sag; σ_i is the associated shape parameters and x is the deviation of voltage magnitude.

In paper [25], the values of ω_i are derived based on Signal-Noise-Ratio (SNR), which is used to quantify the variation of voltage quality in this case

$$\omega_i = \frac{\frac{1}{\eta_i}}{\sum_{j=1}^{4}\frac{1}{\eta_j}} \tag{4.16}$$

where η_i is the SNR of type-i voltage sags. ω_i actually indicates the ratio of reversed SNR for type-i voltage sag over total reversed SNR for all types of voltage sags. The largest is η, but the less severe the voltage variation, the smaller the voltage quality losses are. According to [96], when a signal is monitored, it may vary from time to time, which leads to noise. Normally, to evaluate the noise content, the SNR η could be used and calculated as

$$\eta = 10\lg\frac{A_{signal}}{A_{noise}} \tag{4.17}$$

where A_{signal} and A_{noise} are the root-mean-square magnitude of signal and noise respectively. In the case of voltage quality, the signal refers to monitored voltage magnitude, while noise refers to the difference between monitored voltage magnitude and desired voltage magnitude.

In this voltage quality loss function, represented in [25], a continuous estimation on economic losses due to voltage sags via voltage magnitudes is provided. However, based on Equations-4.15 to 4.17, this function is not capable of providing continuous estimation in terms of duration. As shown in Table-4.2, the effect of duration is only considered a criterion for voltage sag classification in terms of length. Hence, the economic losses are estimated by discrete durations. In addition, other impact factors may affect economic losses due to voltage sags, such as time of occurrence, customer consumption, etc. To fully consider the multiple effects on voltage sags, a reformed voltage sag cost model is proposed, based on the voltage quality loss function.

4.2.2 Voltage Sag Cost Model

As previously discussed, a short interruption will normally cause disruption to a load or an industrial process that is not specifically protected. The same is true for voltage sag, which will affect loads or industrial processes as well, but only parts of them. Due to the fact that economic losses as a result of power quality disturbance are evaluated according to impacted loads or industrial processes, the economic impact of voltage sag is usually a certain proportion of that of short interruption. Moreover, as previously defined, the magnitude of voltage sags varies between 0.1 and 0.9 p.u.; any sags less than or equal to 0.1 p.u. will have the same financial impact as short interruptions and be treated as short interruptions. Accordingly, it can be said that short interruptions are extreme cases of voltage sags, and the maximum economic losses of any voltage sags could be equally treated as short interruption cost with the same characteristics (except magnitude), such as duration, customer types and consumption, etc. Table-4.3 shows the differences between short interruption and voltage sag in cost calculations. It is apparent that, in terms of the impact factors of cost, only the magnitude of voltage differentiates short interruptions and voltage sags. Therefore, it is possible to evaluate the economic losses of voltage sag by using the quality loss function together with the Tobit short interruption cost model.

Table-4.3 The Differences between Short Interruption and Voltage Sag in Cost Calculation

Type of Event	Duration (s)	Magnitude (p.u.)	Other Impact Factors Involved
Short Interruption	0.01~60	≤0.1	Time of Occurrence, Type of Customer, Competition, Consumption, etc.
Voltage Sag	0.01~60	0.1~0.9	The same as Short Interruption

According to Equations-4.14 and 4-15, the voltage sag cost model may be expressed as:

$$L(x) = \begin{cases} C_{si}\left\{1 - exp\left[-\frac{(x-1)^2}{2\sigma^2}\right]\right\} & 0.1 < x \leq 1 \\ C_{si} & x \leq 0.1 \end{cases} \tag{4.18}$$

where C_{si} is the Tobit short interruption cost model discussed in the previous chapter, which consists of multiple factors, such as duration, customer consumption and market factors, and which is represented as unit cost. Hence, the voltage sag cost in this thesis is also expressed as unit cost. Instead of a calculation index for each type of voltage sag in Equation-4.15, except magnitude, the characters of voltage sags are linked with extreme cases, i.e. short interruptions, and quantified in the Tobit short interruption cost model. The x represents the magnitude of observed voltage sags per unit, and the target value is 1, which indicates the ideal voltage magnitude.

Though any voltage sags between 0.9 and 1 p.u. may not lead to economic losses, for the purpose of demonstration, the range of voltage sag variations is increased, as shown in Equation-4.18. For voltage sags which vary between 0.1 and 1 p.u. (but not equal to 0.1 p.u.), the economic losses are evaluated according to a combined Tobit short interruption cost model with quality loss function. When voltage magnitude equals 1 p.u., there are no economic losses, and when voltage magnitude approaches

0.1 p.u., the economic losses are close to maximum values due to voltage sags. For voltage sags that are equal to or less than 0.1 p.u., the economic losses are evaluated as short interruption cost.

According to [94], the shape parameters σ can be calculated by Equation-4.19,

$$\sigma = \frac{\Delta}{4} \tag{4.19}$$

where Δ is the distance from the target value T to the point of quality characteristic x, at which point the quality losses reach the maximum values (shown in Fig-4.6). As stated in [94], for INFL such as in Equation-4.14, the maximum values of quality losses will only be attained when $x = \pm\infty$, and at the point of $x = T \pm \sigma$, the quality loss will be $0.9997K$. Practically, it could be recognized as equal to the maximum value K of quality loss.

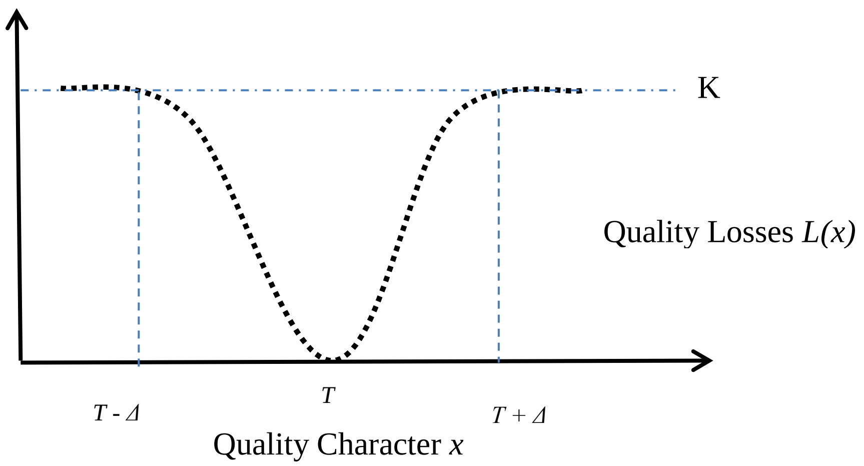


Figure-4.6 Definition of Δ in Shape Parameter σ Calculation

4.5 Case Study

Just as with the short interruption cost studies outlined in the previous chapter, industrial customers have been chosen to demonstrate the voltage sag cost model as the main victims of voltage sags. There are also two groups of industrial customers: continuous process industrial customers and non-continuous process industrial customers. The duration of voltage sags for continuous process industrial customers mainly ranges from 0.1 to 3 seconds, and for non-continuous process industrial customers, the variations of duration are between 0.1 and 60 seconds.

4.5.1 Main Factors Concerned

As short interruptions could be considered as extreme cases of voltage sags, most of the impact factors of voltage sags are actually the same as those for short interruptions. Accordingly, the main effects of voltage sag cost are the same as those shown in Table-3.6 in the previous chapter. They are voltage sag duration in seconds t, squared duration t^2, average monthly consumption of customers *con* and the rival factor r, in addition to voltage sag magnitude x, where the duration, consumption and rival factors are quantified as the Tobit regression parameters in the short interruption cost model *Csi*, i.e. the effects of these voltage sag factors are considered as extreme cases in maximum quality losses, while the effect of voltage sag magnitude is quantified in quality loss function as weighting factors.

4.5.2 Weighting Factors

In this thesis, the voltage sag cost is considered as a proportion of the short interruption cost, and short interruption is treated in the same way as an extreme case of voltage sag. Therefore, taking the short interruption cost as the basic and maximum economic losses of voltage sag, it is possible to quantify the relationship between voltage sag and short interruption according to weighting factors.

As shown in Equation-4.18, the weighting factor *wf* in the voltage sag cost model can be expressed as:

$$wf = 1 - exp\left[-\frac{(x-1)^2}{2\sigma^2}\right] \qquad 0.1 < x \leq 1 \tag{4.20}$$

where x is the voltage magnitude per unit. Obviously, the values of weighting factors are associated with voltage magnitude and quantify the proportion of short interruption cost to voltage sag cost.

As voltage magnitudes only range from 0.1 to 1 p.u. in voltage sag cases, the more drops there are in voltage magnitude, the larger the consequent economic losses will be. Hence, the maximum economic losses of voltage sags occur when x approaches 0.1. Accordingly, the value of Δ will be (1-0.1) = 0.9 p.u. according to the definition of Δ, as shown in Fig-4.7. As voltage sags are defined as voltage magnitudes which drop to less than the ideal voltage, i.e. less than 1 p.u., it should be mentioned that only the left part of the curve in Fig-4.7 with $x \leq 1$ will be investigated for voltage sag evaluations, which is represented in the shaded part of Fig-4.7. However, when voltage variation has a magnitude larger than 1 p.u., it does not necessarily mean the maximum value of quality losses will occur when x= T+Δ = 1+0.9 =1.9 p.u., as the variation may be much larger than 1.9 p.u. and the maximum economic losses are not associated with short interruption cost at all. It is impossible to express this with Equation-4.20. Hence, the curve of quality losses via voltage magnitude may be as that in Fig-4.7.

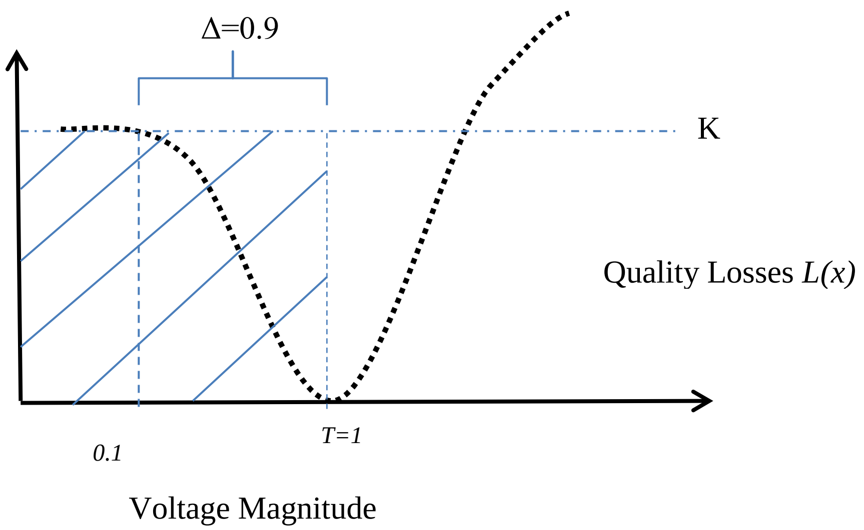


Figure-4.7 Value of Δ in Voltage Sag Calculation

Accordingly, the value of σ = Δ/4 = 0.9/4 = 0.225, and the expression of weighting factors becomes

$$wf = 1 - exp\left[-\frac{(x-1)^2}{2\times0.225^2}\right] \qquad 0.1 < x \leq 1 \tag{4.21}$$

Therefore, the weighting factors of voltage magnitude variation for voltage sags will be as depicted in the following table:

Table-4.4 Weighting Factors via Different Voltage Magnitude Variation

Voltage Magnitude (x) p.u.	**Weighting Factors (wf)**
$\leq$ 0.10	1.000
0.15	0.999
0.20	0.998
0.25	0.996
0.30	0.992
0.35	0.985
0.40	0.971
0.45	0.950
0.50	0.915
0.55	0.865
0.60	0.794
0.65	0.702
0.70	0.589
0.75	0.461
0.80	0.326
0.85	0.199
0.90	0.094
0.95	0.024
1.00	0.000

In Table-4.4, the weighting factors associated with various voltage magnitude variations are derived from Equation-4.21. Compared with weighting factors which are estimated based on experiences in weighting factor dependent models [23] and [24] which are shown in Table-4.5, this new series of weighting factors provides relatively similar and reasonable values. More importantly, it provides continuous variable weighting factor estimation on voltage sag magnitude.

Table-4.5 Estimated Weighting Factors Based on Experiences [23] [24]

Events	Weighting Factors
Short Interruption	1.0
Voltage Sags (< 0.50p.u.)	0.8
Voltage Sags (0.5~0.7p.u.)	0.4
Voltage Sags (0.7~0.9p.u.)	0.1

4.5.3 Voltage Sag Cost Estimation

As the relationship between voltage sag and short interruption is described in terms of weighting factors, according to Equation-4.18, the voltage sag cost could be evaluated using Equations-4.22 and 4.23 based on the short interruption cost model derived in Chapter 3 (Equation-3.26 and 3.27),

$$C_{vsn} = \begin{cases} [Exp(0.2049 + 0.0604t - 0.0004t^2 + 0.0699con + 0.4021r + u) - 1] * \left\{1 - exp\left[-\frac{(x-1)^2}{2\times 0.225^2}\right]\right\} & 0.1 < x \le 1 \\ Exp(0.2049 + 0.0604t - 0.0004t^2 + 0.0699con + 0.4021r + u) - 1 & x \le 0.1 \end{cases} \quad (4.22)$$

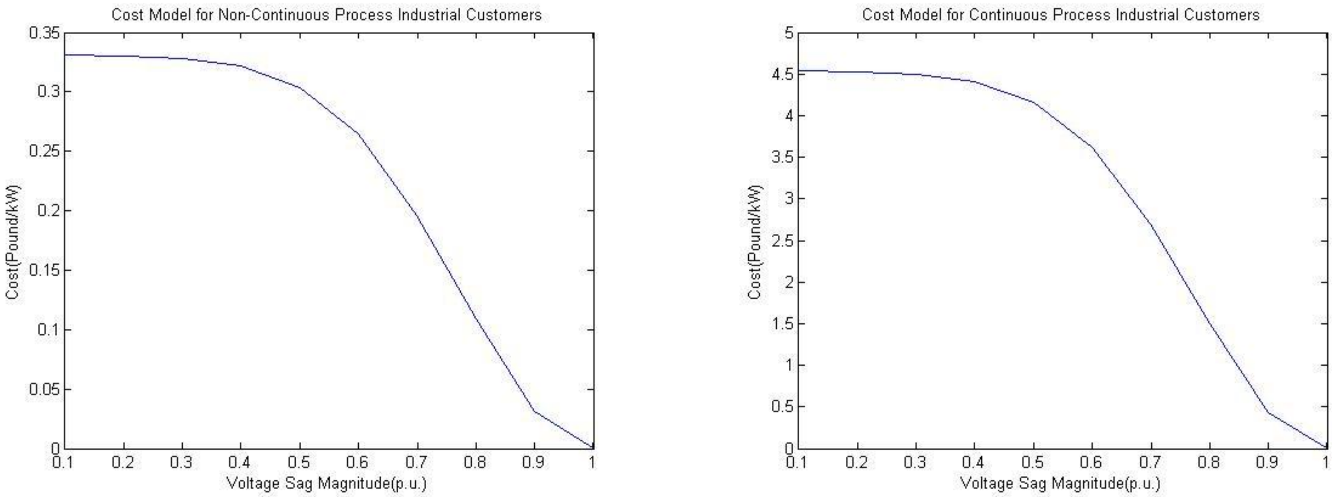
$$C_{vsc} = \begin{cases} [Exp(1.3197 + 0.4601t - 0.0773t^2 + 0.0288con + 0.1347r + u) - 1] * \left\{1 - exp\left[-\frac{(x-1)^2}{2\times 0.225^2}\right]\right\} & 0.1 < x \leq 1 \\ Exp(1.3197 + 0.4601t - 0.0773t^2 + 0.0288con + 0.1347r + u) - 1 & x \leq 0.1 \end{cases} \quad (4.23)$$

Equation-4.22 is the voltage sag cost model for non-continuous process industrial customers, while Equation-4.23 is the voltage sag cost model for continuous process industrial customers. For non-continuous process industrial customers the error term is $u \sim N(0,0.0546^2)$, and for continuous process industrial customers the error term is $u \sim N(0,0.0793^2)$. Both of these are relatively small and can be ignored. The *t* in the original short interruption cost model is the short interruption duration; in this case, it can be considered as the duration of voltage sag due to extreme cases. Accordingly, the con and r are the associated customer consumption and rival information, respectively. x is the magnitude of voltage sag.

Due to use of the same equations as in the short interruption cost model for maximum economic losses, the relationships between voltage sag cost and associated duration, consumption and rival information are almost the same as those discussed in the short interruption cost model in the previous chapter. By holding these three impact factors as constants, it is possible to investigate how the magnitude of voltage sag affects the cost.

Assuming there are two industrial customers, which are continuous process customer and non-continuous process customers, both have the same monthly consumption 3.0MW, and there are no rivals in the same area, the 1 second voltage sag event is observed. Then according to Equations-4.22 and 4.23, the relationship between voltage magnitude and voltage sag cost is calculated and demonstrated in Fig-4.8.

Fig-4.8 (a) describes the relationship between voltage sag unit cost and magnitude for non-continuous process industrial customers, while Fig-4.8 (b) indicates the relationship for continuous process industrial customers. The curves show that the voltage sag cost is zero when the voltage magnitude is equal to 1 p.u., which is the ideal voltage magnitude, and increases while the magnitude decreases. As the magnitude of voltage sag diminishes, the voltage sag cost becomes more similar to that of the short interruption cost.



(a) (b)

Figure-4.8 Voltage Sag Unit Cost Variations with Magnitude for Non-continuous and Continuous Process Industrial Customers

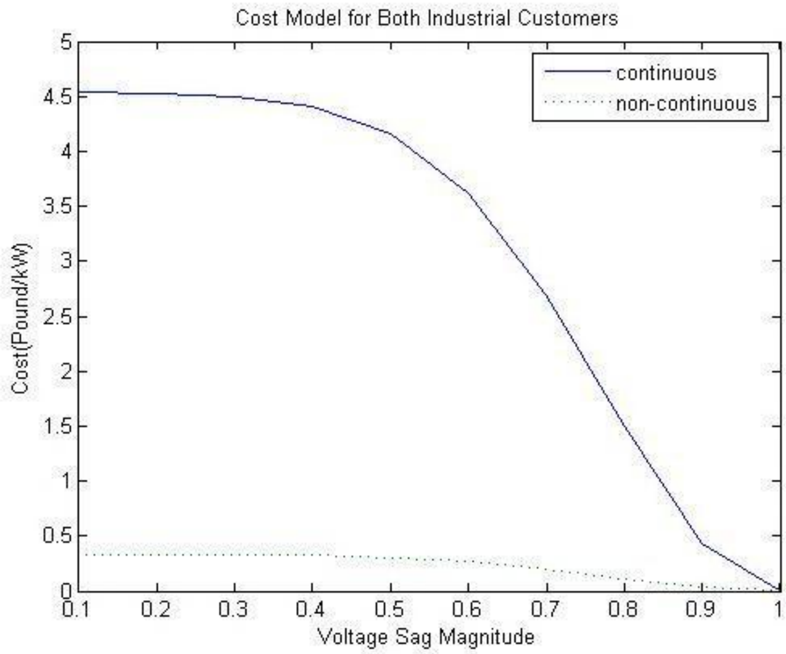


Figure-4.9 Comparing Voltage Sag Unit Cost Variations with Magnitude of Both Industrial Customers

As shown in Fig-4.9, the introduction of weighting factors does not affect the fact that continuous process industrial customers suffer more economic losses than non-continuous process industrial customers during voltage sag or short interruption events.

4.6 Summary

The Quality Loss Function provides a model to evaluate voltage sag economic losses at continuous voltage magnitudes based on maximum losses. After introducing a Tobit short interruption cost model which considers multiple factors in the previous chapter, it is possible to propose a combined cost model based on the economic relationship between short interruptions and voltage sags. The new voltage sag cost model proposed in this chapter consists of Quality Loss Function and Tobit short interruption cost model, and is characterized by the following features:

1) Due to the utilization of Quality Loss Function, the effects of voltage sag magnitudes could be continuously estimated based on maximum voltage sag economic losses. The estimation of voltage sag cost is no longer limited by predefined variation ranges of voltage magnitudes.

2) Based on the fact that the short interruptions could be treated as extreme cases of voltage sags in terms of magnitude, the economic losses of short interruptions could be equal to the maximum voltage sag cost with the same duration and other impact factors except voltage magnitude. In this way, the maximum voltage sag cost in Quality Loss Function could be expressed by the Tobit cost model. The two methods are then combined into one cost model. Thereafter, the multiple impact factors of voltage sags could be considered in the Tobit cost model.

3) The relationship between short interruptions and voltage sags could be quantified in this new model in terms of weighting factors. Compared with traditional weighting factors in voltage sag cost calculations, the weighting factors derived

from Quality Loss Function have been proved to be reasonable and reliable as well as more flexible.

Chapter 5 Harmonic Cost Model

5.1 Introduction

Nowadays, harmonic distortion has become of increasing concern to many power suppliers. A large amount of harmonic pollution is introduced by widely used electronic devices in modern power systems. However, inevitably, modern automatic systems largely rely on more and more sensitive devices. This means that the economic consequences due to harmonic distortion in these sensitive device dependent systems will be costly. Generally, the effects of harmonic pollution will fall into two aspects: additional energy consumption and premature equipment failure. Sometimes, the harmonic pollution may even cause mis-operation of protection systems, which will result in short interruptions. As the economic consequences of harmonic distortion might be significant [97], it is necessary to understand and quantify the harmonic cost.

There are few cost models available to quantify the economic losses of harmonic pollution. Normally, most of the harmonic cost studies focus on energy loss calculations for each harmonic variation. In the long term, the cost of equipment procurement is then taken into consideration. However, the equipment replacement is not caused by a single severe harmonic variation. Every harmonic variation that may damage equipment should be responsible for the replacement. Therefore, to evaluate the economic losses due to harmonics, it is necessary to take the effect of every harmonic variation into account.

In this chapter, the total economic losses due to harmonic variation will be analyzed from two perspectives: energy loss cost and equipment aging cost. The cost model for energy losses will be discussed in Section 5.2, while the existing long term aging cost calculation will be introduced in Section 5.3, followed by introduction of a new short term aging cost model in Section 5.4. Then in Section 5.5, the utilization of a short term aging cost model will be demonstrated though case studies. Thereafter, there is a discussion of the proposed harmonic cost model.

5.2 Energy Loss Cost Model

In most harmonic cost literature [27] [28] [29], the economic results of energy losses are calculated based on the analysis of energy losses and associated average unit cost, which is shown as Equation -5.1

$$D_{losses} = D_0 * (Energy\ Losses) \tag{5.1}$$

where D_0 is the unit cost of electrical energy.

Though the energy losses due to harmonics are precisely described, the literature has neglected two important issues of power quality cost, which are the time and customer characteristics dependent effects on the economic losses. As previously discussed, due to the characteristics of power quality cost, the unit economic losses may vary from time to time, and from customer to customer. It is therefore not accurate to describe unit cost as a constant average value. Indeed, just as with the short interruption cost, it is possible to quantify these varying effects with the Tobit model, which makes the calculation of harmonics cost more precise. However, the most important thing in the energy loss cost model is to derive the value of energy losses.

5.2.1 Existing Energy Losses Calculation

In [27], the losses are calculated in terms of active power rather than energy and are derived from different components of power systems:

1) Transformer

   It is believed in [27], that the losses associated with transformers are composed of three parts: iron losses, copper losses and spray losses. The iron losses are non-load dependent losses caused by the main flux in a magnetic circuit and can be calculated according to Equation-5.2:

$$P_i = \frac{1}{T}\int_0^T v_p * i_0 \, dt \tag{5.2}$$

where T is the observed period, v_p is the primary voltage of the transformer under no load conditions, and i_0 is the magnetizing current.

On the other hand, the copper losses are the load dependent losses associated with winding resistance and can be calculated based on Equation-5.3:

$$P_c = \frac{1}{T}\int_0^T [(R_p * i_p^2) + (R_s * i_s^2)] dt \tag{5.3}$$

where i_p and i_s are the primary and secondary winding currents under load conditions respectively. R_p and R_s are the primary and secondary winding resistance respectively.

The stray losses are produced by leakage flux in conductive materials of the transformer, such as winding, core, etc. As recommended in [27], the stray losses can be estimated as P_s=15%P_i, which are a proportion of iron losses.

By adding the above three sets of losses together, the total losses from transformers are derived as follows:

$$P_t = P_i + P_c + P_s \tag{5.4}$$

2) Cable

According to [27], the losses from cables are simply calculated according to Equation-5.5:

$$\text{Losses} = \frac{1}{T}\int_0^T R * i^2 \, dt \tag{5.5}$$

where R is the cable resistance and i is the current in the cable.

3) Induction Motors

The simplest way of calculating losses in induction motors is to estimate the difference between input and output power. The motor input power can be estimated as:

$$P_{in} = \frac{1}{T}\int_0^T v * i \, dt \tag{5.6}$$

where T is the observed period, v is the motor applied voltage, and i is the motor current.

Output power can be calculated based on motor torque as:

$$P_{out} = Torque * \omega \tag{5.7}$$

where both the *Torque* and ω of motors can be measured and calculated by monitoring parameters. Then, the losses in induction motors could be derived from:

$$Losses = P_{in} - P_{out} \tag{5.8}$$

In this way, the power losses in induction motors can be estimated.

Though the main active power losses of power systems are analyzed in detail in [27], obviously, the calculations of power losses for each component are too complex for a large power system. Furthermore, the losses estimated by using this method consist of not only harmonic losses, but also losses under normal conditions. Therefore, a relatively accurate and applicable estimation of energy losses due to harmonics is required.

5.2.2 PCC Based Energy Losses Estimation

PCC is the Power Control Center, which connects the power network and power consumers. It can be simply illustrated as in Fig-5.1.

PCC

Figure-5.1 Power Control Center Illustration

The PCC acts as a main power control panel; it consists of breakers, monitoring and control devices, etc. All the energy exchanges between networks and consumers are connected by a PCC. As a result, without exception, the harmonic losses could also be estimated through a PCC [98].

Assuming at the PCC point, the measured voltage and current are u and i, respectively, if there was harmonic pollution either from network to consumers or consumers to network, the voltage and current at the PCC point could be represented as follows:

$$u = u_1 + \sum_{h \neq 1} u_h \tag{5.9}$$

$$i = i_1 + \sum_{h \neq 1} i_h \tag{5.10}$$

where u_1 and i_1 are the fundamental voltage and current respectively, and u_h and i_h are the hth harmonic voltage and current respectively. This means that the voltage and current at the PCC point consist of fundamental and harmonic components. The harmonic losses could thus be calculated as:

$$E_{losses} = \int_0^T u_h * i_h \, dt \tag{5.11}$$

where T is the observed duration. However, it is difficult to evaluate harmonic voltage and current directly. As a result, based on the fact that both the harmonic and fundamental components produce energy, they are derived from observed parameters at the PCC point. Meanwhile, it is relatively easy to get the fundamental components. Therefore, it is possible to estimate the harmonic losses as the energy differences between observed energy and fundamental energy, which is represented as the follows:

$$E_{losses} = \int_0^T u * i \, dt - \int_0^T u_1 * i_1 \, dt \tag{5.12}$$

In this way, the energy losses due to harmonics could then be easily derived at the PCC point rather than at each device across the system. Meanwhile, the accuracy is relatively reliable as stated in [98]. This makes this PCC based energy loss estimation more practical than the previous method, and in this thesis, it will also be utilized to estimate the energy losses due to harmonics.

5.2.3 Energy Unit Cost

Unlike short interruption, energy losses due to harmonics are not energy that is being interrupted, but are the wasted energy in the power system. In the short term, it is a matter of energy efficiency rather than non-delivered energy. Though this might not include costs such as restart cost, wasted raw material cost, etc., the economic losses due to harmonics could be estimated in the same way as short interruption cost due to the existence of multiple impact factors.

The original data of energy loss cost can be gathered from surveys by asking customers the estimated energy unit cost associated with duration, customer characteristics, time of day, etc. Then these data are classified into different groups, i.e. industrial customers, commercial and public customers and domestic users. Thereafter, due to the similar impact factors involved, the unit energy loss cost of each group could be derived according to the Tobit cost model mentioned in the previous chapter with almost the same parameter setups.

With the unit energy loss cost derived from the Tobit cost model and PCC based energy losses, it is possible for time and customer characteristics to vary harmonic energy loss cost.

Table-5.1 Parameters of Harmonic Energy Loss Cost Model

Observed Dependent Variable	**Impact Factors (Independent Variables)**
Unit Energy Loss Cost (£/kWh)	Duration
	Monthly Consumption
	Rivals or Not

5.3 Long Term Harmonic Aging Cost

Normally, the aging cost due to harmonics arises from replacement of equipment which has failed prematurely. Obviously, this depends on the useful life time of equipment. The shorter the life time, the more often the replacement occurs, and the greater are the economic losses due to premature aging. As the aging cost is calculated based on the life time of equipment, in most cases, it is represented as a present value rather than economic loss of each harmonic variation.

5.3.1 Useful Life Time of Equipment

Ideally, the electrical equipment functions perfectly under sinusoidal voltage or current. However, under most circumstances, it suffers from non-sinusoidal operating conditions due to harmonics, which are responsible for accelerating the necessity for replacement of equipment. Due to the fact that harmonics could be further divided into fundamental component (sinusoidal condition) and higher order harmonics, the effects of fundamental components should be removed from non-sinusoidal operating conditions to get the actual harmonics aging cost. As a result, the harmonic aging cost for each system component, can be calculated according to the differences between financial investment for purchasing equipment under non-sinusoidal conditions and ideal operating conditions [29] [99], which are represented in Equation-5.13.

$$D_a = D_{ns} - D_s \tag{5.13}$$

where D_{ns} is the total cost for replacing equipment during non-sinusoidal periods, which is associated with the expected number of replacements, while D_s is the total cost for purchasing equipment under sinusoidal operating conditions during the observed period, which is linked to the expected life-time of the equipment under normal conditions. Accordingly, in this case, it is assumed that only premature failture due to harmonics accounts for unexpected replacement during observed periods. Hence, the aging cost due to harmonics could be estimated as shown in Equation-5.13.

For a given observed period, D_{ns} and D_s could be calculated based on the expected life time under non-sinusoidal and sinusoidal conditions respectively [29] [99]. Normally, the useful lifespan of electrical equipment in power systems depends on thermal degradation of the equipment insulation materials [100]; this degradation either appears as decreasing strength of the equipment mechanisms and/or deterioration of the dielectric behaviors of the insulation materials. There is no doubt that thermal degradation is closely associated with the surrounding temperature of equipment. Higher temperatures will always be more prone to causing aging issues. It is widely accepted that thermal degradation can be represented by a chemical reaction equation [100]:

$$\frac{\Delta R}{\Delta t} = Ae^{-E/K\theta} \tag{5.14}$$

where $\Delta R/\Delta t$ is the reduction in properties associated with time, in other words, it is the aging reaction rate. A is a constant which varies with temperature. It represents the frequency of reaction, which could be treated as a constant within small ranges of temperature. E is the activation energy required to trigger an aging reaction. Both A and E depend on the insulating materials and can be derived from experiments. K is the gas constant, which is a physical constant that depends on units used to represent energy and temperature. θ is the absolute temperature. Equation-5.14 represents the rule of a chemical aging reaction, which was derived by Arrhenius. Hence, it is called the Arrhenius Equation.

As shown in Equation-5.14, $\Delta R/\Delta t$ only varies with temperature; it can be represented as a function of temperature, $\Lambda(\theta)$. Thereafter, the total reduction in properties could be estimated by multiplying the rate of the aging reaction by the total useful time of equipment, which could be expressed as:

$$R = T * \Lambda(\theta) \tag{5.15}$$

where T is the useful lifespan of equipment. If the reduction in properties is measured in terms of the percentage of the original status before utilization, then the properties will be reduced from 100% at the beginning of equipment life to 0% at the end of life. Hence the total useful life time of observed equipment can be derived from:

$$T = \frac{100\%}{\Lambda(\theta)} \tag{5.16}$$

As the life time of equipment in systems is normally measured in terms of years, when taking the variable temperature into account, it is assumed that the equipment suffers from the same variation of temperatures each year; thus Equation-5.16 can be rewritten as:

$$T = \frac{100\%}{[\int_0^{\infty}(Ae^{-\frac{E}{K\theta}}) * f(\theta)d\theta]} \tag{5.17}$$

where $f(\theta)$ is the probability density function (pdf) of the temperature per year derived from observed data. As seen in Equation-5.17, knowing the pdf of the temperature of observed equipment, the useful life time of equipment can be deduced based on the degradation of insulating materials of the equipment.

5.3.2 Present Value of Long Term Harmonic Cost

As stated in the previous section, the expected life time of equipment in non-sinusoidal and sinusoidal conditions can be estimated based on Equation-5.17. Without doubt, the probability density function of temperature in non-sinusoidal and sinusoidal conditions will be different, which leads to two unequal expected life times. Accordingly, for a given prediction duration, the differences in tbe frequency of equipment replacement are derived; then the D_{ns} and D_s in Equaiton-5.13 can be estimated based on the frequency and cost of purchasing new equipment.

In most of the literature [29] [99], it is believed that the harmonic cost is a long term cost and is measured year by year. Therefore, it is important to evaluate the present value of harmonic cost. This can be done by taking into account both the variation of the cost for buying new equipment and the present value of the costs in every year of the equipment's life.

Assuming the cost of purchasing equipment increases at a rate of α and the replacement occurs in *n*th year due to estimation. Then the expected purchasing cost at *n*th year is:

$$p_n = p_1 * (1 + \alpha)^{n-1} \tag{5.18}$$

where the p_1 is the cost for purchasing equipment the first time, α is the variation in the purchasing cost, and p_n indicates the expected cost of buying replacement equipment after $n-1$ years use after first purchase.

Then, transferring the expected future purchasing cost into the present value with a discount rate of β, the present value of purchasing replacement equipment could be expressed as:

$$p_p = \frac{p_n}{(1+\beta)^{n-1}} \tag{5.19}$$

where β is the discount rate for the present value.

Thereafter, the total present value of the long term harmonic aging cost for m years prediction (assuming $n<m<2n$, i.e. it is only necessary to purchase the equipment twice within the prediction years) can be evaluated as:

$$D_m = p_1 + \frac{p_1 * (1+\alpha)^{n-1}}{(1+\beta)^{n-1}} \tag{5.20}$$

To clarify how the estimated useful life time of equipment and present value could be used, a simple example can be found in [99].

Assuming a capacitor is subject to harmonics in most of its operating conditions, and the estimated life time under sinusoidal conditions is 40 years, which is equal to the prediction period, the first time purchase cost of this capacitor is £30. As there is no replacement action taken during 40 years of operation under sinusoidal conditions, the purchase cost of the capacitor under sinusoidal conditions will be the first time purchase cost, i.e.

$$D_s = £30$$

Assuming, based on historical data and Equation-5.17, that the reduction rate of this capacitor under non-sinusoidal conditions via variable temperatures could be derived as 0.03, it could be concluded that, from the beginning of its utilization, the capacitor has 1/0.03≈ 33 years of life time in total. Accordingly, within the prediction period of 40 years, this capacitor should be bought twice. When taking the variation of equipment cost into account, which assumes an increase at a variation rate of 0.07, then, according to Equation-5.18, the expected purchase cost in the 33rd year should be:

$$p_{33} = 30 * (1 + 0.07)^{33-1} = £\,261.46$$

The above cost is the expected cost in future. Therefore, to evaluate the present cost, further calculation is needed. Assuming the discount rate of the present value is 0.08, the present value of the expected cost of purchasing replacement equipment in the 33rd year can be calculated according to Equation-5.19 as:

$$p_{33p} = \frac{261.46}{(1 + 0.08)^{33-1}} \approx £22$$

Due to the existence of non-sinusoidal operating conditions, the capacitor needs to be bought twice. Hence, the cost for buying the capacitor twice under non-sinusoidal operating conditions represents the sum of the present value of purchasing a replacement for a second time, and the amount for purchasing this capacitor for the first time:

$$D_{ns} = p_{33p} + p_1 = 22 + 30 = £52$$

Based on Equation-5.13, the total aging cost of this capacitor due to harmonics could be estimated as the differences between the cost of purchasing the capacitor twice under non-sinusoidal conditions and the cost of purchasing the capacitor once under sinusoidal conditions:

$$D_a = D_{ns} - D_s = 52 - 30 = £22$$

5.3.3 Discussion

According to that which is demonstrated in the previous section, undoubtedly, it is a complicated job to evaluate the aging cost of every component in the power system affected by harmonics. As a result, only equipment with a high purchase cost is considered during aging cost calculations, such as transformers, while other relatively low economic losses can be disregarded, such as premature failure in cables.

Normally, as previously described, the long term harmonic aging cost is derived from the present value of purchasing replacement equipment a few years down the line. However, as shown in Equations-5.18 to 5.20, the present value of total aging cost only indicates the value at the beginning of equipment utilization. If the total aging cost in predicted *m* years is considered at the *i*th years after first purchased, and within the *m* years of observation, the equipment requires being purchased a 2nd time at *n*th (where $i<n$) year, as previously defined. Then, the first purchase cost at the *i*th year is:

$$p_{i1} = p_1(1+\alpha)^{i-1} \tag{5.21}$$

and the second purchase cost at the *n*th year is:

$$p_{i2} = \frac{p_1 * (1+\alpha)^{n-1}}{(1+\beta)^{n-i}} \tag{5.22}$$

Hence, the present value of total aging cost under non-sinusoidal conditions in the *i*th year could be derived as:

$$D_{nsi} = p_1(1+\alpha)^{i-1} + \frac{p_1 * (1+\alpha)^{n-1}}{(1+\beta)^{n-i}} \tag{5.23}$$

In this way, the different present value of the total economic losses during equipment life time can be examined every year. However, aging cost calculation cannot be used for short term prediction because this method is not capable of providing cost estimation associated with each detected aging harmonic variation.

5.4 Short Term Harmonic Aging Cost

To calculate the short term aging cost, a method to estimate aging cost upon each harmonic variation is introduced.

5.4.1 Duration Dependent Aging Cost

Though in the long term, the aging cost is evaluated without consideration of duration, when it comes to short term calculation, it is necessary to take the duration effects into account. However, unlike other PQ costs, for most electrical users, the harmonic aging issues have very slight effects on final products. As a result, PQ costs impact factors such as customer consumption, competitor information, etc., do not play an important role in aging cost calculations. Therefore, in this thesis, the harmonic aging cost is mainly determined by the duration of harmonic disturbances.

Due to a shortage of relevant cost data, it is not always possible to evaluate the exact data of aging costs for different durations. However, it is apparent that longer durations result in further premature failure of equipment. Shorter durations will have less impact on premature equipment failure. Therefore, for the purpose of rough estimation, compared with long term aging cost, it is possible to assume that the short term aging cost is in direct proportion with duration, i.e. longer duration comes with larger harmonic aging economic losses, while shorter duration leads to smaller harmonic aging cost. Accordingly, the aging cost for a specified duration can be estimated according to the proportion of specified duration within the total duration of harmonics.

For observed equipment, with years of operation and recording, it is possible to have historical data on a number of harmonics with associated duration. As the chances of encountering the same harmonic durations are relatively small, for the purpose of future prediction, the historical durations are divided into different time frames with 1ms intervals and are represented in terms of approximate value. For example, if the historical durations of harmonics vary within 6ms, it is possible to divide the historical durations into the following time frames, 0~1ms, 1~2ms, 2~3ms, 3~4ms, 4~5ms and 5~6ms. For a rough estimation, each duration allocated within a given frame is represented as the largest duration in the following calculation, as shown in Table-5.2

For example, if there was a harmonic variation lasting 1.2ms, then it could be calculated as 2ms for approximate estimation.

Table-5.2 Examples of Duration Time Frame and Represented Value

Time Frame (ms)	Approximate Value (ms)
0~1	1
1~2	2
2~3	3
3~4	4
4~5	5
5~6	6

From the historical data, the average number of harmonics per year within each frame could be derived according to

$$k_a = \frac{total\ number\ of\ harmonics\ in\ historical\ data}{number\ of\ historical\ years} \quad (5.24)$$

Then the duration dependent harmonic aging cost could be introduced as

$$D_{ai}(t) = D_{ai} * \frac{t_\beta k_\beta}{\sum t_j k_j} \quad (5.25)$$

where D_{ai} is the present value of the total aging cost in ith year after first purchase, which can be calculated by Equations-5.13 and 5.23; t_β is the approximate value for the observed duration within time frame β; and k_β is the associated average number of harmonics per year in time frame β. $\sum t_j k_j$ represents the sum of all detected harmonic durations, which is calculated according to the approximate value for each time frame multiplied by the associated average number of harmonics.

It should be mentioned that Equation-5.25 complies with the assumption that the observed equipment operates within the same environment each year, which means the number of harmonics within each time frame stays at the same average value year after year. In this way, it is possible to represent the total harmonic aging cost in the prediction year by percentage of duration for each year. As a result, Equation-5.25 indicates the total present value of harmonic aging costs varying with durations in terms of duration percentage every year. Therefore, the total aging cost in the observed year associated with a given duration can be estimated according to the percentage of the given duration in the total duration.

5.4.2 Total Harmonic Distortion

As not all of the detected harmonics result in aging issues, in duration dependent aging cost calculation, the results indicate the amount of aging cost for a given duration for all detected harmonics, rather than harmonic variation that could be responsible for aging issues. To evaluate the aging cost per harmonic variation that may truly lead to aging issues, it is necessary to predict the total number of possible variations that may result in premature failure of equipment. The severity of harmonic distortion determines whether or not the equipment will be damaged due to aging issues. As a result, a measurement of harmonic distortion is required.

Normally, the Total Harmonic Distortion (THD) is a common tool to measure the contents and severity of harmonics. It is also called the distortion factor and presented as:

$$\mathrm{THD} = \frac{\sqrt{H_2+H_3+H_4+\cdots+H_n}}{H_1} \tag{5.26}$$

where H_1 is the value of fundamental voltage or current, and H_n is the value of *nth* harmonic voltage or current. Generally, the THD is represented in terms of percentage, which indicates the amount of higher order harmonic content. The IEEE Standard 519 [53] recommends that the limit of THD for utilities companies within normal operation is less than 5% in terms of voltage harmonics. Any harmonics distortion above this limit is considered as harmful to equipment.

Accordingly, in this thesis, to define the aging harmonic issues, the limits recommended by IEEE are adopted, i.e. if the THD of voltage is estimated to be larger than 5%, then the harmonic distortion is considered as a harmonic variation that may result in premature failure and related aging cost. In contrast, if the THD of voltage is less than 5%, then the harmonic distortion is regarded as an acceptable harmonic variation without leading to any premature failure issues. Correspondingly, there is no aging cost for harmonic distortion with THD of voltage less than 5%. Therefore, it is essential to gather historical data that are associated with the number of harmonic variations with THD of voltage above 5%.

5.4.3 Weibull Distribution

It is easy to derive the total average number of harmonics per year according to historical data. However, to evaluate the expected number of harmonics that may result in premature aging, it is necessary to estimate the probability of harmonic variations with THD of voltage above 5% in total detected harmonics. Unlike most of the regular probability distribution calculations, the occurrence of harmonic variation with THD above 5% is quite random in detected harmonics. It is thus not always possible to describe the probability distribution with common distributions like normal distribution, exponential distribution, etc. To represent the irregular character of the possibility of harmonic variations with THD above 5%, the Weibull distribution is used.

The Weibull distribution is named after Waloddi Weibull, who presented this distribution in detail in 1951 [102]. It is a continuous probability distribution that can describe the characteristics of other types of distribution, in other words, it could represent any forms of distribution, even irregular distributions. Normally, the standard form of the Weibull distribution probability density function (pdf) can be written as a 3 parameter function:

$$f(x;\alpha,\beta,\gamma)=\begin{cases}\frac{\beta}{\alpha}(\frac{x-\gamma}{\alpha})^{\beta-1}e^{-(\frac{x-\gamma}{\alpha})^{\beta}}, & x\geq 0\\ 0 & , \ x<0\end{cases} \tag{5.27}$$

where x is a random variable, which is the observed independent variable; and α is called a scale parameter of the Weibull distribution, which indicates the stretch or squeeze of the represented pdf in a graph. Taking a normal distribution pdf represented in terms of Weibull distribution for example, Fig-5.2(a) shows the pdf of a normal distribution with a scale parameter equal to 1, which has a maximum value of 0.4 on the vertical axis, and ranges from -3.5 to 3.5 on the horizontal axis. Fig-5.2 (b) is the pdf of this normal distribution with a scale parameter equal to 3, where due to the stretch of the pdf, the maximum value on the vertical axis is lower than 0.13, and range on the horizontal axis is extended. In Fig-5.2 (c), where the scale parameter equals 1/3, the maximum value on the vertical axis becomes 1.3 and the range on the horizontal axis is squeezed. As a result, it is easy to conclude that scale parameters larger than 1 will stretch the pdf, while less than 1 will squeeze the pdf. Moreover, the non-positive values of scale parameters are not allowed.

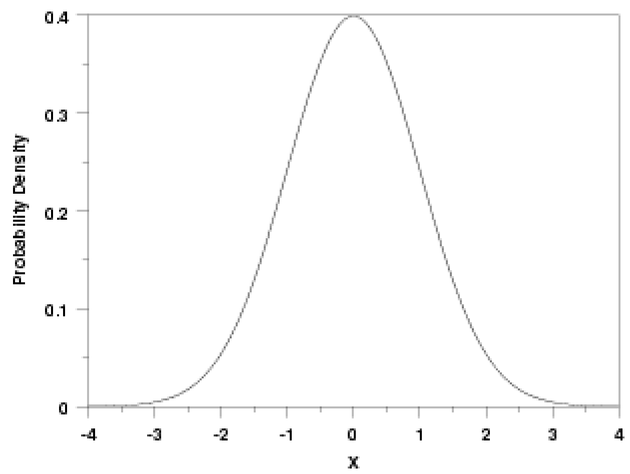


Figure-5.2 (a) The pdf of Normal Distribution with α=1

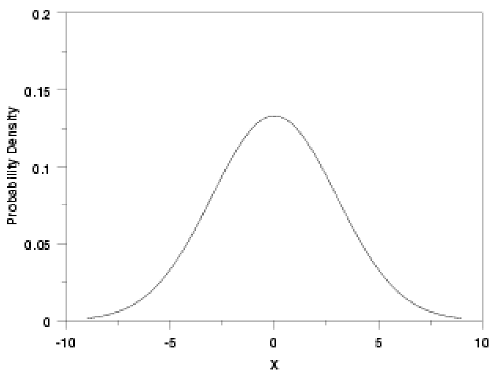


Figure-5.2 (b) The pdf of Normal Distribution with α=3

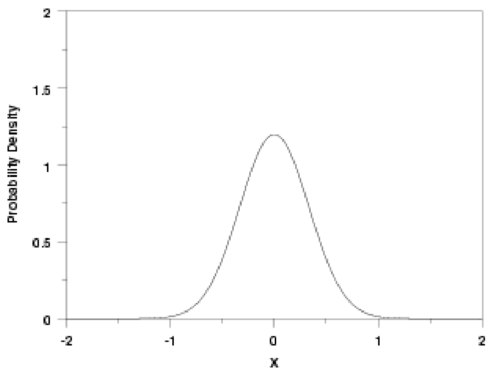


Figure-5.2 (c) The pdf of Normal Distribution with α=1/3

β is the shape parameter of Weibull distribution, which allows a variety of shapes of represented distribution. In Fig-5.3, the different effects of shape parameters on pdf curves are shown. It can be seen that the shapes of pdf curves change diversely according to the shape parameters.

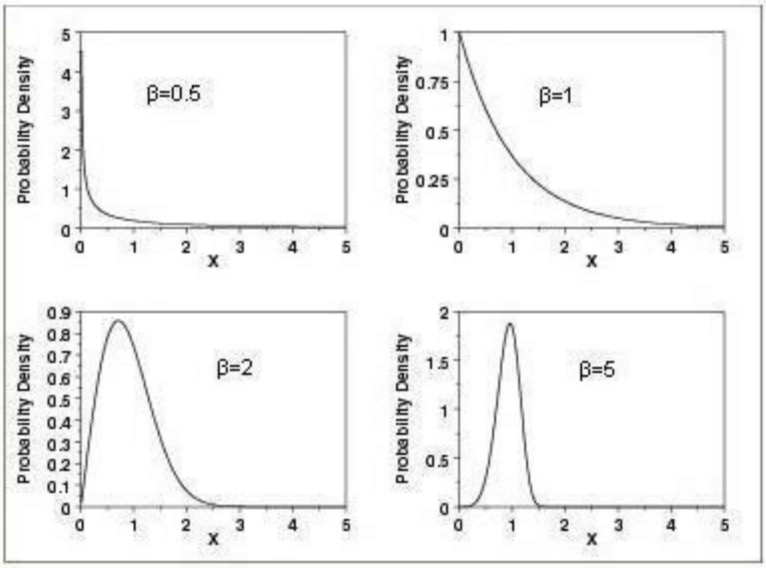


Figure-5.3 The Effects of Shape Parameters

γ is the location parameter of the Weibull distribution, which determines the location of represented distribution. For instance, when it is increased from 0 to 5, the position of the pdf curve shifts 5 units to the right on the horizontal axis.

$f(x;\alpha,\beta,\gamma)$ is called a probability density function of the Weibull distribution. It describes a curve, the areas under which indicate the probabilities associated with the corresponding intervals x.

However, in most cases, it is more interesting to measure the variable x itself rather than the distance from x to γ. As a result, the 2 parameter pdf of Weibull distribution is more common, where $\gamma=0$.

$$f(x;\alpha,\beta) = \begin{cases} \frac{\beta}{\alpha}(\frac{x}{\alpha})^{\beta-1}e^{-(\frac{x}{\alpha})^{\beta}} & , \ x \geq 0 \\ 0 & , \ x < 0 \end{cases} \tag{5.28}$$

Based on Equation-5.28, the cumulative distribution function of 2 parameter pdfs of Weibull distribution could be derived according to $\int[f(x;\alpha,\beta)]$, which is:

$$F(x;\alpha,\beta) = 1 - \exp[-\left(\frac{x}{\alpha}\right)^{\beta}] \tag{5.29}$$

F(x; α, β) suggests the probability when measuring variables less than or equal to *x*.

In terms of the harmonic aging calculation, the measured independent variable is the duration of harmonics represented as approximate values, expressed as *t*. Due to relatively small intervals in each time frame, it is possible to assume that the dependent variables are continuously distributed on durations. As stated at the beginning of this section, the purpose of harmonic aging calculation is to estimate the probability of harmonic variations with THD of voltage above 5%. In this case, rather than the total number of harmonic variations, the numbers of harmonic variations with THD above 5% as well as associated durations are required. As with most probability calculations, measured independent variables are more concerned with durations rather than distance from a certain value. Therefore, for harmonic aging calculations, a 2 parameter expression is used, and Equation-5.29 can be rewritten as:

$$F(t;\alpha,\beta) = 1 - \exp[-\left(\frac{t}{\alpha}\right)^{\beta}] \tag{5.30}$$

where *F(t; α, β)* indicates the probability that the harmonic variation with THD above 5% may occur within a duration lasting less than or equal to *t*, and α , as the scale parameter, represents the time when the occurrence probability is 1-1/e = 0.632, β. As the shape parameter suggests measuring the range of harmonics with THD above 5%, the larger β is, the smaller the range of harmonics with THD above 5% are [103].

With the probability derived from Equation-5.30, the expected number of harmonic variations with THD above 5% can be estimated based on the total average number of harmonic variations per year. Assuming, according to historical data, that the total number of detected harmonics is *N* in *i* years of operation, then the average number of detected harmonics per year is:

$$N_a = \frac{N}{i} \tag{5.31}$$

When harmonics with duration represented as t are observed, the per year expected number of harmonics with THD of voltage above 5% for harmonics with a duration lasting t could be calculated as:

$$N_{THD>5\%} = \frac{N}{i}\{1 - \exp\left[-\left(\frac{t}{\alpha}\right)^{\beta}\right]\} \tag{5.32}$$

Then in m years of prediction, the total expected number of harmonics with THD above 5% is given as:

$$N_{total} = m\frac{N}{i}\{1 - \exp\left[-\left(\frac{t}{\alpha}\right)^{\beta}\right]\} \tag{5.33}$$

If the present value of total harmonics aging cost for duration in this time frame at ith year in m year prediction is given by Equation-5.25, then the expected present value of aging cost for duration presented as t per harmonic variation could be estimated as

$$D_{per} = \frac{D_{ai} * \frac{t_{\beta}k_{\beta}}{\sum t_j k_j}}{m\frac{N}{i}\{1 - \exp\left[-\left(\frac{t}{\alpha}\right)^{\beta}\right]\}} \tag{5.34}$$

5.4.4 Summary

In this section, considering the effects of harmonic durations in short term calculations, the present value of the total harmonic aging cost in the year of prediction is firstly transferred into duration dependent total harmonic aging cost in all years of prediction, which is derived from the percentage of given durations in total durations each year. Therefore, the total harmonic aging cost at the prediction year with given durations can be evaluated. Then, based on the calculation of total harmonic distortion, the effects of harmonics are estimated. According to the recommendations of IEEE, for most utilities suppliers, the total harmonic voltage distortion, when less than 5%, is recognized as an acceptable level for normal operation. Hence, any harmonics with THD above 5% will lead to aging issues. According to this assumption, the number of harmonics with THD above 5% for prediction years is then estimated by the Weibull distribution. Thereafter, the present value of harmonic aging cost per event is derived from the total aging cost over the total number of harmonics with THD above 5%.

5.5 Case Study

In this section, a numeric example will be derived to demonstrate how the harmonic cost model could be utilized in practice.

5.5.1 Assumptions

A manufacturing factory is connected to a distribution network through the PCC, and complies with the following assumptions:

1) The factory possesses a production line that is supposed to operate over 30 years. The operation environment of the production line remains stable for years. For the production line, the purchasing cost of the core equipment is much more expensive than other auxiliary equipment at £9000, and the increasing rate of purchase cost is 0.07 per year. In this case, only the core equipment is examined when estimating harmonic aging cost.
2) The expected life of the core equipment under non-sinusoidal conditions is estimated as 17 years, while the expected life of the core equipment under sinusoidal conditions is estimated as 40 years, and the discount rate for the present value is 0.08 per year.
3) This equipment has already been used for 4 years. The observation takes place in the 5th year of operation and, based on its historical operation data, the periods of detected harmonics vary within 20ms. Accordingly, the total number of detected harmonic variations associated with different periods is shown in Table-5.3

Table-5.3 Historical Data of Harmonics

Time Frame of Harmonic Duration (ms)	**Approximate Duration (ms)**	**Total Number of Detected Harmonics Variations in 4 years** ***(N_i)***	**Total Number of Harmonic Variations with THD>5% in 4 years** **(N_{THDi})**	**Average Number of Harmonic Variations per year** **(k_i)**
0 ~1	1	6	3	1.5
1~2	2	8	4	2
2~3	3	9	5	2.25
3~4	4/	8	6	2
4~5	5	7	4	1.75
5~6	6	5	3	1.25
6~7	7	10	7	2.5
7~8	8	20	11	5
8~9	9	24	14	6
9~10	10	16	8	4
10~11	11	10	9	2.5
11~12	12	5	0	1.25
12~13	13	6	1	1.5
13~14	14	14	8	3.5
14~15	15	7	2	1.75
15~16	16	20	12	5
16~17	17	6	3	1.5
17~18	18	17	7	4.25
18~19	19	19	13	4.75
19~20	20	9	5	2.25

where the approximate value of duration is the maximum value in each time frame. The average number of harmonic variations k_i is derived from the number of harmonic variations recorded in 4 years divided by the number of years of operation, which is 4 years. i.e. $k_i = N_i / 4$.

5.5.2 Harmonic Cost Calculation

Assuming this factory is suffering from a harmonic variation, which lasts 10.5ms,

a) Energy Losses Cost

Assuming the measured voltage *u(t)* and current *i(t)* at PCC could be written as:

$$u(t) = u_1 \sin(\omega t + \alpha_1) + u_5 \sin(5\omega t + \alpha_5)$$
$$i(t) = i_1 \sin(\omega t + \beta_1) + i_5 \sin(5\omega t + \beta_5)$$

where the $\omega = 2\pi f$ is the angular frequency, α *and* β are the phases of voltage and current, respectively. $[u_1 \sin(\omega t + \alpha_1)]$ and $[i_1 \sin(\omega t + \beta_1)]$ are the fundamental voltage and current respectively. In this case, only 5th orders are the dominant harmonics for both voltage and current and the energy losses due to this harmonic variation are evaluated as:

$$\begin{aligned}
E_{losses} = &\int_{t_1}^{t_2} \{[u_1 \sin(\omega t + \alpha_1) + u_5 \sin(5\omega t + \alpha_5)] * [i_1 \sin(\omega t + \beta_1) + i_5 \sin(5\omega t + \beta_5)]\}\, dt \\
&- \int_{t_1}^{t_2} [u_1 \sin(\omega t + \alpha_1)] * [i_1 \sin(\omega t + \beta_1)]\ dt \\
&= \{-\frac{u_1 i_5}{2}\left[\frac{\cos(\alpha_1 + \beta_5)}{6\omega}\sin(6\omega t) + \frac{\sin(\alpha_1 + \beta_5)}{6\omega}\cos(6\omega t) - \frac{\cos(\alpha_1 - \beta_5)}{4\omega}\sin(4\omega t)\right. \\
&\qquad \left. + \frac{\sin(\alpha_1 - \beta_5)}{4\omega}\cos(4\omega t)\right]\}\Big|_{t_1}^{t_2} \\
&+\{-\frac{u_5 i_1}{2}\left[\frac{\cos(\alpha_5 + \beta_1)}{6\omega}\sin(6\omega t) + \frac{\sin(\alpha_5 + \beta_1)}{6\omega}\cos(6\omega t) - \frac{\cos(\alpha_5 - \beta_1)}{4\omega}\sin(4\omega t)\right. \\
&\qquad \left. - \frac{\sin(\alpha_5 - \beta_1)}{4\omega}\cos(4\omega t)\right]\}\Big|_{t_1}^{t_2} \\
&+ \{-\frac{u_5 i_5}{2}\left[\frac{\cos(\alpha_5 + \beta_5)}{10\omega}\sin(10\omega t) + \frac{\sin(\alpha_5 + \beta_5)}{10\omega}\cos(10\omega t) - t\cos(\alpha_5 - \beta_5)\right]\}\Big|_{t_1}^{t_2}
\end{aligned}$$

where t_1 is the start time of this harmonic variation and t_2-t_1=10.5ms.

Here, if the energy unit cost derived from the Tobit model is $C_{u,}$ after considering the duration, and the average consumption and competition are the same as for the short interruption cost model in Chapter 3, then the total energy loss cost due to this 10.5ms harmonic is:

$$D_{losses} = E_{losses} * C_u$$

b) Aging Cost per Event

The expected life time of the core equipment under non-sinusoidal conditions is 17 years in a 30 year production line; in this case, the core equipment needs to be purchased twice in total. Hence, considering the increasing rate 0.07 and discount rate of 0.08, after 4 years' operation, the present value of the first purchase cost in the 5th year is:

$$D_{1st} = 9000(1 + 0.07)^{5-1} = £11797.164$$

the present value of the second purchase cost in the 5th year is

$$D_{2nd} = \frac{9000(1 + 0.07)^{5-1}(1 + 0.07)^{30-5}}{(1 + 0.08)^{30-5}} = £9349.280$$

As discussed in the previous section, under sinusoidal operation conditions, the purchase only happens one time at the beginning of this core equipment operation due to an expected life time of 40 years. Therefore, the present value of total cost for the core equipment in sinusoidal conditions is D_s=D_{1st} =£11797.164. Under non-sinusoidal operation conditions, the purchase occurs twice due to the expected life time of this core equipment. In this case, the present value of the total cost for the core equipment in non-sinusoidal conditions is the sum of the two parts:

$$D_{ns} = D_{1st} + D_{2nd} = £21146.444$$

Accordingly, for the 5th year of observation, the present value of the total harmonic aging cost in 30 years is

$$D_a = D_{ns} - D_s = £9349.280$$

Then, as stated in the previous section, if the core equipment operates in a relatively stable environment, the average number of harmonic variations in 4 years is almost steady from year to year, i.e. the percentage of harmonics with given duration remains the same every year. Hence, a percentage of aging cost lasts 10.5ms in total, so can be calculated according to the percentage of duration with an approximate value of 11ms throughout the total duration per year.

$$\begin{aligned} D_a(11) &= D_a \frac{t_{11}k_{11}}{\sum_{i=1}^{20} t_i k_i} \\ &= 9349.280 * \frac{11 * 2.5}{1 * 1.5 + 2 * 2 + 3 * 2.25 + \cdots + 18 * 4.25 + 19 * 4.75 + 20 * 2.25} \\ &= £\,400.164 \end{aligned}$$

The average number of harmonics per year is calculated as

$$N_a = \frac{\sum N_i}{4} = \frac{6 + 8 + 9 + \cdots + 17 + 19 + 9}{4} = 56.5$$

The probability of the occurrence of harmonic variations with THD above 5% for given duration t is derived from the number of harmonic variations and associated durations. The occurrence distribution of harmonic variations by duration can be expressed in a graph, as shown in Fig-5.4.

Based on this occurrence distribution, it is possible to evaluate the Weibull cumulative probability function (cpf) with the SAS that was introduced in the previous section. Given the number of harmonics with THD above 5% with the associated duration as input, the outputs of the estimated Weibull parameters are shown in Table-5.4, where the ‘estimate’ represents the estimated value of Weibull scale parameter α and shape parameter β respectively. The ‘standard error’ indicates the standard deviation of the estimate, whereas the 95% confidence with lower and upper limits indicates the general range of the estimate.

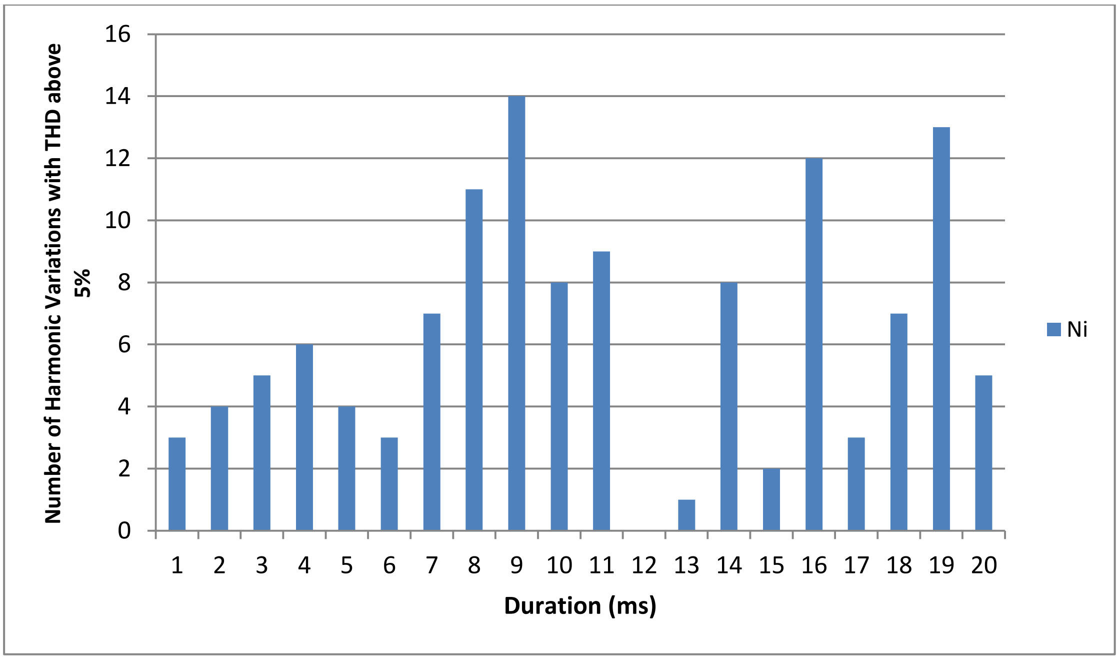


Figure-5.4 Number of Harmonic with THD of Voltage Above 5% via Duration

Table-5.4 Results of Weibull Distribution on SAS

Weibull Parameter	Estimate	Standard Error	95% Confidence Limits	
			Lower Limits	Upper Limits
α	12.619	0.560	11.568	13.766
β	2.112	0.157	1.826	2.442

As shown in Table-5.4, with relatively small deviations according to standard errors, the estimates of scale and shape parameters are acceptable. Therefore, the cdf of the Weibull distribution can be expressed as:

$$p(t) = 1 - \exp[-\left(\frac{t}{12.619}\right)^{2.112}]$$

This Weibull cumulative distribution function estimates the probability of harmonic variations with THD above 5% for durations less than or equal to *t*. Hence, for a harmonic lasting 10.5ms, the probability of harmonic with THD above 5% is

$$p(10.5) = 1 - \exp\left[-\left(\frac{10.5}{12.619}\right)^{2.112}\right] = 0.492$$

Accordingly, the expected number of harmonics with THD above 5% per year is

$$N_E = N_a * p(10.5) = 56.5 * 0.492 = 27.826$$

Furthermore, the total expected number of harmonics with THD above 5% for 10.5ms in 30 years is

$$N_T = 30N_E = 30 * 27.826 = 843.777$$

In this case, the expected present value of aging cost for this 10.5ms harmonic could be calculated as

$$D_{10.5} = \frac{D_a(11)}{N_T} = \frac{400.164}{843.777} = £0.474$$

c) Total harmonic cost

The total cost for this 10.5ms harmonic variation is the sum of the energy loss cost and aging cost, which is expressed as

$$D_{total} = D_{losses} + D_{10.5} = E_{losses} * C_u + 0.474$$

5.6 Summary

In this chapter, the harmonic cost of a given short term duration is divided into two aspects: energy loss cost and aging cost. The energy loss cost is calculated based on the measured voltage and current at the PCC. According to the differences between fundamental energy and measured energy, the energy losses due to harmonics are estimated. Together with the customer and time varying unit cost, which is derived from the Tobit cost model, the total harmonic energy loss cost is then evaluated.

To calculate the aging cost, first the equipment's useful life-time is estimated according to the thermal degradation of the insulation material. After that, the equipment purchase cost in predicted years can be calculated. Based on the differences between purchase cost under non-sinusoidal and sinusoidal operation conditions for equipment, the total aging cost in total prediction years is then evaluated. Thereafter, the present value of the total aging cost can be derived according to equipment's increasing purchase rate and future discount rate. Then, based on the percentage of the given duration in total historical detected harmonic variations, the total harmonic expected aging cost for a given duration is estimated. Finally, to evaluate the harmonic aging cost for a given duration per event, the expected number of total harmonic variations that may result in aging issues is evaluated according to the probability of THD above 5%.

Based on the proposed harmonic cost model in this chapter, it is possible to estimate harmonic costs in the short term. The short term harmonic cost calculation provides benefits for the short term economic analysis of detected harmonic variations. However, the harmonic cost calculation in this chapter is only a rough estimation and requires a lot of additional calculations, such as equipment useful life, present value, etc. Furthermore, this cost model is limited by single equipment calculations. For systems with a number of pieces of equipment, the calculation processes may become much more complicated.

Chapter 6 Time Varying Cost Models

6.1 Introduction

In the previous chapters, the cost models for each main Power Quality (PQ) component, i.e. short interruption, voltage sag and harmonics, have been described. However, as introduced in Chapter 2, the PQ cost is a type of customer, time and consumption varying cost; these proposed PQ cost models have considered the varying impact factors (customer types, duration, customer consumption, competitor information, etc.) except for the time of occurrence factor. As previously discussed, the time of occurrence plays an important role in PQ cost calculations. For the same power quality disturbance, the customer may experience a different amount of economic loss at another time of occurrence. Based on the research in [18], compared with the weekend, the economic losses due to power quality disturbances are higher during working days, while, economic losses in the afternoon appear to be higher than at other times during the day. In these cases, power quality disturbances during periods of higher load demand incur greater economic losses. Therefore, it is possible to suggest that there is a link between the time of occurrence and load demand.

In this chapter, the load curve that represents the variation of load demand is introduced in Section 2. Then, the relationship between load demand and power quality cost is discussed in Section 3. Thereafter, in Section 4, the time varying coefficients are derived based on the daily load curve. In the following section, case studies will be demonstrated to apply the time varying coefficient into each power quality cost model. The conclusion and discussion will be given in the last section.

6.2 Load Curve

In the power system, the loads vary continuously with time, and the variations can be significant from hour to hour, day to day, month to month and year to year. To describe the variations of the loads, a load curve with respect to time is used. The load curves can be easily divided into different types according to the observed time period:

1) For daily load curve, the interest is in the variations in a 24-hour period. Hence, the loads are examined every half or one hour.
2) For monthly load curve, the day to day variations are more significant. In this case, the load variations are expressed in terms of observed day.
3) For yearly load curve, the load variations throughout one year are observed. Therefore, the load variations are represented versus monthly period.

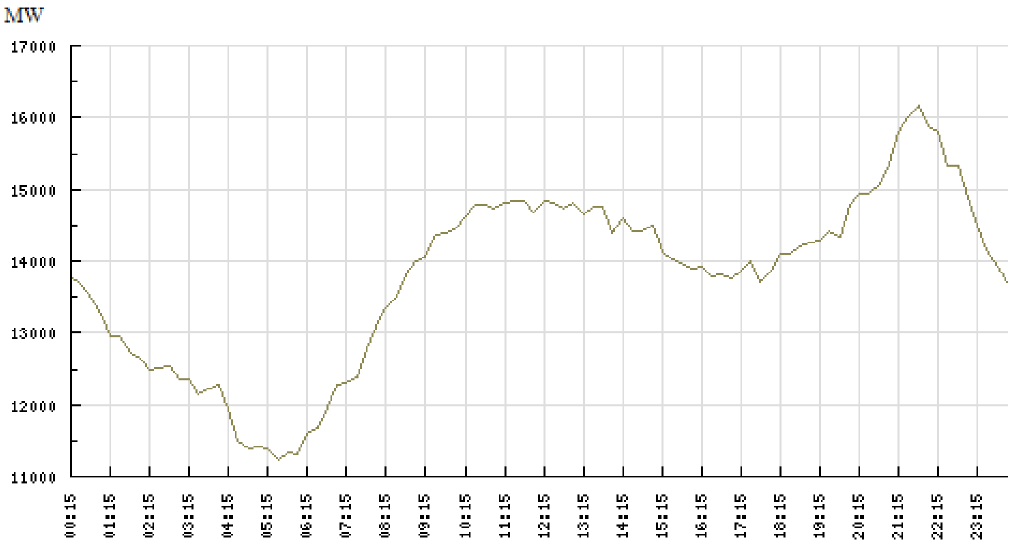


Figure-6.1 Example of Daily Load Demand Curve [104]

Fig-6.1 shows a typical daily load curve for a power grid. The y-axis is the total load consumption in MW, and the x-axis is the time of each observed point at one hour intervals. On the load curve, the highest point indicates the maximum total load demand in the observed day. It is apparent that the main electricity consumers in this area are domestic customers, as the highest load demand appears in the evening, and the load demands become lower late at night as people’s activities slow down.

The load curve shows the relationship between load demand and time and can be examined in a graph, which provides convenience for further analysis.

6.3 The Relationship between Load Demand and PQ Cost

To a certain extent, the PQ economic losses of electricity consumers vary with load demand. For example, when the load demands of industrial customers stay at a relatively high level, it means most of industrial processes are activated. In modern production lines, almost the whole industrial process is linked. During these peak load demand periods, any PQ disturbances affect all the industrial processes online. In this case, a large number of products will be delayed; raw materials in the process will be wasted; and it will take a long period of time to recover for each affected industrial process. Accordingly, the economic losses due to PQ disturbances will be massive.

In contrast, during off-peak hours, if anything, only parts of the industrial processes are in operation; accordingly load demand drops to a relatively low level. In this case, the effects of PQ disturbances are limited. Compared with peak load periods, the affected industrial processes are fewer. Some industrial customers may not operate at all. There may be no scheduled products or raw materials being processed; therefore, the economic losses are much smaller than during peak load demand periods due to limited, or absent production activities.

It is easy to conclude that, during peak load demand periods, electricity consumers, especially large consumers, suffer higher economic losses due to PQ disturbances. However, in off-peak load demand periods, they will experience low economic losses under PQ disturbances.

6.4 The Time Varying Coefficient

In order to quantify the variation of load demand from time to time, a time varying coefficient is introduced in terms of the load demand in this section.

6.4.1 Introduction of the Time Varying Coefficient

Based on the fact that the load demands vary with time, each point of time can be associated with a given load demand on a load curve. Accordingly, the variation of load demands reflects the changes of time. Hence, based on the load curve, the time varying coefficient is represented in terms of variation of load demand, which can be expressed as:

$$\lambda_i = \left(1 + \frac{L_i - L_a}{L_a}\right) * 100\% \tag{6.1}$$

where L_i is the load demand on the observed time point i. L_a is the total average load demand, which can be calculated thus:

$$L_a = \frac{\sum_{i=1}^{N} L_i}{N} \tag{6.2}$$

N is the time of observation. The average load demand can be derived from historical data.

$(L_i\text{-}L_a)/L_a$ is the percentage of deviation of observed load demand from the average load demand.

It should be noted that the load demands are normally recorded discretely rather than continuously. Hence, the observed load demand varies at an interval connected to the observation period. To make the time varying coefficient more precise and useful, the interval of observation is defined as every half or one hour.

6.4.2 Numeric Example

A demonstration of how the time varying coefficient is estimated, taking a 24-hour daily load curve at an interval of 1 hour as an example, is depicted in Fig-6.2

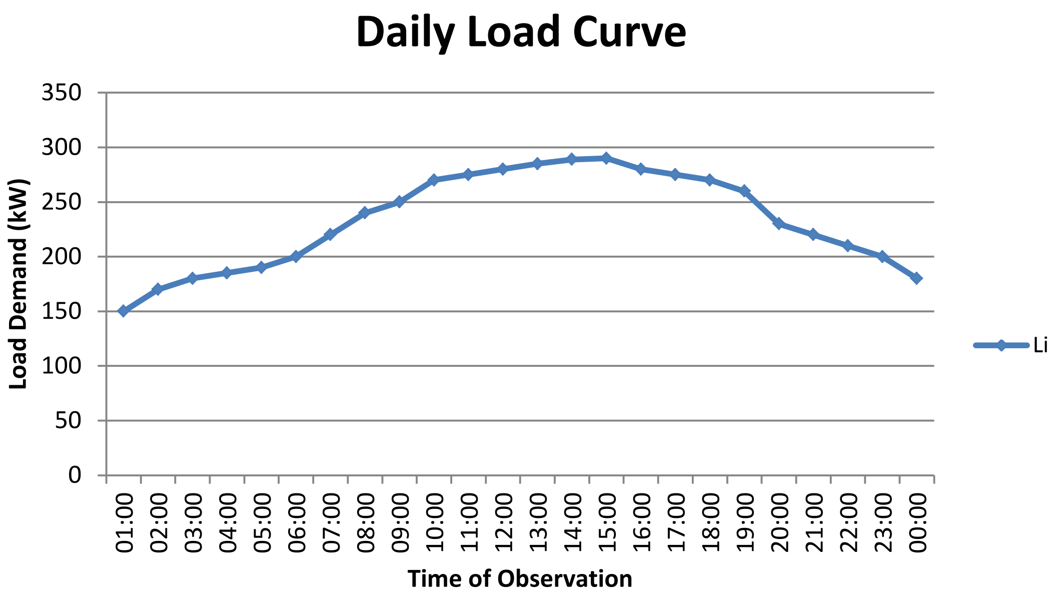


Figure-6.2 24-hour Daily Load Curve

Assuming this daily load curve represents the load demand variation in one day with respect to a power supply area, the peak load demand occurs from 10:00 to 15:00 when most activities are underway. The lowest load demand appears at midnight, when most activities shut down.

According to Equation-6.2, the average load demand can be calculated as:

$$L_a = \frac{\sum_{i=1}^{24} L_i}{24} = 233.292 \text{ kW}$$

Based on Equation-6.1, the time varying coefficient λ_i can be calculated as a variation of the load demand which is shown in Table-6.1.

The variation of the time varying coefficient can be depicted as Fig-6.3.

Table-6.1 Results of Time Varying Coefficient

Time of Observation	**Daily Load Curve L_i (kW)**	**Time Varying Coefficient λ_i**
1:00	150	0.643
2:00	170	0.729
3:00	180	0.773
4:00	185	0.793
5:00	190	0.814
6:00	200	0.857
7:00	220	0.943
8:00	240	1.029
9:00	250	1.072
10:00	270	1.157
11:00	275	1.179
12:00	280	1.200
13:00	285	1.221
14:00	289	1.239
15:00	290	1.243
16:00	280	1.200
17:00	275	1.179
18:00	270	1.157
19:00	260	1.114
20:00	230	0.986
21:00	220	0.943
22:00	210	0.900
23:00	200	0.857
0:00	180	0.772

Fig-6.3 indicates that time varying coefficient λ has the exactly same variation as the daily load demand curve. Based on Equation-6.1, λ is equal to 1 when the load demand is the same as the average load demand. In this case, λ_i is around 0.2 larger than during peak load demand periods and is 0.3 smaller during off-peak load demand periods.

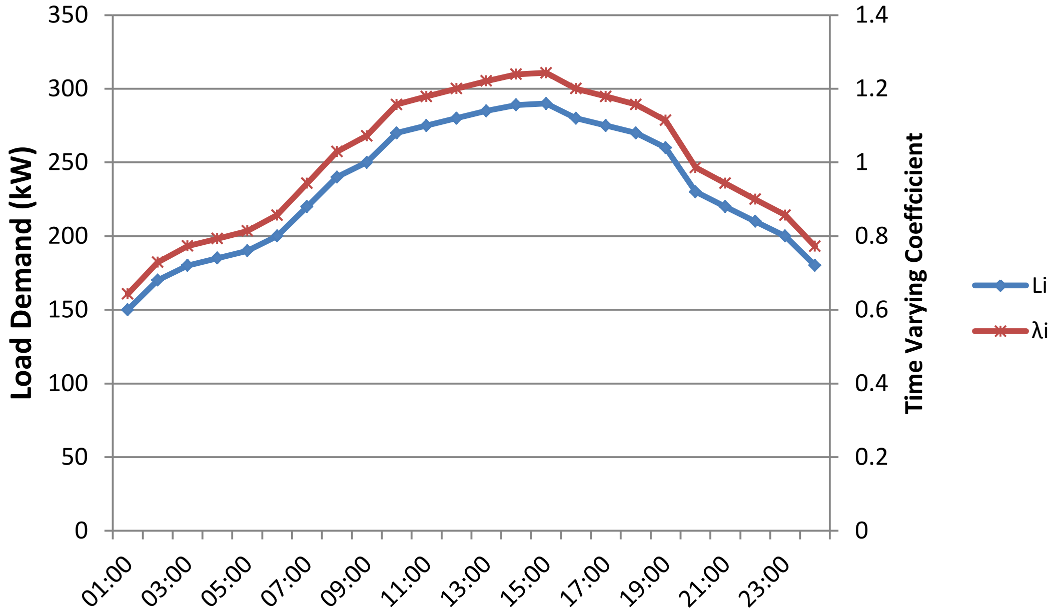


Figure-6.3 Load Demand and Time Varying Coefficient

Due to having the same variations as the load demand, the time varying coefficients are capable of quantifying the effect of time of occurrence in the PQ cost. Thus, the time varying PQ cost can be derived from:

$$C_i = \lambda_i * C_{PQ} \tag{6.3}$$

where C_{PQ} is the cost model for each component of PQ cost and λ_i is the time varying coefficient at time *i*.

In addition, the daily load curve is normally derived based on the total load demand data from the whole power system or subsystem. Hence, it indicates the variation of the total load demand of all customers in this system rather than individual customers. In this case, in order to predict the time varying PQ cost for individual customers, the time varying coefficient requires some adjustments. Here, an adjustment factor is introduced according to individual load shares of the total load demand and can be calculated as:

$$\lambda_k = \frac{load\ demand\ of\ k^{th}\ individual\ customer}{total\ load\ demand\ in\ the\ power\ system} \tag{6.4}$$

In this case, the λ_k represents the proportion of individual demand in relation to the total demand of the system i.e. the sum of each individual proportion $\sum \lambda_k$ =1 for the whole system.

According to this adjustment factor, it is then possible to estimate the time varying PQ cost for individual customers. Correspondingly, the time varying PQ cost can be rewritten as:

$$C_i = \lambda_k * \lambda_i * C_{PQ} \tag{6.5}$$

6.5 Case Study

In this case study, an example of distribution systems will be studied, based on different PQ disturbance scenarios. Accordingly, the time varying cost models for each PQ disturbance will be derived.

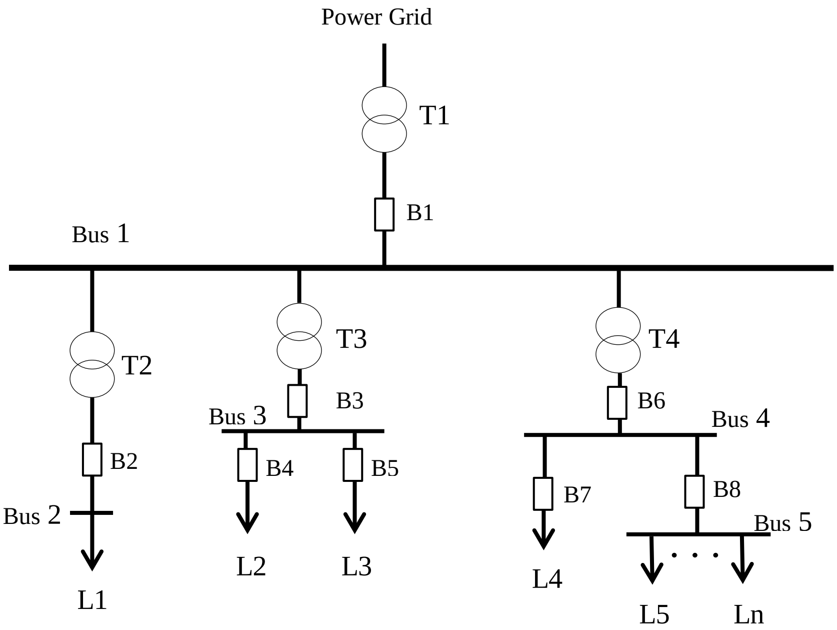


Figure-6.4 Distribution System in Case Study

Fig-6.4 shows a distribution system connected to the power grid, where, T1~T4 represent the transformers in this distribution system; B1~B8 represent the breakers in transmission lines, and L1~Ln represent the loads in the system.

If, in this distribution system

1) L1 is a semiconductor manufacturing company, which is a continuous process industrial customer, for continuous process industrial customers in this power grid, the short interruption unit cost model is the same as the case studies in Chapter 3, which is expressed as the following without error terms:

$$C_{siL1} = Exp(1.3197 + 0.4601t - 0.0773t^2 + 0.0288con + 0.1347r) - 1$$

where *t* is the short interruption duration, *con* is the monthly consumption of continuous process industrial customers, which is estimated to be 2.7MW, and *r* is the competitor information, which is '0' in this case; and that

2) Both L2 and L3 are bread manufacturers, which are non-continuous process industrial customers with the same short interruption unit cost model as that in Chapter 3. As both of them are non-continuous process industrial customers, they share the same short interruption unit cost model, which is expressed as follows without error terms

$$C_{siL23} = Exp(0.2049 + 0.0604t - 0.0004t^2 + 0.0699con + 0.4021r) - 1$$

In this case, the monthly consumption of L2 is estimated as 1.8MW, while the consumption of L3 is 0.9MW. As both of them produce the same products, they become rivals; hence *r* equals 1.

3) L4 represents a bank as it falls into the commercial and public customer category. If, for this type of customer, the PQ disturbance duration, the daily number of customers served and competitor information play the most important roles in short interruption cost estimations, the short interruption unit cost model for this type of customer in the power grid is assumed to be

$$C_{siL4} = Exp(0.1025 + 0.0302t - 0.0002t^2 + 0.0004cum + 0.2010r) - 1$$

where *cum* is the daily number of customers served, which is assumed to be 200, and there are no competitors in this distribution system. Therefore, r =0 in this case.

4) L5…Ln represent the domestic users in this distribution system. For domestic users, only the PQ disturbance duration matters, and the short interruption unit cost model is assumed to be

$$C_{siL5n} = Exp(0.0513 + 0.0151t - 0.0001t^2) - 1$$

5) The daily average load curve of this distribution system is the same as the numeric example in Section-6.4.2， and the daily load curve is drawn as Fig-6.2. Hence, based on the previous calculations, the total average load demand in this area is 233.292 kW.

Based on the above assumptions, the following scenarios will be discussed.

6.5.1 Time Varying Short Interruption Cost

Case I:

At 10:00am, the circuit breaker B1 in Fig-6.4 opens for 3 seconds, which results in a 3 second short interruption for the whole distribution system. Just before the short interruption occurs, the consumption of load L1 is 90kW. For loads L2 and L3, the consumption is 60kW and 30kW respectively, and the consumption of load L4 is 30kW, and for L5…Ln as a whole, the consumption is 20kW.

As the duration of the interruption is so short, the expected load demand during this short interruption is estimated to be the same as the amount just before a short interruption occurs. Therefore, the total load demand for this distribution system at 10:00am is the summary of each load, which is 90+60+30+30+20=230kW. Hence, the time varying coefficient for this distribution system at 10:00am could be calculated according to Equation-6.1 as:

$$\lambda_{10} = \left(1 + \frac{230 - 233.292}{233.292}\right) * 100\% = 0.986$$

- L1: For L1, the 3 second short interruption unit cost is:

$$C_{siL1-3s}{}^{*} = Exp(1.3197 + 0.4601 \times 3 - 0.0773 \times 3^2 + 0.0288 \times 2.7) - 1 = £7.021/\mathrm{kW}$$

Considering the time varying coefficient and the adjustment factor, based on Equation-6.5, the unit cost at this time is:

$$C_{siL1-3s} = \lambda_{k10L1}\lambda_{10}C_{siL1-3s}{}^{*} = 0.391 \times 0.986 \times 7.021 = £2.709/\mathrm{kW}$$

where the adjustment factor λ_{k10L1}=90/230=0.391 is based on Equation-6.4.

- L2: In the case of L2, the short interruption unit cost is:

$$C_{siL2-3s}{}^{*} = Exp(0.2049 + 0.0604 \times 3 - 0.0004 \times 3^2 + 0.0699 \times 1.8 + 0.4021) - 1 = £1.485/\mathrm{kW}$$

Taking the time of occurrence into account, the unit cost becomes:

$$C_{siL2-3s} = \lambda_{k10L2}\lambda_{10}C_{siL2-3s}{}^{*} = 0.261 \times 0.986 \times 1.485 = £0.382/\mathrm{kW}$$

where λ_{k10L2}=60/230=0.261.

- L3: Just as with L2, the short interruption unit cost for L3 is:

$$C_{siL3-3s}{}^{*} = Exp(0.2049 + 0.0604 \times 3 - 0.0004 \times 3^2 + 0.0699 \times 0.9 + 0.4021) - 1 = £1.334/\mathrm{kW}$$

The unit cost at 10:00am for L3 is:

$$C_{siL3-3s} = \lambda_{k10L3}\lambda_{10}C_{siL3-3s}{}^{*} = 0.130 \times 0.986 \times 1.334 = £0.172/\text{kW}$$

where λ_{k10L3}=30/230=0.130

- L4: For the bank, the short interruption unit cost is:

$$C_{siL4-3s}{}^{*} = Exp(0.1025 + 0.0302 \times 3 - 0.0002 \times 3^2 + 0.0004 \times 200) - 1 = £0.312/\text{kW}$$

In this case, the unit cost at the time of occurrence is:

$$C_{siL4-3s} = \lambda_{k10L4}\lambda_{10}C_{siL4-3s}{}^{*} = 0.130 \times 0.986 \times 0.312 = £0.040/\text{kW}$$

where λ_{k10L4}=30/230=0.130

- L5…Ln: As a whole, the short interruption unit cost for domestic users is:

$$C_{siL5n-3s}{}^{*} = Exp(0.0513 + 0.0151 \times 3 - 0.0001 \times 3^2) - 1 = £0.101/\text{kW}$$

Then, the time varying unit cost is:

$$C_{siL5n-3s} = \lambda_{k10L5n}\lambda_{10}C_{siL5n-3s}{}^{*} = 0.087 \times 0.986 \times 0.101 = £0.008/\text{kW}$$

where λ_{k10L5n}=20/230=0.087.

- Distribution System: Based on the above calculations, the total potential unit economic losses due to the 3 second short interruption at 10:00am are

$$\begin{aligned} C_{si\,total-3s} &= C_{siL1-3s} + C_{siL2-3s} + C_{siL3-3s} + C_{siL4-3s} + C_{siL5n-3s} \\ &= 2.709 + 0.382 + 0.172 + 0.040 + 0.008 = £3.311/\text{kW} \end{aligned}$$

In this case, the total unit economic losses of this short interruption for the distribution system shown in Fig-6.4 are the sum of those for each customer connected to the distribution system, which is £3.311 per kW.

Accordingly, the total estimated economic losses due to this short interruption are:

$$TotalCost_{si} = C_{si\ total-3s} * Total\ Losses = 3.311 \times 230 = £761.53$$

where the total losses are equal to the total load demand when interruptions occur, which is 230 kW.

When calculating the economic losses of the whole system due to short interruptions, it is necessary to calculate every component of the system separately due to different characteristics of customer types. Thereafter, the total economic losses of the whole system can be calculated by adding each component together. Based on the above calculations, it can be concluded that the economic losses of short interruptions are not only affected by the duration, customer consumption and market environment that are considered in the short interruption cost model, it also depends on the load demand when the interruption occurs. In other words, the variation of the time varying coefficient reflects the differences in economic losses due to short interruptions in different time periods.

6.5.2 Time Varying Voltage Sag Cost

Case II:

At 18:00, there is a voltage drop on Bus1 of Fig-6.4, which affects every load connected to this bus. In this case, the whole distribution system is affected by this voltage sag. This voltage sag lasts 1 second, and the magnitude of the voltage drops to 0.7p.u. When the voltage sag occurs, the consumption of L1 is 60kW; L2 is 35kW; L3 is 50kW; L4 is 30kW and L5…Ln is 90kW.

The total load consumption of this distribution system during this voltage sag disturbance is 60+35+50+30+90=265kW. Hence, the time varying coefficient of the whole distribution system at this time is:

$$\lambda_{18} = \left(1 + \frac{265 - 233.292}{233.292}\right) * 100\% = 1.136$$

Based on the discussion of voltage sag weighting factors in Chapter 4, the weighting factor for this voltage sag could be calculated as:

$$wf_{0.7} = 1 - exp\left[-\frac{(0.7-1)^2}{2\times 0.225^2}\right] = 0.589$$

- L1: The voltage sag unit cost of L1 due to this 1 second voltage sag could be calculated as:

$$C_{vsL1-1s}{}^{*} = [Exp(1.3197 + 0.4601\times 1 - 0.0773\times 1^2 + 0.0288\times 2.7) - 1]\times wf_{0.7}$$
$$= £2.905/kW$$

Considering the effect of time of occurrence, the adjusted voltage sag unit cost of L1 is:

$$C_{vsL1-1s} = \lambda_{k18L1}\lambda_{18}C_{vsL1-1s}{}^{*} = 0.226\times 1.136\times 2.905 = £0.747/\text{kW}$$

where the adjustment factor of L1, λ_{k18L1}=60/265=0.226.

- L2: For L2, the voltage sag unit cost is:

$$C_{vsL2-1s}{}^{*} = [Exp(0.2049 + 0.0604\times 1 - 0.0004\times 1^2 + 0.0699\times 1.8 + 0.4021) - 1]\times wf_{0.7}$$
$$= £0.712/\text{kW}$$

The time varying voltage sag unit cost of L2 at 18:00pm is therefore:

$$C_{vsL2-1s} = \lambda_{k18L2}\lambda_{18}C_{vsL2-1s}{}^{*} = 0.132\times 1.136\times 0.712 = £0.107/\text{kW}$$

where the adjustment factor of L2, λ_{k18L2}=35/265=0.132

- L3: In the case of L3, the voltage sag unit cost is:

$$C_{vsL3-1s}{}^{*} = [Exp(0.2049 + 0.0604\times 1 - 0.0004\times 1^2 + 0.0699\times 0.9 + 0.4021) - 1]\times wf_{0.7}$$
$$= £0.633/\text{kW}$$

The actual voltage sag unit cost for this time of occurrence is:

$$C_{vsL3-1s} = \lambda_{k18L3}\lambda_{18}C_{vsL3-1s}{}^{*} = 0.189 \times 1.136 \times 0.633 = £0.136/\text{kW}$$

where λ_{k18L3}=50/265=0.189

- L4: For the bank, the voltage sag unit cost is:

$$C_{vsL4-1s}{}^{*} = Exp(0.1025 + 0.0302 \times 1 - 0.0002 \times 1^2 + 0.0004 \times 200) - 1 = £0.237/\text{kW}$$

The time varying voltage sag unit cost at 18:00pm for this bank is:

$$C_{vsL4-1s} = \lambda_{k18L4}\lambda_{18}C_{vsL4-1s}{}^{*} = 0.112 \times 1.136 \times 0.237 = £0.031/\text{kW}$$

where λ_{k18L4}=30/265=0.112

- L5…Ln: For domestic users, the unit economic losses due to this voltage sag can be calculated as:

$$C_{vsL5n-1s}{}^{*} = Exp(0.0513 + 0.0151 \times 1 - 0.0001 \times 1^2) - 1 = £0.069/\text{kW}$$

Taking the time of occurrence into account, the unit cost is adjusted as:

$$C_{vsL5n-1s} = \lambda_{k18L5n}\lambda_{18}C_{vsL5n-1s}{}^{*} = 0.340 \times 1.136 \times 0.069 = £0.026/\text{kW}$$

where λ_{k18L5n}=90/265=0.340

- Distribution System: As a whole, for this distribution system, the total voltage sag unit cost for this voltage sag event can be summarized as:

- $$C_{vs\,total-1s} = C_{vsL1-1s} + C_{vsL2-1s} + C_{vsL3-1s} + C_{svsL4-1s} + C_{vsL5n-1s}$$
  $$= 0.747 + 0.107 + 0.136 + 0.031 + 0.026 = £1.047/\text{kW}$$

As the above calculations show, the total voltage sag unit cost is the sum of those for each customer connected to Bus1 in this distribution system.

Accordingly, the total economic losses due to this voltage sag event are:

$$TotalCost_{vs} = C_{vs\,total-1s} * Total\ Load\ Impacted$$
$$= 1.047 \times 265 = £277.455$$

where the total load impacted is the total load demand when this voltage sag occurred, which is 265kW in this case.

Compared with the short interruption cost in the previous section, the total economic losses due to voltage sag are much smaller. This is not only a result of shorter duration and the introduction of weighting factors, but also of variations in time. This voltage sag occurred during an off-peak time period with a much smaller time varying coefficient than in peak hours. Accordingly, the economic losses are much smaller.

6.5.3 Time Varying Harmonic Cost

Based on previous calculations of harmonic cost in Chapter 5, rather than the different types of customers, the harmonic cost is estimated based on the core equipment of individual customers. Therefore, in this case study, only the calculation of L1 is discussed to demonstrate the time varying harmonic cost.

Assuming the L1 is the same manufacturing factory as that in the case study of Chapter 5, which has core equipment which is worth £9000 in a production line supposed to operate for 30 years, and the cost of purchasing the core equipment increases at a rate of 0.07 per year, the expected useful life-time of the equipment is 17 years. Based on the calculations in Chapter 5, when the discount rate is 0.08, the present value of the total harmonic aging cost in 30 years is:

$$D_a = D_{ns} - D_s = £8656.741$$

The historical data of harmonics are shown in Table-5.3, which gives the probability of THD of voltage above 5% as:

$$\mathrm{p(t)} = 1 - \exp[-\left(\frac{t}{12.619}\right)^{2.112}]$$

The average number of harmonics per year is thus N_a=56.5

Based on the above assumed data and equations, there is a harmonic variation described as follows which occurs in L1

Case III:

At 13:00, there is a harmonic variation with THD of voltage above 5% being detected in Bus2 of Fig-6.4. This harmonic variation lasts 10.5ms, and results in a 0.01kWh total energy loss of L1 at a unit cost of £2/kWh. At the time of harmonic variation, the consumption of L1 is 80kW, while the consumption of the whole distribution system is 300kW. In this case, the time varying coefficient of the whole distribution system at this time is:

$$\lambda_{13} = \left(1 + \frac{300 - 233.292}{233.292}\right) * 100\% = 1.286$$

and the adjustment factor is:

$$\lambda_{k13} = \frac{80}{300} = 0.267$$

According to this assumption, the energy loss cost of this harmonic variation is calculated as:

$$D_{losses} = E_{losses} * C_u = 0.01 \times 2 = £0.02$$

Based on the results and historical data in Chapter 5, the amount of total harmonic cost per year for a duration of 10.5ms is:

$$D_a(10.5) = D_a \frac{t_{11}k_{11}}{\sum_{i=1}^{20} t_i k_i} = 8656.741 \times 0.043 = £370.522$$

Thus, the aging cost for this harmonic variation is:

$$D_{10.5} = \frac{D_a(10.5)}{30N_a * p(10.5)} = £0.444$$

Hence, the total harmonic cost of this 10.5ms harmonic variation is:

$$D_{total} = D_{losses} + D_{10.5} = 0.02 + 0.444 = £0.464$$

where the total harmonic cost is the sum of the cost of energy loss due to harmonics (£0.02) and cost of aging issues (£0.444). In this case, for a customer with core equipment that is worth £9000, the total economic losses of a single harmonic variation lasting 10.5ms are only around £0.5, which is much smaller compared with the short interruption and voltage sag costs. However, it does provide the cost information of a single harmonic variation. In this way, the short term harmonic cost can be estimated.

Considering the effect of time of occurrence, the time varying harmonic cost at this time is calculated thus:

$$D_{total-13} = \lambda_{k13}\lambda_{13}D_{total} = 0.267 \times 1.286 \times 0.464 = £0.159$$

In this case, as the harmonic cost is calculated based on the individual load L1, the adjustment factor should be considered. Due to the introduction of the time varying coefficient and adjustment coefficient, the actual harmonic cost for this harmonic variation is even smaller, though this harmonic variation occurred during peak hours. The main reason is the small proportion of load demand of L1 in the total load demand at this time.

6.5.4 Individual Load Demand and PQ Cost

In this section, the relationship between individual load demand and PQ cost will be examined. There are no differences for each component of PQ cost calculation in terms of individual load demand variation. Here, the short interruption cost model of L1 is an example, assuming the total load demand of this distribution system is the same as in Table-6.1 at each point of observation. The same short interruption that lasts 3 seconds will be examined at each point of observation.

According to the results from the previous section, a 3 second short interruption will cost L1 £7.021 per kW.

- With λ_k =0.4 as a constant, which refers to the percentage of individual demand L1 in total, distribution system stays at 40% for each point of observation. In this case, the individual demand and the time varying unit cost (based on Equation-6.5) are shown in Table-6.2

Table-6.2 Individual Short Interruption Cost when holding λ_k

Time of Observation	Individual Load Demand L1 (kW)	λ_i	λ_k	Short Interruption Unit Cost £/kW	Total Short Interruption Cost £
1:00	150×0.4=60	0.643	0.4	1.806	108.348
2:00	170×0.4=68	0.729	0.4	2.047	139.218
3:00	180×0.4=72	0.773	0.4	2.171	156.304
4:00	185×0.4=74	0.793	0.4	2.227	164.803
5:00	190×0.4=76	0.814	0.4	2.286	173.739
6:00	200×0.4=80	0.857	0.4	2.407	192.544
7:00	220×0.4=88	0.943	0.4	2.648	233.052
8:00	240×0.4=96	1.029	0.4	2.890	277.425
9:00	250×0.4=100	1.072	0.4	3.011	301.060
10:00	270×0.4=108	1.157	0.4	3.249	350.926
11:00	275×0.4=110	1.179	0.4	3.311	364.221
12:00	280×0.4=112	1.200	0.4	3.370	377.449

Time of Observation	Individual Load Demand L1 (kW)	λ_i	λ_k	Short Interruption Unit Cost £/kW	Total Short Interruption Cost £
13:00	285×0.4=114	1.221	0.4	3.429	390.912
14:00	289×0.4=115.6	1.239	0.4	3.480	402.243
15:00	290×0.4=116	1.243	0.4	3.491	404.938
16:00	280×0.4=112	1.200	0.4	3.370	377.449
17:00	275×0.4=110	1.179	0.4	3.311	364.221
18:00	270×0.4=108	1.157	0.4	3.249	350.926
19:00	260×0.4=104	1.114	0.4	3.129	325.370
20:00	230×0.4=92	0.986	0.4	2.769	254.756
21:00	220×0.4=88	0.943	0.4	2.648	233.052
22:00	210×0.4=84	0.900	0.4	2.528	212.315
23:00	200×0.4=80	0.857	0.4	2.407	192.544
0:00	180×0.4=72	0.772	0.4	2.168	156.102

where the total short interruption cost is calculated based on the unit cost multiplied by individual load demand. For example, when the time of observation is 5:00, the individual load demand of L1 is 76 kW; the short interruption unit cost is 2.286 £/kW; in this case, the total short interruption cost is 76×2.286 = £173.739. Based on Table-6.2, the following comparisons can be depicted as Fig-6.5 and Fig-6.6.

Fig-6.5 describes the relationship between individual load demand and short interruption unit cost, while holding the percentage of individual load demand in the total distribution system demand constant. The variation of short interruption unit cost reflects exactly the same changes of individual load demand. When individual load demand is high, the unit cost will be high. Accordingly, the unit cost decreases as individual load demand drops.

Fig-6.6 indicates the relationship between individual load demand and the total economic losses due to a 3 second short interruption. Although, the shapes of the two lines may not be exactly the same, the total economic losses do appear as higher during peak load periods and lower in off-peak load periods.

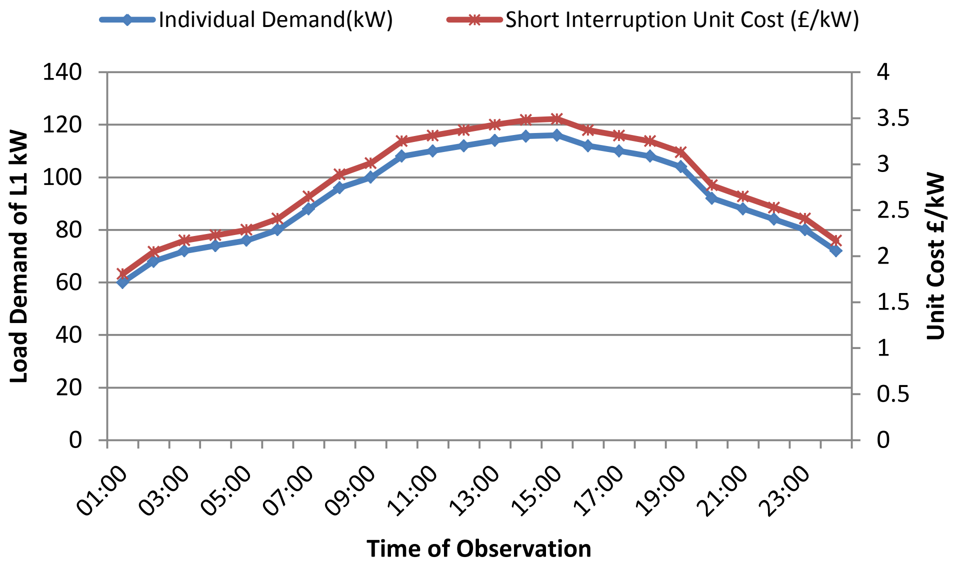


Figure-6.5 Individual Load Demand and Short Interruption Unit Cost (fixing the percentage in total demand)

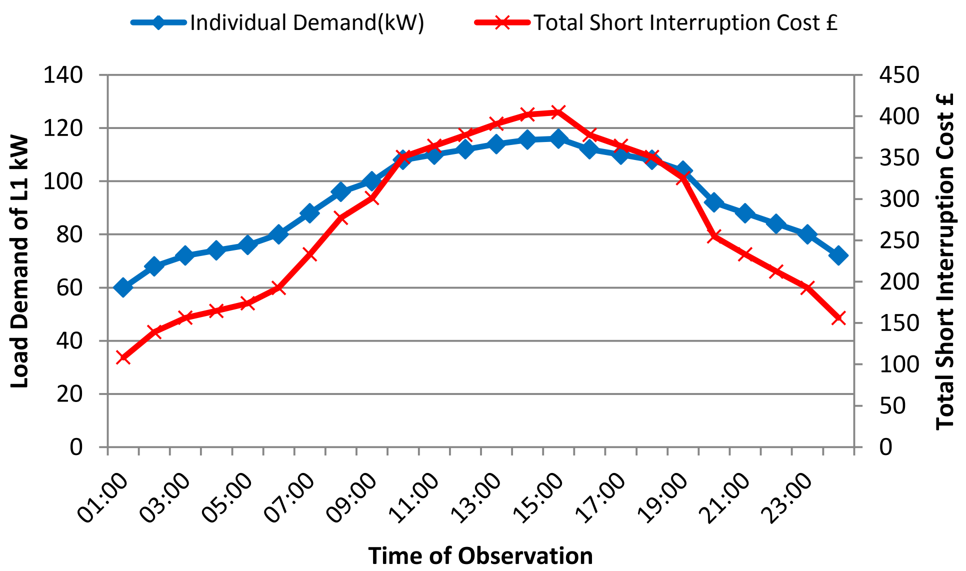


Figure-6.6 Individual Load Demand and Total Short Interruption Cost (fixing the percentage in total demand)

➢ The percentage of individual load demand in the total distribution system varies from time to time, i.e. λ_k varies with time, as shown in Table-6.3.

Table-6.3 Individual Short Interruption Cost when varying λ_k

Time of Observation	Total Demand in Distribution System (kW)	Individual Load Demand L1 (kW)	λ_i	λ_k	Short Interruption Unit Cost £/kW	Total Short Interruption Cost £
1:00	150	30	0.643	0.200	0.903	27.087
2:00	170	28	0.729	0.165	0.843	23.604
3:00	180	31	0.773	0.172	0.935	28.975
4:00	185	29	0.793	0.157	0.873	25.310
5:00	190	32	0.814	0.168	0.963	30.801
6:00	200	34	0.857	0.170	1.023	34.778
7:00	220	45	0.943	0.205	1.354	60.941
8:00	240	65	1.029	0.271	1.957	127.183
9:00	250	90	1.072	0.360	2.710	243.859
10:00	270	97	1.157	0.359	2.918	283.082
11:00	275	100	1.179	0.364	3.010	301.009
12:00	280	120	1.200	0.429	3.611	433.296
13:00	285	128	1.221	0.449	3.850	492.822
14:00	289	130	1.239	0.450	3.913	508.697
15:00	290	125	1.243	0.431	3.762	470.210
16:00	280	123	1.200	0.439	3.701	455.232
17:00	275	130	1.179	0.473	3.913	508.706
18:00	270	127	1.157	0.470	3.821	485.262
19:00	260	110	1.114	0.423	3.309	363.996
20:00	230	89	0.986	0.387	2.679	238.412
21:00	220	65	0.943	0.295	1.956	127.150
22:00	210	59	0.900	0.281	1.775	104.743
23:00	200	51	0.857	0.255	1.534	78.251
0:00	180	41	0.772	0.228	1.235	50.619

where λ_k= **(**Individual Load Demand of L1)/ (Total Demand in Distribution System). Based on the results of Table-6.3, the following relationships can be seen in Figs-6.7 to 6.10.

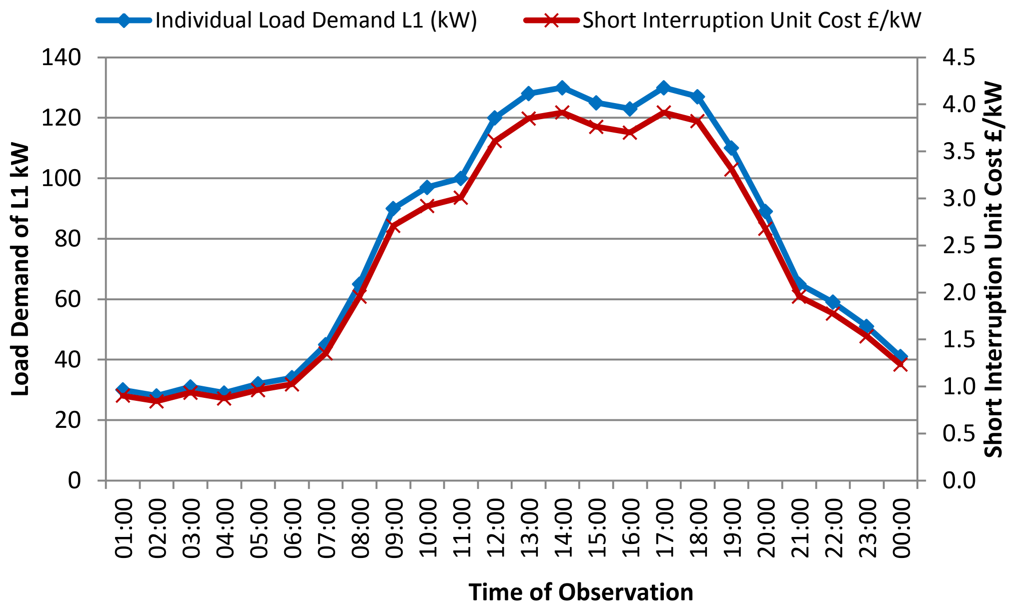


Figure-6.7 Individual Load Demand and Short Interruption Unit Cost (varying the percentage in total demand)

In this case, the variation of short interruption unit cost is slightly different from the variation of load demand of L1. Compared with Fig-6.5, where the short interruption unit cost and load demand possess the same variation, the deviation of the short interruption unit cost curve from the load demand curve does not appear to be dramatic. This is because the variation of λ_k is not large enough to affect the outcomes dramatically. Then what are the effects of λ_k on short interruption unit cost?

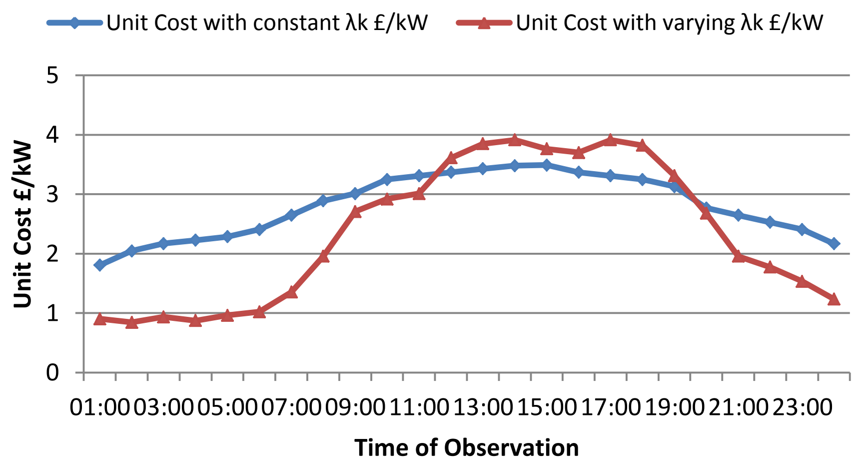


Figure-6.8 The Effect of λ_k on Short Interruption Unit Cost

Based on Fig-6.8, when λ_k is constantly equal to 0.4, the short interruption unit cost is higher during the period between 12:00 and 19:00, where λ_k is higher than 0.4. When λ_k drops to lower than 0.4, the short interruption unit cost decreases.

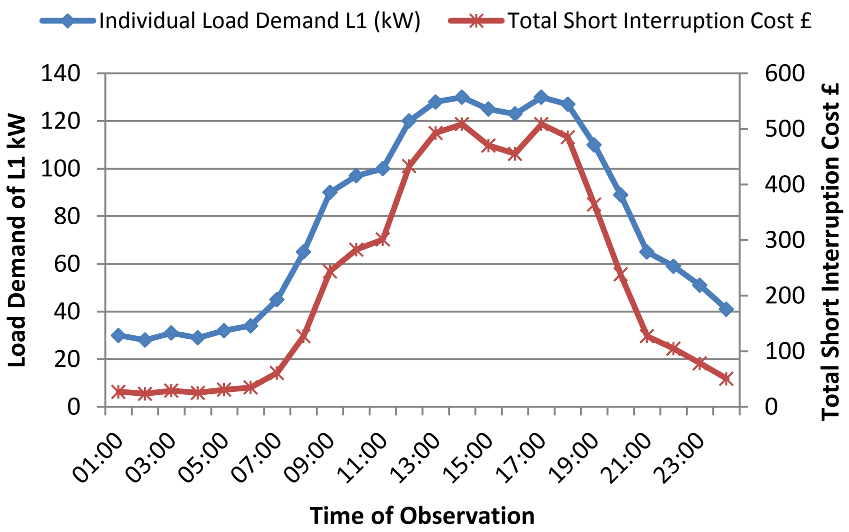


Figure-6.9 Individual Load Demand and Total Short Interruption Cost (varying the percentage of total demand)

Fig-6.9 indicates the relationship between individual load demand and total short interruption cost when varying the percentage of total demand. Though there are slight deviations, it can be said that the curve of the total short interruption cost fits the load demand curve well. The total short interruption cost varies with individual load demand.

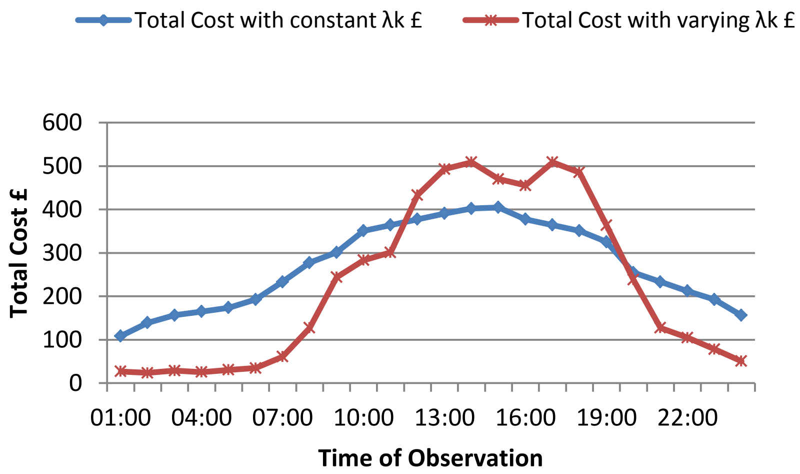


Figure-6.10 The Effect of λ_k on Total Short Interruption Cost

As shown in Fig-6.10, the total costs with constant and varying λ_k are compared. The curves show that the larger the percentage of individual demand in relation to total demand, the higher the total economic losses due to short interruption.

According to the above analysis, it can be concluded that, the higher the percentage individual load demand of the total load demand, the greater the PQ unit cost and total economic losses. Conversely, the lower the percentage of individual load demand in relation to total load demand, the smaller the PQ unit cost and total economic losses.

6.6 Summary

In this chapter, the effect of time of occurrence is considered in PQ cost. Based on the relationship between load demand and economic losses due to PQ disturbances, a time varying coefficient is proposed to quantify the effect of time of occurrence. According to the relationship between individual load demand and total load demand, an adjustment factor is then added to calculate the individual PQ cost. Together, the time varying PQ cost can then be estimated. The case studies demonstrate how to calculate each component of PQ cost at a given time (i.e. a given load demand) and the total PQ cost in the system. By comparing the constant value of the adjustment factor with the varying adjustment factor, it can be seen that the individual PQ cost also varies with the percentage of individual load demand in relation to total demand.

Chapter 7 Conclusions and Future Work

7.1 Conclusions

With the wide utilization of sensitive devices, as well as the increasing availability of wind power, power supply quality in power systems has been challenged. The requirements of power supply quality of electricity consumers are rising and different types of electricity consumers may require different levels of power supply quality. To find the balance between investment and the proper level of required power quality, the potential economic losses due to power quality disturbances need to be assessed. Currently, most of the power quality cost studies focus on long term cost. However, a short term economic analysis may also be required. Consequently, the purpose of this thesis is to study and develop short term power quality cost calculation models.

In this thesis, three common components of power quality are studied, namely, short interruption, voltage sag and harmonics. Each of these is investigated individually from various perspectives in terms of power quality cost, such as customer characteristics, time of occurrence and duration, etc. Accordingly, electricity consumers of power systems are divided into different types based on their power quality requirements. These are non-continuous process industry, continuous process industry, commercial and public business, and domestic users. Each type demands different power quality cost models. A summary of each component is presented below.

- Short Interruption Cost Model

Due to the limitations of the traditional Tobit cost model, a modified Tobit short interruption cost model is introduced to evaluate the short term interruption cost in this thesis. Unlike the traditional Tobit cost model, rather than considering the Tobit coefficients in one cost model, this proposed Tobit cost model introduces the effect of customer type as different expressions of cost models. In this way, the differences between types of customers are clear and fully expressed. Meanwhile, the effect of time of occurrence is quantified by a time varying coefficient which is proposed based on the relationship between load demand and economic losses due to power quality disturbances. These two modifications enable the modified Tobit cost model to fully consider both the effects of customer types and time of occurrence. Moreover, this model is still capable of quantifying other impact factors of short interruptions, such as duration and customer characteristics, as well as market information. Hence, based on the modified Tobit short interruption cost model, the multiple impact factors of short interruptions can be quantified properly. The illustrative examples and case studies in this thesis have verified the application of this short interruption cost model.

- Voltage Sag Cost Model

In this thesis, a combination of the Tobit cost model and quality loss function is proposed to evaluate the short term voltage sag cost. In this proposed model, the Tobit cost model describes the maximum economic losses due to voltage sag with multiple impact factors, while the quality loss function determines how the observed voltage sag could be weighted based on the maximum economic losses in terms of voltage magnitude. After being multiplied by the time varying coefficient, this proposed voltage sag cost model is applicable to evaluate economic losses due to voltage sag with multiple impact factors. The impact factors in this case may include duration and magnitude of voltage sags, time of occurrence, customer characteristics and competitor information. In addition, compared with the traditional weighting factor methods, the weighting factor provided by this model is more continuous and flexible. Results of case studies have proved the advantages of this voltage sag cost model.

- Harmonic Cost Model

In this thesis, the energy loss cost is calculated as a customer and time varying energy unit cost, which is provided by the Tobit cost model. By considering the multiple impact factors of the energy unit cost, a varying unit cost is derived to indicate the cost variation in the short term. The aging cost is also converted into a short term cost by the expected number of harmonics that may be harmful to equipment. The sum of the energy loss cost and aging cost is presented in the harmonic cost model. With the help of the time varying coefficient, the harmonic cost model provides the capability to evaluate the economic losses due to a single harmonic variation with customer and time variations in the short term, which has been illustrated in the case studies.

Based on the proposed cost models, possible applications have been discussed in a designed distribution system. It has been demonstrated that the economic losses due to different PQ disturbances can be estimated at different times of occurrence with different customer characteristics and other impact factors.

7.2 Future Work

This thesis contributes to the power quality economic calculation, and proposes time varying power quality cost models. Though these proposed cost models are analyzed in detail and their application is demonstrated based on a sample distribution system, it is possible to make some developments in the future:

- Although the market factors of power quality cost are quantified in terms of a switching variable that indicates whether or not there are other competitors in the Tobit cost models, there are always more details of market factors that could be involved as Tobit coefficients, such as market shares and individual profits.

- It should be noted that the accuracy of these power quality cost models largely depends on survey results, which may vary widely among different customers. In this case, either careful processing of original data or consideration of the data variation in cost models is required.

- Due to a lack of real practical data, it is impossible to test these time varying cost models in real practical systems as well as to make real time calculations. Tests with real practical data are always beneficial to deal with any possible practical issues. In addition, some calculation processes may be simplified to make them more efficient when the cost models are utilized in real calculations, such as using representative customers to calculate the harmonic cost rather than evaluating the losses one by one.

- Besides the three main components of power quality cost discussed in this thesis, there are a few more components which may be included, such as transients, overvoltage and unbalance, which may also result in economic losses. However, there is a lack of evaluation methods for this and it is difficult to estimate the amount of economic losses without cost models.

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