School of Civil and Mechanical Engineering
Department of Civil Engineering

Utilising Artificial Neural Networks (ANNs) Towards Accurate Estimation of Life-Cycle Costs for Construction Projects

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DECLARATION

To the best of my knowledge and belief this thesis contains no material previously published by any other person except where due the acknowledgement has been made. This thesis contains no material which has been accepted for the award of any other degree or diploma in any university.

Signed

Ayedh Mohammad Alqahtani

ABSTRACT

Life Cycle Cost Analysis (LCCA) is a principal consideration for civil-engineering and the construction industry as it strives to maintain sustainability; LCCA provides stakeholders with a means to review and compare their initial design specification choices, and assess comparative (sub-component) impacts beyond the initial feasibility and construction stage, throughout an asset's (whole) life-span operation and maintenance, and subsequently into its decommissioning. It has become increasingly important to provide clients with a means to design and control built-assets during their whole-life cycle, from early planning phases through to disposal. LCCA seeks to improve decision-making systems in the ownership of assets by taking into account whole-costs. Currently however, industrial application of LCCA is limited; techniques are deemed somewhat overly theoretical, resulting in industry's reluctance to realise (and pass onto the client) the advantages to be gained in an objective (LCCA) comparison of the full range of sub-component materials and specifications. There is a need for a more user-friendly structured approach, able to facilitate complex processing.

Previous studies identify limitations for using the concept of LCC as: a lack of predictive data, absence of a standardised methodology and, incomprehension of the complex process. In addition, current estimation methods have several disadvantages, such as being time consuming, being costly in method, having the need for accurate information to improve the result, seeming to be problematic when applied to the early stages of the asset life-cycle due to a lack of information and, that the result may be inaccurate especially when applied on a system level. This project aims to address the implementation gap; a main objective of this research is to develop a new (user-friendly) model for LCCA of construction projects. This model will acknowledge Artificial Neural Networks (ANN_s) to compute the whole-cost(s) of construction projects; ANN_s have been commonly employed in numerous construction applications such as predicting building productivity, estimating organisation bankruptcy and measuring project economic performance. The ANNs models as a tool for predicting total cost at each stage of building life depends largely on their ability to address the limitations of the previous and existing estimating methods.

The (new) approach to LCCA suggested here, identifies the main cost factors of all the principal sub-components of a built-asset during all phases of life-cycle of the constructed facility and, given that ANN_s are a powerful means to handle non-linear problems and subsequently map between complex input/output data, address uncertainties. The validity of this (developed) model has been tested by comparing LCC results from model application with corresponding actual values using data from previous construction projects case-studies. The model proposed for development by this research facilitates a more accurate (future) prediction of whole costs, packaged in an accessible format, for use by an industry with limited time to carry-out predictive analyses.

Five models were developed to predict the cost of each stage of building life. The data of 113 building projects were used from BCIS. A number of issues in the design of approach of ANNs were discussed. It was found that ANNs have the ability to predict the cost at each stage of building life with an average accuracy between 91%-95%. The connection weight method was applied to discover the relative importance affecting independent factors to estimate the cost for each model. Cost Significant Items (CSIs) are most important variables influencing estimating cost for all five models, with number of elevator and foundation type of lesser importance.

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LIST OF PUBLICATIONS

The following publications have resulted from the work carried out for this degree.

Refereed journal paper:

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3- Alqahtani A, Whyte A (2014), 'Clarification of the Essentials of Life Cycle Cost upon Decision-Making Process: An Empirical Study in Building Projects'. World Academy of Science, Engineering and Technology, International Science Index 96, International Journal of Civil, Architectural, Structural and Construction Engineering, 8(12), 1143 - 1147.
4- Alqahtani, A and Whyte, A (2013), 'Artificial neural networks incorporating cost significant items towards enhancing estimation for (life-cycle) costing of construction projects', Australasian Journal of Construction Economics and Building, 13 (3) 51-64;

Refereed conference papers

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2- Alqahtani A, Whyte A, (2015). 'Important of Life Cycle Cost on Building Projects, in 'the Fifth International Conference on Civil, Environmental and Medical Engineering', Melbourne, Australia.

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1. CHAPTER ONE: INTRODUCTION

1.1. Background

An increase in the level of goods and services are an indicator of the growth of a country's development; physical infrastructure, services provision and building projects require to be sustainable. For continuous future economic growth, (sustainable) physical infrastructural development is a significant prerequisite (Tabish & Jha, 2011). Indeed, Erkelens (1991) asserts that building and construction projects contribute significantly to the gross domestic product and gross fixed capital formation but that increases in economic growth in the future, require increased construction and building projects in line with socio-economic trends.

Governmental agencies, corporations, and the private-sector spend trillions of dollars on construction and infrastructure systems. Organisations must protect their enormous facility investment and assign particular resources among numerous other competing needs to their life-cycle maintenance (Ottoman, Nixon, & Lofgren, 1999). In order to preserve public (and private) sector infrastructure's operational and safety performance, there is a need for a suitable management system (Farran, 2006). Often costly and disruptive replacements will be required due to the (potentially careless mismanagement of refurbishments and retro-fitting. The continuous rehabilitation of both existing and future infrastructure is challenging due often to the restrictions of the (set-aside) financial elements of resources upkeep. Therefore, improving and developing the usage of funds through accurate cost (prediction) requires a suitably robust decision support system (Farran & Zayed, 2012); this current research argues that life cycle cost analysis provides such a system.

1.2. Life Cycle Cost Assessment (LCCA)

Stakeholders of built assets are increasingly required to extend their viewpoint beyond the initial capital cost to build, to include all stages of an asset's life cycle. The American Society for Testing and Materials establishes a sequence of approaches for construction finances like benefit to cost ratio, internal rate of return

(IRR) and, life cycle cost analysis (LCCA) to evaluate the total life cost of a construction (Anurag Shankar, El-Gafy, & Abdelhamid, 2010). Life cycle costing analysis (LCCA) aims to compare different design, elements and sub-elements specification and material opportunities on the basis of their whole life cost from capital cost to install through operation and maintenance and residual cost to dismantle devastations. This approach is a recognised theoretical approach within construction and engineering industries. An LCC analysis assesses all the cost components of the particular project, converting them into a cost at a specific point in time: the present. (Olubodun, Kangwa, Oladapo, & Thompson, 2010).

One reason behind utilising LCCA is the ability to reduce the cost during the operation stage even if that requires spending more during early (construction) stages; updating/retrofitting older buildings (where no life-cycle analysis has been done) is a significant factor that encourages the use LCCA at the early stages of a projects development (Sterner, 2000).

However, Sterner (2000) admits that the importance of the output of a LCC models is often considered as somewhat 'too' uncertain for industry to fully embrace the techniques available and implement them into the design stages. A lack of understanding and the absence of a standardised methodology for LCC result in a somewhat complex process which is a main limitation to the implementation of LCC concepts (Olubodun et al., 2010). For example, from the performed survey in 1999, there is a limitation in using LCC models when making investment decision, by Swedish clients. The lack of availability of important data and incomprehension in utilising LCC models are major factors that lead to constraints and the non-implementation of LCC models (Sterner, 2000).

These key areas could be solved by, it is argued, improved LCC education for construction experts and the development of consistent methods for undertaking LCC analyses (Olubodun et al., 2010). Sterner (2000) believes that establishing databases that are suitable with LCC calculation models and education programmes that explain the advantages of LCC models are some ways to motivate the use of LCC by industry.

Schuman and Brent (2005) attempted to create an asset life cycle management model (ALCM) which integrates project management frameworks with operation reliability to address causes of inefficiency in LCC and support decisions made at the early stage of a project life. The limitation of this ALCM model, it is argued here, concerns the maintenance cost and that it does not include all factors affecting the asset.

Statistical tools have been utilised commonly to create construction cost models (Singh, 1990). For example, a regression model is one of the statistic methods towards identifying the impact of factors on construction costs. Selecting the best regression equation to estimate construction cost depends on the relations between the factors and construction costs. This method may become complex when numerous cost elements are considered as the dependent variables (Sonmez, 2011). From the previous research, traditional methods are potentially restrictive to predict the construction costs because there are a huge number of variable factors that affect the value of the construction cost and there is interaction between these factors, leading to complicated process (Cheng, Tsai, & Sudjono, 2010). This project seeks to address these gaps.

1.3. Simulation tools applicability

Using simulation and modelling tools at all stages of an asset's life cycle provides a way to anticipate the behaviour of an asset before it is built (Mackenzie & Briggs, 2006). Artificial intelligence methods such as expert systems, neural networks (NNs), fuzzy logic (FL), and genetic algorithms (GAs) are able to implement to solve the prediction problems (Cheng et al., 2010). Neural networks are considered potentially the most applied methods in the field of cost estimation problems. Wilmot and Mei (2005) created a neural networks to predict highway construction cost over a period of time. Ehab, Hazem and Hosny (2009) utilised neural networks to estimate the finical cost and maximum capital requirement to carry out a new construction project. Chang, Pei and Sy (2010) suggested two models to predict maintenance cost for university buildings. These researchers used neural networks for first model and multiple-regression for the second model.

It may be concluded that a network method is more concrete than multiple-regression in the estimating costs. Ali, Ahmad and Raymond (2011) developed a satisfactory model that uses artificial neural networks to analyse the bridge LCC. This work shall build upon these isolated cases towards the development of (combined) LCCA tool.

1.4. Purpose

The main purpose of this research is to establish a new model of Life Cycle Cost (LCC) of construction projects. This model will be developed by using Artificial Neural Networks (ANN_s) to study all cost components during all stages of life cycle of construction projects (design and plan, construction, maintenance and operation and disposal). Whilst attempts have been made to partially address whole-cost using ANNs in some aspects, the work proposed here shall seek to go beyond the current application towards full and executive coverage. Identifying the main factors that affect the LCC in construction project is a significant key to gain an accurate estimate of LCC by using ANN_s. Ali, Ahmad and Raymond (2011) define ANN as the data modelling method that attempts to solve complicated issues by formulating the relationship between different data, and that there is no simplistic equation that can map between data from linguistic variables.

Artificial neural networks (in methods deemed to be similar to the performance of human brain) are beneficial in the case for which conditions are not known or very difficult to identify. It has been commonly employed in many construction applications like estimating construction productivity; predict corporate bankruptcy and measuring project financial performance. This project shall seek to extend the concepts towards the whole-life costing of an asset. The validity of this model will be examined in a testing phase by comparing the model result(s) with their corresponding actual values utilising information from samples of previous construction projects.

1.5. Aim & Objectives

The primary aim of this research project is to use artificial neural networks to accurately estimate the life-cycle cost of construction projects. Towards this goal, artificial network(s) applications are selected for incorporation due to their capability to address complex problems such as estimating LCC. In order to attain the most accurate LCC estimation, this research will be focused upon the contribution of the different input factors that represent the main variables that affect the LCC and analysis of the techniques used to measure them. As a result, objectives are defined as:

1. Review literature to investigate the limitation of the current practice of LCC.

2. Review literature to identify non-cost factors (variables) which are significantly affecting accurate estimation of cost estimation in building projects.

3. Conduct qualitative research incorporating survey research to rank non-factors and provide the views of cost practitioners about how these factors can affect the accuracy estimation of LCC.

4. Analyse the existing data (of building projects) to clarify the relationship between capital cost and running costs (maintenance and operation costs).

5. Ensure utilisation of the principle of cost-significance items (CSIs) in order to simplify the process of estimating and identify the most important cost factors affecting the total cost at each stage of LCC.

6. Confirm utilisation of artificial neural networks to be employed to develop a new model for LCC; the validation of which to be a testing phase, using actual LCC values from number of previous completed construction projects to compare with model results.

1.6. Problem Statement

Asset management approaches have numerous goals, including improving the net (built) asset value (total investment during the asset's life cycle). It is argued here that this goal can be achieved by implementation of life cycle cost analysis (LCCA). Accurate estimation of LCCA will assist organisations to evaluate the value of current assets, towards making better decisions in the planning and building of new facilities and the choice of optimum ways/ approaches for operation & maintenance & 'best' disposal of unneeded components.

Previous studies identify limitations for using the concept of LCCA as: a lack of predictive data, absence of a standardised methodology; and, incomprehension of the complicated process. To gain accurate results, a new LCCA approach is required and subsequently presented here, that develops methods for standard data tracking and a summation of procedural needs.

1.7. Significance

It is observed that there is ongoing growth in construction projects and investment in numerous countries. Organisations and agencies must estimate respective (whole-life) cost and benefits to make an assessment about the desirability of carry out projects. This information helps in shaping the opinion of financial and banking institutions that are associated with the project. Life cycle cost analysis is one method that can assist organisations and agencies make informed decisions.

LCCA is deemed to be one of the fundamental foundations of asset management. Previous research (below) illustrates that there is a weakness in a prediction of the LCC of construction project because the current models of life cycle cost suffer disadvantages such as inconsistent data collection, and longitudinal review requirements. Past studies don't provide adequate models able to estimate all/whole cost incurred during a construction project's life cycle. Currently, organisations and agencies are seeking predictive models able to deal better with uncertainly, and that are flexible and easy to use. This research sets out as its main goal to develop a new model for LCC using artificial neural networks.

1.8. Research Method

The first step of the research methodology adopted here examined the limitation of the current application of LCC. Then, the new framework of LCC estimation process has been developed. After that, the most important non-cost factors affecting the LCC have been identified. Qualitative (survey) research has been conducted to rank these factors and provided the view of experts about these factors. The Statistical Package for Social Sciences software (SPSS) was used to analysis the result of survey. In addition, an analysis of the existing data of building projects has been conducted to examine the relationship between capital cost and running cost and applied the concept of cost-significant-items CSIs to identify the most important cost factors affecting the total cost of each stage of building life cycle.

The proposed ANNs model of LCC has been developed. The artificial neural networks proposed modelling to be a Multilayers Perceptron model that consisted of input, hidden and output layers. The factors affecting LCC were used as input to the developed artificial neural network and the actual value of LCC for past construction projects, was used as output during the so-called training stage. Traditional parametrics were employed to identify the number of hidden layers and the number of hidden nodes. During the training process, the number of hidden layers and hidden nodes was adjusted. The best artificial neural network model which gives the minimum value for the Mean Square Error (MSE) for the estimated LCC was selected. In order to review the model, back-propagation supervised learning algorithm(s) was used to modify network weight(ings).

MATLAB software was employed in training/reviewing for/of the model. The purpose of a training/reviewing stage was to learn model intricacies and to seek minimum error between the different estimated value(s) of LCC and case-study actualities. The model was ready to use when the minimum error was reached. Finally, validation of the model was done, at a post testing stage, by utilisation of case-study values from previous completed construction projects to allow comparison of developed model output(s).

1.9. Outline of thesis

Chapter one provides a description of the problem and a brief introduction to the current research. This chapter also provides the lists of the main objectives of this research with a brief explanation of research methodology. Chapter two describes the general concept of cost estimation, advantages of the application of LCC, limitation of the current practice of LCC, non-cost factor affecting life cycle cost during building's life, and implementation of the concept of CSIs.

Chapter three provides general information about the basic concepts of the artificial intelligence techniques. The implementation of ANNs in the construction sector has been included in this chapter. This chapter also provides the new framework of LCC estimation with more details. Chapter four aims to review and identify the applicability of previous research on determining factors and their influence on the accuracy of construction cost estimating. This chapter also attempts to present the clarification for each phase of LCC, the current classifications of project components, the significant cost items concept and previous application of the significant cost items method on construction projects.

Chapter five is the methodology discussion. This chapter aims to describe the basic methodological considerations for the realization of the research. It begins with a discussion around the selecting of method and describes the processes of conducting the study. The overview of the research producers is presented in a research design section. This chapter provides more details about the methods used to reach each objective of this research.

Chapter six is the data analysis of qualitative (survey) research. It provides the description analysis of survey research. Several statistic tests have been conducted in this chapter. Chapter seven focuses upon data analysis of existing building project. The first part of this chapter examines the relationship between capital cost and running costs. The most important factors affecting the LCC have been identified in the second part of this chapter.

Chapter eight includes the development of the ANNs model. This chapter explains the necessary steps for the development ANNs model with more details. Five models have been developed in this chapter. The validation and accuracy of the each model has been discussed in this chapter. Chapter nine summarises the conclusion of this research and presents the limitations of this research. Some suggestion regarding the future work has been included in this chapter.

2. CHAPTER TWO: LITERATURE REVIEW

2.1. Introduction

This chapter clarifies the importance of construction projects and explains the effect of accurate estimates for the total whole cost of construction. In addition, this chapter aims to introduce general concepts about the field of life-cycle costing. The purpose is to provide the essential background which will allow the work implemented in this study to be understood.

2.2. Significance of construction project

An increase in the level of goods and services are an indicator of the growth of a country's development; physical infrastructure, services provision and building projects requires to be sustainable (Tabish and Jha 2011).

In 1990's, 1 million jobs was provided by the industry in UK. About 20 % of these jobs are self-employed and involved in some type of construction work. This demonstrates that the construction industry continues to play an important economic and social role. It supplies a large section of the country's construction projects such as its dams, bridges, transportation structure and the like, alongside opportunities for jobs across related sectors, increasing income in states and countries (Manser 1994). Furthermore, construction projects have been considered as the second largest economic activity and a significant asset for improving the international competition, in locations such as the USA (Grant 1995). The total amount of money spending for new construction projects was US$508 billion which was about 8% of the gross domestic product (GDP) in 1994. These projects provided employment for 6 million individuals with knock-on renovation projects amounting to $342 billion which was about 5% of GDP and 4 million jobs in the USA (Wright 1995).

In Australia, the construction sector was the fourth largest industry during 2008-2009. $151.3 billion was contributed to Australia's GDP by the construction industry (6.8% of GDP in 2008-09), a rise of 11.0% from previous year. The construction

industry employs 984,100 people representing 9.1 % of the Australian workforce. It is the fourth largest employer in Australia at 10.3% and increasing. Engineering and building construction increased by approximately 10% and 84.2% respectively during the last five years (2005 to 2009). Construction is one of Australia's most significant industries influencing greatly social, economic and political trends ("Australian Bureau of Statistics,"2010).

The construction sector is also extremely essential to the Saudi Arabian economy. The industry contributes to about 40% of Saudi's (2010) GDP. It is projected to increase by 5.4% in 2012 due to increasing government spending in economic and social infrastructure such Schools, Universities and hospitals. Currently, the kingdom of Saudi Arabia has announced the development of six new economic cities; these cities. already underway, will provide more than 1.3 million jobs and contribute $150 billion to the Saudi GDP by 2020 (Nour et al. 2010).

For continuous future economic growth, (sustainable) physical infrastructural development are a significant prerequisite (Tabish and Jha 2011). Indeed, Erkelens (1991) asserts that building and construction projects contribute significantly to the gross domestic product and gross fixed capital formation albeit that increases in economic growth in the future, require increased construction and building projects to keep pace with socio-economic trends. However, construction projects become more complex; completing successfully in terms of quality on-time standards, budgeted costs will be increasingly difficult.

All construction projects are unique and construction costs are dependent on an estimation of resources usage and associated costs. Therefore, there are several risks and uncertainties facing managers throughout all stages of a project's life-cycle; correct acknowledgement of all factors must be taken to avoid delay and cost blowout. One of these problems perhaps inaccurate cost-estimation and a lack of applied cost data are key. This problem may lead to incomplete projects, and failure to achieve objectives. Therefore, accurate and reliable cost predictions should be developed in order to enhance construction and ensure that projects satisfy objectives and mange uncertainties throughout the project's life-cycle (Yaman and Tas 2007).

Knowledge gaps in research in the area of accurate cost prediction, especially for the building construction industry, and the need for better cost estimation methodologies and tools are the motivations for this research; the next section details the concept of cost estimation and the effect of inaccurate estimation on construction projects.

2.3. Cost estimation

There are numerous ways to define the concept of cost. Generally, cost is the financial value of all goods and services consumed in order to achieve an organisation's goals (Yaman and Tas 2007). Cost estimating is one of the most crucial functions in decision making at the early phase of a project life-cycle (Murat Günaydın and Zeynep Doğan 2004). All decisions about cost estimating and the implications for the project at hand, requires a range of stakeholders including the owner, contractor, designer, and lending company, involving economic analysis of number of alternative project components, clarifying the feasibility of a project or identifying an initial cost of a project (Sonmez 2004). The next section identifies the importance of cost estimation on construction projects, and discusses the length of time it can take to recoup the initial amount invested on a project.

2.3.1. Importance of cost estimation on construction projects

Cost estimation is an important financial issue to be taken into account as part of the project management exercise. It involves estimation of total costs and benefits of the project and alternatives. The project management team subsequently measures the return on investment or the payback period (the period of time that project will take to recoup the initial cost invested on project) to make an assessment about the desirability of the chosen alternative. This information also helps in shaping the opinion of financial and banking institutions that are associated with the project.

The significance and influence of construction cost estimating is supported by research. Carr (1989), for example, has contended that cost estimation delivers substantial information for cost planning, resource controlling and decision making. Cost estimation is one of the most important factors to the success of project (Dysert

and Elliott 2002). Alcabes (1988) articulated that cost estimators duties include preparation of all estimates, check lists and pricing information; he also asserts that cost estimation is the heart of construction work as it involves cost reporting, accurate cost classification and calculation of profit. Akintoye and Fitzgerald (2000) surveyed 84 building companies in UK and found that cost estimation is a key method for construction contractors in terms of construction planning purposes rather than construction evaluation. Several surveys have been conducted by Hegazy and Moselhi (1995) to identify the main elements of cost estimation and the kinds of methods used for estimation of these elements by building construction constructors in Canada and the USA; they found that the majority of contractors estimated direct and project overhead costs in a detailed manner. Assaf (2001) studied the overhead cost of construction project in Saudi Arabia and found that the decision about the optimum level of overhead costs is difficult for construction companies to make it due to unstable construction market which enables them to win and carry out large projects.

Aibinu and Pasco (2008) studied the importance and accuracy of cost estimation of building construction projects in Australia. Their study involved examining 56 building construction projects and surveying 102 companies. Their results indicate that size of project is the most influential factor in cost estimation of building construction project in Australia. Overestimated cost by a large amount often occurred in small projects rather than under-estimations. In order to improve cost estimation, they recommended several methods such as using probability estimation and simulation of past estimates; such methods are discussed further below.

2.3.2. The effect of inaccurate cost estimation on construction projects

Accurate cost estimation is a challenging task in the construction project, in which cost estimation is the determination of the total project cost and prepared based on limited information and under situations of high uncertainty (Flood 1997). There are three possible results of cost estimation which are: accurate estimate overestimates and underestimate. The relationships between these outcomes can be seen in the figure 2.1. This figure has been represented by Frank Freiman who developed fast

cost estimation system for Radio Corporation of America (RCA). Overestimates may lead to higher cost out-run than projected due to under-utilisation of resources such as staff, acquiring excess capacity and the company becoming weak because it is unable to provide a suitable product for a reasonable price. On the other hand, a cost under-estimate means the total cost of project is more than predicted. Poor estimation and planning are often the causes of under-estimate. The outcome of an under-estimated project may lead to increasing the cost of projects due to reorganisation and replanning resulting in delay (Daschbach and Apgar 1988). In this case, Construction client has three options(Peter and Peter 2001):

1. A construction client will terminate the project and incur loss.
2. A construction client will carry out the project while seeking extra funding.
3. A construction client will decrease the quality of the project to avoid the additional funding.

Good cost estimation requiring realistic estimates and economical project cost-ings help achieve a project's goals as illustrated by Daschbach and Apgar (1988) in figure 2.1 below.

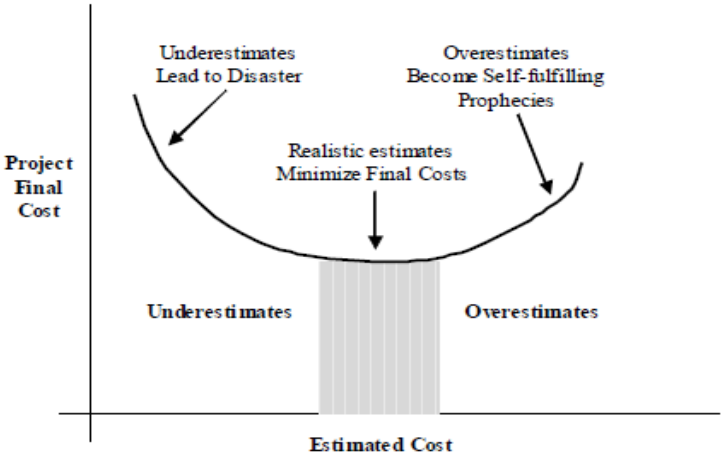


Figure 2-1 The Freiman Curve

Source: Deschbach and Agpar (1988)

The next section illustrates the impact of making-decisions about the project based on capital costs instead of considering total costs including capital costs, maintenance and operation and disposal cost.

2.4.The important of taking into account all total cost instead of the initial cost

In the past, decisions in the construction of many civil engineering systems and buildings throughout the design phase were made basically by comparing initial capital costs. The main motivation for utilising this method was its simplicity (Dhillon, 2009, p. 1). Furthermore, construction clients always give a high priority to initial cost as the most visible one. They are unable to determine the inter-dependant relations between life cycle cost of the construction and the initial construction cost (Barrett & Stanley, 1999).

Previous studies indicate that often the total cost of ownership of engineering system exceed initial costs. According to several studies, the total cost of ownership of engineering system (i.e., maintenance and running cost) is about 10 (and in some cases to 100) times the original initial costs (Dhillon, 2009, p. 1). In the civil engineering sector, the initial cost of building a project represents only a small amount of its life cycle cost. It has been predicted that the initial cost of building projects is about five times less than their life cycle cost (Evans, Haryott, Haste, & Jones, 1998). For example, the National Building Research Institute of South Africa reported that the initial cost of a hospital building is only between 6 to 10 % of the total life cycle cost. In addition, they found that from 2 to 3 years after the project construction completing, the operation costs exceed the initial cost (John W. Bull, 1992).

Moreover, Roger, George, Justin and Graham (1989) studied the life cycle cost of different types of building such as Primary schools, homes for the elderly and Secondary schools and indicated that the initial cost of these projects is less than half of the total life cycle cost as in figure 2.2-2.4. The same result has been found by O'Rourke (1984) in UK as in figure 2.5.

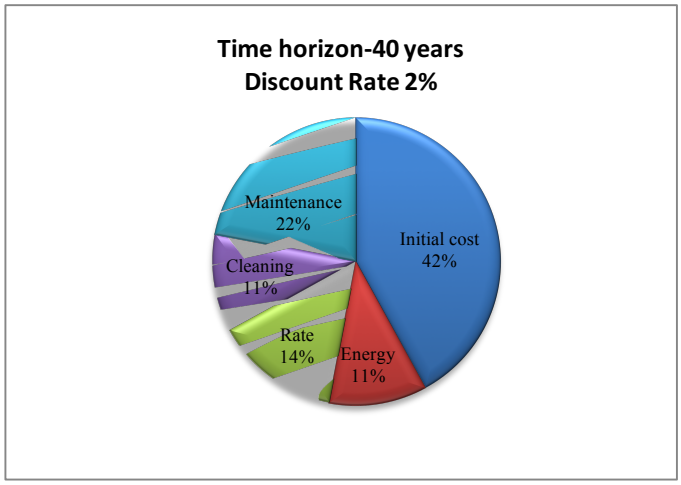


Figure 2-2 Life cycle cost for homes for elderly school
Source: (Roger et al., 1989)

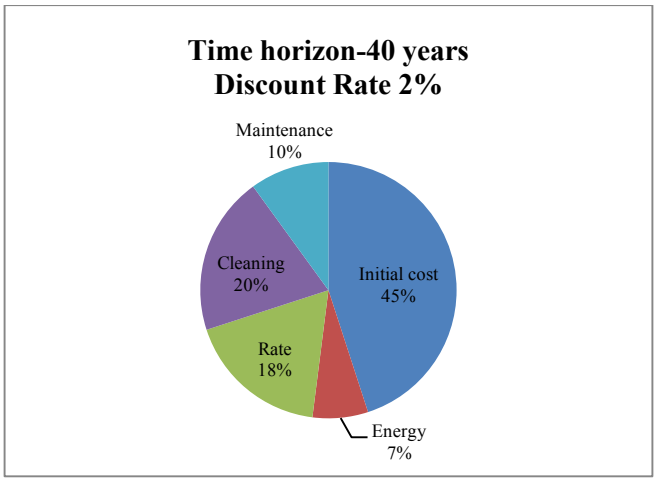


Figure 2-3 Life cycle cost for Primary school
source: Source: (Roger et al., 1989)

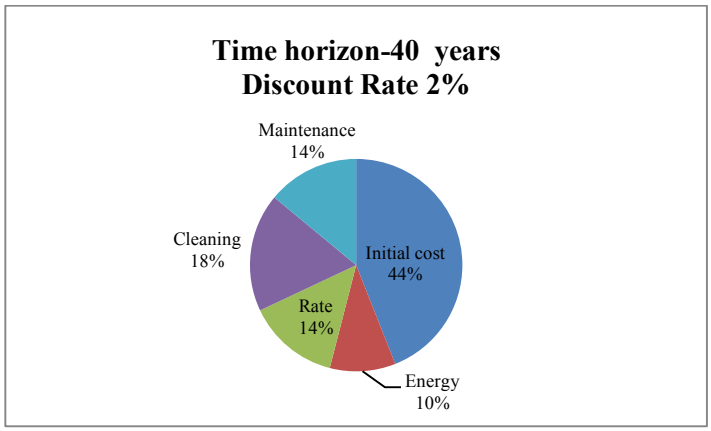


Figure 2-4 Life cycle cost for secondary school
source: Source: (Roger et al., 1989)

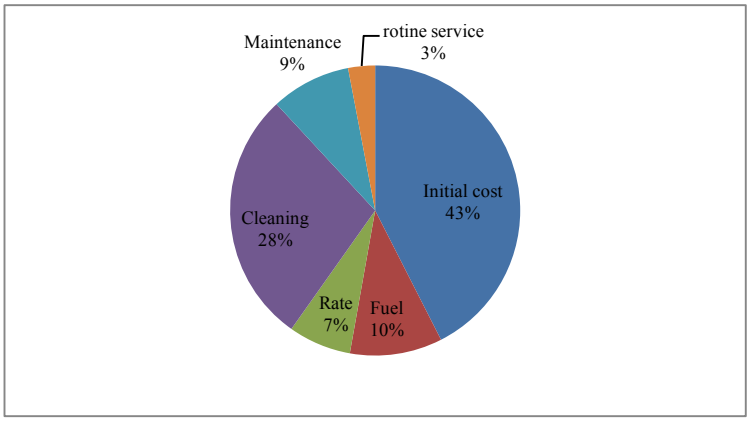


Figure 2-5 Life cycle cost for National school
source: (O'Rourke, 1984)

In order to successfully complete projects and make long term profit, stakeholders now recognise that the acquisition decisions of construction project elements, at the design stage, should be based on life cycle costs rather on initial costs. Appropriate cost reduction measures can be easily taken to predict life cycle cost at an early design phase; however, when the construction project moves from early design stage to construction stage, possibilities to influence the whole construction project cost are decreased quite significantly. (Khanduri, Bedard, & Alkass, 1993b). Figure 2.6 below, shows that the ability to decrease costs of projects during all stage of project's life cycle (Dell'Isola & Kirk, 1981).

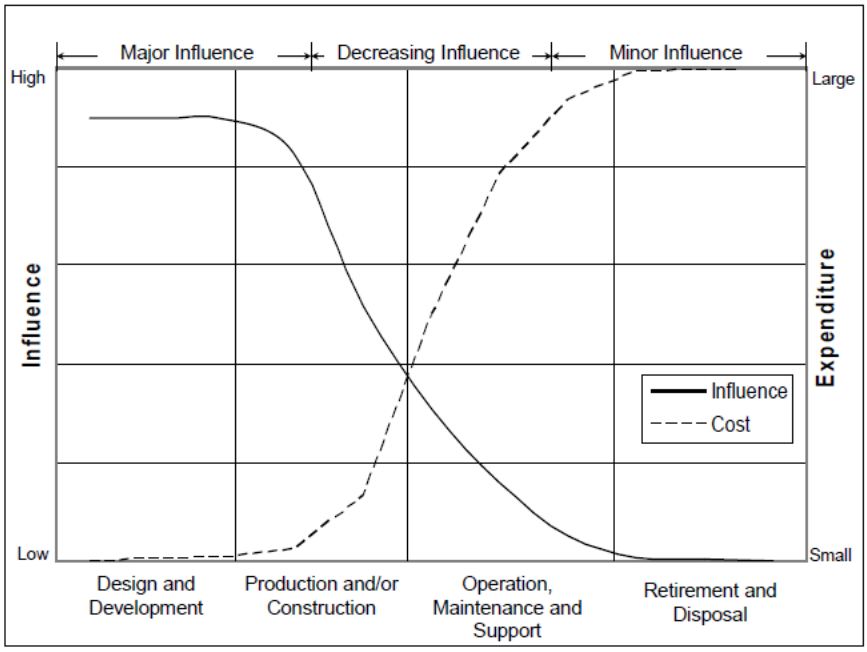


Figure 2-6 The ability of decrease cost of project during all stage. Source (Mackenzie and Briggs, 2006)

The utilizing of life cycle cost approaches may lead to increase the initial cost of building but at the same time may decrease the amount of the overall cost over the life of this project. The significance of an implementation of a LCC approach is enhanced by injecting the maximum information into the design phase, assisting to decrease waste and to improve efficiency of design and construction as well as operation and maintenance. (Evans et al., 1998).

2.5. Importance of LCC as asset management tools

2.5.1. Asset

According to the Oxford English dictionary, the definition of assets is "All the property of a person or company which may be made liable for his or their debts." (OED, 1989). The experts have noted that there are three main points from the assets definition: object (property), to which Legal entity (person or company) applies, and attributes of a Value (debts). The asset's object are classified in two categories. First category is financial objects such as, securities traded on stock exchanges and the second category is engineering objects which include all properties that are required to be managed by engineering asset managers such as, equipment and building. In figure 2.7, it is obvious that engineering assets objects are a primary base-case and everything above this base might be turned as financial assets object. Therefore, engineering and built asset objects are considered as the basis of an asset object with financial assets derived from them (Amadi-Echendu et al., 2010).

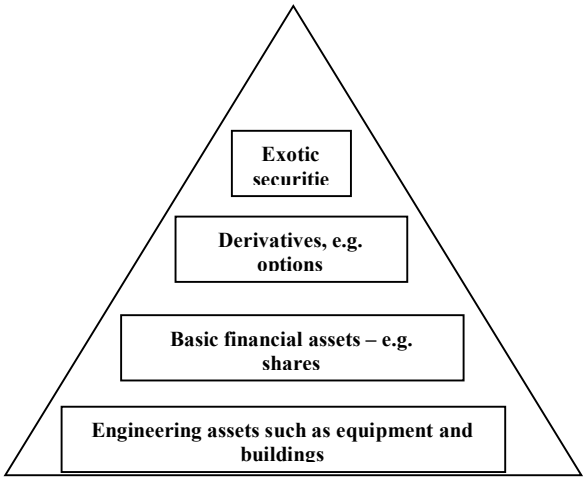


Figure 2-7 The foundation nature of engineering asset

From the figure 2.7 above, the base of the pyramid requires review of engineering asset management (EAM). There are two basic types of value for (EAM). First of all, capability value is measured on physical scale. For example, the probability of building requiring maintenance during an operation stage is considered as measurement scale of the capability of the building. Physical measurers are various and include different scales such as, weight, unit and length etc. The second type of value is financial value which can take many forms and is measured on a monetary scale such as the measurement of economic value or worth. Both types are imperative in any analysis of an engineering asset. Figure 2.8 provides application of integrated asset model towards decision making.

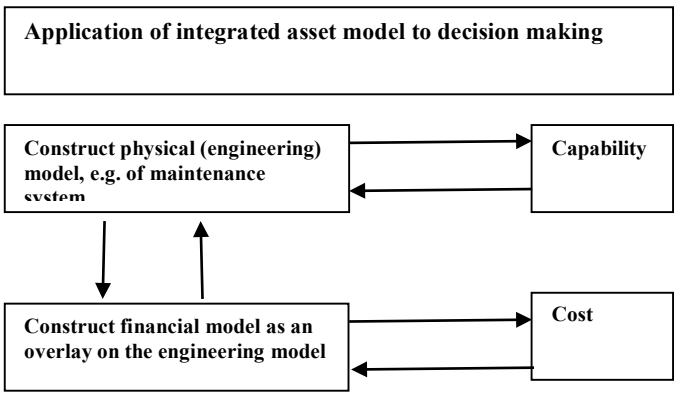
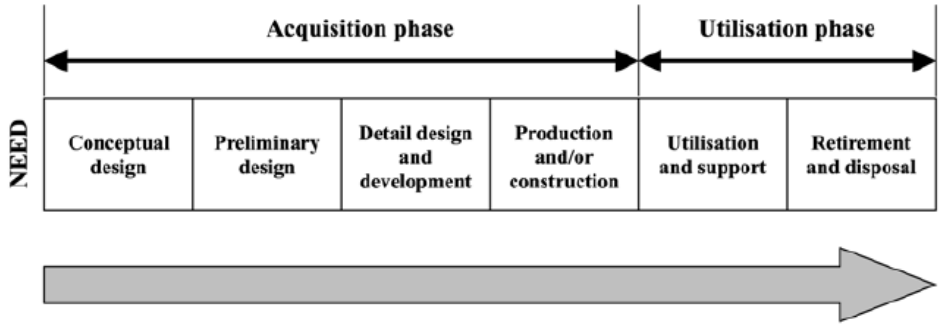


Figure 2-8 The relationship between capability and financial cost

Source (Amadi-Echendu, et al., 2010)

2.5.2. Asset Management

Mitchell and Carlson (2001) defined asset management as fully integrated a strategic, cultural and procedural system to achieve maximum lifetime effectiveness, utilisation and return from physical assets. These processes should consist of stages which must be conducted in order to transform the ideas, and rationale that prompted its development, products and services significantly. In this respect, the asset life cycle in figure 2.9 has created to gain greater value (Blanchard & Fabrycky, 1998). More details for each stage of building's life cycle will be presented in the chapter four.



Source: Blanchard and Fabrycky (1998)

Figure 2-9 Building's life cycle cost

Construction projects such as building, bridges, roadway or any other type of project, represent huge investments for both government and taxpayers. Often costly and disruptive replacements will be required due to failure to maintain these projects (Farran & Zayed, 2012). This emphasises the need for a strategic method in order to manage these projects. Therefore, research in the area of asset management is rising due to the increasing knowledge of both the public and private sector about the high costs associated with poor management of buildings and works.

Progressively, companies are beginning to understand the significance of asset management as a valuable method for utilising and strategically managing construction projects. Buildings are durable assets, which could face structurally deficient or functionally obsolescence long before the end of their structural life expectation (McGeorge, Zou, & Palmer, 2012, p. 280). This leads to either demolition or rehabilitation of these buildings because of deteriorated components. Today, one of the primary purposes of management practice is illustration of the potential benefits of the project other than costs from a sustainable development perspective (Labuschagne & Brent, 2005). In this respect, Life cycle cost is one of the major components that significantly influences the result of an asset management programme.

Several researchers have suggested the use of LCCA principles for analysing the total cost of construction assets. The aims of using life cycle management as a tool of asset management can be summarized into dimensions (Ferry, Flanagan, Research, & Association, 1991):

a. Life cycle management is management system that can be utilized by asset managers to seek maximum functionally at minimum LCC.
b. Life cycle management is a strategic plan for long-term function of asset's operation and maintenance.

In addition, life cycle management can be utilized as suitable tools to ensure that construction projects are sustainable on term of healthy and comfortable for their occupants and economical to operate and maintain. The conservation of asset resources such as energy, water, and raw material and reducing the production and using of toxic material at all asset's life cycle stages can be achieved by using the principle of life cycle management ("State of Florida," 2010).

As mentioned early, the greatest chance to influence construction project life and life cycle cost will be occurring during design stages when significant decisions are made about selecting project resources (materials and equipment). According to Khanduri, Bedard,and Alkass (1993a) between 75-95 % of the total cost of construction projects are set at the early stages. A suitable asset management programme will use LCC as tools to assist the decision makers and plans to balance out the unlimited organizational requirements.

This research will consider life cycle cost as a technique to improve the accurate cost estimation of building construction cost. The next section will provide more details about the concept of life cycle cost and more explanation for the rationale to choose life cycle cost as the key direction for this research.

2.6. History and Definitions of LCC

The principle of Life-cycle Costing (LCC) is not new. The first extension of LCC dates back to World War II when the U.S Department of Defence (DOF) used LCC in the procurement of weapons and weapon support system (Kabbani, 1993).

In the early 1960s, the LCC theory was developed by the DoD to increase the effectiveness of their procurement policies (Shields & Young, 1991). These policies

were discussed by several researchers in the following references- Metzler(1974), Gansler (1974), Earles (1974), Dixon & Anderson (1976), Caver (1979)and Dighton(1980).

The Japanese are considered the first country to use LCC concepts widely to overcome regeneration concerns after World War II, and to refresh their economy as the second objective by saving costs in the long term (Emblemsvag, 2003). In the 1970s idea of integrating product design and economic modelling was narrowly applied. In the late 1970s, LCC was employed in construction projects in the U.S.A. with an aim to discover the alternative energy design choices in construction projects (Raymond & Eva, 2000).

Prior to the 1970, procurement decisions were based only on capital costs. During that time, 'Terotechonology' discussed that there were alternative and more effectiveness methods of making decisions than being based only on capital costs (Boussabaine & Kirkham, 2007). The LCC idea was widely beginning; the argument of spending more ion initial cost would save more in the long term when compared with cheaper options. While the concept of LCC was created on long established philosophies of mathematics, economics, engineering and risk analysis, implementation of LCC in construction engineering sector is still under improvement (Pelzeter, 2007). The main aim of any construction engineering activity has always been to analyse and determine how they can design and arrange physical factors in order to create benefits in a way that meet the need at the lowest possible cost. Therefore, a principle of LCC was always included in engineering designs. It was often thought that it, LCC, can achieve economic competitiveness and be strengthened through a life-cycle attitude in engineering. Although this philosophy is deeply rooted, engineering economics has been confirmed by engineers at the early stages of the project's life cycle, to focus primarily on the performance of an early design which ignored generally the project's life cycle performance, financial factors and consequences of operational and maintenance phases at the later phases of the project life-cycle (Fabrycky & Blanchard, 1991).

The term cost-in-use refers to operation costs of projects and appeared in the literature in the early 1970s. However, the main weakness of this term model was its

incapability to predict future costs (Boussabaine & Kirkham, 2007). Recognizing that prediction was a key element, the concept of the LLC appeared as a new methodology for assessing the costs through the late 1970s. The utilisation of LCC in UK construction sector received a motivation with the publication by the Royal Institute of Chartered Surveyors study by Flangan (1983) on the concept and implementation of LCC. In addition, the society of the Chief Surveyors in Local government provided a report in the form of practice manual. Ashowrth (1989) has tried to focus more on the reasons behind the difficulties in an application of LCC.

Internationally, the application of LCC has been gaining consideration; back in 1985 there was conference held in New Zealand concerning the impacts of decision making at early stages of asset's life cycle on the value of building assets. There was general agreement on the principle of total life cycle cost's importance, but no proof was presented of its normal employ as a management tool by designers and project owners in New Zealand (Al-Hajj, 1991, p. 37).

According to Ashworth (1989) LCC had been widely applied in North America as recommended by Jelen and Black (1983), Ahuja and Walsh (1983); Lawl and Ruegg to have carried out surveys in the U.S.A. and found that eight organisations had 14 LCC documents guiding internal LCC practise. Four documents were represented to investment in general, seven to energy investment, two to renovation decision and one to investment in hospitals.

Moreover, again as described by Al-Hajj (1991), the Department of Energy expanded the utilization of LCC; the purpose of this programme was to present practical and effective ways and processes to Federal agencies for the prediction of life-cycle cost and the knock-on potential to present savings in terms of proposed renewable energy (Al-Hajj, 1991, p. 37). Numerous explanations of what constitutes the life-cycle of assets have been suggested at various times; there is no one definition of LCC that has been agreed upon by researchers and organisations. Table 2.1 below illiterates several definitions of LCC provided by a range of researchers and organisations across various studies.

Table 2-1 Definition of LCC

Researcher	Source	Definition
UK Department of Industry 1977	(Boussabaine & Kirkham, 2007)	'A concept which brings together a number of techniques – engineering, accounting, mathematical and statistical- to take account of all significant net expenditures arising during the ownership of an asset. Life-cycle costing is concerned with quantifying options to ascertain the optimum choice of asset configuration. It enables the total life-cycle cost and the tradeoff between cost elements, during the asset life phases to be studied and for their optimum selection use and replacement'.
The American Institute of Architects 1977	(Architects, 1977)	'A technique that allows assessment of a given solution or choice among alternate solutions by considering all relevant economic consequences over a given time'.
U.S. Army Corps of Engineers (USACE) (1986)	(Army, 1986)	The total costs that are projected to be spent as the facility or system performs its function over a period of time.
Neely and Neathhammer (1991)	(Neely & Neathammer, 1991)	The amount of all costs to construct, operate and maintain facilities.
US General Services Admin. 1992	("Public Buildings Service Value Engineering Programs," 1993)	The summation of all costs over the useful life of building, system or product. It includes all relevant costs to the Government to acquire, own, operate, maintain and dispose of a building, system or product for a specified period of time, less any salvage value
The U.S. President's Executive Office of Management and Budget 1993	("Office of Management and Budget," 1993)	'The total cost of a system, building, or other product, computed over its useful life. It includes all relevant costs involved in acquiring, owning, operating, maintaining, and disposing of the system or product over a specified period of time, including environmental and energy cost'
Dell'Isola and Kirk	(Kirk & Dell'Isola, 1995, p. 8)	An economic valuation of system or an item that takes into account all important costs of ownership over the economic life of an item or system.
The national institute of standards and	(Standards, 1996, p. 2) Handbook	The amount of all cost of owing, operating, maintaining, and disposing of a building or a building system over specific period of time with all cost discounted to

technology (NIST) 1996		represent the time-value-of money.
Hudson, et al (1997)	(Hudson, Haas, & Uddin, 1997)	Represent the amount of all costs related to facility over a specific analysis period.
Smith (1998)	(Smith, 1999)	The total cost of system from design stage through to occupancy and ultimate demolition which is the final stage.
Australian Standard AS/ NZS 4536:1999	(Smith, 1999)	the total costs of acquisition cost and ownership cost of an asset throughout its life cycle from early phase to disposal phase.
Bourke and Davies (1999)	(Bourke & Davies, 1999)	The costs related to the period of financial interest.
Al-Hajj (1999)	(Al-Hajj, 1999)	The costs associated with acquiring, using, caring for and disposing of physical assets
Defense Acquisition Guidebook 2004	(U.S. Defense Acquisition Guidebook, 2004)	'Life-cycle cost consists of research and development costs, investment costs, operating and support costs, and disposal costs over the entire Life-cycle. These costs include not only the direct costs of the acquisition program, but also include indirect costs that would be logically attributed to the program'
International Organization for Standardization ISO 15686-2:2012	International Organization for Standardization ISO 15686-2:2012	A valuable approach which is utilized for forecasting and evaluating the cost performance of constructed assets.

In light of the above definitions, LCC can be thought as a systematic assessment of total cost of asset from cradle to grave (and for many residual items back to cradle). It is a structured technique which assists in analysis alternatives, and therefore in reducing total expenditure over its anticipated life-span. This technique can be used from the simplest to the most complex projects. For example, when purchasing a new house, several factors may be considered such as maintenance, original cost, insurance, mortgage liability and so forth. This is an example of the LCC principle.

The outcome of LCC can be utilized to aid management in the decision making procedure when there is alternative option.

2.7. The objective of LCC

The life cycle costing principle can be utilized for numerous different purposes. Many researchers (Aouad, Bakis, Amaratunga, Osbaldiston, & Sun, 2002; Aye, Bamford, Charters, & Robinson, 2000; Boussabaine & Kirkham, 2007; Cole & Sterner, 2000; Ferry et al., 1991; Kirkham, Boussabaine, & Awwad, 2002; Schade, 2007; Seldon, 1979) have attempted to highlight the main purposes of using LCC.

These purposes are summarised in the following subsections.

A) Benefits for shareholders of project:

Investment in the industry involves several of decisions for difference purposes. Some of these decisions are about budget and cost, some about benefits, some have immediate effect, and some have long term impact. Using LCC as tools of making decision can be useful for shareholders of project (Client, Project team and contractor).

1- Client: The client may use LCC to:

i. Evaluate project viability
ii. Make a correct decision about the project (continuing or aborting a project)
iii. Analysis all costs budget which are required for carry out the project.
iv. Measure the capability of pay for design facility.

2- Project teams: The project teams may use LCC to:

i. Choose best alternative among options and the most useful procurement approach.
ii. Identify cost drivers and predict future budget requirements.
iii. Create significant decisions policy and design trade-offs.
iv. Control programmes and minimise total cost.
v. Clarify issues linked to the ultimate disposal of the asset.

3- Selection contractor:

Comparing the contractor's price with the total life cycle cost estimation of project, LCC can be used to select contractor when the project is placed for tender.

B) Tools for design professional:

There are many number of recent trends have appeared as issue of worry for the design professional, involving: environmental sustainable, total quality management, value engineering, operation effectiveness, facility obsolescence. LCC can be utilized to deal with these issues (Kirk, 1995, p. 1).

i. Facility Obsolescence:

New materials, technology, and process of structure and operation; new air pollution; and new laws and regulation are an examples causing facility building obsolescence. Considering innovative alternatives at design stage will lead to minimize premature obsolescence. LCC is mostly valuable for designer in evaluating life cycle consequences of alternatives being considered to reduce facility obsolescence(Kirk, 1995, p. 1). LCC has applications of numerous purposes such as evaluating financial consequences to utilize an existing construction project (bridge, roadway and office building) , or component of this project, in comparison with cost of replacing alternative which may increase the productivity of staff, improve performance of work, or changing organizational structure. Facilities must be appropriate and accommodated new technology and material, and law and regulation to avoid obsolescence issue. The demand for increasing security as result violence and green building requirements for new construction projects in some countries around the world are social and political cause for obsolescence. Several methods can be applied to solve these recent trends such as:

a) Determine changes that can be lead to obsolescence.
b) Carrying out pre-design analysis and responding to future needs over innovative and flexible solution at design stage.
c) Adapting current approaches during construction, and operation and maintenance

Project teams should concern about emerging issues through review published

literature before the design stage. Currently, some organizations have provided new technology and tools to update project teams with current emerging issues such as the Environmental Protection Agency (EPA) which have developed forums to aware project team of emerging environmental problems.

ii. Environmental Sustainable:

The main concept of environmental sustainability is optimum efficiency in the use of resources of project and selects materials and approaches of construction that will not harm environment. Life-cycle costing approach has been used in decisions about construction options and selection best choice for a given owner or user (Kirk, 1995, p. 1). For example, Building Life Cycle Cost (BLCC) program has the ability of prediction annual life cycle CO2, SO2 and NOx emission coincident with the energy use of the building being evaluated. The calculation of these emissions covers some type of energy's resources such as electricity, fuel oil, natural gas, LPG and coal. The aim of this method is to save energy and reduce these kinds of emission by select a suitable design on the construction projects (Sieglinde, 2005).

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iii. Total Quality Management (TQM):

Continuously improved, customer-focused, people-oriented and management-led are considered the most fundamental total quality management principles and have revolutionized the way businesses approach their work. Today, design teams are required to reconsideration about their method at design stage in order to become more TQM-based. For example, design team should solve owner issues of international competition and increasing cost of maintenance and operation in order to become customer-focused. The utilizing of LCC aids design team to analysis alternatives to these problems (Kirk, 1995, p. 1).

iv. Value Engineering:

Value engineering is an effective management tool for seeking the best value of money in facility management over 30 years and concerns in facility function. It is a function-oriented technique. LCC is an efficient prediction tools and can be used in value engineering. It can be used for total cost savings or analysis several alternative

options for the objective of selecting the optimum solution (Kirk, 1995, p. 1). Table 2.2 below list the recent trends and concern, where the LCC tools can be used.

Table 2-2 Recent Trends and Their LCC Concerns source (Kirk & Dell'Isola, 1995)

LCC Concerns	**Recent Trends**				
	Total Quality Management	Obsolescence	Environmental Sustainability	Operational Effectiveness	Value Engineering
Initial project cost					✓
Energy/Fuel cost			✓		✓
Maintenance and Repair			✓		✓
Administrative costs		✓			✓
Alterations & Replacement		✓	✓		✓
Administrative Costs	✓			✓	✓
Staffing Costs	✓			✓	✓
Safety/Security Systems		✓		✓	✓
Real Estate Taxes					✓
Water & Sewer Costs			✓		✓
Flexible Furniture Costs	✓		✓	✓	✓
Air/Water Quality		✓	✓		
Healthful Environment		✓	✓		
Sustainable Materials			✓		
New Business Technology	✓	✓		✓	✓
Communication Systems	✓	✓		✓	✓
Automation Equipment	✓	✓		✓	✓
Site Environment			✓		
Occupant Comfort/Control					
Business Profitability	✓	✓	✓	✓	
Business Profitability	✓	✓	✓	✓	✓

In light of above one may conclude that life-cycle costing can be utilized as a management tool to support decision making process that may be incurred during all phases of construction project's life cycle (more details about construction project life cycle stages will be discussed in next chapter). A consensus of researchers believe that making decisions at early stages of construction project life cycle have the most important effects on the running costs of construction project over their life span. Therefore, this research will use LCC as estimation tools of the total project cost at early stage.

2.8. The key barriers that limit expand implementation of LCC

The key barriers causing limitation in the implementation of LCC in the construction industry can be summarized in following points:

2.8.1. Lack of understanding of LCC

Olubodun, Kangwa, Adebayo and Thompson (2010) conducted research to identify the main key barriers which cause the limitation of use LCC in the construction industry. They found that lack of understand of LCC is the most limiting factor to the usage of LCC. This confirms the view by Bull (2003, p. 120) that there is a lack of knowledge and understanding on part of both clients and practitioners. This may lead to increase the level of personal decision making.

2.8.2. Absence of a systematic methodology

Absence of standard approach in recording historical, collection and analysis data is one major difficulty in using the LCC in practice (J.W. Bull, 2003, p. 120). This absence of standards means that each organisations and individuals have to create their own standards to undertaken the project. The creating of several standards to carry out the same project wastes time and spend money (Olubodun et al., 2010). Bull (2003, p. 148) recognise that the initial cost of project is separated from the operation and maintenance costs because the cheapest initial cost is almost accepted and after that hand over the project to others to maintain. This is one of factors that

frustrate in developing standard approaches for LCC. Furthermore, the processes of LCC require predicting costs often 20 years or more into future; this makes the LCC process more complex (Olubodun et al., 2010). One of the objectives of this research is developing a new model of LCC which can be easily used and followed by a wide range of organisations and individuals.

2.8.3. Problems with current analysis tools of LCC

There are various methods for preparing cost estimates. These methods can be classified into three main generations as follows:

2.8.3.1.Cost Estimating Methods

Cost estimating methods used in the construction projects can be generally classified as engineering procedures models, parametric models and analogous models (Fabrycky and Blanchard 1991).

I. engineering procedures models:

Engineering procedures or detailed or activity-based or unit cost estimates are typically the most definitive of this type of estimating and use information down to the lowest level of information available. The accuracy of this method depends on the accuracy of available data.

Advantages in using this method include:

a) providing a greater level of accuracy
b) Providing massive information that can be utilized for difference purpose such as better monitoring, change control, etc.
c) improved scope and individual activity definition
d) providing better resource basis for the planning and schedule purpose

However, the main disadvantages of this method are time consuming and costly method and needs accurate information to get better result.

II. Parametric Models:

The cost drivers in this method are linked to cost by cost estimation relationship (CER). Capacity and equipment factoring are simple examples of this method. This

type of estimation aims to collection and analyse previous project cost information in order to create the cost estimation relationship.

Advantages in using this method include:

a) Easy modified when the design change and can be used at any level (system, subsystem, component, etc.)
b) Ability to apply sensitive approach and measures of validity and standard error.

However, the main disadvantage of this method is that it may be difficult to apply at early stages of the project life-cycle due to lack of information.

III. Analogy Method:

This method uses the actual costs from previous projects as a basis for a prediction of costs for the current project. It can be carried out based on a system level or on task level. A high degree of judgment is required; this is considered as the cheapest of the three methods. This method is useful to apply to new projects when there are no databases available.

Advantages in using this method include:

a) Easy to develop
b) Cheaper comparing to other types of estimation cost.

However, the main disadvantage of this method is that the result may be (the most) inaccurate especially when applied on a system level.

Life cycle cost (LCC) of projects takes into account operation, maintenance and disposal costs; the calculation of the LCC should consider the time-value of money (Fabrycky and Blanchard 1991). As result, all future costs should be discounted to present value. Inflation rate are considered by many LCC methods (Fabrycky and Blanchard 1991; Woodward 1997). Selecting inflation and the right discount rate for the project may be a challenge as there is uncertainty and risk that effects LCC results. Many researchers recommend sensitivity and probability analyses, and statistical tools to address the problem of uncertainty (Singh, 1990). The sensitive and probability analysis will be presented in next section.

2.8.3.2. Probability and sensitive analysis

The two leading methods to address an uncertainty are the probability and sensitive analysis methods. Regression modelling is another method towards identification of construction cost impact factors, where regression equations estimate construction cost depending upon on cost-factor interrelationships. These methods become complex when numerous cost elements are considered as the dependent variables (Sonmez, 2011). Sensitivity analysis is a method to indicate how the value of LCC is affected by changing the interest and inflation rate parameters. It is often the case where small variations in a parameter lead to a significant change in LCC result. In these cases a further analysis can be done utilizing probability analysis (Kirk, 1995, p. 84), incorporating Monte Carlo simulation of variables, presented as a probability distribution of all total costs of all alternative options. Resultant findings illustrate the most likely cost of all alternative options and the range within which it can be expected to lie (R. Flanagan & Norman, 1993). However, these adaptations have disadvantages including:

i. Probability subjectively evaluated today may differ in the future (Whyte & Scott, 2010).
ii. Nominal account is taken of non-cost factors that affect LCC estimation.
iii. Complex processes cannot fit input and output variables easily.
iv. Sensitivity analysis does not quantify risk but rather identifies factors that are risk sensitive where only one parameter is varied at a time (R. Flanagan & Norman, 1993).

These disadvantages relating to current analysis tools of LCC suggest that an alternative method might be more appropriate. To tackle some of the key barriers presented above and to provide a useful tool to decision makers to assist them in estimation the total cost of construction projects, this research suggests that developing a new model of LCC. The new method here will address the issue of absent standardised methodologies for both data collection and analysis. The review of cost modelling will be discussed in the next section in order to select the suitable model which can address the limitation of current cost estimation.

2.9. Building cost modelling

Modelling, in general, can be defined as a process where critical real life issues are presented as a simpler issue situation (Adedayo *et al.,* 2006). The building cost modelling can be described as a representative presentation of a construction system, which defines every component of the system in terms of the features that impact the cost. The modelling of building cost consists of the most important cost elements of building. These elements can be presented in a form which enables easy analysis, as well as prediction of the total cost (Ferry *et al.,* 2000). These models must support the evaluation of changing in some construction characteristic, such the design variables, timing of events, type of construction methods and others.

Therefore, how models can be classified for enhanced understanding and evaluation of the situation. Several researchers have recommended that the development of cost models has proved its usefulness in the following aspects (Ashworth, 1998; Raftrey et al., 1993):

I. A dependable system for taking more-informed decision.
II. A quick process for generating cost data.
III. It helps in the creation of proper cost information at an early stage of designing.
IV. Produces output that is more reliable and hence, offers more confidence in making decisions.

Ashworth (1998) and Raftrey (1993) suggested that cost model should consist of some criteria in order to be useful tool in generating such advantages listed above. The following are such criteria:

I. It should also support continual updating through inclusion of fresh data.
II. Availability of sufficient data is important. The data needed for the model must be accessible in proper form and number.
III. The model must be able to accurately and sufficiently represent what it is trying to predict.

IV. The total modelling process must be completed speedily, efficiently and without making high expenses.

V. The model should also be able to accommodate changes to meet the needs of the changing situations of the construction industry.

The above criteria can be considered as the guiding concept in the select of best method in cost modelling.

2.10. Types of cost modelling in construction projects

There are several methods for modelling the cost of construction projects. Some approaches that can be used for cost modelling of construction projects are elucidated below (Mawdesley *et al.,* 1997; Ashworth, 1994):

2.10.1. Empirical Method

The empirical method uses the common-sense process for understanding, implementation, as well as presentation. These methods are developed and employed on the basis of "the good feeling"; with Bill of quantities as an example of this method.

Here, the physical outlook of the construction projects and the processes utilised are modelled according to both description and dimension. To achieve a realistic relationship between the Quantities and Price, the process is continuously refined.
It is an easy to represent quantities and price in algebraic terms. For example, the concrete cost for a column can be calculated from the equation (2.1):

$$\boldsymbol{C = L * W * D * R} \ldots\ldots\ldots\ldots\ldots (\mathbf{2.1})$$

Where: L= length on plan; W=width on plan; D= thickness of concrete; R= Measured rate for Concrete in cubic meters in this Location and C=cost of floor slab.
Therefore, the realistic approach proposes that there might be different costs related to the concrete. Hence, they should be classified into classes. The benefits of this approach are:
a. Simplicity in understanding, and

b. It is possible to relate quickly and easily to the construction project.

However, this method do not considered the complex plan form or large number of storeys (Ashworth, 1994).

2.10.2. Multiple regressions Analysis

Multiple regressions are a process of finding a mathematical expression that are able to represent the data of construction projects in the most efficient way. This method is often applied in cases where the variables do not bear an exclusive relationship. It is actually a straightforward mathematical process that tries to measure the relationship within two variables. This method was developed by Dr. Geoffrey Trimbler, while working at Loughborough University of Technology. Many researches were performed to confirm the feasibilities of its application; as stated by Raftrey et al. (1993), the following suppositions worked as the base for considering that the regression analysis was suitable:

i. The suggested model is a connection between the total cost and the in-project's details data;
ii. It employs only a few number of cost codes to develop the result;
iii. It includes typical processes for creating a classification model and strives to note cost against it.

Another way of evaluating is to use regression analysis for completing the projects. This can be appropriate for particular clients who deal with similar type of projects, for example, the hospital boards.

Multiple regression models are formed as equation (2.2):

$$\mathbf{Running\ Costs} = \mathbf{a} + \mathbf{b1} * \mathbf{X1} + \mathbf{b2} * \mathbf{X2} + \cdots .. + \mathbf{bn} * \mathbf{Xn} \ldots\ldots\ldots\ldots\ldots\ldots .. (\mathbf{2.2})$$

Where: a- intercept b_1 to b_n; regression coefficients- X_1 to X_n ; independent variables

For evaluation of the multiple-regression model, the adjusted R^2-value and P-value are key. The R^2-value represents the percentage variability in the costs that can be determined by the parameters (variables) involved in the model. If R^2 is equal or close to 1, then there is good correlation (a good fit) between the actual value and the estimation model output. Furthermore, In order to improve the result of multiple-

regression, a significance level (p-value) can be used to identify the variables to be eliminated. In general, the variables with p-value close to or less than 0.1 are considered to have an important contribution to the model (Ontepeli, 2005). The stepwise method can be applied to identify the most important variables. The procedure of this method starts by including all input variables in the model; then an identification of the p-value for each variable, if a variable has p-value more than 0.1; and, subsequent elimination until identification of the best model with a consistent variable, p-value equal or less than 0.1.

2.10.3. Simulation

A simulation model attempts to replicate the working of a system under study, by investigating the collaborations between its constituents. The simulation results are usually presented in a structure which shows its performance. The purpose of simulation can be described by the next points:

i. Direct experimentation can be expensive and difficult to manage. Direct experimentation can be avoided with simulation in different cases.

ii. Similar to any other mathematical technique, simulation is also expected to include experimental errors. Therefore, simulation should be treated like a statistical experiment and any disturbance of the performance should be used for statistical analysis.

iii. A computer is sufficient tool for carrying out simulation experiments. In this case, a number of intricate mathematical functions that are usually critical to evaluate can be presented with better flexibility.

However, at the same time, simulation can turn out to be a time consuming process, specifically at the time of optimizing the models. Monte-Carlo techniques that are based on the universal idea of employing sampling to evaluate the expected output are commonly applied for sorting out this problem.

The process includes description of a component, after it is presenting through probability distribution; computers carry out successful simulation due to a capability to deal with large data. In case of the simulation models, collecting samples from any probability distribution depends on the application of random numbers.

2.10.4. Heuristic

The Heuristic model depends on instinctive or experimental rules with the capacity to define a better solution related to the one at hand. Normally, in case of Heuristic modelling, there is a set of goals which are to be achieved. Hence, there are search methods that might be established and might be moving from one solution point to another.

According to Ashworth (1994), heuristic models can be defined as a search process that smartly moves from one solution point to the other, with the objective of improving the result of the model target. At the point when no more enhancements are possible, the best-achieved solution is taken as the estimated solution for the particular model. In case of development of machine intelligence, a heuristic is considered as an instruction that determines development of action, as per the state of the present information obtainable at a specific period.

2.10.5. Expert Systems

Expert systems are actually computers which work like experts. The result produced by this type of system depends on the information fed into it to create the output. The system works like a person's brain, with knowledge to the solution, and generates the desired output by carefully implementing the thumb rules set by the programmer.

One example of this kind of expert system is called Artificial Neural Networks (ANNs), which uses a collection of rules to predicate a result. However, the effectiveness of the system is (somewhat) subjective, because it is trained for producing the expected patterns and trends in the output. The input variables can also be altered based on the available information or the information being processed. Hence, the generated output can be used for cost planning and management.

There are a number of factors that can affect estimation process of cost planning. According to MacCaffer et al. (2000), it can be considered from the perspective of

design and construction phase and efficient only when an effective cost model of design base is implemented.

The cost model is selected by the purpose of estimation cost that the model is designed to measure and a number of other factors. During the design and construction phases, some of these factors affect the estimation cost.

The new approach of LCC modelling proposed in this research is a combination of the previous type of cost model and builds upon and develops and extends theoretical approaches (more information will be discussed in next chapter).

2.11. Summary of this chapter

This chapter illustrates the importance of construction projects and estimating costs. There is general widely held agreement that construction projects must continue to move away from and evolve from the old method of investment which emphasises initial cost, and increase progression towards the concept of life cycle cost methods embracing all/whole costs occurring at all stages of an asset's life cycle.

This chapter also clarifies the historical development of the concept of life cycle cost from its early utilisation in military purposes to a broader approach. LCC remains a systematic assessment of total cost of an asset from cradle to grave (and for residuals, back to cradle). It continues to remain important to estimate the total cost of an asset from the early stage to the asset-disposal/(regeneration) stage.

Past studies state that wider usage of LCC methodology in construction projects is (still) hampered by factors such as absence of a systematic methodology and problems arising from contemporary information modelling. These disadvantages relating to current analysis tools of LCC suggest that an alternative method might be more appropriate and is still being sought by industry stakeholders.

This research suggests that developing such a new model will address some of the key barriers that (still remain that) limit implementation of LCC in the construction projects. The new model (proposed and developed here) addresses the issue of the (ongoing) absence of standardised methodologies for both data collection and analysis.

3. CHAPTER THREE: PROPOSED NEURAL NETWORK MODEL

3.1. Introduction

Researchers became aware of the potential of computers to carry out the tasks which needed repetitive calculations between the world wars. In the 1940s' artificial intelligence also came into the picture as a problem solving technique. Artificial neural networks (ANNs) become a predominant part of artificial intelligence (AI) such that the computer performs by using the problem's data as the input and generates the solution as the output, with the human brain as the inspiration behind this technique. Artificial neural networks follow the way the human brain does work; it applies the knowledge acquired from previous tasks to complete unknown new ones. During the training period, the computer is taught by examples to figure out the relationships independent input variables and the targeted output values.

ANNs have been successfully utilized on many occasions in various applications. The fields of applications vary as well as the problems. It has been used in finance, medicine, engineering, geology physics and chemistry for problem solving. The area of application has extended recently as it is applied now in areas of classification estimation, prediction and function synthesis. The definitions, history, concept, architecture and its structures are discussed in this chapter. The framework of the new proposed model of LCC (incorporating ANNs) is also presented in this chapter.

3.2. History of neural networks

There are two mandatory things required for the development of any technology: conceptual innovations and application of those in reality. The neural network has also development with the help of these two elements. Some of these developments took place in the late 19th and early 20th centuries, in the fields of physics, psychology and neurophysiology.

The first formal elementary computing neuron model was outlined by McCulloch and Pitts (1943). The model can perform logic operations as it has all the required elements. So it operated as an arithmetic logic-computing element.

After some years, a new feature was added to the networks by Hebb (1949), who introduced the connectivity between single neurons. This was the first mathematical rule for execution of learning of an artificial network.

In 1954, Minsky built and tested the first neuron computers. Automated connection was the unique feature of these computers. In 1958, a neuron-like element, preceptor, was invented by Frank Rosenblatt (1958). ADALINE (ADAptive LInear NEuron) network and LMS (Least Mean Square) algorithm became the learning rule of the neuron network as suggested by Bernard Widrow and his graduate student Marcian Hoff. It was very much similar to the perceptron except the transfer function in the ADALINE network was linear. Researchers were not so keen to do more studies in 1970s after the results of theoretical study by Allen, Minsky and Papert was published (1969). It claimed that the perceptron developed by Rosenblatt has its own limitations which are quite serious in nature. It was thought that this limitation is present in all the neural networks.

The next 10 years saw the decrease in research on ANN due to this study. (although there was some important work that happened in 1970s like Kohonen (1972) and Anderson (1972), independently developing the linear associator neural networks; whereby systems could perform as memories)

Almost one decade later research in this area once again started gaining attention. At this time, Hopefield (1982) invented two key concepts to address the limitations identified by Minsky and Papert. The two concepts were: the feedback between the input and output and the nonlinearity between the total inputs received by a neuron and the output it produces (Marini, Magrì, & Bucci, 2007). Minsky's criticism about ANN was also answered by the concept of the backpropagation algorithm to train multilayer perceptron networks; notably where backpropagation neural networking was attributed to Rumelhart and McClelland.
Growing numbers of researchers are now returning to assessing neural networks.

3.3. Definitions of neural networks

Artificial neural network has different names given by different scientists. Lippman Lippmann (1988) and Adeli and Wu (1998) defined it as a model that has an arrangement of linear and non-linear mathematical elements. These elements are parallel in operation and its configuration and pattern make it look like biological related things.

ANNs are described as parallel information distribution structure by Nelson Hecht-Nielsen (1990). This structure can retain local memory and function logical inferential operation and information processing.

Nielson Hecht-Nielsen (1990) , Adeli and Wu (1998), Arciszewski and Ziarko (1992) referred to ANNs as information processing systems operating with internal control mechanism that is based on self-adjustment of internal parameters. The configuration and architectural skeletal structures of ANNs are influenced by the biological systems of human body.

Klimasauskas (1993) described ANNs as the information processing technology that acts as the human nervous system having the groups of neurons arranged in layers and the brain.

According to Flood and Kartam (1994) and Salchenberger, Cinar, and Lash (1992), ANNS are the arranged system of neurons that can operate information-processing in a fast manner transferring the information actively between the computing systems.

Gagarin, Flood, and Albrecht (1994) and Paulson (1995) described ANNs as an Alternative Information Software Technology. This technology delivers the information in nodal form and expresses the inter-relation as links. In network training topology and configuration, Weights and layers are used very frequently (Hagan, Demuth, & Beale, 1996)

The artificial network is commonly referred to as a data processing system. It consists of enormous numbers of simple, profoundly interconnected processing elements (mainly artificial neurons). It is found in such an architecture which is mainly inspired by the structure of brain's cerebral cortex region and it is brought under the lime light of discussion by the scientists Tsoukalas and Uhrig (1997).

Haykin (1998) described the Neural Network as a massively parallel distributed processor and also stated that this network has a natural tendency to store experiential knowledge; knowledge is stored for further usage. This network, according to Haykin, resembles the brain in two ways:

i. The network gains the knowledge by a learning process.
ii. Interneuron connection strengths are called as synaptic weights; this part accumulates the knowledge.

3.4. Advantages and application of ANNs

Artificial Neural Networks (ANNs) with their ability to gain meaning from complicated data can be used to estimate costs that are 'too' complicated to be solved by other techniques, with advantages of ANNs deemed to include that:

1. ANNs are capable of automatically learning how to perform work (by example) based on the information gathered for training; thus it is relatively easier to generate prediction models over other traditional nonlinear statistical methods;
2. whilst unable to explain explicitly the relationships between input and output variables, a main objective for creating a decision model as that of being capable of estimating a result, more accurately explains relations between variables;
3. ANNs are able to create the estimation model based on data forms of ordinal data or mixed forms of nominal and ordinal data; and in addition,
4. ANN generalisation is beneficial, as is capabilities to utilise data that a model has collected during training stages to synthesize input-output mapping with new data.
5. After an ANNs model is created, no more programming is needed. The only need is to feed data to the ANNs model and train it.
6. ANNs are capable to adjust solutions over time and to compensate for changing situations.

There are numerous applications of ANNs in the aspect of real-life application. The application of ANNs includes, for example, function approximation, data classification, data processing, system identification, game playing, webo-metrics, vehicle tracking, pattern recognition face and hands identification and tracking, sequence recognition, process control and decision making, identifying and correcting wrong spelling, extraction of detail from accounting related packages, biometrics, structural design, pile-fault diagnosis, detailing of structural damage in building. It also includes group decision making, remote sensing, road maintenance, stock and bond prediction, bi linear moment rotation, bankruptcy prediction, thrift failure, bond rating prediction and determination of effectiveness of construction firms among many others.

3.5. Natural neural networks

Discussion of natural neural networks must firstly consider the human brain; a vast number of highly connected neurons are inside the brain. The cortex of the human brain has approximately ten billion neurons with 60 trillion of synapses or inter-connection (Shepherd, 2004). The basic parts of a neuron are cell body, dendrites, synaptic connections and axon, as shown in Figure 3.1 below; the cell body's work is to process the incoming signals coming from the dendrites. Dendrites receive the electrical signals and they carry the signal to the cell body. Neuron interaction is a result of the synaptic connections among the neurons. These units sum up the interaction between the neurons. They also interact with the synapses either from the axons of various other neurons or from any other area of central nervous system.

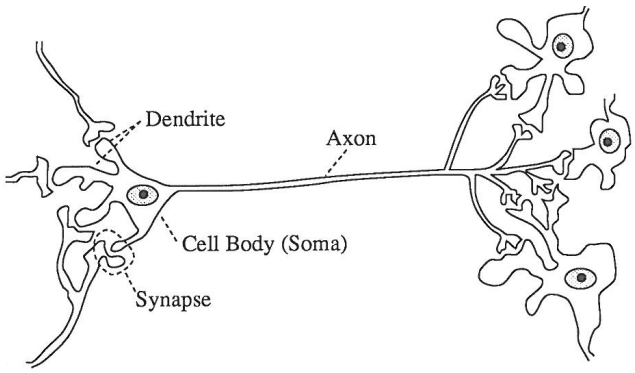


Figure 3-1 The biological neuron

(Source: Lee (1991)).

The information flow starts when the incoming signals are transferred through the synaptic connections. This process happens in the neurons. The signals are the electronic impulses. These electronic impulses are sent through the synaptic gaps to the dendrites by the method of chemical process (Fausett, 2006). The strength of the signal depends upon the synapse strength. If the synapse is weak then the strength of the signal will also become weak. Through the dendrites the signals are transmitted into the cell body. The total electrical energy from various signals is required to active the inactive neuron. The total electrical energy should be above of some threshold value for the activation of neuron. The summed signal is changed by the cell and an output signal is generated. This output signal is then passed to the adjacent cells by the axon.

A section of the neural structure of a human being is determined at the time of birth and keeps on changing during the entire lifetime. The resemblances between biological and artificial neural networks can be observed as two prime features; firstly both the networks have simple constituents that are expansively linked with each other; and secondly, the action of the whole network is decided by the links that exist between the neurons. The neurons are much slower compared to the electrical circuits, but a human brain has the capacity to execute many actions even faster than any computer invented till date. This phenomenon can be attributed to the parallel organization of the biological neural network and the extreme number of neural links present in the human brain.

3.5.1. Neural network operation

Figure 3.2 below shows the structure of the back-propagation network with three layers. In case of directed training the networks, the input information as well as the specific target number for every sample is provided to the ANNs, and at the time of the training, a specific pattern from the input layer is transmitted to each hidden neurons.

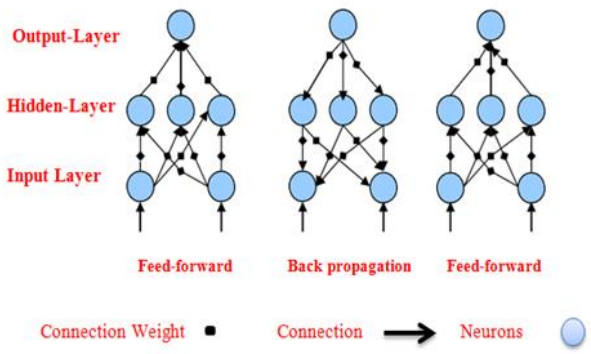


Figure 3-2 Phases in Neural Network Working Procedure

(Source: (Boussabaine, 1996))

In the next step, the specifications mentioned in Figure 3.1 below are followed to probe the system to compute an output value in a feed-forward way. A critical computational capacity is given to the system by the hidden middle layer.

Subsequently, Figure 3.3 below describes the actions of the nodes:
for simple cases, only two inputs, X(1) and X(2) along with their respective weight factors W(1) and W(2) are provided to the node; it computes the sum, X(1)W(1) + X(2)W(2) and gives an output value which is acquired from a distinct sigmoid function known as the activation function, and can take various forms. The output received through the above process is presented to the node; if the node is present on the output layer, then the received value can be considered to have arrived at its ultimate destination. The design of the links or the topology of the network determines how every node is linked to the other components present within the network. A real number (weight) represents the strength of each connection in the network (Boussabaine, 1996).

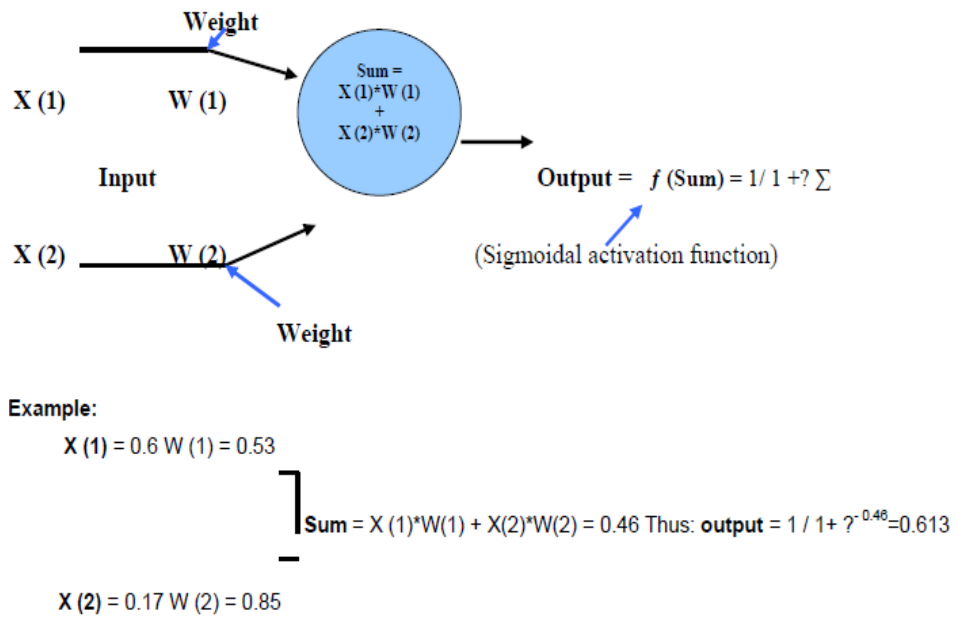


Figure 3-3 Activities at the Neural Network Node (Source: (Boussabaine, 1996))

Error in the system output is determined by the difference. It should be decided at this stage if the system requires further learning, and this can be done by equating the received total difference with the acceptable error specified by the system developer.

If the final decision indicates to continue with the learning process, the products of the error in accordance with the weights and the result are computed by the output neurons, and sent back to all the hidden layers of the system. In the process, the weighed sum of the error is computed by every hidden neuron present in the system.

To compensate the correction, each neuron present in the hidden layer & the output layer adjusts their weights accordingly. After the weights have been altered, the feed-forward calculation starts again from the beginning. The process generates new output values and the cycle goes on until a preferred outcome is received. The training phase of the system ends here and the testing phase can start from this point. Now the system can be fed with inputs unknown to the ANN and used to predict the outcome.

3.6. Structure of neural networks

3.6.1. Artificial Neurons

Real or simulated neurons make the main component of the artificial, as well as biological, neural networks. These neurons are extensively connected with each other and are capable to transmit information. The awareness of a particular network is dispersed across the links between the neurons.

Processing elements, units, nodes or cells are the other names used to describe neurons, and every neuron receives the signals from several other neurons.

The output given by a neuron is calculated through finding the weighed summation of the inputs, creating a level of instigation and then sending it through an output or relocation function. The point of communication of two neurons is termed as a connection, which is similar to synapse for biological neural networks. The strength of the link between the two neurons is known as weight (Lawrence & Luedeking, 1994).

3.6.2. Network Layers

Layers of neurons connected with each other make a neural network. The particulars of the connection between the neurons can offer vital insights for making a neural network. In this case, some of the neurons are used for connecting with the external world, whereas some are used for interacting with the other neurons; and these neurons are the hidden ones. Neurons can be located in any of the three areas namely the input layer, the output layer or the hidden layers (Lawrence & Luedeking, 1994). A multilayered ANNs with 3 layers has been described in Figure 3-4. The layers of the ANNs consist of a number of nodes or neurons which are connected with each other and also with the nodes in the next layer. The nodes present in the input and output layers perform the task of communication with the external world.

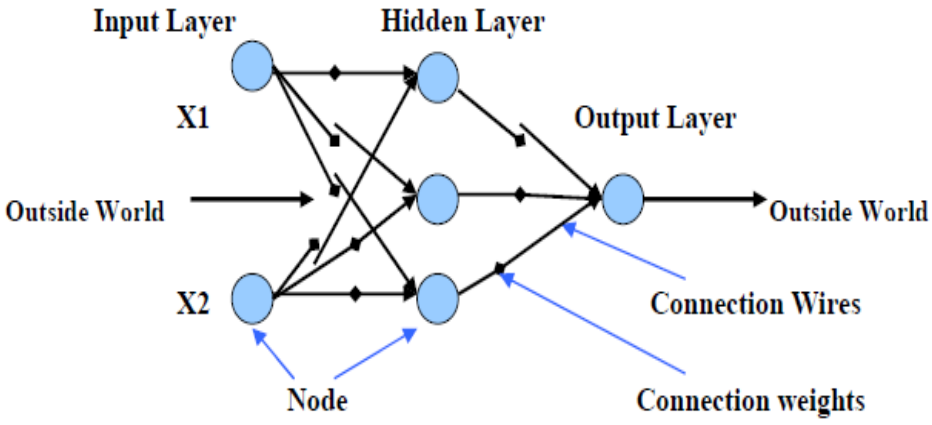


Figure 3-4 An Artificial Neural Network with Three Layers (Source: (Boussabaine, 1996)).

3.6.3. Connection weights

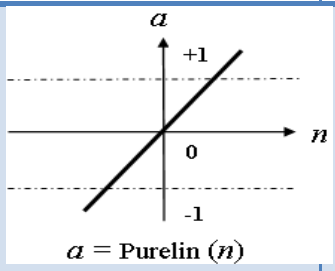
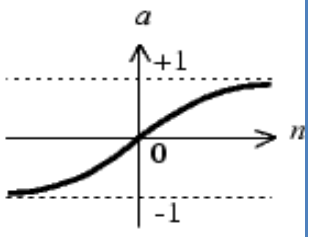
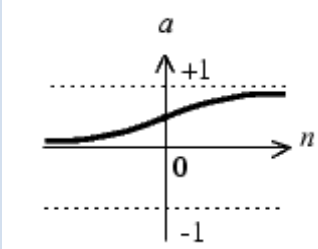
In case of the biological neural networks, the complementary part of the synapse is represented by the weight. The strength of the links between the neurons is determined by the scalar weights.

A zero weight means that there is no link between two particular neurons and a negative value of the weight indicates an unaffordable connection.

3.6.4. Transfer function

Transfer functions describe how the neuron's activation value is the result of applying a transfer function to the sum of the weighted inputs. It avoids results from reaching very large values which can destroy neural networks and thus constrain training. It may be a liner or non-liner function of the net input (x). The most common are the sigmoid, threshold and linear functions (Duch & Jankowski, 1999). Table 3.1 below illustrates the graphical and mathematical form of these three functions.

Table 3-1 The graphical and mathematical form of these three functions.

FunctionName	Graphical Illustration	Mathematical
1. Linear: It is useful for liner mapping and classification.		$f(x) = x$
2. Hyperbolic Tangent Sigmoid: It is used when the required output range between (-1 and 1)		$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$
3. Logistic Sigmoid: It is usually applied when the desired output range between 0 and 1.		$f(x) = \frac{1}{1 + e^{-x}}$

3.7. Architecture of neural network

3.7.1. Feed forward Networks

A neural network where the neurons take the inputs only from the preceding layer, and directs the output only to the succeeding layer, is known as feed forward network. In these networks, the neurons of a particular layer are not connected with each other, and hence these networks are capable to compute extremely first. In feed forward networks there is no lapse of time due to interaction of neurons to reach a stable state. A feed forwards network with two layers has been presented in Figure 3.5. The feed forwards networks can be directed or undirected as per the

requirements. A directed network weighs its outputs against the known correct values provided during the training, whereas, for un-directed networks this step is omitted all together (Lawrence & Luedeking, 1994).

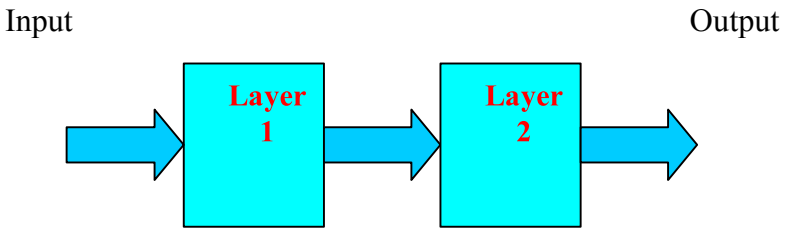


Figure 3-5 General Structure of Two-Layer Feed forward Network

3.7.2. Feedback Networks

Networks where the neurons can accept the input from any other neuron including their own outputs are known as the feedback networks. As the neurons in this type of networks are able to communicate with any other neuron so they usually bear only a single layer. To calculate an output, a feedback network should keep on computing till all the neurons reach a stable condition and the time taken for the process to complete cannot be predicted. However, in most of the systems, it takes only a few repetitions to come up with a result. A simple feedback neural network with one layer has been presented in Figure 3.6.

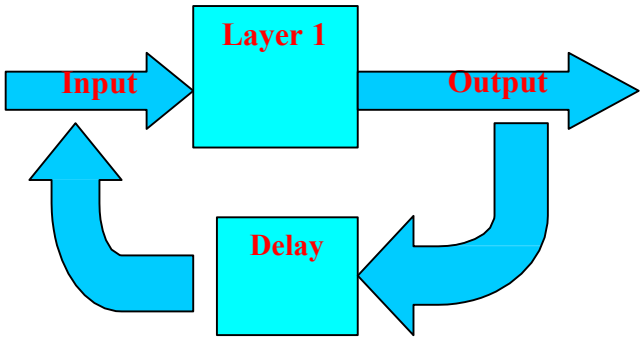


Figure 3-6 General Structure of a Sample Feedback Network

3.7.3. Learning Algorithm

There are several methods for training neural networks.

Most fall into one of two categories:

a) Supervised training methods: the teacher or trainer tells the model if its result was correct. This method requires two input and output vectors.
b) Unsupervised training method: there is no teacher or trainer during training tells the network whether its output was correct. This method does not require output vectors.

There are a number of mathematical algorithms which are used to update the connections weight and perform network training. The common one is called *back propagation*. It is considered as a preferred choice due to its simplicity as well as high efficiency. This algorithm is basically a variation of the Delta Rule used in networks with hidden layers; and is also known as the Generalized Delta Rule. The process of training the network includes running the patterns in the forward direction through the layers of the network, and then transmitting the errors in the backward direction which finally leads to apprising of the weights for harnessing the errors. The process reduces the amount of the mean square error (Lawrence & Luedeking, 1994).

3.8. Neural networks application in construction projects

This research, seeking improved estimation accuracy, builds upon previous research that confirms that neural networks have been employed in economic related areas in providing answers in cases of complicated mathematical calculation, and, can be employed for several purposes such as data trade analysis and forecasting. Past implementation of this method to solve construction issues such as cost estimation is discussed briefly below.

Garza and Rouhana (1995) conducted research to predict the material cost of carbon steel pipes using a neural-network model. The accuracy level of the result of the neural-network model was between 66.8% and 77.96%; the research shows that the neural-network model is able to resolve disadvantages in the regression approach. Similarly, Creese and Li (1995) sought prediction of timber bridge costs using a neural-networks model, finding accuracy of estimation of total cost increased as the

input variable used increases, concluding that prediction accuracy of neural-networks model is superior to regression approaches.

Williams' (1994) study into neural network abilities in estimating a construction cost index created two back-propagation neural network models to estimate the change in cost index for one and six month periods, and concluded that the estimated result from neural networks modelling gave greater error than both regression approach and exponential smoothing. Equally research studies by McKim ((1993) developed neural networks to estimate the cost of pumps, arguing that neural network modelling provides a more accurate prediction of total cost for pumps than other industrial methods. Al-Tabtabai (1999) reviewed 40 highway projects to develop a neural-network model to estimate the percentage increases in the cost from a baseline, with nine variables using input-layers such as environmental and project specific factors - estimating a mean absolute percentage error of 8.1%.

Boussabaine and Elhag's (1998) work investigated neuro-fuzz (neural-network-system/fuzzy-theory) to estimate cost/duration of (building-cost-information-service) construction-projects, training/testing the model towards an 83-93% model-accuracy. Also in 1998 Hegazy and Ayed created a simple neural-network model to manage construction-cost data, developing parametric cost-estimating for highway-projects and determining network-weighting by simplex-optimisation and genetic-algorithms (GAs), and back-propagation towards training-process optimisation concluding that a neural-network model improved estimate-accuracy over multiple-regression-analysis. Arafa et al. (2011) (extending Emsley's (2002) work) also developed a neural-network model to predict construction-project cost, developing input-layers, one hidden-layer, seven-neurons and one output-layer, concluding that neural-networks can estimate building-cost without detailed design.

Kim and Kang (2004) concluded that neural networks models gave more accurate perdition results than multiple regression or case-based reasoning models in Korea, albeit that the neural network models are unable to provide an explanation due to inherent 'black box' techniques. In Turkey Gunaydin and Dogan (2004) also examined cost estimation for residential buildings by artificial neural network(ing), concluding that neural network model can estimate 93% of building cost/m2.

Sodikov(2005), in Poland and Thailand, used neural network approaches to predict total costs of (new-technology) highway projects arguing that error, relatively, in multiple regression models was higher than neural network modelling.

Kim et al. (2005) adopted hybrid-modelling of neural-networks and genetic-algorithms to predict cost, optimise parameters and obtain 'trained' model-weightings. Wheaton et al's work (2007) developed hedonic cost models for residential and office properties focusing on 'true' trends and analysing cost/building activity correlation; cost-indicators/drivers, whilst were not central to Wheaton, direct similar semilog regression-models in this present study . Elkassas (2009) also conducted research to predict construction-project cost using neural-network-modelling, creating 3 back-propagation neural-network to develop/train/test model. The input-layer in all models of 15 variables includes type/duration/time-lag/interest-rate, and concluded that neural-network-modelling gives a good, accurate estimation. Chang (2010) also sought to predict maintenance costs/budgets developing 4 neural-networks-models, comparing result(s) with regression-approaches to identify which model has the least-mean-square-error. Four main factors affected costs (age/floor/classroom/elevator number). Four neural-networks were classified based on the number and type of variables in model input-layers, concluding that the prediction accuracy of neural-networks-modelling is better than a regression-approach.

Upon reflection, the studies above find that ANNs techniques can interpret relationships between costs and specific variables. Artificial Neural Networks (ANNs) with their ability to gain meaning from complicated data can be used to estimate costs that are 'too' complicated to be solved by other techniques.

However, disadvantages for this technique are flagged: literature regards ANNs as a 'black box' approach, where the model is built and utilised without any explanation of what the model has learned, thus is suitable if the main objective is only to apply ANNs to make estimations from existing data. This disadvantage builds upon several researchers who applied numerous techniques to open up the 'black box' to explain how ANNs is making its estimation, and what factors affect the estimation and final result (Garson, 1991; Gevrey, Dimopoulos, & Lek, 2003; Milne, 1995; Olden &

Jackson, 2002; Recknagel, Cao, Kim, Takamura, & Welk, 2006). Indeed Connection Weight (CW) methods suggested by Olden and Jackson (2002) seem to outperform other approaches in assigning the relative contribution of input variables in estimation of output and allows CW to clarify 'black box' output.

3.9. Framework of proposed ANNs model

The process developed here for a new model of cost estimation follows a number of systemic procedures. There are five basics steps proposed here:

(1) Identify the purpose of estimation;

(2) identify main cost factors affecting cost estimation;

(3) Create database for cost and non-cost factors;

(4) Design, train and test ANNS; and

(5) Approval of final model of ANNs.

Figure 3.7 and the text below further clarify these five items:

3.9.1. Purpose of estimation

The purpose of estimation may range from an estimate of construction cost only, to estimating the total life-cycle costs of new projects which include construction, operation and maintenance.

3.9.2. Identification of the main input factors for estimation

Estimation factors can be classified into two sections:

3.9.2.1. Identification of cost factors

Construction projects have several factors impacting upon the value of LCC. Interaction between factors is somewhat complex with current LCC models suffering arguably from an absence of both standardisation and a simple methodology to collect and interpolate data (Olubodun et al. 2010).

The concept of Cost-Significant-Items (CSIs) is argued to be able to help future analysts to simplify estimation methodologies by determining the key items contributing most to construction project LCC. CSI ideology owes much to Pareto's classic 80:20 rule. In the construction sector, various building-sector scholars have applied CSIs to construction cost estimate research, finding that CSIs theory is able to determine the small number of items which represent a constant percentage of the total cost of construction projects (Al-Hajj and Horner 1998, Asif 1988, Elcin and Hakan 2005, Horner and Zakieh 1996).

If the Cost-Significant-Items (CSIs) could be *simply* recognized, it would motivate estimators to direct attention to such specific items, and would reduce the time taken for estimation. In this way, cost information required to estimate total cost could be collected, analysed and recorded in a manner which will provide a more significant and realistic method of prediction.

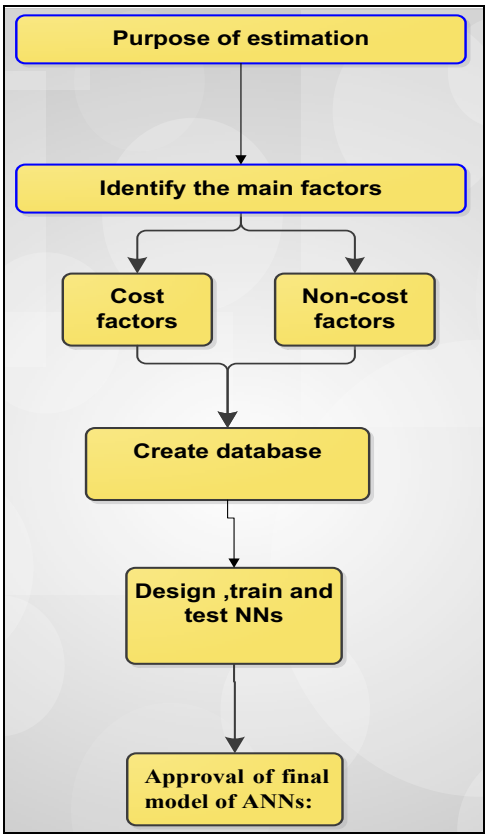


Figure 3-7 Framework of proposed ANNs model.

3.9.2.2. Identification of non-cost factors

A main restriction of most of the current models of cost estimation is that they only consider significant factors that can be readily quantified. However, non-cost factors should be considered because they seem to play a vital and important role to the accuracy of cost estimation (Elhag et al. 2005).

Non-cost factors affecting the accuracy of estimating come from a large range of categories. These factors are qualitative such as type of project (residential, commercial, industrial), type of structure (concrete, steel, masonry), and project size. These factors can be identified from an analysis of literature, historical data and practitioner experience.

3.9.2.3. Data base creation

Database creation consists of taking the most significant cost/non-cost factors, already identified in earlier steps and actual values of unit-rate costs for past projects. This data is used to exemplify input and output information in the proposed model during the training/testing stages.

3.9.2.4. Design of neural networks

The initial steps in the design of neural network modelling are selecting, collecting and preparing suitable data. In estimation cost modelling, there are two types of data needed to create a neural network model: input data consisting of data identified as key to the result of the cost estimation model (collected from the database) representing Cost-Significant-Items (CSIs and the important non-cost factors; and output data consisting of the data collected from the database representing the actual value of total costs of previous projects.

After collecting the data, the designer specifies the number of hidden layers; neurons in each layer and transfer functions. In general, traditional parametric 'trial & error' is performed to select the number of hidden layers and hidden nodes. During the training process, the number of hidden layers and hidden nodes will

be adjusted until identification of the best model which gives the lowest values for the Mean Square Error (MSE) for output parameters.

Transfer functions then describe how the neuron's activation value occurs as a result of applying a transfer function to the sum of the weighted inputs. Key transfer functions are the sigmoid, threshold and linear functions (Duch and Jankowski 1999). Finally, the best ANNs model developed in training stage can be tested with the new data.

3.9.2.5. Approval of final model of ANNs

Once the model is built, it can be utilised to predict the cost of new construction projects. It should be noted that a building practitioner is then able to use the final model to estimate new project costs without performing changes to the design structure of the ANNs model such as the transfer function, the number of inputs (important cost and non-cost factors) and hidden nodes, which had been selected at an initial stage.

3.10. Summary of this chapter

This chapter provides brief information regarding the ANNs. The history of ANNs has been discussed in first part of this chapter. The main components and the structure of ANNs techniques were explained.

The main advantages of the ANNs were also presented in this chapter. The application of ANNs in construction projects has reviewed in this chapter. Previous study indicates that artificial neural networks are being considered for construction project estimation. Artificial Neural Networks (ANNs) with their ability to find the relationship between the complicated data.

Finally, the proposed framework of ANNs model was introduced in this chapter. This frameworks consists of five basics (1) Identify the purpose of estimation; (2) identify main cost factors affecting cost estimation; (3) Create database for cost and non-cost factors; (4)design, train and test ANNS; and finally, (5) Approval of final model of ANNs

4. CHAPTER FOUR: IMPORTANT FACTORS AFFECTING LIFE-CYCLE COST

4.1. Introduction

Any framework of a life-cycle costing (LCC) approach requires various types of information to perform LCC. This information must be governed by the main objective of LCC. Identification the significant information affecting the output of LCC is the important step before embarking upon the collection of progress information. Furthermore, components of construction differ in their cost and time - importance, and thus management effort must be equivalently distributed.

Therefore, this chapter consists of two parts: the first aims to critically review and identify the applicability of past studies on determining non-cost factors and their influence on the accuracy of construction cost estimating. The second part aims to present the explanation for each stage of LCC, the current classifications of asset components, the significant cost items concept and previous practise of the significant cost items on construction sector.

4.2. Non-cost Factors affecting the accuracy of life cycle-cost estimating

Non-cost factors should be considered in the cost estimation process as they seem to play a significant role in the result of the estimation (Elhag et al. 2005). Liu and Zhu (2007) categorised the factors affecting cost estimation into two types, namely, idiosyncratic and control factors. Idiosyncratic factors involve elements outside the control of estimators such as weather condition, type of procurement system and other similar factors. Conversely, control factors comprise factors that estimators are able to determine, control and include in the process of cost estimation. This research will only focus on the latter type of non-cost factors.

Elhag at al. (2005) identified 67 factors and classified these into six categories. They conducted a questionnaire survey and comparison analysis of respective impact towards reliable costing. They found that consultant and design parameters are the

most important category, with an average severity index of 82%, with contractor-attributes category scoring the least average severity index of 67%.

The research above builds upon work by Akintoye (2000), who sought to gain an understanding of the factors influencing contractors' cost estimating practice. He used a comparative study of eighty-four UK contractors. He initially considered 24 factors in the study and found 7 main factors relevant to the cost estimating practice, namely: complexity of the project, scale and scope of construction, market conditions, method of construction, site constraints, client's position, build-ability, and the location of the project. The caveat is that his study focused only on the contractor.

Citing this and other studies, Liu and Zhu (2007) noted that most previous research into cost estimation paid attention to specific estimation approaches, with little focus on unique requirements at each project stage. This motivated them to identify the critical factors for effective estimation at numerous phases of typical construction projects. Based on organization control theory and cost estimating literature, they created a theoretical framework that identifies 19 factors for effective cost estimation throughout every project stage of a conventional construction project. These factors were grouped to 6 categories: project information, team experience, cost information, estimation process, and team alignment, and estimation design.

Identification of the major cost overrun factors in the construction sector of Pakistan was the main aim of the study conducted by (Azhar et al. 2008). They identified 42 factors by review of past research and asking expert opinions. Their survey questionnaire asked respondents to rank and score those 42 factors according to their experience. They stated that both internal and external aspects of business settings are present as the major factors behind cost overruns. Their results show that fluctuations in prices of raw materials, unstable costs of manufactured materials, high costs of machinery, additional work, improper planning, the lowest-bidding procurement method, the long period between design and time of bidding/tendering, inexact methods of cost estimation, and inappropriate government policies were the top ten factors behind cost overruns.

Most prior research, including those reviewed above, identified and ranked the important factors based on expert opinion; this technique is straightforward, easy to utilize and commonly available. However, this method is not fully suitable for explicitly displaying relationship factors and cost estimation. Some researchers have used non-traditional methods, such as multiple-regression and a case-based reasons (CBR) and experts system, to identify key non-cost factors affecting the accuracy of the estimation process.

The data of 30 projects was used to develop two ANNs models to predict the lowest tender price of primary and secondary school buildings (Elhag & Boussabaine, 1998). The first model consists of four cost-influencing factors as input attributes and the second model involves 13 input cost variables. It was established that the more significance the factors contributed in developing an ANN model, the better the outcomes achieved.

Later Emsley et al. (2002) conducted a research aimed at comparing the performance of the estimation accuracy of two statistical methods, namely, regression analyses and neural networks. They used a data pool of 288 completed projects in the UK. They used 41 independent variables to develop both models and found that the necessary input (41 independent variables) was extensive, causing difficulties when applying it in the early design stages.

In another case study conducted by Attalla & Hegazy (2003) was carried out to investigate the risky environment of reconstruction projects and identify the significant factors affecting their cost performance, they discovered that 18 factors have high impact on the cost performance of reconstruction by means of literature reviews, discussion with construction professionals and a questionnaire survey. All these factors were used to develop ANN and only 5 of them were used to develop a regression model to predict the cost performance of reconstruction projects. They concluded that ANNs produced accurate results.

In 2003, Skitmore and Ng conducted a study to develop several models for actual construction time and cost prediction when client sector, contractor selection method, contractual arrangement, project type, contract period, and contract sum

were known. A total of 93 Australian construction projects were used to achieve the main objective of the study.

Independently, Heng Li & Love (2005) applied the concept of stepwise regression to develop a cost model of office buildings in Hong Kong using the data of 30 completed office building projects. The results of their study provided a clear explanation about the relationship between a number of independent variables and total cost. They found that total floor area and total building height account for over 96 per cent of the accuracy of the model for reinforced office buildings. For steel office buildings, total floor area, average floor area and total building height account for over 95 per cent of the accuracy.

An, Kim& Kang (2005) conducted a study to compare the performance of the two methods of estimating construction costs (CBR and ANN). The study included the data of 580 residential buildings and was carried out in Korea by general contractors between the years 1997 and 2002. Nine variables were considered as the input variables for the model based on the interviews with experts who had good experience of construction companies in Korea. In the CBR method, they applied the Gradient Descent Method (GDM) and regression analysis method to evaluate the weights of the variables. The result from the regression method was better than GDM and they found that only eight factors are significant. Two years later, they developed a case-based reasoning cost estimation model which was proposed to incorporate experience employing an analytic hierarchy process (AHP) (An, Kim & Kang, 2007). The same data and independent variable was used. The result of this study concluded that AHP provided a more accurate result but depended for expert experience and judgment than other approaches and therefore, this method generates both uncertainty and imprecision because of the requisite for human involvement and it may not provide the best results.

In 2007, a cost estimation model was developed by Wheaton and Simonton based on data available for over 60,000 properties (including 42,000 residential properties) and primarily concerned six American markets. Their work was concerned with the "true" trends of the cost during a period of 35 years and they analysed the correlation between costs and building activity.

In Australia, Albino and Pasco (2008) studied the importance and accuracy of cost estimation of building construction projects. Their study involved 56 building construction projects and the survey of 102 companies. They reviewed previous research and identified and collected the main factors affecting accuracy of the cost estimation which included factors of project value, gross floor area, number of storeys, location, procurement route, project type, type of structure and price intensity. The importance levels of these factors were further investigated using a traditional multiple linear regression technique. Their results indicated that the size of project (project value, number of storeys and gross floor area) is the most influential factor affecting cost estimation of a building construction project in Australia.

Moving from Australia to Germany, based on 70 German residential properties, the relevant building construction cost drivers were identified (Stoy, Pollalis, & Schalcher, 2008). They reviewed the previous studies, supplied a list of cost drivers and re-examined experts in interviews. The outcome of this introductory study was a ranked list of more than 90 cost drivers. In addition, their fundamental relationships were examined in a regression model. They concluded that compactness of the building, number of elevators, size of the project, expected duration of construction, proportion of openings in external walls, and region are the most important variables affecting building construction cost. This study's experts ranked four of the six recognised variables of the model amongst their ten important variables.

Applications that use a series of artificial intelligence (AI) techniques include Cheng et al. (2009) to predict project cash flow trends and gain strategic control over project cash flow. In their work, fuzzy logic and neural network are used to develop a neural-fuzzy-model which enables dealing with uncertainties and knowledge mapping. A genetic algorithm was used to optimise the membership functions of the model. They used the data of 52 construction projects, with 9 significant factors in order to develop the model. These factors were number of floor; contract cost, total area, duration, cost ratio of foundation engineering, cost

ratio of structural engineering, cost ratio of decoration engineering, cost ratio of facilities and cost ratio of indirect cost.

Elkassas, Mohamed and Massoud (2009) conducted research to estimate the financial cost of construction projects using the neural network model. They created three back-propagation neural network models to predict the financial cost of three types of construction project; namely, pipeline projects, industrial projects and building projects. 215 of the building projects were used to create, train and test the models. The type of project, duration of project, estimation contract value, advance payment, time lag, interest rate, mark-up, time unit of the first payment, retention, project location, weather conditions, safety condition, possibility increment in the project duration, owner payment, delay and inflation were considered as important variables in the input layer. They found that the neural network model provided a clear and accurate estimation.

Again in terms of ANNs, Change, Pei & Syjye (2010) sought to predict maintenance costs and a budget for University buildings using the neural networks model. This study developed four neural networks models and their results were compared with the result from the regression approach in order to identify which model had the least mean square error. There were four main factors affecting the maintenance costs and budget of the university buildings: building age, number of floors, number of classrooms and number of elevators. Four neural networks were classified based on the number and type of variables in the input layer for each model. The research concluded that the prediction accuracy of the neural networks model is superior to the regression approach.

Cheng et al. (2010) combined artificial intelligence with the concept of fuzzy neural networks to estimate costs both overall (total cost) and category (engineering) cost. They considered 10 factors as input variables (significant variables) to estimate overall cost using qualitative and quantitative factors. These factors were floors underground, total floor area, floors above ground, site area, number of households, households in adjacent buildings, soil condition, seismic zone, interior decoration and electro-mechanical infrastructure.

In another study, the data of 164 apartment buildings from 15 housing complex projects in Korea were utilised to create a CBR cost estimate model for building projects. A Euclidean distance concept and genetic algorithms were used. (Ji, Park, & Lee, 2011). Based on a previous research review and an expert interview, twelve variables were employed to assign the weight values of cases and to evaluate case similarity. These factors were number of households, gross floor area, number of unit floor households, number of elevators , number of floors, number in household scale(s), number of households of unit floor per elevator, height between stories, depth of pit, roof type, hallway type and structure type (RC).

Moving to America, data collected from 20 U.S. building projects were used to develop a conceptual cost estimating model (R. Sonmez, 2011). The model was created based on integrated neural networks and the bootstrap resampling technique. A total of 20 factors were used to develop this model and these factors involved information of time and location of project, project duration, project characteristics such as total gross building area and number of storeys, site conditions, structural frame and exterior finish types.

In the Middle East, an artificial neural network model was used to develop a model to estimate the cost of the structure system of the building at an early stage in the Gaza Strip (Mohammed & Mamoun, 2011). The data of 71 completed building projects in the Gaza Strip were used along with seven significant parameters considered as input variables of the model. The sensitive analysis technique was applied to recognise the most significant variables affecting the result of the model and they concluded that the ground floor area, number of storeys, type of foundation and number of elevators are the most significant factors affecting the model.

A practical hybrid conceptual cost estimating model for large building projects was presented by H-J Kim (2012) , including multiple mixed-use buildings. They tested the accuracy and the efficiency of the proposed model through a case study involving eight mixed-use projects. For the test of the model, input variables consisted of only project characteristics such as type of project and gross floor area. This built upon previous work by Kim, Seo & Kang (2005), who adopted hybrid models of neural networks and genetic algorithms to predict the preliminary

cost of residential buildings in Seoul, Korea. A genetic algorithm was used to optimise the parameter of the neural network model and obtain a set of trained weights for the model. They used the data of 498 projects of residential buildings built by general contractors between 1997 and 2000. Eight variables were selected to be input variables of the model. These variables were total floor area, number of stories, total units, duration, type of roof, type of foundation, type of basement and grades of finishing.

Jin et al. (2012) conducted a research to improve performance of cost estimation. They applied multiple regression analysis and found that site area, underground area, ground area, building area, number of underground floors, number of floors and landscape area were the most effective parameters influencing the proposed model.

The literature review and analysis of previous techniques leads this study to break down and manage the methods and key factors used in previous forecasting modelling in the tabulated form suggested by Table 4.1. The managing and tabulating of previous techniques assists with recognising the influential parameters in construction cost. The process of influential parameters identification facilitates the elimination of non-influential parameters.

Table 4-1 Input, aim, and method references of the cited publications

Location	Author	Method	Factors affecting cost estimation
Korea	(S.-Y. Kim, Choi, Kim, & Kang, 2005)	CBR and ANNs	Location, Total area, Roof types, Total unit, Average area of unit, Foundation types, Usage of basement and Duration
	G. Kim, et al., 2007	CBR and ANNs	Gross floor area (m2), Number of storeys, Total unit , Unit area (m2) l, Location, Roof types, Foundation types, Usage of basement and Finishing grades.
	(Ji, Park, & Lee, 2011)	CBR	Number of households, Gross floor area , Number of unit floor households, Number of elevators, Number of floors, Number of piloti with household scale, Number of households of unit floor per elevator, Height between stories, Depth of pit, Roof type, Hallway type and Structure type (RC)
	(Jin et al., 2012)	CBR and Multiply-regression	Site area, underground area, ground area, building area, number of underground floors, number of floors and landscape area
	(H.-J. Kim, Seo,&Hyun, 2012)	ANNs and GA	Site area, Building area, Gross floor area, Building-to-land ratio, Floor space index, Number of buildings, Story, Type of Structure and Type of project.
Switzerland	(Thalmann, 1998)	Multiple-regression	Usable floor area, Proportion of external wall areas underground, Proportion of openings in external wall areas and Year of construction.

United Kingdom	(Elhag & Boussabaine, 1998)	ANNs	Type of building (primary, secondary school), Gross floor area, Number of stories and Project duration.
German	(Stoy, Pollalis, & Schalcher, 2008)	Multiply-regression	Compactness of the building, number of elevators, size of the project, expected duration of construction proportion of openings in external walls and region.
China	(Heng Li & Love, 2005)	Multiply-regression	Average floor area, total floor area and total building height
Australia	(Martin Skitmore & Thomas Ng, 2003)	Multiple-regression	Client sector, Contractor selection method, Contractual arrangement, Project type, Contract period and Contract sum.
	Aibinu & Pasco, 2008)	Multiple-regression	Project value, Gross floor area, Number of storeys, Location, Procurement route, Project type, Type of structure and Price intensity.
United States	(Wheaton & Simonton, 2007)	Multiple-regression	Number of stories, Absolute size, Number of units, Frame type and Year of construction.
	(Sonmez, 2008)	CBR with bootstrap resampling technique.	Demolition on site, site waste treatment, Wood exterior finish, city index, Masonry structure, steel and concrete frame, Vinyl exterior finish, Masonry exterior finish, Number of elevator stops, Project duration in months, Total gross building area per residential unit, Number of stories, Percent area of commons and nursing facilities in the total building area, Percent structured parking area in total area, Wood frame, Steel frame and concrete frame.
	(R. Sonmez, 2011)	Integrate ANNs with bootstrap resampling technique.	
Taiwan	Cheng, Tsai, & Sudjono, 2010)	Artificial intelligent fuzzy neural networks.	Floors underground, Total floor area, Floors aboveground, Site area, Number of households, Households in adjacent Buildings, Soil condition, Seismic zone, Interior decoration and Electro-mechanical Infrastructure.
	(Chang Sian, Pei Jia, & Sy Jye, 2010)	ANNs and multiple-regression	Predict maintenance costs and budget for University buildings.
Meddle East	E.M. Elkassas et al., 2009)	ANN	Project type, Project duration, Estimation contract value, Advance payment, Time lag, Interest rate, Mark-up, Time unit first payment, Retention, Project location, Weather condition, Safety condition, Possibility increment in project duration, Owner payment delay and Inflation.
	(Mohammed & Mamoun, 2011)	ANN	Area of ground floor, Number of stories, Type of foundation and No. of elevators.

4.3. Building life cycle stages

As mentioned before, building's life cycle consists of several stages which must be conducted in order to transform the ideas, and rationale that prompted its development, products and services significantly. In this respect, the building's life cycle (previously presented in Figure 2.9) has been created to gain greater value. It consists of four stages which are

(i) design and construction stage, (ii) operation and (iii) maintenance stage and a (iv) residual stage. The following section presents more details [based largely on work by Ashworth (1994)] for each stage.

4.3.1. Design and construction stage

In this stage the project manager defines what the project is and what the users hope to achieve by undertaking the project. This phase also includes a list of project deliverables, the outcome of a specific set of activities. The project manager works with the business sponsor or manager who wants to have the project implemented and other stakeholders those who have a vested interest in the outcome of the project (Ashworth, 1994, p. 234).

Furthermore, the project manager lists all activities or tasks, how the tasks are related, how long each task will take, and how each tasks is tied to a specific deadline. This phase also allows the project manager to define relationships between tasks, so that, for example, if one task is x number of days late, the project tasks related to it will also reflect a comparable delay. Likewise, the project manager can set milestones, dates by which important aspects of the project need to be met (Ashworth, 1994, p. 234) and define requirements for completing the project.

In addition, the project manager identifies how many people (often referred to as "resources") and how much expense ("cost") is involved in the project, as well as any other requirements that are necessary for completing the project. The project manager will also need to manage assumptions and risks related to the project. The project manager will also want to identify project constraints. Constraints typically relate to schedule, resources, budget, and scope. A change in one constraint will typically affect the other constraints. For example, a budget constraint may affect the number of people who can work on the project, thereby imposing a resource constraint. Likewise, if additional features are added as part of project scope, that could affect scheduling, resources, and budget (Ashworth, 1994, p. 234).

Moreover, the project manager knows how many resources and how much budget they have to work with for the project. The project manager then assigns those resources and allocates budget to various tasks in the project. Now the work of the project begins. The project manager is in charge of updating the project plans to reflect actual time elapsed for each task. By keeping up with the details of progress, the project manager is able to understand how well the project is progressing overall. A tool such as *Microsoft Project* facilitates the administrative aspects of project management. Finally, the project manager and business owner pull together the project team and those who have an interest in the outcome of the project (stakeholders) to analyse the final outcome of the project. Total costs of this stage are called capital cost or initial cost which represents several costs of several elements (Ashworth, 1994, p. 235).

4.3.2. Operation and maintenance stage

This stage is the largest stage of asset's life cycle. It start at early occupancy and ends when the end life of asset. It concerns to maintain and review the asset at frequent intervals to evaluate its implication within management of cost-in-use as the cost of this do not remain uniform or static throughout a asset's life. For example, the taxation rate and allowances will alteration during the asset's life, and can have an influence on the maintenance policies being utilized. Grants may become obtainable for asset repairs or to solve particular problem such as energy or environmental considerations. The change in the method that the asset is utilized and hours of occupancy, for instance, should be monitored and control to maintain an economic life cycle cost, as the asset developed to reach new demand placed on it (Ashworth, 1994, p. 234).

Before the end of asset's life, careful decision should be exercised before future expenditure is apportioned. The decision for replacing a component is making based on a comparison of the rising operation and maintenance with the cost of its replacement and the linked operation and maintenance costs. For instance, the improved productivity of heating boiler and its systems recommend that these, in

term of economic, need to be replaced every 10-12 years regardless of its performance condition(Ashworth, 1994, p. 235).

It is essential to breakdown of the asset into its basic the cost elements over time, in order to estimate the LCC of an asset. The choice of a suitable the level to which it is broken down will reflect three specific issues (*Life Cycle Costing Guideline*, 2004):

1- The element needs to be a clearly defined activity that creates costs.
2- The time line for the element's costs needs to be known.
3- The relationship between the resources (labour, materials, fuel/energy and the like) utilized by the element and the resulting cost need to be known.

It becomes obvious that the cost at each stage of asset's life must be broken down into more manageable parts. There is one method to do this: to identify and then analyse individual building elements at each stage of asset's life, and then aggregate these to obtain the total cost. The next section illustrates the classification of elements of each stage of asset's life cycle.

4.4. Classifications of elements of each stage of building's life cycle

4.4.1. Construction stage

Quantity surveyors in the UK first established an elemental format after World War II in order to assist the Department of Education develop a cost planning and cost control method in rebuilding and expanding the British school system, encouraging the Royal Institution of Chartered Surveyors (RICS) to develop a standard format of elements in 1960. By 1972, the Canadian Institute of Quantity Surveyors published its own standard of elements for buildings which was accepted by the Royal Architectural Institute of Canada (RAIC). The demand for a worldwide elemental classification led the International Council for Building Research Studies and Documentation (CIB) and the Construction Economics European Committee (CEEC) to develop an elemental list to collect costs for international exchange. A major objective of this format is to make it suitable with the present formats of as many European countries as possible. However, the CEEC format has not been

widely accepted (Robert & Harold, 1999). Figure 4-1 below summarizes the four elemental formats.

UNIFORMAT General Services Administration (GSA)	CANADIAN INSTITUTE OF QUANTITY SURVEYORS (CIQS)	THE ROYAL INSTITUTION OF CHARTERED SURVEYORS (RICS-UK)	CONSTRUCTION ECONOMICS EUROPEAN COMMITTEE (CEEC)
01 FOUNDATIONS	A1 SUBSTRUCTURE	1.0 SUBSTRUCTURE	(1) SUBSTRUCTURE
011 Standard foundations	A11 Foundations	2.0 SUPERSTRUCTURE	SUPERSTRUCTURE
012 Special foundations	A12 Basement excavation	2.1 Frame	(2) Frame
02 SUBSTRUCTURE	A2 STRUCTURE	2.2 Upper floors	(3) External walls
021 Slab on grade	A21 Lowest floor construction	2.3 Roof	(4) Internal walls
022 Basement excavation	A22 Upper floor construction	2.4 Stairs	(5) Floors
023 Basement walls	A23 Roof construction	2.5 External walls	(6) Roofs
03 SUPERSTRUCTURE	A3 EXTERIOR ENCLOSURE	2.6 Windows and exterior doors	(7) Stairs
031 Floor construction	A31 Walls below grade	2.7 Interior walls & interior partitions	(8) Windows & external doors
032 Roof construction	A32 Walls above grade	2.8 Interior doors	(9) Internal doors
033 Stair construction	A33 Windows & entrances	3.0 INTERNAL FINISHES	FINISHES
04 EXTERIOR CLOSURE	A34 Roof covering	3.1 Wall finishes	(10) Internal wall finishes
041 Exterior walls	A35 Projections	3.2 Floor finishes	(11) External wall finishes
042 Exterior doors & windows	B1 PARTITIONS & DOORS	3.3 Ceiling finishes	(12) Floor finishes
05 ROOFING	B11 Partitions	4.0 FITTINGS AND FURNITURE	(13) Ceiling finishes
06 INTERIOR CONSTRUCTION	B12 Doors	4.1 Fittings and furnishings	(14) EQUIPMENT AND
061 Partitions	B2 FINISHES	5.0 SERVICES	FURNISHINGS SERVICES
062 Interior finishes	B21 Floor finishes	5.1 Sanitary appliances	(15) Plumbing
063 Specialties	B22 Ceiling finishes	5.2 Services equipment	(16) Heating
07 CONVEYING SYSTEMS	B23 Wall finishes	5.3 Disposal installations	(17) Ventilating & air-conditioning
08 MECHANICAL	B3 FITTINGS & EQUIPMENT	5.4 Water installations	(18) Internal drainage
081 Plumbing	B31 Fittings & equipment	5.5 Heat source	(19) Electrics
082 HVAC	B32 Equipment	5.6 Space heating & air treatment	(20) Communication
083 Fire Protection	B33 Conveying systems	5.7 Ventilation systems	(21) Lifts, escalators, etc.
084 Special mechanical systems	C1 MECHANICAL	5.8 Electrical installation	(22) Protective installations
09 ELECTRICAL	C11 Plumbing & drainage	5.9 Gas installation	(23) Miscellaneous services inst.
091 Distribution	C12 Fire protection	5.10 Life & conveyor installation	EXTERNAL SITE WORKS
092 Lighting & power	C13 HVAC	5.11 Protective installations	(24) Site preparation
093 Special electrical systems	C14 Controls	5.12 Communication installations	(25) Site enclosure
10 GENERAL CONDITIONS & PROFIT	C2 ELECTRICAL	5.13 Special installations	(26) Site fittings
11 EQUIPMENT	C21 Services & distribution	5.14 Builders work in connection with services	(27) Site services
111 Fixed & moveable equipment	C22 Lighting, devices & heating	5.15 Builders profit & attendance on services	(28) Site Buildings
112 Furnishings	C23 Systems & ancillaries	6.0 EXTERNAL WORKS	(29) Hard and soft landscaping
113 Special construction	D1 SITE WORK	6.1 Site works	(30) PRELIMINARIES
12 SITE WORK	D11 Site development	6.2 Drainage	
121 Site preparation	D12 Mechanical site services	6.3 External services	
122 Sit improvements	D13 Electrical site services	6.4 Minor building work	
123 Site utilities	D2 ANCILLARY WORK		
124 Off-Site work	D21 Demolition		
	D22 Alterations		

Figure 4-1 Elemental Classifications sources ((Robert & Harold, 1999).

This research argues that The Royal Institution of Chartered Surveyors (RICS) Standard Classification, also termed the Standardized Method of Life Cycle Costing for Construction Procurement (SMLCC) remain an important taxonomy. This Standard was classified elements into four levels:

Levels 1 to 3 is heading under which actual work items (i.e. group element, element and sub-element) are allocated. Table 4.2 below summarizes the three level of the elemental classification of RICS.

Table 4-2 SMLCC classification of capital costs elements

Building Classifications: (RICS-UK)					
Group element		Element		Sub-element	
1	Substructure	1	Substructure-transfer the load of the building to the ground and to isolate it horizontally from the ground	1	Standard foundations.
				2	Specialist foundation systems
				3	Lowest floor construction
				4	Basement excavation
				5	Basement retaining walls
2	Superstructure	1	Frame-provide a full or partial system of structural support, where this is not provided by other Elements	1	Steel frames
				2	Space decks
				3	Concrete casings to steel frames
				4	Concrete frames
				5	Timber frames.
				6	Other frame systems
		2	Upper floors provide floor space on upper levels (i.e. above the lowest floor level)	1	Floor
				2	Balconies
				3	Drainage to balconies
		3	Roof-provide the horizontal component of the external enclosing envelope	1	Roof structure
				2	Roof covering.
				3	Specialist roof systems
				4	Roof drainage
				5	Rooflights, skylights and openings
				6	Roof features
				7	Painting and decorations
		4	Stairs and ramps- allow vertical circulation	1	Stair/ramp structures
				2	Stair/ramp finishes
				3	Stair/ramp balustrades and handrails
				4	Ladders/chutes/slidess
				5	Painting and decorations
		5	External walls-provide the vertical component of the external enclosing envelope in conjunction with 2.6 Windows and External Doors	1	External walls above ground floor level
				2	External walls below ground level
				3	Solar/rainscreen cladding
				4	External soffits
				5	Subsidiary walls, balustrades, handrails, railings and proprietary balconies
				6	Façade access/cleaning systems
				7	Painting and decorations
		6	Windows and external doors-allow access through external walls for physical movement, natural ventilation and light and provide the vertical component of the external enclosing envelope in conjunction with 2.5 External Walls	1	External windows
				2	External doors
		7	Internal walls and partitions-divide the floor space	1	Walls and partitions
				2	Balustrades and handrails
				3	Moveable room dividers
				4	Cubicles
		8	Internal doors-allow physical circulation between internally divided floor space	1	Internal doors
3	Internal finishes	1	Wall finishes-provide a functional and/or decorative finish to walls	1	Finishes to walls.
		2	Floor finishes-provide a functional and/or decorative finish to floors	1	Finishes to floors
				2	Raised access floors
		3	Ceiling finishes-provide a functional and/or decorative finish to ceilings	1	Finishes to ceilings.
				2	False ceilings.
				3	Demountable suspended ceilings
4	Fittings, furnishings and equipment	1	Fittings, furnishings and equipment-provide functional and/or decorative items	1	General fittings, furnishings and equipment Furnishings
				2	Domestic kitchen fittings and equipment
				3	Special purpose fittings, furnishings and equipment
				4	Signs/notices.

				5	Works of art.
				6	Equipment.
				7	Internal planting.
				8	Bird and vermin control.
5	Services	1	Sanitary installations-provide sanitary appliances	1	Sanitary appliances
				2	Sanitary Ancillaries
				3	Pods
		2	Services equipment-provide serviced equipment	1	Services equipment
		3	Disposal installations-remove liquid and solid waste from the building	1	Foul drainage above ground
				2	Chemical, toxic and industrial liquid waste drainage
				3	Refuse disposal
		4	Water installations-provide water and steam	1	Mains water supply
				2	Cold water distribution
				3	Hot water distribution
				4	Local hot water distribution
				5	Steam and condensate distribution
		5	Heat source-provide a central source of heat	1	Heat source
		6	Space heating and air conditioning-control the internal temperature and/or air quality	1	Central heating
				2	Local heating
				3	Central cooling
				4	Local cooling
				5	Central heating and cooling
				6	Local heating and cooling
				7	Central air conditioning
				8	Local air conditioning
		7	Ventillation systems-provide the movement of air	1	Central ventilation
				2	Local and special ventilation
				3	Smoke extract / control
		8	Electrical installations-provide electrical power, and to control the light levels (electrically)	1	Electrical mains and sub-mains distribution
				2	Power installations
				3	Lighting installations
				4	Specialist lighting installations
				5	Local electricity generation systems
				6	Earthing and bonding systems
		9	Fuel installations / systems-provide fuel as a source of energy	1	Fuel storage
				2	Fuel distribution systems
		10	Lift and conveyor installations-provide vertical and horizontal mechanical transportation	1	Lifts Enclosed hoists
				2	Escalators
				3	Moving pavements
				4	Powered stairlifts
				5	Conveyors
				6	Dock levellers and scissor lifts
				7	Cranes and unenclosed hoists
				8	Car lifts, car stacking systems, turntables and the like
				9	Document handling systems
				10	Other lift conveyor systems
		11	Fire and lightning protection-protect the building and its inhabitants from hazards	1	Fire fighting equipment
				2	Fire suppression systems
				3	Lightning protection
		12	Communication, security and control systems-provide systems for communication to and between inhabitants for information and security	1	Communication systems
				2	Security systems
				3	Central control/building management systems-
		13	Specialist installations-provide electrical and mechanical systems related to the user function of the building, not included elsewhere	1	Specialist electrical /electronic installations systems
				2	Water features
				3	Other specialist installations
		14	Builder's work in connection-provide	1	Builders work in connection

			builder's work for services with services		
		15	Testing and commissioning of services	1	Testing and commissioning of services
6	Complete buildings and building units	1	Prefabricated buildings-provide enclosed usable floor area installed as a prefabricated unit. Note: Not a building Element, included to account for general works that cannot be allocated to Elements	1	Complete Building
				2	Building units
7	Work to existing buildings	1	Minor demolition works and alteration works	1	Minor demolition works and alteration works
		2	Repairs to existing services	1	Existing services
		3	Damp-proof courses/fungus and beetle eradication	1	Damp-proof courses
				2	Fungus/beetle eradication
		4	Facade retention	1	Façade retention
		5	Cleaning existing surfaces	1	Cleaning existing surfaces
				2	Protective coating to existing surfaces
		6	Renovation works	1	Masonry repairs
				2	Concrete repairs
				3	Metal repairs:
				4	Timber repairs
				5	Plastics repairs
8	External works	1	Site preparation works-prepare the site for building	1	Site clearance
				2	Preparatory groundworks
		2	Roads, paths and pavings-provide unenclosed usable hard surfaces	1	Roads, paths and pavings
				2	Special surfacing and paving
		3	Soft landscaping-provide unenclosed usable soft surfaces and decorative and usable planting	1	Seeding and surfing
				2	External planting
				3	Irrigation System
		4	Fencing, railings and walls-enclose and divide the site-provide fittings required to make the site usable	1	Fencing and railings
				2	Walls and screens
				3	Retaining walls
				4	Barriers and guardrails
		5	Site/street furniture and equipment	1	Site/street furniture and equipment
				2	Ornamental features
		6	External drainage-remove liquid waste from the building and the site	1	Ancillary drainage systems
				2	External laboratory and industrial liquid waste drainage
				3	Land drainage
				4	Testing and commissioning of external drainage installations
		7	External services-provide services to the building and the site	1	Water mains supply
				2	Electricity mains supply
				3	External transformation devices
				4	Electricity distribution to external plant and equipment
				5	Gas mains supply
				6	Telecommunications and other communication system connections
				7	Fuel storage and piped distribution systems
				8	External security systems
				9	Site/street lighting systems
				10	Local/district heating installations
				11	Builder's work in connection with external services
				12	Testing and commissioning of external services
		8	Minor building works and ancillary buildings-provide buildings required by external services and minor buildings to support the function of the building	1	Minor building works
				2	Ancillary buildings and structures
				3	Underpinning to external site boundary walls

4.4.2. Operation and maintenance costs

This information includes external and internal cleaning; utilities, such as gas and electricity; and administration and overheads costs, such as security and rates. The Standardized Method of Life Cycle Costing for Construction Procurement (SMLCC) has given detailed definitions of these items. These are presented in Table 4.3 and 4.4 below.

Table 4-3 SMLCC classification of maintenance costs elements

Element	Sub-element	Definition
2.1 Major replacement		Scheduled replacement of major systems and components. This will form the detailed building life cycle cost programme
	2.1.2 Superstructure	
	2.1.3 Finishes	
	2.1.4 Fittings	
	2.1.5 Services	
	2.1.8 External works	
2.3 Redecorations		Scheduled redecorations. Excludes redecorations carried out in connection with 2.1, 2.2, 2.4 and 2.5.
	2.3.2 Superstructure	
	2.3.3 Finishes	
	2.3.4 Fittings	
	2.3.5 Services	
	2.3.8 External works	
2.4 Minor repairs, replacement and maintenance		Scheduled replacement of parts and scheduled maintenance and repairs to components; associated making good and minor redecorations including planned preventative and/or reliability centred maintenance.
	2.4.2 Superstructure	
	2.4.3 Finishes	
	2.4.4 Fittings	
	2.4.5 Services	
	2.4.8 External works	
2.5 Unscheduled replacement, repairs and maintenance		Allowance for unforeseen or unplanned maintenance arising from early failure, inappropriate use, etc.
	2.5.2 Superstructure	
	2.5.3 Finishes	
	2.5.4 Fittings	
	2.5.5 Services	
	2.5.8 External works	
2.6 Grounds Maintenance		Where it is costed separately (e.g. tree replacement, lawn mowing and landscape maintenance). Note: normally grounds maintenance is included with the external works element.
	2.6 External works	

Table 4-4 SMLCC classification of operation costs elements

Element	Sub-elements	Definition
3.1 Cleaning		Cleaning costs including periodic, routine and specialist cleaning.
	3.1.1 Windows and external surfaces	
	3.1.2. Internal cleaning	
	3.1.3 Specialist cleaning	
	3.1.4 External works cleaning	
3.2 Utilization		Utilities costs can be split into two main categories, energy and water.
	3.2.1 Fuel-gas	
	3.2.2 Fuel-Electricity	
	3.2.3 Water and drainage	
3.3 Administrative costs		User support costs related to the operation of the building and external works.
	3.3.1 Property management	
	3.3.2 Staff engaged in servicing the building	
	3.3.3 Waste management	
3.4 Overheads		Property insurance. Premiums for insuring the property.
	3.4.1 Property insurance	
3.5 Taxes		Rates and other local charges payable in connection with the building.
	3.5.1 Rate and other local charges	

There are two elements of construction cost items that should be identified to estimate the total life cycle cost of construction projects. These elements are quantity of the cost item and, unit price of the cost item. As mentioned before, each stage of construction project's life cycle usually consists of several of costs items. It is time consuming and very costly to gain the quantity estimate and unit prices of all items in construction projects.

Much research (alluded to previously and revisited again below) has looked at Cost Significant Items (CSI) towards solve this ‘complexity’ problem. As mentioned the CSI suggests generally that 80% of the total project cost can be identified by 20% of the cost items. As a result, estimation the quantities and unit prices of the top 20% important cost is useful method to save time and money and provide the accurate estimation. This research will only utilized the top 20% of important cost factors to develop a new model of life cycle cost of construction projects (neural networks model). The next section will provide information about the CSI principle.

4.5. Cost Significant Items (CSI)

Construction projects have numerous numbers of variable factors affecting the value of LCC and there is interaction between these factors, leading to what can be a complicated integration; arguably the current LCC models suffer from the absence of a standardized and a simple methodology of both collection data and estimation LCC (Olubodun, Kangwa, Oladapo, & Thompson, 2010). The concept of CSIs is a best approach to simplify estimation methodology as well as the collection data of construction projects. In general, CSIs aim to determine the small number of items which represent a constant percentage of the LCC of construction projects.

As alluded to above the CSIs idea was derived from the Pareto's principle. In 1897, Vilfredo Pareto conducted study on wealth and poverty and attempted to create formula to determine the unequal distribution of income in Italia. He found that 20% of the people earned 80% of the Italia's wealth. This idea becomes called as Pareto's Law or 80:20 rule which refers to fact that 80 % can be reached by 20% (Tas & Yaman, 2005).

In the construction sector, it had previously been somewhat of a truism that the majority of the value of bill of quantities is contained in only a small proportion of the total number of items. Various scholars found and noted biased distribution of bill item prices.

In 1981, in order to address the 80:20 rule, Shereef suggested that CSIs, which represent 20% of the total number of item, should be equal or greater than (V/N) where:
V: total value of measured items
N: total number of the measured items.

He studied 25 bills of quantities and noted that the value of 20 % of items greater than or equal to V/N which is exhibited the 80:20 rule (Shereef, 1981). Saket (1986) utilized 85 bills of quantities from both building and civil engineering projects in order to test Shareef's hypothesis. The result of this research concluded that 18.5% of items represent 81.5% of the total cost of these projects. Similar result to Saker was

found by Asife (1988). He was carrying out a study to develop an estimating system based on the 80/20 principle. 100 bills of quantities of bridges, road and sewer projects was utilized and found that the contribution of the 22.6% highest value items and represent 81.7% of the bill value.

In 2005, Tas and Yaman developed a building cost prediction model based on the concept of a cost significant items for Turkish construction sector public projects in its detailed design phase (Tas & Yaman, 2005). They examined 21 bills from residential building project to identify the important cost items. They concluded that the number of cost significant items of these was between 16 and 21 of the total number of items 53 to 57, and the mean value was 19.24. These cost significant items is about 36% of the total number of items and the average bill value of these items was 81.86%. These cost significant items was grouped in work package in order to reduce the numbers as to the 80:20 rule. Those items were summarized in 12 cost significant work packages (CSWP) which include reinforced concrete, masonry, formwork, scaffolding, roofing, doors and windows, reinforcement, painting, flooring, wall finishes, wall and ceiling plasters and glazing. The final step was created the ratio of the total cost of these CSWP to the total project cost. This ration is known as the cost model factor. After creating cost model factor, the total cost of project can be calculated by only pricing CSWP and applying the suitable cost model factor that represents for the value of the non-cost significant items and work package. They used the data of 20 projects to test the model. They found that the accuracy of the model between -16.6% and +8.58% with mean accuracy -5.1%. The CSWP represent 77.8% of the total bill value of 20 projects.

Al-Hajj and Horner (1998) argued that the Building Maintenance Cost Information Service (BMCIS) offer a comprehensive framework for collection of whole cost data for LCC and subsequently developed a model to predict the total running cost (operation and maintenance costs) based on CSIs concept. They identified 11 elements (only 16% of the total number of items) as CSIs of this model and created cost model factor. Their model was able to estimate the total running cost of building with an accuracy of between 2.5 and 5%, and annual costs with an accuracy of 7%. They concluded that CSIs concept is able to simplify the estimation process because their model only used 16% of items which would be extracted from BMCIS. If the

CSIs can be identified and generated from BMCIS, then this would lead to a simplification of the current estimation process of LCC, for those who believe the present process to be unwieldy.

In 1990, Bouabaz and Horner dealt with research into simple models as a means for predicting the new-build cost of bridges, which in turn led to the development of equally simple models for predicting the cost of repair contracts exceeding £10,000 in value.

Similar approach models for estimation the total costs are available. In 1990, Bouabaz and Horner developed a model for estimation the new-build and repair cost of bridges. This model was created based on the concept of CSWP. They identified only 10 items as the CSIs of this model and this model is able to estimate the cost of new bridge within 10% accuracy and 0.73 the cost model factor. They improve the accuracy of this model to 5% by modification of the model to consist of an additional 11 elements within cost model factor 0.82. A computer package called BRIDGET has been built based on this model to be able to calculate the price of a new build bridge in less than 15 minutes. The same concept was used to develop a model to estimate the repair costs of bridge. 14 elements were considered as the CSIs of the cost model used for repair bridges and this model is able to estimate the cost of repair bridges within 10% accuracy and 0.82 the cost model factor (Branco, 2004, p. 161).
As evidence in support of CSIs, Horner and Zakieh also argued (1996) that quantity-significant items are worthy of note in estimation total cost. They found that there is a surprisingly liner relationship between value and quantity when a model was developed based on the field of the effect of quantity-significant in estimation project cost and duration.

One significant conclusion from the above discussion is that enhancements in prediction process of total cost in construction projects would stem from a shift towards highlighting high-cost items. If the CSIs could be simply recognized, it would motivate estimators to concentrate their attention towards such items, and to reduce the time required for pricing. Moreover, cost information required to estimate total cost could be collected, analyzed and recording in a manner which will boost a more significant and realistic method to predicting total cost.

4.6. Summary of this chapter

This chapter discussed the main factors affecting the estimation of life-cycle costing (LCC). It attempted to identify generally the applicability of previous research on determining the full range of non-cost factors affecting the value of LCC at all phases of building's life-cycle. The most important non-cost factors are argued to be varied based on the different goals and purposes required to be achieved when research was conducted.

The literature revealed a number of standards of classifying building life cycle costs. The Standardized Method of Life Cycle Costing for Construction Procurement (SMLCC) developed by The Royal Institution of Chartered Surveyors (RICS) has been identified as an important historical resource which remains important to today's analyses.

It was and is clear that building projects have several numbers of cost factors affecting the value of LCC. The significant cost factors affecting LCC can be identified by using the concept of Pareto analysis in order to simplify estimation methodology as well as clarify the collection data of construction projects.

5. CHAPTER FIVE: RESEACRH METHODOLOGY

5.1. Introduction

The primary aim of this chapter is to describe the basic methodological considerations for the realization of this research study. The chapter starts with discussion of method and describes the processes of conducting the research. The overview of the research approach is presented in research design section.

5.2. Research Development

Research development refers to the conceptual structure of scientific investigation development; a clear procedure that will guide the collection data and analysis. This study includes six steps: the first step is a proposal for clarify and determining the problems and development of the main objective and sub-objectives of the research. The second step of the research is reviewing the previous studies. The third step identifies and establishes the types of the research applicable in this study. This step provides the definition, advantages, and disadvantages of each type of research. Unobtrusive qualitative survey research is described and subsequently used in this work. The method of data collection is the fifth step. Analysis of existing data and semi-structured survey methods used are highlighted The final step of theis research design focuses result and data analyses using statistical methods such as correlation test and Pareto analysis. The diagram of this research project's conceptual structure and methodology and process is presented in Figure 5.1.

5.3. Research objectives

The primary aim of this research project is to use artificial neural networks to accurately estimate the life-cycle cost of construction projects. Towards this goal, artificial network(s) applications are selected for incorporation due to their capability to address complex problems such as estimating LCC. In order to attain the most accurate LCC estimation, this research focused upon the contribution of the different (significantly weighted) input factors that represent the main variables influencing LCC and subsequent analysis of the techniques used to measure them.

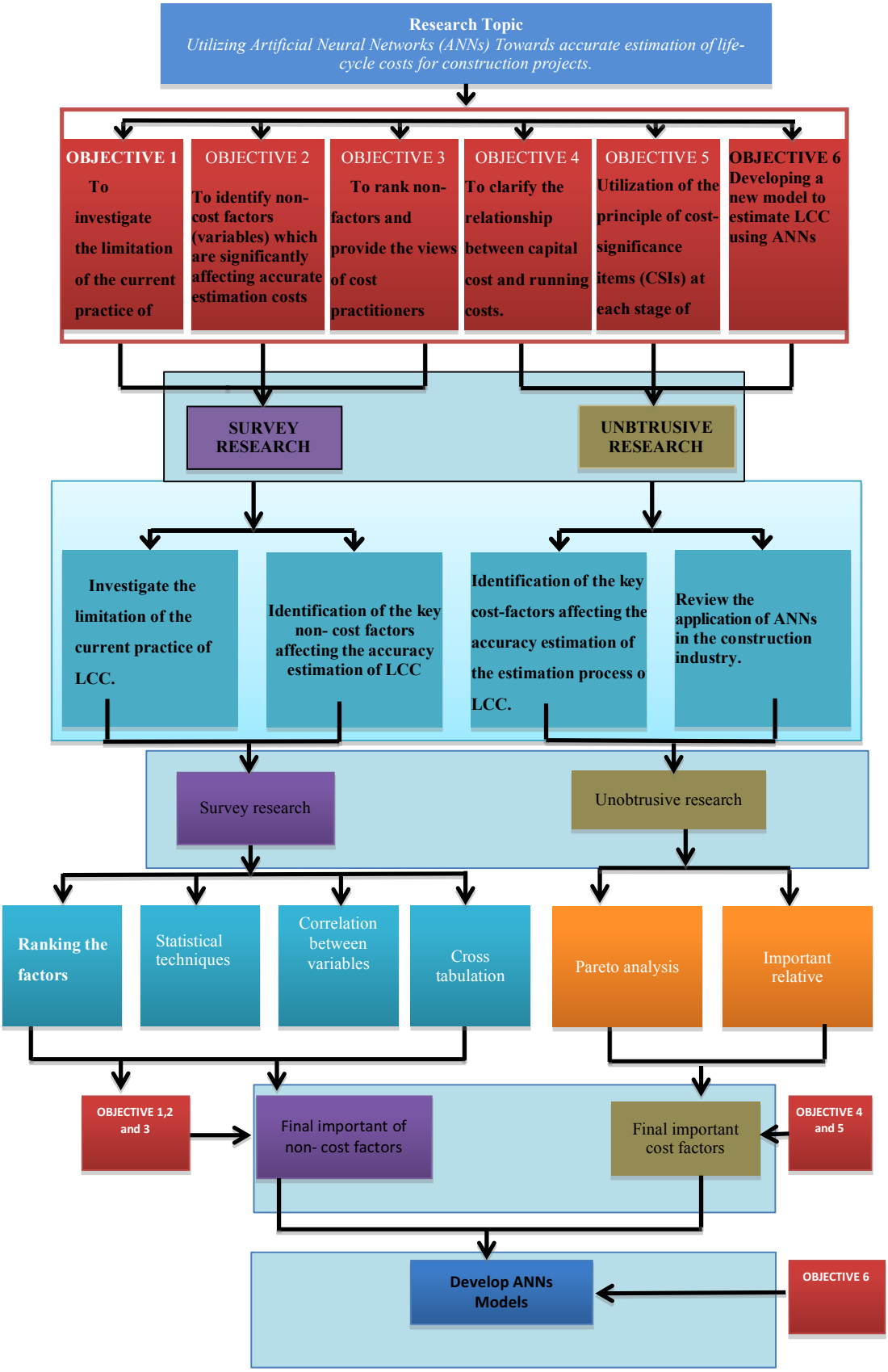


Figure 5.1 Flow chart of research methodology

Objectives are defined as:

- Review literature to investigate the limitation of the current practice of LCC.
- Review literature to identify non-cost factors (variables) which are significantly affecting accurate estimation of cost estimation in building projects.
- Conduct qualitative survey research to rank *non-factors* and provide the views of cost practitioners about how these factors can affect the accuracy estimation of LCC.
- Analyse the existing data (building projects) to clarify the relationship between capital cost and running costs.
- Utilisation of the principle of cost-significance items (CSIs) in order to simplify the process of estimating and identify the most important cost factors affecting the total cost at each stage of LCC.
- Utilisation of artificial neural networks to be employed to develop a new model for LCC; the validation of which to be a testing phase, using actual LCC values from number of previous completed construction projects to compare with model results.

5.4. Research strategy

There are two types of the research strategy utilized generally, these being qualitative or quantitative research. The selecting of which type of the research to employ is dependent upon the objectives of a study. Quantitative research seeks to test the objective theories by studying the relationship among facts, but qualitative research is a means to gain insight and understanding of the meaning individuals or groups ascribe to a social or human problem (J.W. Creswell, 2003).

Table 5.1 summaries the essential differences between both research approaches based on several criteria such as their analytical objectives, the forms of data they produce and data and question format.

Table 5.1 Qualitative versus quantities research

	Qualitative research	Quantitative research
Process of the research	Inductive (analysis by the researcher)	Deductive (analysis by the statistical methods)
Nature of reality	Subjective	Objective
Result	Impressionistic	Conclusive
Variables	Holistic, interdepend variables	Independent and dependent variables
Data format	Focus on word	Focus on number
Focus	Probing	Counting

Source: (Biemans, 2003)

Different authors have identified different *types* of qualitative and quantitative research. The common types of approach are described in Table 5.2 below (Babbie, 2010; John W. Creswell, 2011; Dantzker & Hunter, 2011; Denzin & Lincoln, 1994; Merriam, 2009; Parse, 1985; Potter, 1996).

Table 5.2 the common types of qualitative and quantitative researches

Qualitative research	*Quantitative research*
1. Phenomenological study: It aims to understand people's opinion and feeling about the specific topic. It is rapidly becoming one of the major qualitative researches.	1. **Survey research**: Becoming one of the major quantitative research approaches. The researcher collects the data through asking semi-structured questions of an expert sample.
2. Field observation: aims to collect primary data by researcher's own direct observation of relevant individuals, cases actions without interaction with subjects.	2. Field observation: It aims to collect primary data by researcher's own direct observation for numerical assignment.
3. Ethnographic study: It seeks to collect and analysis of data about cultural groups. The researcher often enters the environment of the study in order to understand the patterns of the	3. Experimental research: The research conducts action and observing the results of that action.

individuals in their familiar environment.	
4. Sociometry: The researcher attempts to measure social dynamic or relational structures.	4. Unobtrusive Research: Researcher uses '***document analysis***' to investigate without disturbing whatever is being studied in order to obtain research information.
5. Historical research: It evaluates and analysis of the data of the events, action, phenomena and so forth which have already happened. The research tries to link these past events occurring to the present and the future.	5. Evaluation research: It aims to develop new skills or approach by evaluated of the influence of social intervention.
6. Case Study: It is an ideal methodology when in-depth investigation of individual, group of individual, institution and so forth.	
7. Grounded Theory: The researcher seeks to develop theory by collecting the data and analysed from a body of text.	

Based on the objectives and sub-objective of this research, a quantitative research is deemed applicable. Two types of quantitative research will be used in this study. Firstly, survey research was used to identify the most important non-cost factors affecting the accuracy estimation of the life cycle cost in building construction projects. One of the disadvantages of this approach is that the respondent may answer in order to look well informed. However, it is easy, quick, & low cost compared to different quantitative research. Questionnaire is used to conduct survey research.

Unobtrusive document analysis research is the second approach used in this research in order to identify the most important cost factors affecting the accuracy estimation of life cycle cost of building construction project by studying the existing data. The analysis of existing data-sets might suggest that the researcher has less control over the data contents, quality and quantity. However, the main advantage of this approach is that the researcher does not require involving and interacting with other parties as data are often saved from the available documents. Analysis of existing data (extensive document analysis) was used to conduct unobtrusive research.

5.5. Literature Reviews

Secondary research was undertaken by way of a literature review. The overall purpose of a review of the literature provides the background information and knowledge for the current research. In reviewing the previous studies, it was established how this study was connected to the previous research. For this study, the literature review concerned the problems relating to life cycle cost and estimation methods as implemented to building construction projects. The review of life cycle cost ideas and methodology established knowledge of existing methods and needs, to find its current potential application in building construction costs.

The implementation of neural networks on construction projects was also assessed as part of the initial research strategy to clarify the processes and identify any data requirements for developed the model and analysis steps.
Four outcomes were achieved by conducting this review. These include:

- Identification of the main limitation of the implementation of LCC building construction projects.
- Clarification of the suitable method (Pareto's analysis) towards identification of the key cost-factors affecting accuracy estimation of procedural LCC.
- Identification of the key non-cost factors affecting the accuracy estimation of LCC in building construction projects.
- Gaining an understanding of the application of ANNs in the construction industry and the suitability of each of this method in different construction aspects such as identification of cost drivers.

Sources utilised in order to achieve these outcomes included accessing academic journals, online databases, online journals, governmental and other publications, and a range of references covering life-cycle cost in the construction industry.

5.6. Data collecting

Data collection remains key to research; the type of information and method used to collect the data is discussed below

5.6.1. Analysis of existing data methods

Existing data was collated towards extensive secondary research. Four steps, as shown in Figure 5.2, clarified analysis of data sets; these are discussed below.

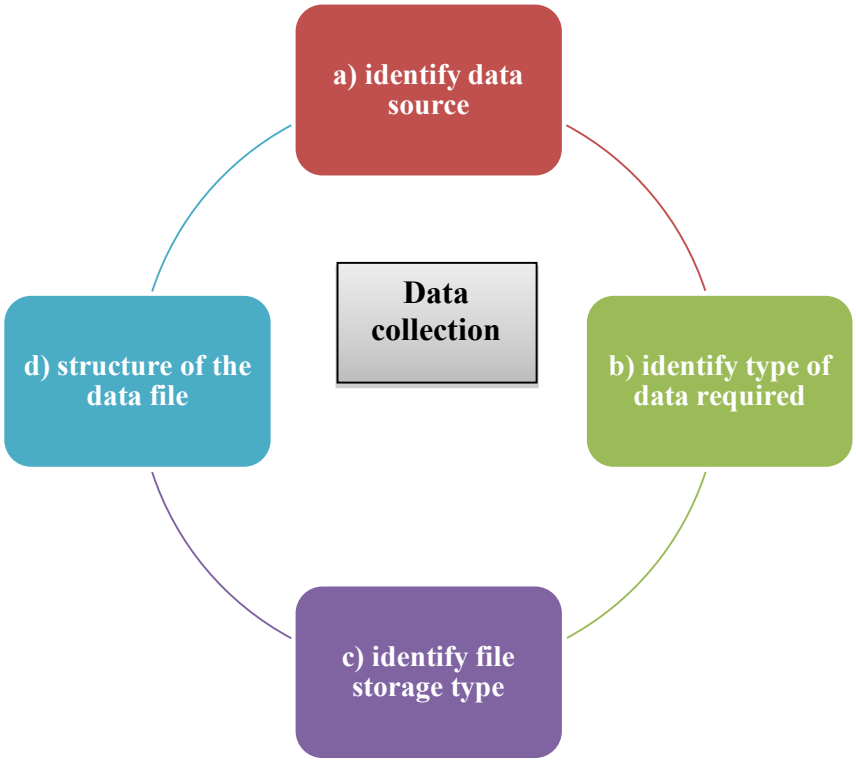


Figure 5.2 Steps of data collection of analysis existing data

a) Identify data sources:

The gathering and collecting of the life cycle costs data of building construction projects was a challenging step because of the limitation related to good and reliable record keeping. Few construction companies develop their own database; few maintain good valuable sources for the historical building projects completed. Unfortunately, any companies who do keep extensive records do not feel able to share that kind of data as they consider such data to be proprietary; adding value to the company and enhancing the company's competitiveness. The existing historical projects cost's records were often kept but shared only in-house. In addition, the life cycle cost information for some projects needs collection from several companies as project was executed by several sub-contracted construction companies. After project completion typically the project will be handed over to another firm to operate and maintain the projects. Resultantly only few data sources could be deemed suitable in order to prepare a range of objective data-sets. To address this concern this research

utilized the Building Cost Information Service (BCIS) database of The Royal Institution of Chartered Surveyors (RICS). This database consists extensive data of life-cycle costs for many, many building construction projects.

b) Identify types of data required:

Historical life-cycle cost building project data was the most crucial input to the neural network model (prepared, developed and analysed extensively) in this study. This data (input) necessarily needed to cover all the main costs of all the principal sub-components of building project, during all phases of life-cycle, of the constructed facility.

In addition, general information of each project was collected such as number of storeys, type of building, gross floor area, location, number of elevators, type of structure and roof type. This information was analysed to identify the most important factors considered for necessary 'inputs' to the ANNs model developed by this study.

Table 5.3, 5.4 and 5.5 highlight the data required to be collected for each project and subsequently used as necessary 'inputs' to the developed model

Table 5.3 Data required to be collected for each project (initial cost)

Element Total cost	Definition
1 Substructure	Substructure-transfer the load of the building to the ground and to isolate it horizontally from the ground
2A Frame	Frame-provide a full or partial system of structural support, where this is not provided by other Elements
2B Upper floors	Upper floors provide floor space on upper levels (i.e. above the lowest floor level)
2C Roof	Roof-provide the horizontal component of the external enclosing envelope
2D Stairs	Stairs and ramps- allow vertical circulation
2E External walls	External walls-provide the vertical component of the external enclosing envelope in conjunction with 2.6 Windows and External Doors
2F Windows and external doors	Windows and external doors-allow access through external walls for physical movement, natural ventilation and light and provide the vertical component of the external enclosing envelope in conjunction with 2.5 External Walls
2G Internal walls and partitions	Internal walls and partitions-divide the floor space
2H Internal doors	Internal doors-allow physical circulation between internally divided floor space
3A Wall finishes	Wall finishes-provide a functional and/or decorative finish to walls
3B Floor finishes	Floor finishes-provide a functional and/or decorative finish to floors
3C Ceiling finishes	Ceiling finishes-provide a functional and/or decorative finish to ceilings
4 Fittings	Fittings, furnishings and equipment-provide functional and/or decorative items
5A Sanitary appliances	Sanitary installations-provide sanitary appliances
5B Services equipment	Services equipment-provide serviced equipment
5C Disposal installations	Disposal installations-remove liquid and solid waste from the building
5D Water installations	Water installations-provide water and steam
5E Heat source	Heat source-provide a central source of heat
5F Space heating and air treatment	Space heating and air conditioning-control the internal temperature and/or air quality
5G Ventilating systems	Ventilation systems-provide the movement of air.
5H Electrical installations	Electrical installations-provide electrical power, and to control the light levels (electrically)
5I Gas installations	Fuel installations / systems-provide fuel as a source of energy
5J Lift and conveyor installations	Lift and conveyor installations-provide vertical and horizontal mechanical transportation.
5K Protective installations	Fire and lightning protection-protect the building and its inhabitants from hazards
5L Communications installations	Communication, security and control systems-provide systems for communication to and between inhabitants for information and security
5M Special installations	Specialist installations-provide electrical and mechanical systems related to the user function of the building, not included elsewhere.
5N Builder's work in connection	Builder’s work in connectio-provide builder’s work for servicesn with services
5O Builder's profit and attendance	Testing and commissioning of services

Table 5.4 Data required to be collected for each project (operation and maintenance costs)

Element	Sub-element	Definition
2.1 Major replacement		Scheduled replacement of major systems and components. This will form the detailed building life cycle cost programme
	2.1.2 Superstructure	
	2.1.3 Finishes	
	2.1.4 Fittings	
	2.1.5 Services	
2.3 Redecorations		Scheduled redecorations. Excludes redecorations carried out in connection with 2.1, 2.2, 2.4 and 2.5.
	2.3.2 Superstructure	
	2.3.3 Finishes	
	2.3.4 Fittings	
	2.3.5 Services	
2.4 Minor repairs, replacement and maintenance		Scheduled replacement of parts and scheduled maintenance and repairs to components; associated making good and minor redecorations including planned preventative and/or reliability centred maintenance.
	2.4.2 Superstructure	
	2.4.3 Finishes	
	2.4.4 Fittings	
	2.4.5 Services	
2.5 Unscheduled replacement, repairs and maintenance		Allowance for unforeseen or unplanned maintenance arising from early failure, inappropriate use, etc.
	2.5.2 Superstructure	
	2.5.3 Finishes	
	2.5.4 Fittings	
	2.5.5 Services	
3.1 Cleaning		Cleaning costs including periodic, routine and specialist cleaning.
	3.1.1 Windows and external surfaces	
	3.1.2. Internal cleaning	
	3.1.3 Specialist cleaning	
	3.1.4 External works cleaning	
3.2 Utilization		Utilities costs can be split into two main categories, energy and water.
	3.2.1 Fuel-gas	
	3.2.2 Fuel-Electricity	
	3.2.3 Water and drainage	
3.3 Administrative costs		User support costs related to the operation of the building and external works.
	3.3.1 Property management	
	3.3.2 Staff engaged in servicing the building	
	3.3.3 Waste management	
3.4 Overheads		Property insurance. Premiums for insuring the property.
	3.4.1 Property insurance	
3.5 Taxes		Rates and other local charges payable in connection with the building.
	3.5.1 Rate and other local charges	

Table 5.5 Data required to be collected for each project (general information)

1	Location
2	Total gross Area
3	Number of storeys
4	Type of building
5	Roof type
6	Type of structure
7	Building life
8	Number of elevators
9	Type of foundation
10	Total cost at each stage of building's life cycle

c) Identify file storage file:

The file storage type defines how data is stored in the data file. The LCC data was represented in different formats in the BCIS database. Therefore, the data was collected and transferred into Microsoft Excel program. The prepared re-collation consisted of several lists of spreadsheet functions that can be suitable to be subsequently used to analyse the data. The (final) important cost and non-cost factors could then be imported into MATLAB in order to develop the ANNs/ANNs model for life-cycle costing.

d) Structure of the data file:

Excel consists of a header specifying the storage type and size of data, followed by the storage value. The cost data collected consists of a header specifying the data such as type of building and total area followed by the storage value (commercial building and 590 m^2). For example 'sex/ or classification' files have been developed to structure the data. Each file concerned one stage of a building's life cycle. For example, the value of the tenth non-cost data variable for each project was collected into one file. After that the data was entered in each file accordingly.

5.6.2. Questionnaire methods

As mentioned above, the questionnaire is one of the most commonly used data collection research devices for conducting qualitative 'surveys'. Questionnaires are a suitable method to be utilized for qualitative descriptive and analytical survey

purposes in order to discover the underlying facts and contributory viewpoints. It requires developing formal lists of questions to ask of all respondents consistently. There are five steps, as illustrated in Figure 5.3 below, towards the need to clarify and collect suitable best data by this method.

a) Questionnaires design:

Reference is made to Table 5.6 below; questions have been assembled around the 10 factors affecting the accuracy of estimation of the life cycle costs in building construction projects. Questions are selected based upon these factors commensurate with the nature of building construction projects and problems.

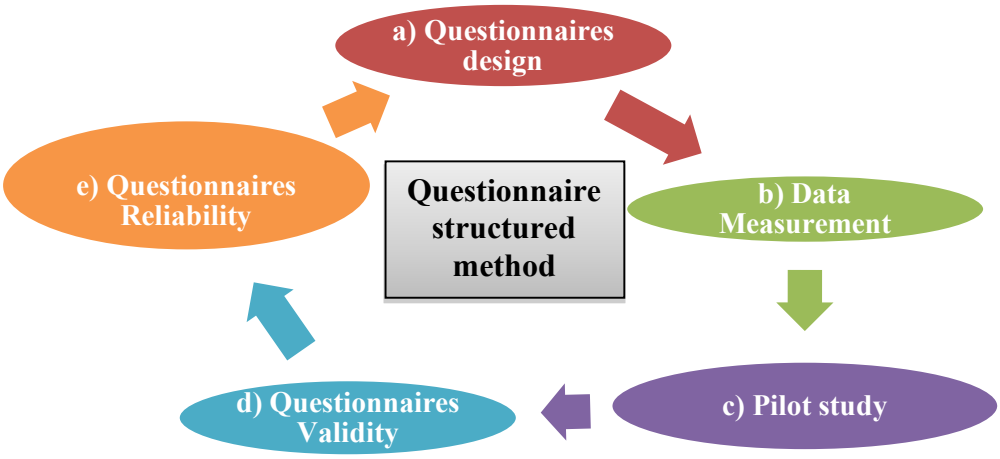


Figure 5.3 Steps of data collection of questionnaire methods

The final questionnaire format contains 10 factors influencing life cycle costs in building construction projects. The participants were asked to give their expert-opinions, fill the questionnaire format and have been assured that the information will be confidential and only for research purposes.

The questionnaire(s) consist of two parts to achieve the second sub-objective of this research, as follows:

I. First part: General information about the respondents.
II. Second part: Factors affecting the accuracy estimation of life cycle cost of building construction projects. This part aimed to achieve the third objective

towards ranking the most important factors affecting the accurate estimation of the life cycle cost of building construction projects.

The final list of factors affecting the accuracy estimation of life cycle cost of building construction projects contained a total of 10 factors are shown in Table 5.6, which were necessarily prepared from secondary research

Table 5.6 Most significant non-cost factors affecting LCC in building construction project

Factors	References
1. Number of stories	(Aibinu & Pasco, 2008; Chang Sian, Pei Jia, & Sy Jye, 2010; Cheng, Tsai, & Liu, 2009; Elhag & Boussabaine, 1998; Jin, Cho, Hyun, & Son, 2012; G. Kim, Seo, & Kang, 2005; H.-J. Kim, Seo, & Hyun, 2012; Mohammed & Mamoun, 2011; Rifat Sonmez, 2011; Stoy, Pollalis, & Schalcher, 2008; Wheaton & Simonton, 2007)
2. Type of building	(Aibinu & Pasco, 2008; E.M. Elkassas, H.H. Mohamed, & Massoud, 2009; Elhag & Boussabaine, 1998; H.-J. Kim, et al., 2012; Martin Skitmore & Thomas Ng, 2003)
3. Gross floor area	(Aibinu & Pasco, 2008; An, Kim, & Kang, 2007; Cheng, Tsai, & Sudjono, 2010; Elhag & Boussabaine, 1998; Heng Li & Love, 2005; Ji, Park, & Lee, 2011; G. Kim, et al., 2005; H.-J. Kim, et al., 2012; R. Sonmez, 2008; Rifat Sonmez, 2011; Thalmann, 1998)
4. Project duration	(Elhag & Boussabaine, 1998)Kim, Choi, Kim, & Kang, 2005;Stoy, et al., 2008;Cheng, Tsai, & Liu, 2009;R. Sonmez, 2008;Rifat Sonmez, 2011;H.-J. Kim, Seo, & Hyun, 2012; E.M. Elkassas, H.H. Mohamed, & Massoud, 2009)
5. Location	(An, Kim, & Kang, 2007;Cheng, Tsai, & Sudjono, 2010;Stoy, et al., 2008;E.M. Elkassas, H.H. Mohamed, & Massoud, 2009;Aibinu & Pasco, 2008)
6. Roof types	(An, Kim, & Kang, 2007;Kim, Choi, Kim, & Kang, 2005;Ji, et al., 2011;H.-J. Kim, Seo, & Hyun, 2012)
7. Foundation types	(An, Kim, & Kang, 2007;Kim, Choi, Kim, & Kang, 2005;(R. Sonmez, 2008) H.-J. Kim, Seo, & Hyun, 2012)
8. Number of elevators	(Ji, et al., 2011;Stoy, et al., 2008;R. Sonmez, 2008;Mohammed & Mamoun, 2011;Rifat Sonmez, 2011;Chang Sian, Pei Jia, & Sy Jye, 2010)
9. Type of structure	(Aibinu & Pasco, 2008; Ji, et al., 2011; H.-J. Kim, et al., 2012; R. Sonmez, 2008; Rifat Sonmez, 2011)
10. Inflation rate	(E.M. Elkassas, et al., 2009)

The ten factors identified by secondary research are outlined generally below:

1- Number of stories:

The LCC of tall buildings are greater than those of low-rise buildings. Construction costs for taller building tend to increase due to the costs of increased loads, roof, foundation, and elevators. Regarding maintenance costs, extra costs would be needed for the tools and equipment utilized to perform the maintenance works. For example, scaffolding is required to perform numerous maintenance works at taller buildings such as painting task and window cleaning (Skinner, 1982).

2- Type of building:

Type of building has an effect on LCC. The total amount of cost of design, construction and maintenance and operation will depend on the degree of specialization of the project and the type of the material to be used. For example AL-Hajj (1991) developed several CSIs models general model (for all type of building) and specific model (for specific building such as teaching, residences and laboratory buildings model). He found that models of specific building have a higher accuracy than the general model. This means that the type of building affects the result of estimation. In this case, type of project affects the estimation process.

3- Project life:

Usually the longer the lives of a building project lead to gains-in/high costs because of the increases in the resource and operation and maintenance cost.

4- Location:

The location of the project affects the LCC of the building project by conditions imposed by specific locals. For example, the delay in resources deliveries may occur and large vehicles may damage, when a transport route is poor. This situation will lead to increased costs. Moreover, long distances to transport these resources may

lead to increased transport charges. Similar to transportation problems, labour availability is another issue as each location has different amount of available skilled and unskilled labours. The labour cost will be increased due to import the labour from other location as there is unavailable labour at the project location.

5- Foundation types:

There are several type of foundations selections based on the characteristics of the building design and the type of structure. The cost of the foundation is variable: Pile and raft foundation are more expensive than ordinary foundation. Consequently, this capital cost factor can affect the future (technical method of) refurbishment LCC of building projects.

6- Roof types:

Similar to foundations, there are numerous types of roof using in building projects and the cost of these types are also varying: flat roofs are likely to be rather expensive (related to operation/maintenance of the flat surface than pitched roofs, alongside comparable quality due to the simplicity of spanning large parts with roof trusses rather than deep beams. Consequently, this factor can affect both capital and the LCC of building projects as the both construction and maintenance costs increased.

7- Number of elevators:

If the project involves elevators, the LCC would increase due to the increases in the resources and operational and maintenance knock-on costs.

8- Gross floor area:

Gross floor area is one of the most important factors to be considered in generating Building LCC. The large area of the building means that additional costs would be required for the resources utilized to carry out all the design, construction and operation and maintenance tasks.

9- Type of structure:

The type of structure is another factor influencing the LCC of building projects. The (capital and operational and maintenance and not least the future refurbishment) cost of the types of structure also varies. For example, the steel structure is the cheapest option in term of structure costs alone and the best and most popular solution for multi-storey flooring in some most countries, and not least lends itself to retrospective re-fitting more so that structural concrete. This variability in the cost also depends on several factors such as the price of the material by location. In addition, maintenance cost is significantly subjected to the type of structure in buildings, and not least the cladding (maintenance and periodic replacement) applied to the structural components.

10- Inflation rate:

The general state of the economy will affect the life cycle cost of building projects. Inflation can cause increases in the initial estimates of life cycle cost of building project. Inflation may have been considered in the initial estimates, but if the rate of inflation rises above the estimated level throughout the project's life, then the initial life cycle cost estimate will be exceeded. Therefore, the effects of inflation rate on construction projects cannot be ignored. Indeed the discount rate calculation and application remains a related area of influence.

It must be recognized that each of these factors separately or in combination with others can cause an effect on the accuracy of the estimation cost. Variations in 'non-cost' factors from one project to another would cause varieties in the cost obtainable of project, mostly, when those factors are differently configured. Non-cost factors would be considered while formulating input-variables for the neural network model to be utilized for building and testing model in this research.

b) Data Measurement

A measurement scale was identified in order to find out the suitable method of the analysis; Likert scales are the most widely used scaling technique to measure

variables, knowledge, perceptions and values. (Vogt & Johnson, 2011). In the subsequently developed questionnaires, Likert scales were used to obtain respondents' degree of agreement with a statement or set of statements. Table 5.7 shows the general example of Likret scale using in this research:

Table 5.7 General example of Likret scale using in this research

Items	Strongly Disagree	Disagree	Somewhat agree	Agree	Strongly Agree
Factor	1	2	3	4	5

c) Pilot study

The aims of pilot study is testing the language and wording of questions, clarifying the ambiguous question and proving that the respondents are able to answer the question which help to achieve the objective of this part of the research. According to Fellows and Liu (2009) all questionnaires should originally be piloted; completed by small sample of respondents.

A pilot study (content validity) was conducted by sending and distributeing ten copies of the questionnaire to experts to fil-in. This helped the researcher to find out the questions that were well understood or not, and any other ambiguity that may appear during the questionnaire formalisation process.

A pilot study (of content validity) was conducted by asking five expert-practitoners in constructions and 4 academic lecturers to review the questionnaire format, evaluate the content validity, check readability of language and give their opinions regarding to the factors and the questions. Furthermore, interview with these (pilot-sample) respondents was conducted in order to adjust, delete and add factors.

d) Questionnaires Validity:

Validity refers to the extent to which an instrument is able to measure what is intended to be measuring (Burns & Grove, 2009). There are three types of measure to assess the validity of quantitative research are summarised in Table 5.8 (adopted from (Cormack, 2000; Knapp, 1998; Peat, Mellis, & Williams, 2002).

Table 5.8 Three types of measure to assess the validity

Type of measure validity	Definition
Content validity	Whether instrument appears to experts (in the field) to be able to measure what it intends to measure.
Criterion validity	Concurrent validity : compares the new measurement result with existing and well-accepted result.
	Predictive validity: measures the degree to which current measurement can predict a future event of interest.
Construct validity	It aims to link the new measurement result and the underlying theory.

Source: (adopted from (Cormack, 2000; Knapp, 1998; Peat, et al., 2002).

This research used two type of validity. First: content validity as mentioned before. Criterion validity was also used by comparing the result of the survey with result of the previous researches. The results of the criterion validity is presented in the next chapter (chapter 6).

e) Reliability:

Reliability means that, very similar results should be attained when the measurement isrepeated (Bollen, 1989). Typical methods to measure reliability are: test-retest reliability, alternative forms, split-halves, inter-rater reliability, and Cronbach Alpha. Table 5.9 below illustrates the definition of each type of reliability.

Table 5.9 The definition of each type of reliability

Type of measure reliability	Definition
Test-retest reliability	It aims to find out the temporal stability of a result from one measurement session to another.
Alternative forms	It is similar to the test retest method, but using different measures of behaviour to collect the data at different times (Bollen, 1989).
Split-half approach	Total set of item divided by half and the score of both groups are correlated to attain the estimation of the reliability(Bollen, 1989).
Inter-rater reliability	It aims to evaluate the extent to which different judges agree in their assessment result(Rosenthal & Rosnow, 2008).
Cronbach's alpha	It is the average of all possible split-halfs reliabilities. It was designed to a measure of internal consistency (Cronbach, 1951).

This research used Cronbach's alpha to measure the reliability of the questionnaire. The normal range of Cronbach's coefficient alpha value between 0.0 and + 1.0, and the closer the Alpha is to 1 reflects a higher degree of internal consistency. Cronbach's Alpha can be calculated as a function of the number of test items and the average inter-correlation among the items.

Equation 5.1 below is the formula (used here) for the standardized Cronbach's alpha:

$$\boldsymbol{\alpha} = \frac{\boldsymbol{n}}{(\mathbf{1}+(\boldsymbol{n}-\mathbf{1})\boldsymbol{r})} \ldots\ldots\ldots\ldots (\mathbf{5.1})$$ (Cronbach, 1951)

Here α: Cronbach's Alpha, n : the number of items; r: represent the average inter-item covariance among the items.

The result of Cornbach's Alpha will be presented in the next chapter.

5.7. Data analysis and result

5.7.1. Data analysis for questionnaire data

Statistic methods were used to analyse finalised-questionnaire responses and existing documented-project data. The following statistical methods were used for the analysis of the data collected by questionnaire. These methods are summarized in Table 5.10 below.

The definition, formula and purpose for each method will be presented in the next chapter (6).

Table 5.10 Statistical methods used for analysing questionnaire

STATISTICAL METHODS	Aim	Method
Statistical techniques	Aims to provide numerical descriptive result.	Mean, Standard Deviation, Coefficient of Variation, standard error of mean, confidence interval, skewness and , kurtosis.
Ranking the factors	Aims to present the final rank for non-cost factors affecting the LCC.	Relative importance index (RII)

Rank Agreement	Aims to measure the respondents' agreement regarding the most important factors affecting accuracy of life-cycle cost estimation in building projects.	Analysis of variance (ANOVA)

5.7.2. Data analysis for existing data

Statistic methods were used to clarify the relationship between capital cost and running cost and also to identify the important cost factors. The percentage of capital, maintenance, operation cost from total LCC was calculated for each project over 10 and 20 years with different inflation rate(s).

Pareto's 80/20 rule was also used to identify a significant /small number of cost elements which represent high percentage of the total design/construction costs, total maintenance and operation costs and disposal cost. This part consists of two mean phase(s). The concept of Pareto's rule was applied in the first phase. The important cost factors were identified at each stage of building's life cycle. The objective of second phase was to select the CSIs for use in the ANNs modelling of costs. Application of the mean value was used to identify CSIs at each stage of building life. The definition, formula and purpose for each phase were presented in the chapter 7 below.

5.7.3. Develop ANNs models

After identification of both significant non-cost and cost factors apt to be affecting LCC, all input data requires applicability to the developed neural network approach to be made available at the final stage. The aim of this stage was to develop five models of cost estimation. The table 5.11 below provides the summary of input and output of each model. More details of each models will presented in chapter 8 below.

Table 5.11 Input and output of each ANNs models

Model	Aim	Input factors	Output factor
Model 1	Estimate capital costs	Cost and non-cost factors at construction stage only.	capital costs
Model 2	Estimate operation costs	Cost and non-cost factors at operation stage only.	maintenance costs
Model 3	Estimate maintenance costs	Cost and non-cost factors at maintenance stage only.	operation costs
Model 4	Estimate running costs	Cost and non-cost factors at maintenance and operation stages only.	running costs
Model 5	Estimate Life cycle costs	Cost and non-cost factors at all stage of building's life cycle.	Life cycle costs

5.8. Summary of this chapter

In this chapter, a research methodology was described within a summary flow-chart of a research strategy - the process of 'dispute' identification and research methodology design in selecting a research methodology.

Questionnaire and analysis of existing data-sets was highlighted towards a necessary collecting of the useable data-set. Methods were described by its definition, analysis procedure, and major issues in analysis process in this chapter.

Statistical analysis methods used subsequently in this research were summarized above by the type of statistical analysis for analysis questionnaires data. Pareto's analysis method was described as applicable for use for analysis of the secondary data.

These discussions become the theoretical background of this research framework and methodology for this work. Based on this research methodology, the data analysis will be explained in the following chapters.

6. CHAPTER SIX: DATA DESCRIPTIVE, ANALYSIS AND RESULT OF SURVEY RESEARCH

6.1. Introduction

This chapter was designed to address the first three objectives in this research: namely, to identify the most importance non-cost factors affecting accuracy in life-cycle cost estimation in building projects. This chapter describes the results that have been deduced from questionnaire survey. Section one presents all necessary information about the respondents and focuses on describing the respondent's characteristics. Section two presents some the statistic techniques (including more basic Means, Standard Divisions and Coefficients of Variations).

Section three will present the final rank for variables based on Relative Importance Index concept (RII). The final section presents the relationship between the perspectives of respondents related to the essential factors affecting accuracy of life-cycle cost estimation in building projects by applying the key statistic methods such as, ANOVA. The results are analysed below by using Statistic Software such as SPSS and Excel. The statistical methods used for the analysis of the data collected are shown in Figure 6.1.

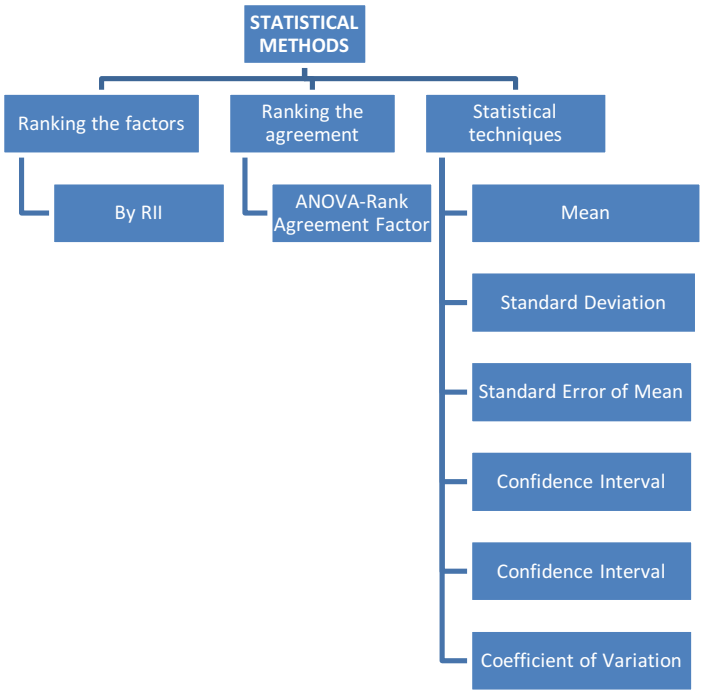


Figure 6.1 Statistical methods

Tables and charts have been produced and analyzed by the methods summarised in Table 6.1. An explanation of each method is presented in the following section.

6.2. Survey Purpose

Upon attempting to simplify the estimation of life cycle cost process, it is important to clarify what the most important factors are affecting estimation process. These factors are difficult to identify due to their highly subjective nature. They mean different things to different people; and indeed, the importance of these factors cannot represent the views of each individual. However, there are some universally agreed regarding to these factors, which encapsulate what estimation process should be considered as. In Chapter 5, it was identified 10 factors that affect the estimation of life cycle cost.

The main objective of the survey was to identify and rank these factors and provide the views of cost practitioners about how these factors can affect the estimation of life cycle cost.

The utilisation of questionnaires was chosen by the researcher as the most suitable method for eliciting the views of cost practitioners regarding the most important factors affecting life cycle cost. Choosing questionnaires, instead of using an interview or any other data collection methods, has a number of advantages:

a) Easy to reach individuals from around the world.
b) It does not need several media to carry out (compared to interviewing each participant, for instance) and
c) The investigator does not interfere with the participants of the questionnaires (therefore, preventing any bias introduced due to the investigator's presence).

6.3. Survey Design

The design of the survey was developed in advance by studying literature sources regarding survey design, as well as conducting a necessary validity check of the survey tool before distribution; questions were developed for each stage of survey.

The survey consisted of Likert scales, and it was created on a web page format, utilizing a commercial survey host facility. The participants were directed to the survey's website and answer the questionnaire online. This survey's website has used a tool that allowed the researcher to reduce any problems and collect more information about a participant's response (such as time spent to answer the questionnaire, location, and so on).

At the end of the online survey a participant was encouraged to provide any more information and comment they had regarding to the important factors; as well as any other general notes they may have on the topic.

The utilization of Likert scales to measure participant opinions allowed the researcher to measure the reliability of the overall survey, as an instrument of data collection. As mentioned in previous chapter, the reliability of a data could be defined as the degree to which the method of data gathering produces consistent results when the measurement repeated. Cronbach's alpha was used to measure the reliability of the questionnaire. It was calculated as 0.862 for questionnaire which means a very solid reliability of the entire questionnaire Table 6.1. Therefore, it can be supposed that the researcher has concluded that the questionnaire was valid, reliable, and can be distribute for the population sample.

Table 6.1 Reliability test result

Reliability Statistics	
Cronbach's Alpha	N of Items
0.862	10

6.4. Data Descriptive

This part provides general information about the participation of respondents in this questionnaire and aims to reflect the strength of respondents' characteristics, and consequently show the degree of reliability of the information provided by respondents.

The main survey was distributed to 203 professionals who often deal with cost issue in construction industry. After distributing the survey, 124 (61%) were returned by the respondents over a period of time.

Table 6.2 Statistical data of questionnaires sent and recived

	Total number	Percentage of Total (%)
The total questionnaire Sent	203	-
Total questionnaires received	124	61%

Table 6.2 shows the total response rate of 61 percent, which is reasonable and reflects a very solid result (Polit & Beck 2004).

a) Occupation of the respondent:

In terms of the employment position of the respondents, Figure 6.2 demonstrates that 21% (26 of 124) of respondents were directly involved in a quantity surveyor position, 17% (33 of 124) of the respondents were in a cost estimators position, 24% (30 of 124) were in a project manager position and28% (35 of 124) were in a cost engineer position. The respondents had key positions that ensured quality information.

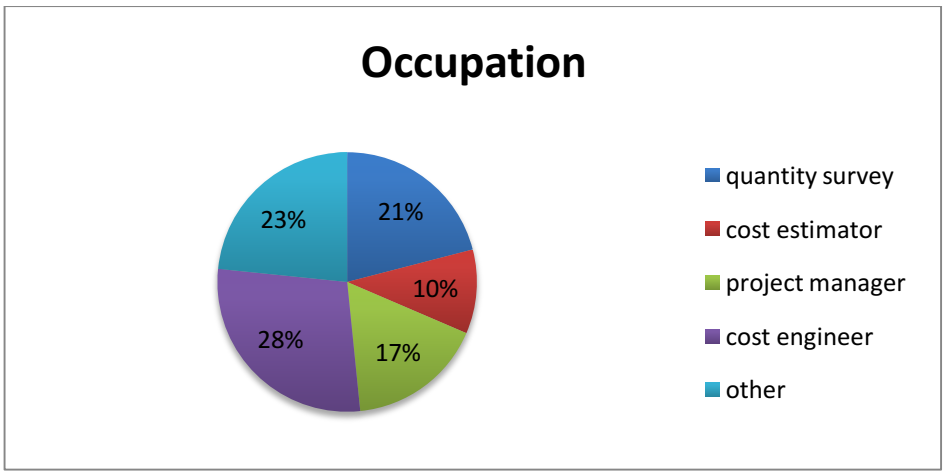


Figure 6.2 Respondents' position

b) Highest Formal Education Qualification

In an attempt to determine respondents' education qualifications and therefore the skill base, respondents had been requested to provide their highest education qualification attained. Figures 6.3 below presents the results regarding to the highest qualification of respondents.

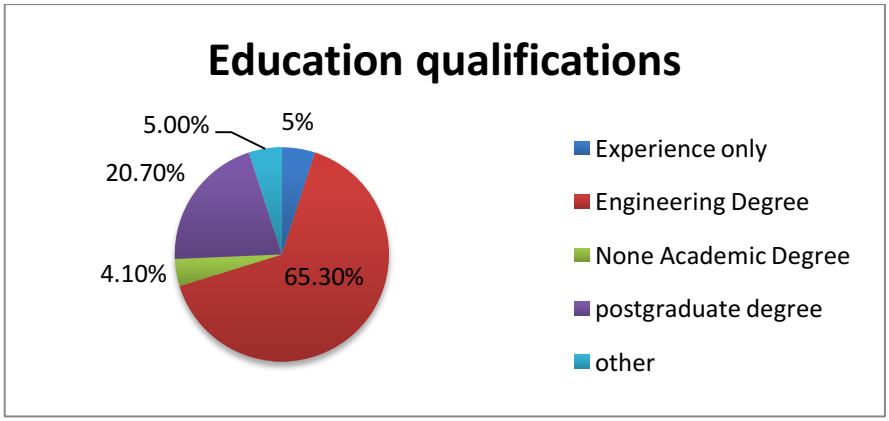


Figure 6.3 Respondents' education level

The majority of the respondents in this sample (107; 86%) reported having graduate or postgraduate qualifications, while 5 (4%) had a non-academic degree. It can be assumed that the respondents in this sample had sufficient knowledge and were capable of understanding the concepts and theories for estimation and the controlling cost of projects.

c) Respondent's years of experience

Figure 6.4 below shows that,

4.1% (5 of 124) of respondents have years of experience between 1-3 years.

9.9% (12 of 124) of respondents have years of experience between 3-5 years.

30.6% (37 of 124) of respondents have years of experience between 5-10 years.

55.5% (67 of 124) of respondents have years of experience more than 10 years.

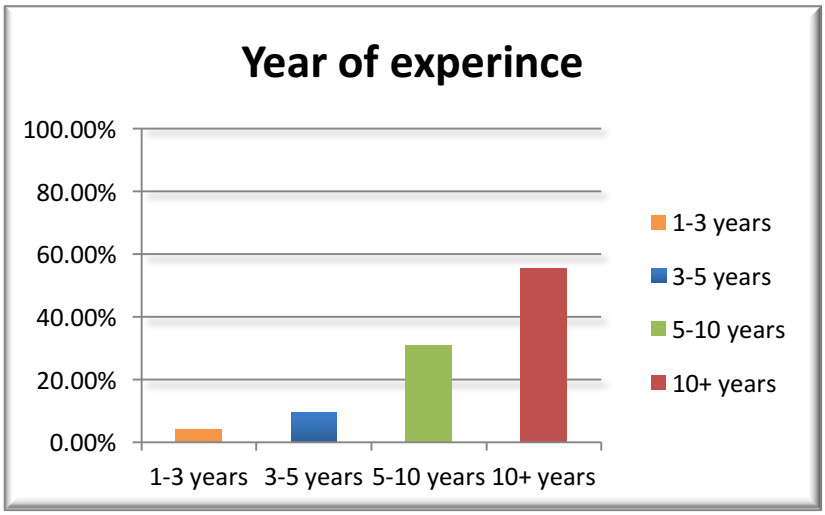


Figure 6.4 Respondents' experience

These results illustrate that the majority of the respondents (86.0%) in the sample had experience of more than 5 years, and more than half of the respondents (55.5%) had experience of more than 10 years. These results supported the notion that the data gathered reflected its intended purpose. The respondents had responsible positions in their work and were able to provide accurate and specific data.

d) Understanding the concept of Life Cycle Costing:

Figure 6.5 indicates that the levels of understanding of LCC as follows: approximately all the respondents (99%) understand the main theory and concept of LCC. Among them, 44 of 124 (35.5%) respondents reported that they are very well familiar with the LCC's concept, 56 of 124 (45.2%) respondents reported that they are well familiar with the LCC's concept, 15 of 124 (12.1%) respondents reported that they are somehow familiar with the LCC's concept and 8 of 124 (6.5%) respondent reported that they are little familiar with the LCC's concept.

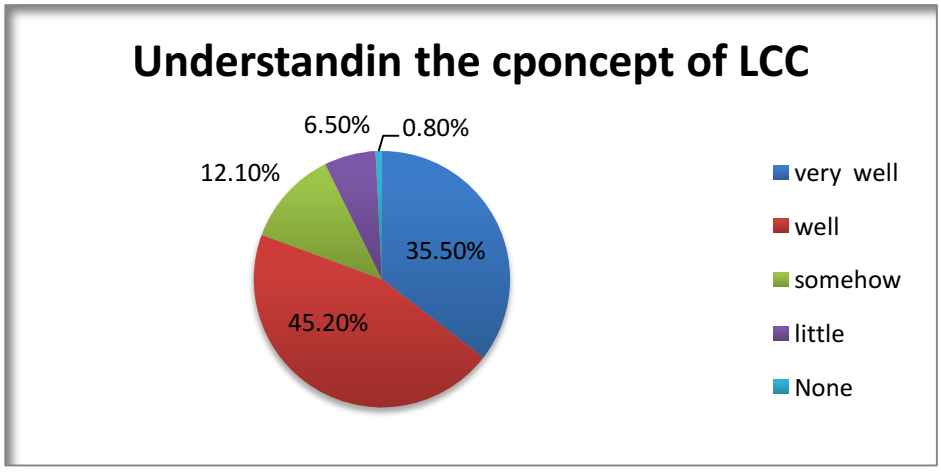


Figure 6.5 Understanding of LCC

e) the method applied to calculate the Life cycle cost:

Figure 6.6 shows that the form of economic methods being applied by respondents to calculate LCC. Some of the respondents applied more than one method as follows:

52% (64 of 124) of respondents applied net present value method (NPV), 27.3% (34 of 124) of respondents applied equivalent annual cost method (AC), 21.5% (27 0f 124) of respondents applied internal rate of return method (ROR), 19.8 % (24 of 124) of respondents applied pay back method (PB),

6.6 % (8 of 124) of respondents applied discounted pay back method (DPB) and

9% (11 of 124) of respondents applied other method of analysis.

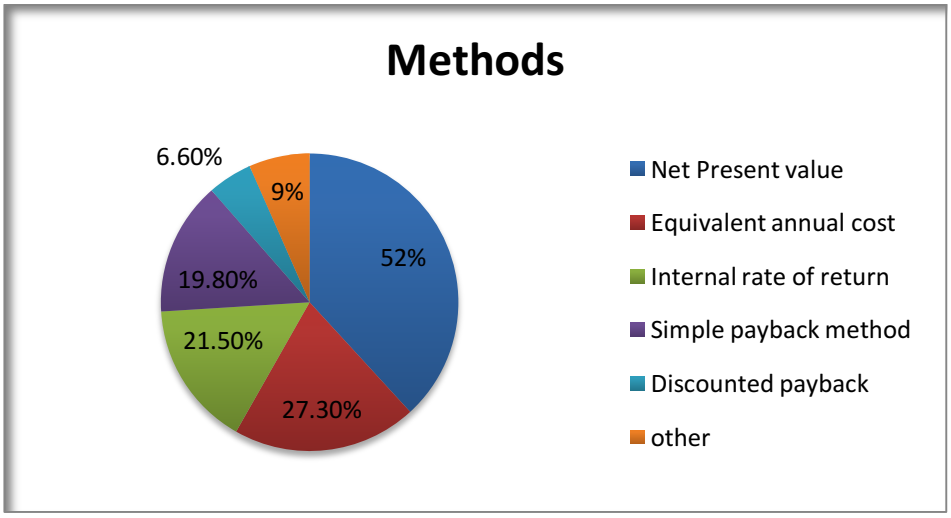


Figure 6.6 Type of methods used

f) The main objectives to apply the LCC:

Figure 6.7 shows that the main objective being utilized LCC by respondents.
Some of the respondents utilized LCC for more than one purpose as follows: 49.1% (61 of 124) of respondents utilized LCC to choose between alternatives, 41.1% (51 of 124) of respondents applied LCC as part of value engineering (VE), 40.3% (50 0f 124) of respondents utilized LCC as a mean for budgeting,
38.7 % (48 of 124) of respondents utilized LCC concept to estimate future running costs,
4.8 % (6 of 124) of respondents utilized LCC to other purpose such as for product feasibility.

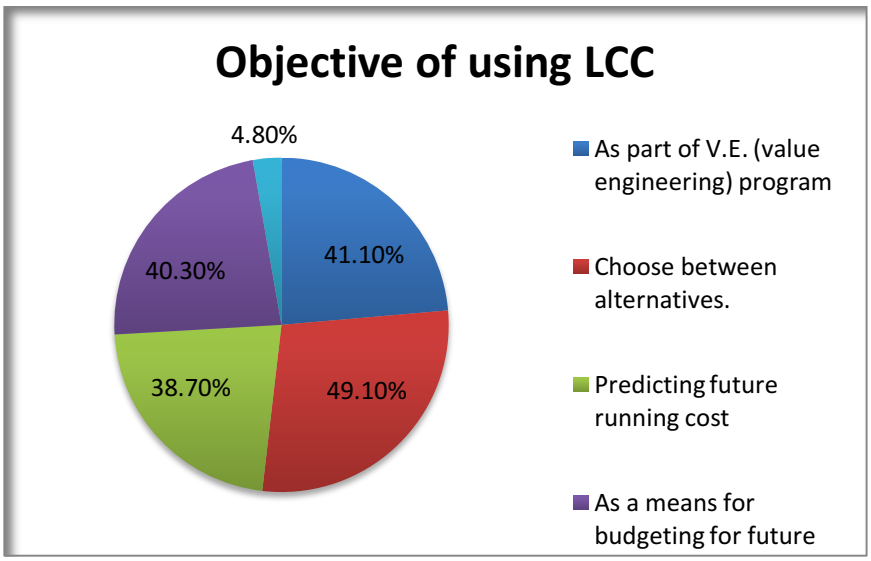


Figure 6.7 Objective of using LCC

g) The main problems of application of Life Cycle Costing:

The respondents were asked to identify what are the most important problems of application LCC. Some of them have selected more than one problem as follows:
54 of 124 respondents considered unavailable data as the most important problems, 38 of 124 respondents believe that unavailable standard method for collecting and recording of the data leads to limit the utilization of LCC and 31 of 124 respondents think that misunderstand relation between capital and running costs is the main

reason for not using LCC more widely. Figures 6.8 below presents the results regarding to the main problems of application of LCC.

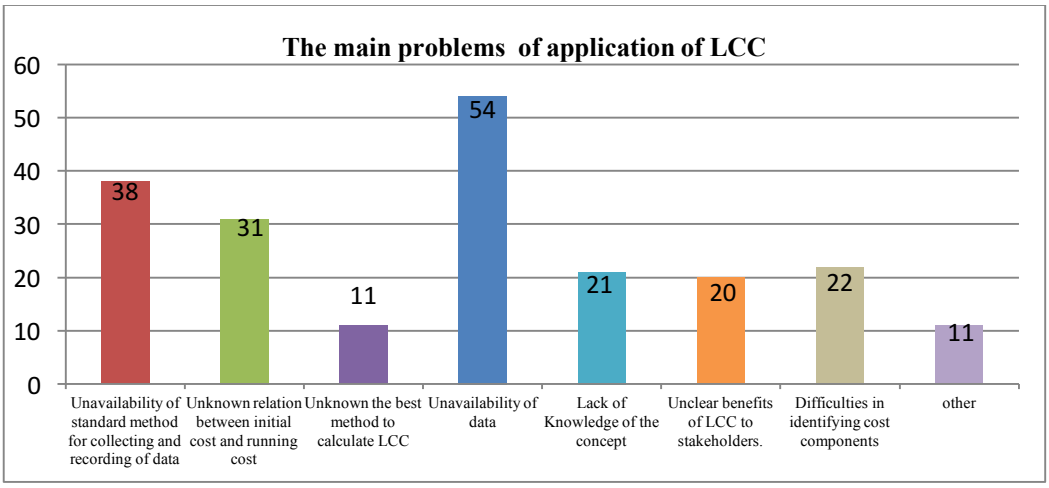


Figure 6.8 Current problems of application of LCC

The results indicate that providing suitable data, clear consistently standard method for collection data and recording LCC could be increased the application of LCC. This will also help to easily improve and save time of the estimation process.

However, data relating to LCC will not become accessible unless it is professionally communicated /instructed. This required developing a model that consists of the most important information related to LCC and can be easily followed by an estimator to provide an accurate result.

Estimators should consider both future and capital costs and help stakeholders to understand the concept of LCC by providing several options that are most cost effective. This required implementation of LCC to differences designs options. It also helps to study the sensitivity of LCC to differences designs options such as type of project, type of structure, total area of projects and the like.

6.5. Data analysis and result

The main objectives of second part of the questionnaire are to study the perspective of respondents of the essential factors affecting accuracy of LCC estimation in

construction building projects. This section consists of some the statistic techniques (mean, standard division and coefficient of variation); also, the final rank for variables based on relative importance index concept according to equation 6.1 below and the relationship between the perspectives of respondents of the essential factors affecting accuracy of life-cycle cost estimation in building projects has been studied by applying some statistic methods such as, ANOVA.

6.5.1. Statistic technique

The weighted mean, standard deviation, standard error of mean and coefficient of variation have been utilized to assist the researcher to examine probability of characteristics of population based on the characteristics of this research's sample.
Table 6.3 shows the summary of the result of statistical techniques used to analyse the collected data. This table contains the calculation of the following statistical techniques:

a) The Mean:

It is the value usually described as the average and the average of the sampling is representing the average of the population from which the scores were sampled. Consequently, if a population has a mean value of μ, then the mean of the sampling is also μ.

It is calculated as the sum of all the observed results from the sample divided by the total number of respondents.

$$\mu = \frac{\mathbf{1}}{\boldsymbol{n}} \sum_{\boldsymbol{n}}^{\mathbf{1}} \boldsymbol{X} \ldots\ldots\ldots\ldots (\mathbf{6.1})$$

Where μ is the sample mean, n is the sample size and the x correspond to the observed valued.

b) Standard Deviation:

To further examine the result of sample, standard deviation was calculated. It is one of the most statistics techniques commonly used to measure distribution or dispersion of the data. The value of standard deviation provides information on how the values of the results of sample are varying, or deviating, from the mean of the sample. It is calculated by the following formula:

$$\boldsymbol{\sigma} = \sqrt{\frac{\sum_{i=1}^{n}(\boldsymbol{x}-\boldsymbol{\mu})^2}{\boldsymbol{n}-\mathbf{1}}} \ldots\ldots\ldots\ldots (\mathbf{6.2})$$

Where σ *is the standard deivition,* μ is the sample mean, n is the sample size and the x correspond to the observed valued.

c) The standard Error of Mean:

Error of mean is commonly used to measure deviation of the sample mean from the actually population mean. It is calculated by the following formula:

$$s = \frac{\sigma}{\sqrt{n}} \ldots\ldots\ldots\ldots (6.3)$$

Where**s is the stander devistion of the mean**, **σ is the standard deivition**, and n is the sample size.

d) Confidence Interval (95%):

The coefficient interval is used to estimate a value in population based on the value of respondents in sample. The confidence coefficient used in this research is 95%. This means that if the same population is sampled on several times, the results of these samples would contain the actual mean of the universe within 95 % of the cases. . It is calculated by the following formula:

$$\textbf{Confidence interval } (\mathbf{95\%}) = \mu \pm \mathbf{1.96} * \mathbf{s} \ldots\ldots\ldots\ldots (\mathbf{6.4})$$

Where s is the stander deviation of the mean, and μ is the sample mean.

e) Coefficient of Variation (CV):

The Coefficent of variation is commonly used to measure the variation which is expressed as percentage. It is formed as equation () below:

$$\boldsymbol{CV} = \left(\frac{\boldsymbol{s}}{\mu}\right) * \mathbf{100\%} \ldots\ldots\ldots\ldots (\mathbf{6.5})$$

Where s is the stander deviation of the mean, and μ is the sample mean.

Table 6.3 Summary of the result of statistical techniques

Factors	Mean		Std. Deviation	95% confidence Interval		Coefficient of Variation (C.V)%
	Statistic	Std. Error	Statistic	Upper	Lower	
Number of stories	3.18	0.104	1.155	3.381	2.974	36.352
Type of building	3.69	0.095	1.053	3.879	3.508	28.506
Gross floor area	3.48	0.100	1.115	3.680	3.288	32.010
Project life	3.98	0.074	0.821	4.120	3.831	20.652
Location	3.57	0.102	1.135	3.772	3.373	31.759
Roof type	3.32	0.101	1.123	3.520	3.125	33.797
Foundation type	3.13	0.107	1.189	3.338	2.920	38.004
Number of elevators	3.17	0.099	1.102	3.363	2.975	34.779
Type of structure	3.69	0.096	1.068	3.882	3.506	28.921
Inflation rate	3.72	0.095	1.056	3.904	3.532	28.400

All factors has been answered by all (124 one hundred and twenty four) respondents which confirmed consistency in taking the data. The statistical mean results for all the factors falls between 3.98 and 3.13 which illustrate some of divergence on this issue. The highest value of standard deviation is 1.18 in the ranking of foundation type. These statistics results also prove that there was a small amount of disparity on the ranking factors by respondents. The result of coefficient of variation (C.V.) falls between 38% and 20%. These results show that data seem to be homogenous.

6.5.2. The Relative Importance Index (RII)

The data received was analysed by a relative importance index (RII) method to determine the significance of the factors affecting accuracy of LCC estimation in building projects. The respondents were asked to rank the importance of each factor on a 5-point Likert scale using 1 for not all important, 2 for not very important, 3 for somewhat important, 4 for very important and 5 for extremely important. The relative importance index (RII) was evaluated using the following equation:

$$\mathbf{RII} = \frac{(\mathbf{5n5 + 4n4 + 3n3 + 2n2 + 1n1})}{(\boldsymbol{AN})} \ldots\ldots\ldots\ldots (\mathbf{6.6})$$

Where n1 is number of respondents for ‘not at all important’, n2 is number of respondents for ‘not very important’, n3 is number of respondents for ‘somewhat important’, n4 = number of respondents for ‘very important’, n5 = number of respondents for ‘extremely important’, A is the highest weight (5 in the research) and N is the total number of samples (124 samples in this research). The relative importance index ranges from 0 to 1.

Table 6.4 Relative importance Index results

Factors	The Relative Importance Index	Final Rank
Project life	0.80	1
Inflation rate	0.76	2
Type of building	0.75	3
Type of structure	0.74	4
Location	0.72	5
Gross floor area	0.70	6
Roof types	0.67	7
Number of stories	0.65	8
Number of elevators	0.64	9
Foundation types	0.63	10

This table above (6.4) illustrates the overview of relative importance and the ranking of each factor**.** The results show that the respondents ranked project life in the first position with a relative importance index (RII = 0.8), which indicates the value of a project's life is an important part in a LCC application. Buildings consist of several components and the components will have varying lifespans. Some components will expect to retain their performance over the entire project's life, such as the foundation, whereas others will require frequent renewal or upgrading such as the electrical and mechanical systems.

This result is in line with the results of Rudbeck (1999), Stillman (Stillman 1992) and Bourke and Davies (1999). An appropriate description of this agreement is that an estimate of the project life based on the assessment of the building component's service life can be used in conjunction with LCC to provide a clear picture of the status of the building's assets. Generally the longer the life of the building project leads to higher costs because more resources (labours, materials and equipment) will be required.

The second important factor ranked by respondents was inflation rate (RII=0.76). The general state of the economy will affect the life cycle cost of building projects. Inflation can cause an increase in the initial estimates of the life cycle cost of a building project. Inflation may have been considered in the initial estimates, but if the rate of inflation rises above the estimated level throughout the project's life, then the initial life cycle cost estimate will be exceeded. The results of Elkassas, et al (2009), Ashworth (2010) are similar to this research's finding. This factor cannot be ignored, especially, when the LCC approach use to evaluate options.

Type of building (RII = 0.75) was ranked as the third factor affecting accuracy of LLC estimation in building projects. The total amount of cost of design, construction and maintenance and operation will depend on the degree of specialisation of the project and the type of the material to be used. The results of AL-Hajj (1991), Aibinu & Pasco, (2008), E.M. Elkassas, et al., (2009), T.M.S. Elhag & Boussabaine, (1998), H.-J. Kim, et al., (2012) and Martin Skitmore & Thomas Ng, (2003) agreed with the results of this study.

For example, AL-Hajj (1991) developed several CSI models; general model (for all types of building) and specific model (for particular buildings such as for education, residences and laboratories. He found that models of specific buildings have a higher accuracy than the general model. This implies that the type of building affects the result of the estimation. In this case, the type of project affects the estimation process.

The fourth important factor ranked by respondents was type of structure (RII = 0.74). The cost of the type of structure is also variable. For example, the steel structure is the cheapest option in terms of structure costs alone and the best and most popular solution for multi-storey flooring in some countries. This variation in the cost also depends on several factors, such as the price of the material. In addition, maintenance cost is significantly subjected to the type of structure in buildings. The results of Aibinu & Pasco (2008); Ji, et al., (2011); H.-J. Kim, et al., (2012) Akintoye (2000); Elhag, Boussabaine and Ballal (2005) and Odusami and Onukwube (2008) coincide with this finding.

Table 6.4 shows that respondents ranked the location (RII =0.72) as the fifth factor affecting accuracy of LCC estimation in building projects. The location of the project affects the LCC of the building project by conditions imposed by specific location. A delay in resources deliveries may occur and large vehicles may be damaged when the transportation route is poor. This situation will lead to an increase in costs. Moreover, if there is a long distance to transport these resources it may lead to increased transport charges. Labour availability is a further problem as each location has diversity in the number of available skilled and unskilled labourers. The labour cost will be increased if it is necessary to import labour from another location.

The research results of E.M. Elkassas, et al., (2009), An, et al (2007), Elhag and Boussabaine (1998), Akintoye (2000), Elhag, Boussabaine and Ballal (2005) and Odusami and Onukwube (2008) show similar results in that every building project's location has its own characteristics. A building project's location differs from one place to another in terms of labour costs, the cost of equipment, the costs and accessibility of materials and also accommodation.

Gross floor area and type of roofs were ranked 6th and 7th by respondents with RII of 0.70 and 0.67 respectively**.** The large area of the building would require additional costs for the resources utilised to carry out all the design, construction, operation and maintenance tasks. In addition, there are numerous types of roof used in building projects and the costs of the different styles vary. A flat roof is likely to be more expensive than a pitched roof of comparable quality due to the spanning of large areas with roof trusses rather than deep beams.

Consequently, these factors can affect the LCC of building projects as both the construction and maintenance costs increase. These results are consistent with the findings of previous research undertaken. (and tabulated in the previous chapter).

As shown in Table 6.4, the respondents ranked the number of storeys, number of elevators and foundation types as the three factors least affecting accuracy of LCC estimation in building projects.

They believe that if the project includes an elevator, the LCC would increase due to the increase in the resource, operation and maintenance costs. Similarly, the LCC of tall buildings is greater than those of low-rise buildings. Construction costs for taller buildings tend to rise due to the costs of increased loads, roof size, foundation resources, and elevators. In addition, there are several types of foundation selecting based on certain characteristics of building design such as the type of structure. The cost of the foundation varies. Pile and raft foundations are more expensive than ordinary foundations.

The results of Ji, et al., (2011), Stoy, et al., (2008), R. Sonmez, 2008;Mohammed & Mamoun, (2011),Rifat Sonmez (2011) and Chang Sian, Pei Jia, & Sy Jye, (2010) did not agree with this finding. The reason behind this is that the majority of respondents believed that these three factors have more impact on the capital costs and less effect on operation and maintenance costs

6.5.3. One- Way ANOVA F Test

Analysis of variance (ANOVA) refers to measure the difference between three or more group sample means by partitioning variation. The ANOVA (F statistic) is calculated the following formula:

$$\mathbf{F} = \frac{\mathbf{S_i}}{\mathbf{Sj}} \ldots\ldots\ldots\ldots (\mathbf{6.7})$$

Where S_i is the variance between groups and S_j is the variance within groups.

One hypothesis that was tested in this study related to the respondents' agreement regarding the most important factors affecting accuracy of life-cycle cost estimation in building projects:-

H_0: There is no differences between the groups regarding the ranking of factors affecting accuracy of life-cycle cost estimation in building projects at significance level a = 0.05.

Statistically, H_0 is accepted with either the p value being .0.05 (significance level) or the F coefficient of the ANOVA test being less than the critical F value.

There are three assumptions require using one-way ANOVA F test:

a) Independence: each respondent should participate only once in the study, and should not affect the participation of others. This assumption has been considered before and during data collection.

b) Homogeneity of variance: the population variances are equal in each set of scores. This assumption was assessed by using Leven's test for homogeneity of variance. This test was assessed by using SPSS.

c) Normality: the sample value comes from a normally distributed population. This assumption can be assessed by constructing a normal probability histogram and the value of both Skewness and Kurtosis. Skewness was used to measure of degree and direction of a distribution. Kurtosis was used to measure of peakedness or flatness of a distribution when compared with a normal distribution. The value of skewness and kurtosis should be close to the zero and the Z scores for both tests less than ±1.96 to consider that the sample data come from a normal distribution. This assumption was assessed by also using SPSS.

In the following Sections, the results of the ANOVA tables are presented for each of the sub-groups across the overall survey sample.

I. Compare the mean rank of factors based on job position of respondents:

one way analysis of variance (ANOVA) test was used to measure the difference in the means for the five groups of opinion (quantity surveyors, cost estimators, project managers, cost engineers and others) at significance level a =0.05.

The normality test was assessed based in the results of both skewness and kurtosis which is very close to the zero and the Z scores for both tests are less than ±1.96. This means that the sample of data was likely drawn from a normally distributed population. The Table 6.5 consist of more details of these test's results and Figure from 6.9 to 6.18 also shows a normal probability histogram for each variables.

The next step was to investigate if there are any differences in the variances between groups. Levene's statistic was non-significant, p-vale more than 0.05, and thus the assumption of homogeneity of variance was not violated as Table 6.6 shows in the summarised results. Table 6.6 shows the main results of ANOVA test.

These results indicate that there is no differences between the groups regarding the ranking of factors affecting accuracy of life-cycle cost estimation in building projects at significance level a = 0.05 and F-critical = 4.5. The Appendix II presents more details of the ANOVA test's results.

Table 6.5 Skewness and kurtosis results

Factors	Z (score) = Statistic/ Standard Error									
Number of Stories	quantity surveyors		Cost estimators		Project mangers		cost engineers		Others	
	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis
	-0.74	-1.47	1.1	-0.51	-0.92	-0.57	-0.53	-0.01	-0.29	-0.09
Type of building	quantity surveyors		Cost estimators		Project mangers		cost engineers		Others	
	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis
	-0.7	-1.32	-0.28	-1.75	-1.22	-0.11	-0.84	-0.9	-1.54	-0.59
Gross floor area	quantity surveyors		Cost estimators		Project mangers		cost engineers		Others	
	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis
	-1.57	0.19	-0.04	-1.14	0.11	-0.67	-1.25	-0.58	-1.33	0.18
Project life	quantity surveyors		Cost estimators		Project mangers		cost engineers		Others	
	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis
	-0.49	-1.64	0.32	-1.12	-0.5	-0.66	0	-1.85	-2.92	4.45
Location	quantity surveyors		Cost estimators		Project mangers		cost engineers		Others	
	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis
	-0.96	-1.11	-0.38	-1.06	-0.74	-0.74	-0.81	-1.25	-1.16	0.47
Roof type	quantity surveyors		Cost estimators		Project mangers		cost engineers		Others	
	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis
	-1.73	-0.18	-0.86	-0.79	-1.24	0.48	-1.07	-0.88	0.45	-0.67
Foundation type	quantity surveyors		Cost estimators		Project mangers		cost engineers		Others	
	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis
	-0.62	-0.94	-0.25	-0.88	-1.68	1.27	-1.12	-0.73	-0.16	-1.48
Number of elevators	quantity surveyors		Cost estimators		Project mangers		cost engineers		Others	
	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis
	-0.47	-0.41	0.08	0.04	-0.83	0.2	0.37	-0.18	-0.82	-0.99
Type of structure	quantity surveyors		Cost estimators		Project mangers		cost engineers		Others	
	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis
	-0.91	-0.48	-0.59	-1.12	-1.06	-0.31	-1.07	-1.46	-1.15	-0.98
Inflation rate	quantity surveyors		Cost estimators		Project mangers		cost engineers		Others	
	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis
	-0.86	-0.33	-1.14	-0.6	-1.68	0.27	-0.85	-1.01	0.11	-1.37

Table 6.6 Levene and ANOVA results

	Test of Homogeneity of Variances				ANOVA	
Factors	Levene Statistic	df1	df2	P-vale	F	P-vale
Number of stories	2.481	4	119	0.06	0.792	0.533
Type of building	1.316	4	119	0.27	2.161	0.077
Gross floor area	0.728	4	119	0.57	0.749	0.561
Project life	1.366	4	119	0.25	1.314	0.269
Location	1.546	4	119	0.19	1.274	0.284
Roof type	0.578	4	119	0.68	0.772	0.546
Foundation type	1.950	4	119	0.11	0.599	0.664
Number of elevators	0.620	4	119	0.65	0.449	0.773
Type of structure	2.473	4	119	0.06	0.456	0.768
Inflation rate	1.844	4	119	0.12	1.414	.234

6.6. Summary of this chapter

The main objective of this chapter is to identify the main non-cost factors affecting accurate estimation of LCC in building projects. A survey was developed and used to rank these factors and provide the views of cost practitioners about how the factors could affect the accuracy estimation of LCC.

Ten factors affecting LCC were identified through literature and a pilot study.

A sample, covering 124 respondents made up of quantity surveyors, cost estimators, cost engineers, and project managers who were involved in the construction industry, was selected for the survey.

The first section of the questionnaire provided general information about the participation of the respondents in it. This part was aimed at reflecting the strength of the respondents' characteristics, and consequently to show the degree of reliability of the information provided by them.

7. CHAPTER SEVEN: IMPLEMENTATION OF PRINCIPLE OF COST SIGNIFICANT ITEMS TO TOTAL LIFE CYCLE COSTS

7.1.Introduction

Life Cycle Cost estimation process in buildings contain many items which have little or no influence on the life-cycle cost of a building. The examination of insignificant items makes life-cycle costs difficult to collect, administer, and apply. It has also been suggested that one way of dealing with these shortcomings is to modify the estimating approach in a way that reduces the effort and complexity in current estimating. This can be achieved through eliminates the insignificant items and focuses effort on those items which have a significant influence on total expenditure, has obvious advantages.

The main objective of this chapter is to use the principle of cost-significance which will both simplify the process of estimating and reduce the time it requires without adversely affecting the accuracy of the final estimate significantly. It will demonstrate the way in which capital; maintenance; operation and life cycle costs can be represented by a small number of cost-significant items, and to derive corresponding cost models. For each phase of life cycle cost, a set of cost-significant items which contribute a constant proportion of total cost values was identified.

The Cost-significant items included in the ANNs models were selected from those which were seen to recur consistently over the life time of a building. Thus, future costs can be estimated by costing only those items included in the ANNs model. In addition, the relationship between capital cost and running costs has been studied.

This chapter explains these procedures in detail and presents the resulting of the most important factors affecting LCC.

7.2.Source of Data

As mentioned in the methodology (chapter 5), the sample data collected from the Building Cost Information Service (BCIS) database of The Royal Institution of Chartered Surveyors (RICS). This database provides the data of life cycle costs of several building construction projects. Data on 113 actual building projects constructed in United Kingdom (UK) have been collected and used in this study. Table 7.1 below provides more details of the data collected concerning the type of structure, number of stories, gross floor area, type of building, location, number of elevators and type of foundation.

In terms of the type of the buildings,
26% (29 of 113) of the data are collected from education buildings,
26 % (29 of 113) of the data are collected from residential buildings,
20% (23 of 113) of the data are collected from commercial buildings,
18% (21 of 113) of the data are collected from Health buildings and
10% (11 of 113) of the data are collected from recreational buildings.

Both the capital costs and running costs (maintenance and operation costs) for each building type have been considered. In most cases running costs are over 50% of the total LCC of the building illustrated.

The pattern of running costs also varies between building types. In the commercial building, the running costs are between 60-74% of the LCC in most projects, while for residential building running costs they are between 40%- 55% of the LCC in most projects .

The reason for the main difference in the running costs between buildings is the number of hours and the occupancy of the buildings. Buildings in health and commercial categories are usually in use 24 hours a day throughout the year.

This will lead to an increase in the operation and maintenance costs of these buildings compared with other types of building as is shown in Figure 7.1 and 7.5.

In addition, Figure 7.6 gives a snapshot of the effect of project life on the total value of LCC.

It is clear that the percentage of running costs increases by approximately 5% at discount rate of 2% and 3%, at discount rate of 3.5% during the period of analysis from 30 to 60 years for the five building types.

Furthermore, figure 7.6 illustrates that the discount rate has a significant impact on the total value of LCC. It can be seen that the percentage of running costs decreased by approximately 5% at the 30 years period of analysis and by 8% at 60years period of analysis which caused the discount rate from 2% to 3.5% for the five building types.

It is clear that considering LCC as part of the decision support tools will aid stakeholders in their evaluation of the most desirable alternative and their decision of which projects to exclude.

They will then be able to utilise better resources with a higher return in the remaining projects to preserve the projects with the highest return or value. In addition, implementation of LCC provides valuable and maximum information at an early stage, supporting the decrease in waste and the increase in efficiency of design and construction together with operation and maintenance

Table 7. 1 General description of 113 projects used in developed ANNs models.

Group	Sub-group	Number of projects	Group	Sub-group	Number of project
Location	England	80	Gross floor area	15000-24999 m2	2
	Scotland	19		25000-35000 m2	1
	Wales	12		10000-14999 m2	3
	Northern Ireland	2		5000-9999 m2	7
Number of stories	1	15		2500-4999 m2	15
	2	27		1000-2499 m2	38
	3	46		500-999 m2	18
	4	17		less than 500 m2	29
	5	4	Type of structure	RC frame	15
	6	0		steel frame	79
	7	2		timber frame	19
	8	1	Foundation	Piles	23
	9	1		strip and pad	74
Number of elevators	0.00	65		raft	4
	1.00	34		trench	12
	2.00	7	Type of building	1-Recreational building	11
	3.00	3		2-Commerical building	23
	6.00	2		3- education building	29
	7.00	1		4- Health building	21
	10.00	1		5- Residential building	29
Inflation rate; LCC was calculated in 2.9 and 4.4% inflation rate			Project life; LCC was calculated in 30 and 60 years		

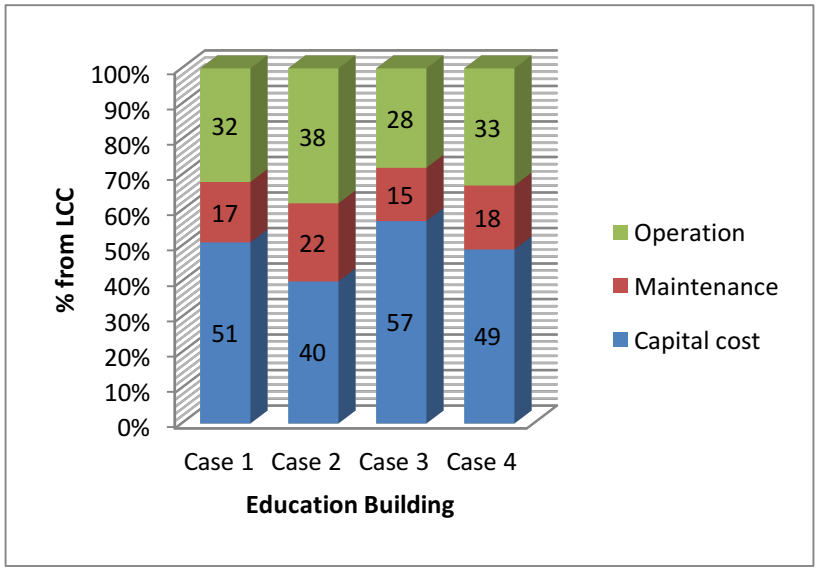


Figure 7. 1 Capital, operation and maintenance costs for education building

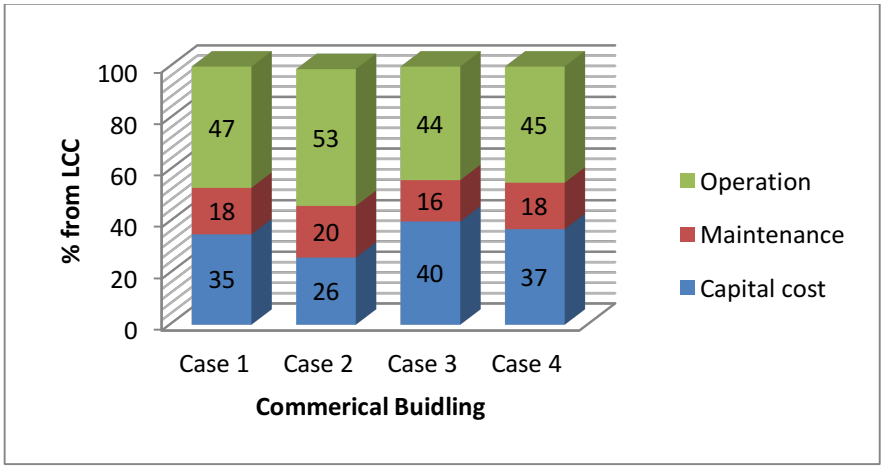


Figure 7. 2 Capital, operation and maintenance costs for commercial buildings

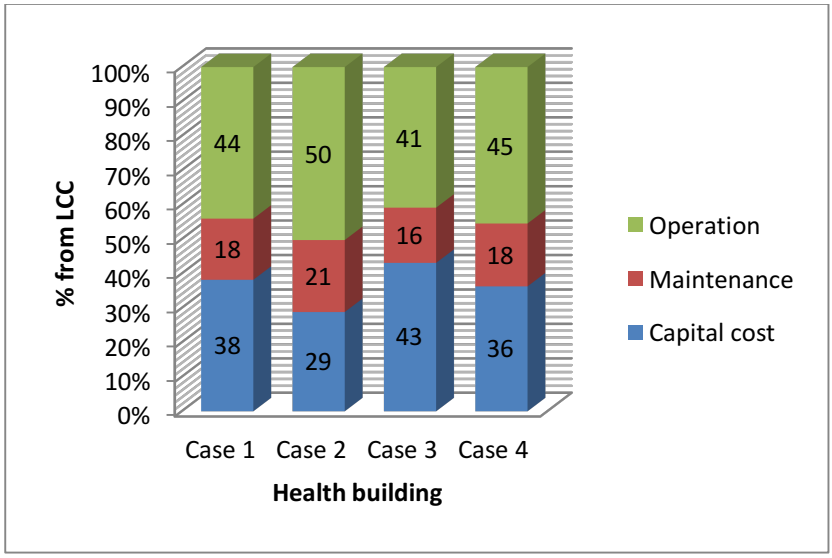


Figure 7. 3 Capital, operation and maintenance costs for health buildings

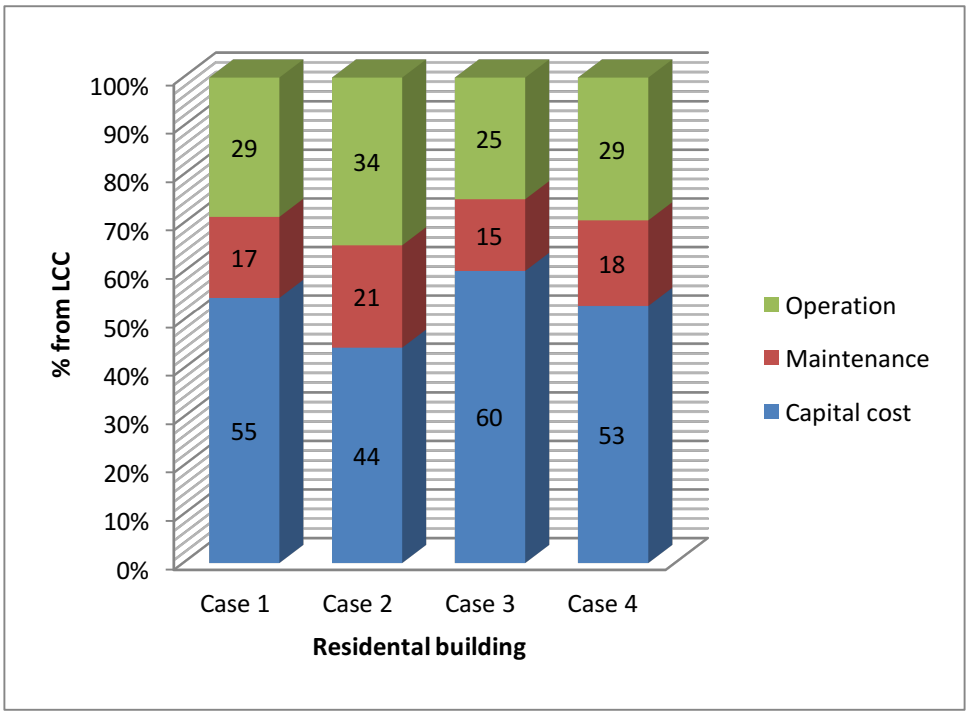


Figure 7. 4 Capital, operation and maintenance costs for residential buildings

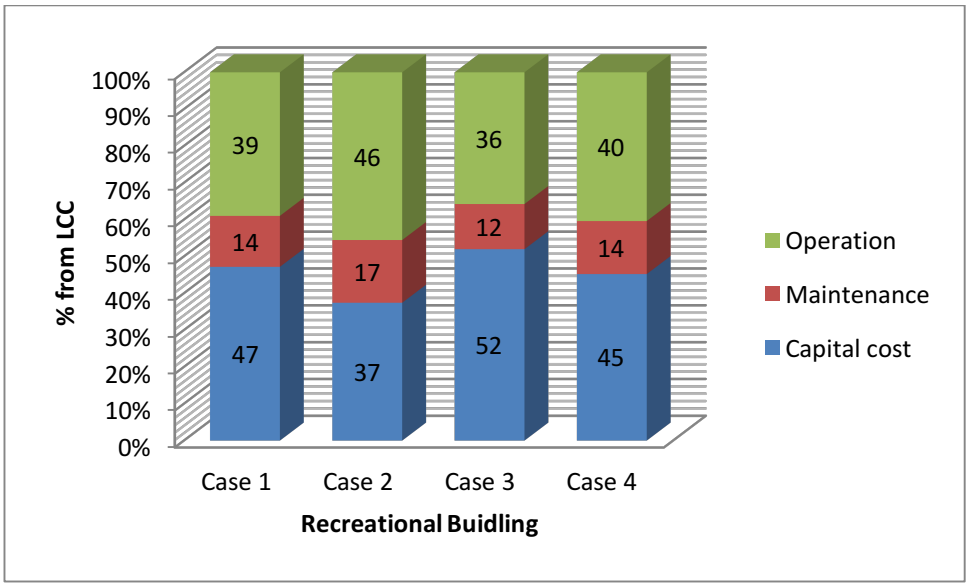


Figure 7. 5 Capital, operation and maintenance costs for recreational buildings

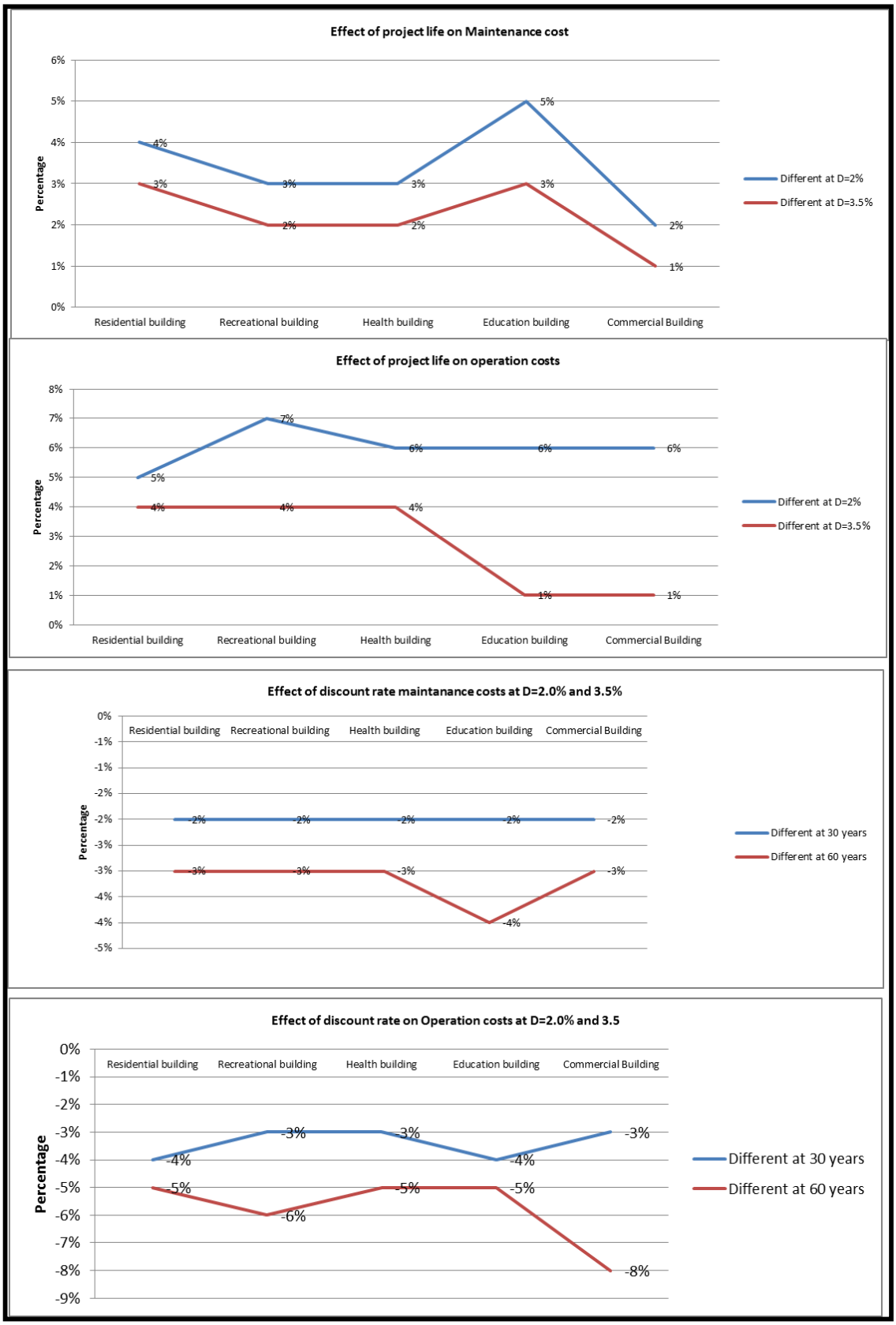


Figure 7. 6 Effect of project life and discount rate

7.3. Cost-Significant Items

In an attempt to identify cost-significant items, a sample of 15 projects was analysed. These projects were randomly selected from over 113 projects. The sample covered a very wide range of building projects, with a gross internal floor area ranging between 200 and 8000 m^2. Table 7.2 below provides more details of the data used concerning the type of structure, number of stories, gross floor area, type of building, location, number of elevators and type of foundation.

Table 7. 2 General descriptive of 15 projects used in identification CSIs

Project number	Gross internal area	External area	Number of stories	Type of structure	Total capital cost	total maintenance costs	total operation costs
1	744	368	2	steel-framed	598837	299969	828094
2	481	104	1	steel-framed	685987	306539	1023358
3	642	2023	1	steel-framed	810160	614289	1769572
4	763	664	1	steel-framed	753971	496955	1358332
5	1150	19503	1	steel-framed	3822286	2185951	3264938
6	1175	1062	2	steel-framed	1929546	692276	1859253
7	8000	2591	2	steel-framed	10914656	3009867	11282326
8	3290	11553	1	steel-framed	3541856	2347810	4716385
9	200	767	2	Timber-framed	3481854	888984	2963280
10	843	535	2	Timber-framed	1186467	385601	1275452
11	712	644	2	steel-framed	1320785	733769	1614292
12	1357	3656	2	steel-framed	15951212	9900752	29152214
13	1078	857	2	steel-framed	782458	627387	1904266
14	1930	778	3	steel-framed	2281112	991951	3135962
15	861	38520	2	Timber-framed	3147889	1935750	1177645

In all cases, running costs are over 50% of the total LCC of the building illustrated, as can be noted from Figure 7.7.

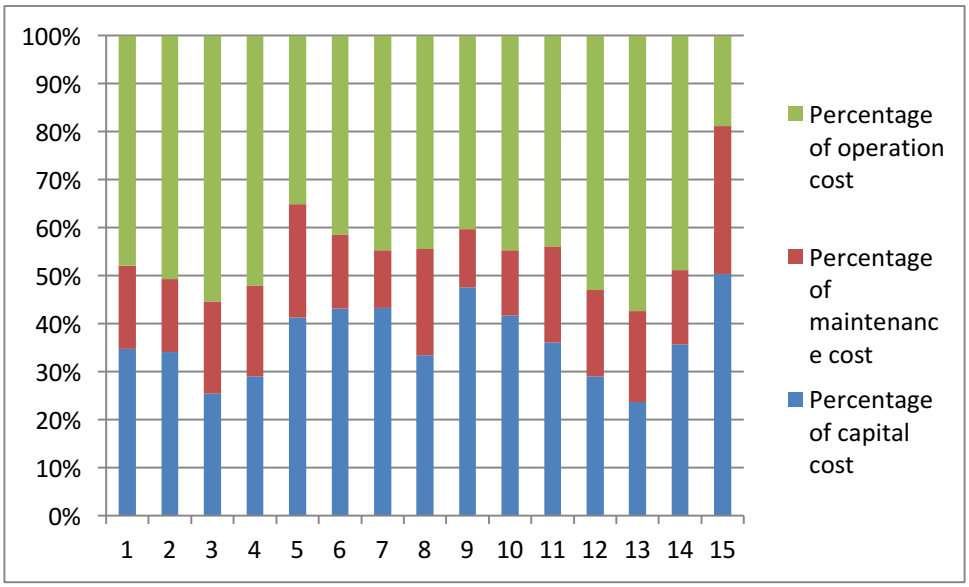


Figure 7. 7 Capital, operation and maintenance costs for 15 projects

As mentioned in the previous chapter, the analysis was prepared in accordance with the new Standardized Method of Life Cycle Costing for Construction Procurement (SMLCC). This new standard has additionally split the various repair categories into costs for fabric and service maintenance to allow the estimator to make a reasonable comparison with previous analyses.

The purpose of the analysis was to find out the proportion of total value and the number of measured items which the cost-significant items represent. The definition of cost-significant items (CSIs) used in this analysis was those measured items whose individual values were greater than the mean value of all measured items.

The aim here was to arrive at the CSIs by following a logical and systematic step-by-step procedure. This can be achieved by breaking down the analysis into two distinct phases, as shown in Figure 7.8.

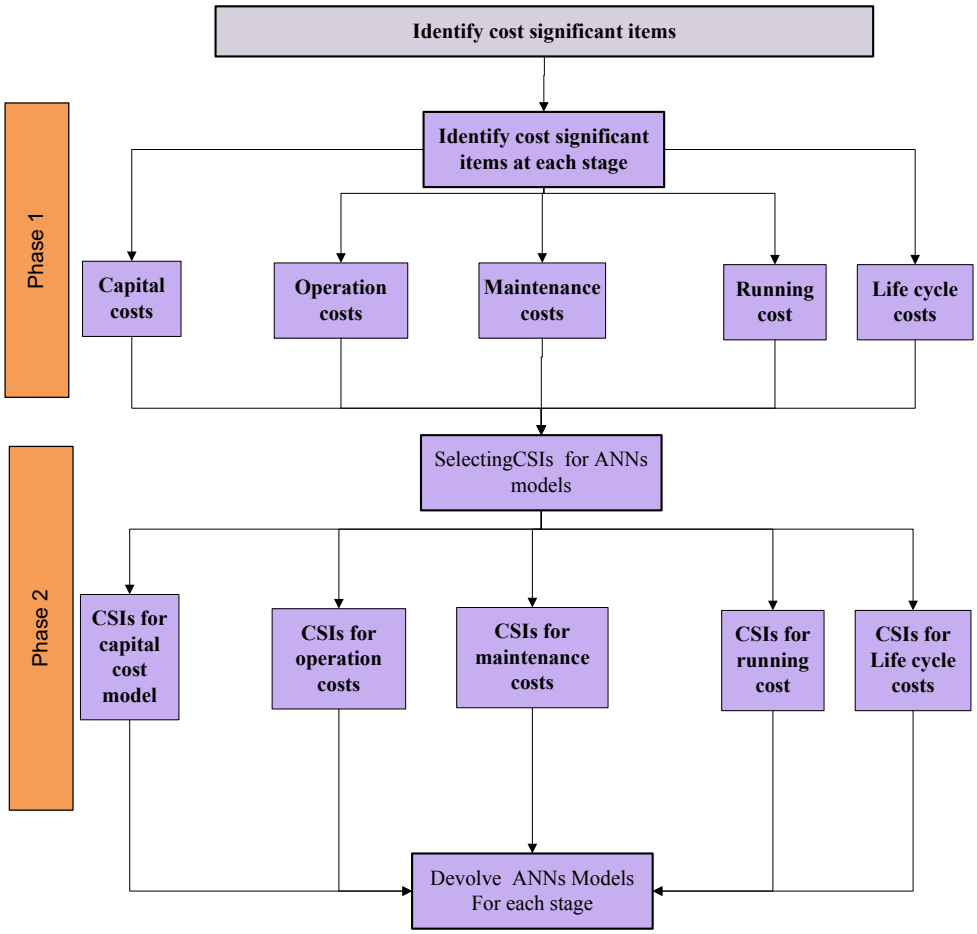


Figure 7. 8 Phases of CSIs

7.4. PHASE 1: Identification of Cost-Significant Items

In this phase the CSIs for each project for 20 years at different building stages are identified. They are identified based on the following step:

1- Create a table listing all cost elements and amount at each stage of construction projects and arrange the cost elements from the highest to lowest, based on the amount of cost. This can easily be achieved using the spreadsheet (Excel) programme.

2- The average value of the cost items is calculated by dividing the total cost of items by the number of priced items.

3- Then all the cost items whose values exceed the average are selected as the CSIs.

4- The values of these CSIs are summed up and divided by the total value of the project to calculate the proportion that the CSIs contribute to the total cost.

5- The number of these CSIs are summed up and divided by the total number of items of project to calculate the proportion that the CSIs contribute to the total number of items of the project.

6- Plot the cumulative distribution curve which is the cumulative percentage item value versus cumulative percentage of item number. These items represent the majority of the total value, so they potentially offer an efficient way to handle the total value of a set of data by controlling only the significant items.

The method by which this was done is outlined in the following sections.

7.4.1. Identification of Cost-Significant Items for capital costs

The SMLCC was used to classify the format of the elements of the project. The project was analysed based on the element level, as mentioned in chapter 5, Table 5.3.

This stage consists of 28 elements used in the calculations. Each project was analysed separately. Table 7.3 below represents the results of the analysis of the first project after applying the previous six steps.

Table 7. 3 Cumulative value, quantity and number of items for first project (capital cost)

Element Number	Total cost (£)	Cumulative cost (£)	Cumulative percentage total number of items	Cumulative percentage total value
1	**499175**	**499175**	**4%**	**14.09%**
2	**436296**	**935471**	**7%**	**26.41%**
3	**380680**	**1316151**	**11%**	**37.16%**
4	**302790**	**1618941**	**14%**	**45.71%**
5	**286689**	**1905630**	**18%**	**53.80%**
6	**253602**	**2159232**	**21%**	**60.96%**
7	**217140**	**2376372**	**25%**	**67.09%**
8	**183275**	**2559647**	**29%**	**72.27%**
9	**153783**	**2713430**	**32%**	**76.61%**
10	106829	2820259	36%	79.63%
11	84422	2904681	39%	82.01%
12	83519	2988200	43%	84.37%
13	68805	3057005	46%	86.31%
14	65819	3122824	50%	88.17%
15	62081	3184905	54%	89.92%
16	49285	3234190	57%	91.31%
17	46062	3280252	61%	92.61%
18	41799	3322051	64%	93.79%
19	38785	3360836	68%	94.89%
20	36780	3397616	71%	95.93%
21	34846	3432462	75%	96.91%
22	25695	3458157	79%	97.64%
23	24391	3482548	82%	98.33%
24	21951	3504499	86%	98.95%
25	11757	3516256	89%	99.28%
26	10272	3526528	93%	99.57%
27	8374	3534902	96%	99.80%
28	6954	3541856	100%	100.00%
Total	3541856			
Average	126494.9			

The results indicate that 32% of the items (9 items of the total number of items) account for about 77% of the total capital cost of the first project. Figure 7.9 below

shows the plots of cumulative value versus the cumulative number of items. It shows the high contribution of a relatively small number of items to the total capital costs. Similar analyses were conducted to identify CSIs for all 15 projects.

The summary of the results for all projects is also shown in Table 7.4. These results indicate that on average, CSIs account for 73% of the total capital costs of the projects, representing, on average, 32% of the total number of measured items.

The resulting coefficients of variation (CVs) of both the CSI values and the numbers are 15% and 7%, respectively. These results show that the data seem to be homogenous. Figure 7.10 below shows the plots of cumulative value versus the cumulative number of items for all 15 projects.

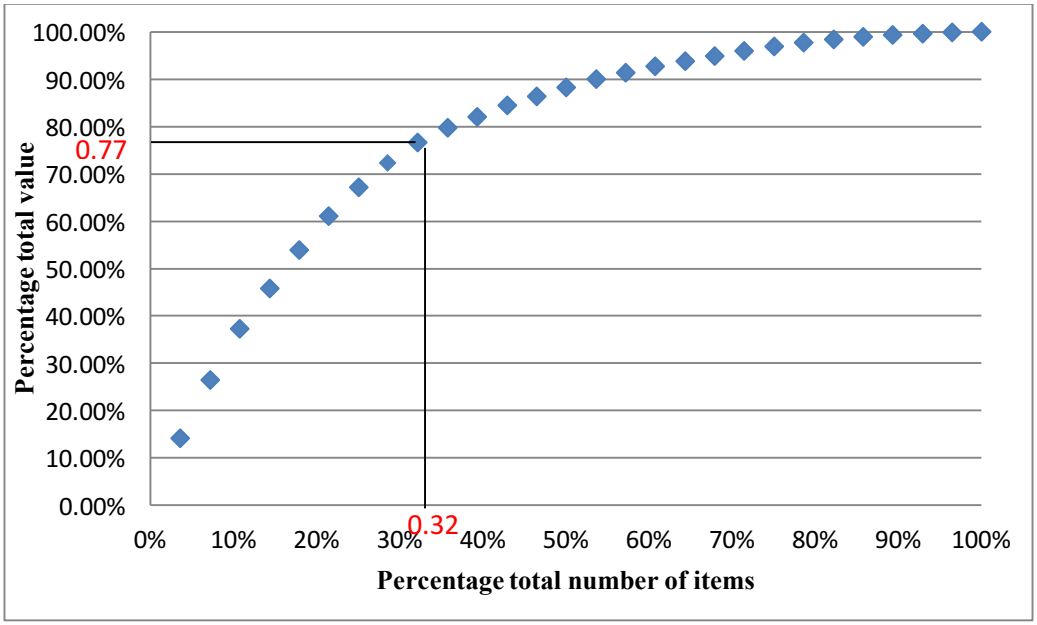


Figure 7. 9 The plots of cumulative value versus cumulative number of items of first project (capital cost)

Table 7. 4 Cumulative value, quantity and number of items for all project (capital cost)

Project Number	Total cost (£)	Mean	CSIs Number	CSIs Value	Percentage total number of items (%)	Percentage total value (%)
1	598835	26036.3	7	459278	30	77
2	685988	34299.4	9	526697	45	77
3	922705	48563.4	8	709746	38	77
4	753971	34271.4	9	553547	41	73
5	3822286	159261.917	6	2875094	25	75
6	1929547	91883.2	8	1388175	38	72
7	10914656	454777.3	8	7453679	33	68
8	3541856	126494.857	9	2713430	32	77
9	3481852	174092.6	9	2681865	45	77
10	1186467	59323.35	8	889646	40	75
11	1320788	57425.5652	9	931662	39	71
12	1832212	67859.7037	10	1308296	37	71
13	782457	39122.85	8	592065	40	76
14	2451115	129006.053	6	1379459	32	56
15	3105836	124233.44	8	2320705	32	75
Average	2488704.733	108443.4218	8	1785556.267	37	73
Coefficient of variance (%)					15.41	7.31

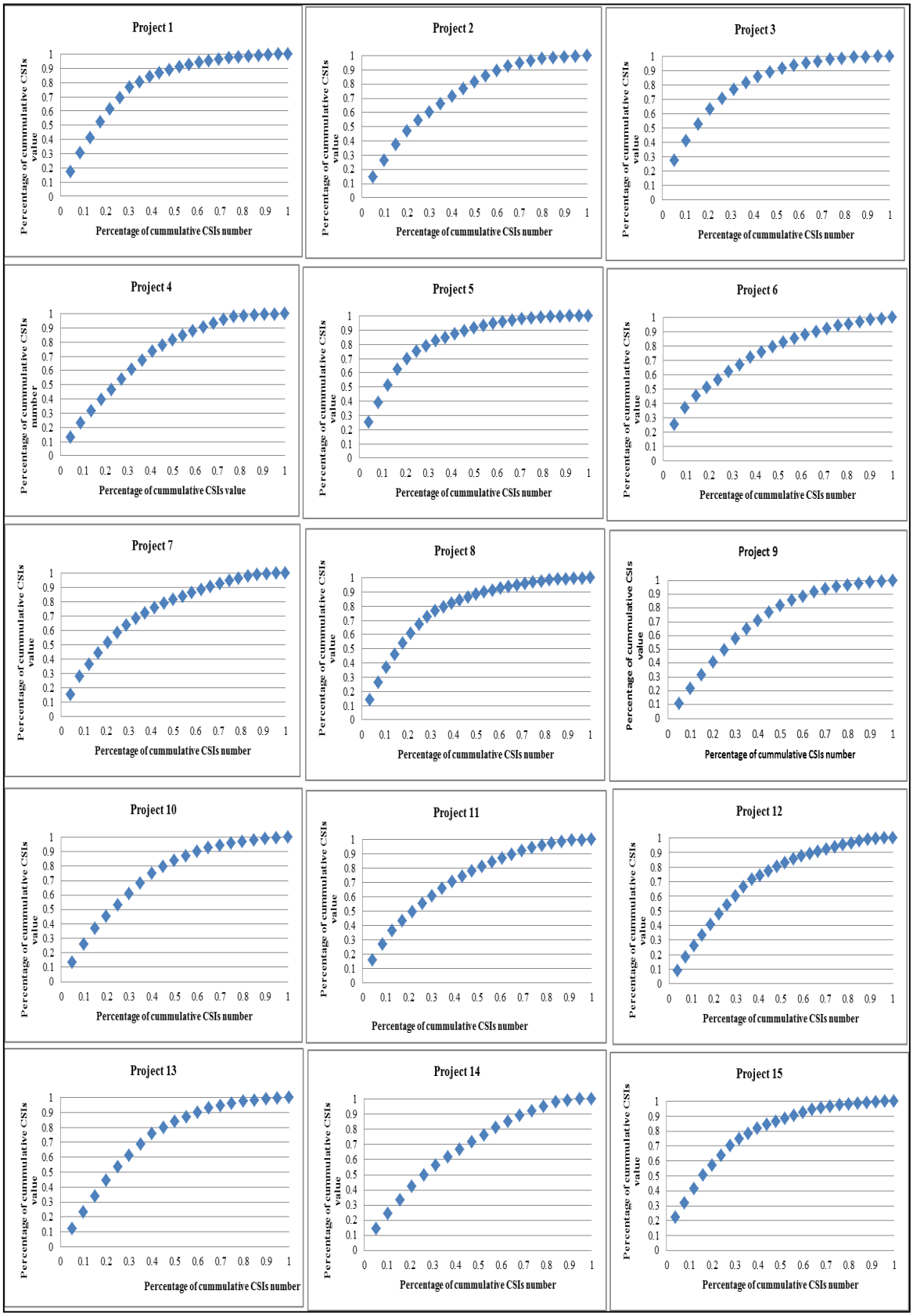


Figure 7. 10 The plots of cumulative value versus cumulative number of items of all project (capital cost)

Each of the elements identified as being a CSI and accepted for inclusion into the next phase, according to the decision rules defined in the beginning of this phase, was tabulated according to the categories of buildings. This information is presented in Table 7.5 below, which reveals that some elements appear as CSIs in all projects. However, some elements may occur less consistently than others but still have a greater effect on the total capital costs.

Table 7. 5 The plots of cumulative value versus cumulative number of items of all project (capital cost)

	Project Number														
Element	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
2C Roof	CSI	CSI		CSI	CSI	CSI	CSI	CSI	CSI	CSI	CSI	CSI	CSI	CSI	CSI
2E External walls	CSI		CSI	CSI	CSI	CSI	CSI	CSI	CSI	CSI	CSI	CSI	CSI	CSI	CSI
1 Substructure	CSI	CSI	CSI	CSI	CSI	CSI	CSI	CSI	CSI	CSI	CSI	CSI	CSI		
2A Frame	CSI	CSI		CSI		CSI	CSI	CSI		CSI	CSI	CSI	CSI	CSI	CSI
5F Space Heating and Air Conditioning			CSI	CSI		CSI	CSI	CSI	CSI	CSI	CSI	CSI	CSI	CSI	CSI
5H Electrical installations			CSI	CSI	CSI	CSI	CSI	CSI	CSI		CSI	CSI	CSI	CSI	CSI
6A Site works	CSI	CSI	CSI	CSI	CSI				CSI	CSI	CSI	CSI	CSI		CSI
2F External Windows and Doors	CSI	CSI	CSI	CSI		CSI			CSI	CSI	CSI	CSI	CSI		
2G Internal walls and partitions						CSI	CSI	CSI				CSI			
3B Floor finishes		CSI		CSI			CSI								
4 Fitting									CSI	CSI					CSI
5J Lift and conveyor installations	CSI				CSI						CSI				
5L Communications installations								CSI				CSI			
2H Internal doors									CSI						
3A Wall finishes		CSI													

5G Ventilating systems								CSI							
5N Builder's work in connection														CSI	
6B Drainage		CSI													
6C External services		CSI													CSI

7.4.2. Identification of Cost-Significant Items for maintenance costs

The SMLCC was used to classify the format of the elements of the project. The project was analysed based on the element level, as mentioned in chapter 5, Table 5.4. This stage consists of 20 elements used in the calculations. Each project was analysed separately.

The summary of the results for all projects is also shown in Table 7.6. These results indicate that on average, CSIs account for 78% of the total maintenance costs of the projects, representing, on average, 26% of the total number of measured items.

The resulting coefficients of variation (CVs) of both the CSI values and the numbers are 29% and 6%, respectively. These results show that the data seem to be homogenous. Figure 7.11 below shows the plots of cumulative value versus the cumulative number of items for all 15 projects.

Each of the elements identified as being a CSI and accepted for inclusion into the next phase, according to the decision rules defined in the beginning of this phase, was tabulated according to the categories of buildings.

This information is presented in Table 7.7 below, which reveals that some elements appear as CSIs in all projects. However, some elements may occur less consistently than others but still have a greater effect on the total capital costs.

Table 7. 6 Cumulative value, quantity and number of items for all project (maintenance cost)

Project Number	Total cost (£)	Mean	CSIs Number	CSIs Value	Percentage total number of items (%)	Percentage total value (%)
1	299968	16664.9	6	247343	33	82
2	306537	15326.9	4	229457	20	75
3	614290	32331.1	6	531914	32	87
4	496954	31059.6	4	352686	25	71
5	2185949	115049.9	3	1756264	16	80
6	692275	34613.8	7	575879	35	83
7	3009865	167214.7	6	2505411	33	83
8	2347808	123568.8	5	1778043	26	76
9	126603	6330.2	6	94164	30	74
10	310182	16325.4	8	242133	42	78
11	2841147	149534	4	2338576	21	82.3
12	3634383	191283	4	2706502	21	74.5
13	627387	33020.4	4	466055	21	74.3
14	991953	49597.7	5	711049	25	78
15	1906898	95344.9	3	1463920	15	76.8
Average	1359480	71818	5	1066626	26	78
Coefficient of variance (%)					29.05	5.64

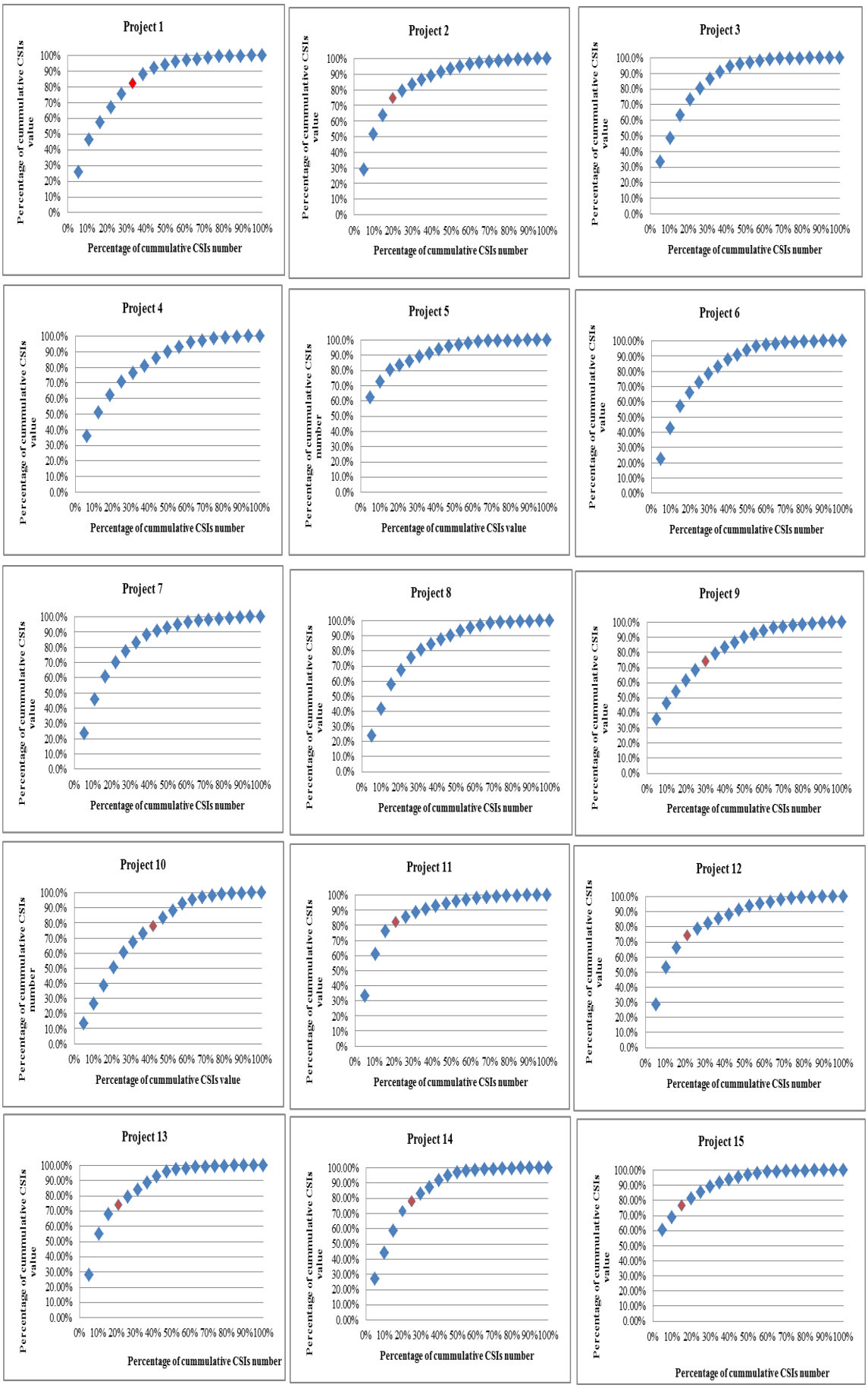


Figure 7. 11 The plots of cumulative value versus cumulative number of items of all project (maintenance cost)

Table 7. 7 Maintenance Cost significant Items identification

	Project Number														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
2.4.5 Services	CSI	CSI	CSI	CSI	CSI	CSI	CSI	CSI	CSI	CSI	CSI	CSI	CSI	CSI	CSI
2.1.5 Services	CSI	CSI	CSI	CSI		CSI	CSI	CSI	CSI	CSI			CSI	CSI	CSI
2.3.3 Finishes	CSI	CSI				CSI	CSI		CSI	CSI	CSI	CSI		CSI	
2.4.2 Superstructure	CSI	CSI		CSI		CSI	CSI			CSI	CSI	CSI		CSI	
2.1.3 Finishes			CSI	CSI		CSI	CSI	CSI					CSI	CSI	
2.1.8 External works	CSI		CSI		CSI	CSI	CSI	CSI		CSI					
2.4.8 External works			CSI						CSI	CSI	CSI	CSI	CSI		
2.6 External works			CSI		CSI	CSI		CSI	CSI						CSI
2.1.4 Fittings									CSI	CSI					
2.3.2 Superstructure	CSI									CSI					

7.4.3. Identification of Cost-Significant Items for operation costs

The SMLCC was used to classify the format of the elements of the project. The project was analysed based on the element level, as mentioned in chapter 5, Table 5.4. This stage consists of 12 elements used in the calculations. Each project was analysed separately.

The summary of the results for all projects is also shown in Table 7.8. These results indicate that on average, CSIs account for 70% of the total operation costs of the projects, representing, on average, 28% of the total number of measured items. The resulting coefficients of variation (CVs) of both the CSI values and the numbers are 24% and 11%, respectively.

These results show that the data seem to be homogenous. Figure 7.12 below shows the plots of cumulative value versus the cumulative number of items for all 15 projects.

Each of the elements identified as being a CSI and accepted for inclusion into the next phase, according to the decision rules defined in the beginning of this phase, was tabulated according to the categories of buildings.

This information is presented in Table 7.9 below, which reveals that some elements appear as CSIs in all projects.

However, some elements may occur less consistently than others but still have a greater effect on the total capital costs.

Table 7. 8 Cumulative value, quantity and number of items for all project (operation cost)

Project Number	Total cost (£)	Mean	CSIs Number	CSIs Value	Percentage total number of items (%)	Percentage total value (%)
1	720656.6	60054.7	4	526874	33	73
2	1123136	93594.7	3	861120.4	25	77
3	1385207.6	115434.0	2	763004	17	55
4	1152341.4	96028.5	5	809786.8	42	70

5	1867412.8	169764.8	2	1240506	18	66
6	1799953.8	149996.15	3	1262751	25	70
7	11570346.2	1051849.7	3	9584022	27	83
8	4453284.8	404844.1	3	3586294	27	81
9	106028	10602.8	4	84428	40	80
10	194848	27835.4	2	123628	29	63
11	1429217.2	119101.4	3	969455.2	25	68
12	2493813.2	207817.8	3	1761014	25	71
13	1681676	140139.7	3	1013677	25	60
14	2771097	230924.7	3	1847693	25	67
15	1170220	97518.3	4	802240	33	69
Average	2261282.6	198367.1	3	1682432.9	28	70
Coefficient of variance (%)					24.8	11.1

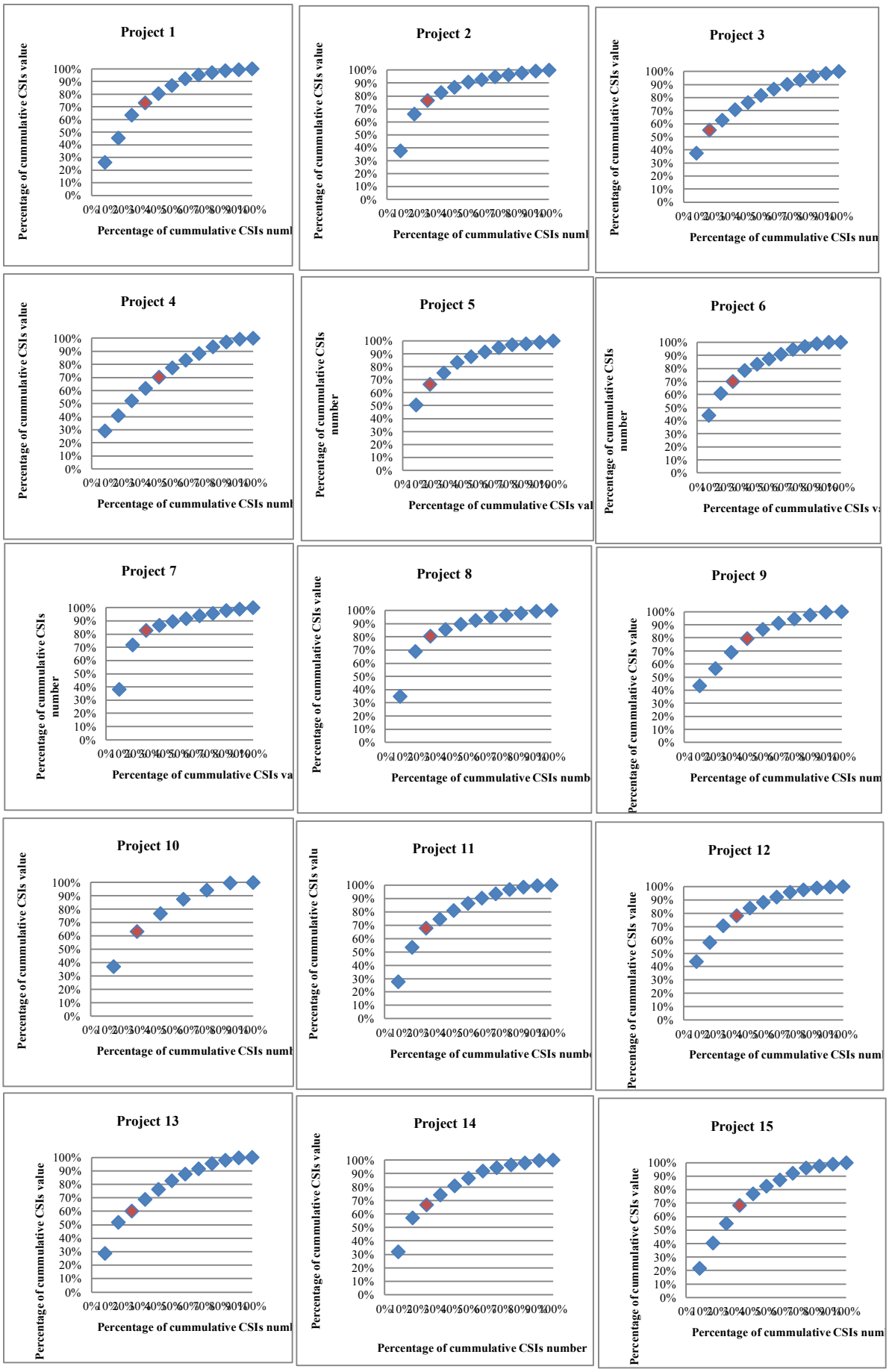


Figure 7. 12 The plots of cumulative value versus cumulative number of items of all project (operation cost)

Table 7. 9 Operation Cost significant Items identification

	Project Number														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
3.1.2. Internal cleaning	CSI	CSI	CSI	CSI	CSI	CSI	CSI	CSI			CSI	CSI	CSI	CSI	CSI
3.5.1 Rate and other local charges	CSI	CSI	CSI	CSI	CSI	CSI	CSI	CSI			CSI	CSI	CSI	CSI	CSI
3.3.1 Property management	CSI					CSI		CSI	CSI	CSI					
3.2.2 Fuel-Electricity				CSI									CSI	CSI	CSI
3.3.2 Staff engaged in servicing the building				CSI					CSI		CSI	CSI			
3.4.1 Property insurance							CSI		CSI	CSI					CSI
3.2.1 Fuel-gas	CSI	CSI		CSI											
3.1.1 Windows and external surfaces									CSI						

7.4.4. Identification of Cost-Significant Items for running costs

The SMLCC was used to classify the format of the elements of the project. The project was analysed based on the element level, as mentioned in chapter 5, Table 5.4. This stage consists of 32 elements used in the calculations. Each project was analysed separately.

The summary of the results for all projects is also shown in Table 7.10. These results indicate that on average, CSIs account for 78% of the total running costs of the projects, representing, on average, 28% of the total number of measured items. The resulting coefficients of variation (CVs) of both the CSI values and the numbers are 21% and 4 %, respectively. These results show that the data seem to be homogenous. Figure 7.13 below shows the plots of cumulative value versus the cumulative number of items for all 15 projects.

Each of the elements identified as being a CSI and accepted for inclusion into the next phase, according to the decision rules defined in the beginning of this phase, was tabulated according to the categories of buildings.

This information is presented in Table 7.11 below, which reveals that some elements appear as CSIs in all projects. However, some elements may occur less consistently than others but still have a greater effect on the total capital costs.

Table 7. 10 Cumulative value, quantity and number of items for all projects (running cost)

Project Number	Total cost (£)	Mean	CSIs Number	CSIs Value	Percentage total number of items (%)	Percentage total value (%)
1	1020624.6	34020.8	9	800941	30	78
2	1429673	44677.3	7	1134421	22	79
3	1999497.6	64499.9	10	1587310	32	79
4	1649295.4	58903.4	10	1274965	36	77
5	4053361.8	135112.1	7	3312291	23	82
6	2492228.8	77882.2	8	1889017	25	76
7	14580211.2	502765.9	5	10963299	21	75
8	6801092.8	226703.1	6	4944238	20	73
9	232631	7754.4	9	171009	30	74
10	505030	19424.2	10	378200	38	75
11	4270364	137754	7	3308031	23	77.5
12	6128195.7	197683.7	8	4650981	26	75.9
13	2309063	74485.9	10	1897283	32	82.2
14	3763049.8	117595.3	11	3260903	34	86.7
15	3077118	96159.9	8	2363220	25	76.8
Average	3620762.4	119694.8	8.3	2795740.6	28	78
Coefficient of variance (%)					20.63	4.62

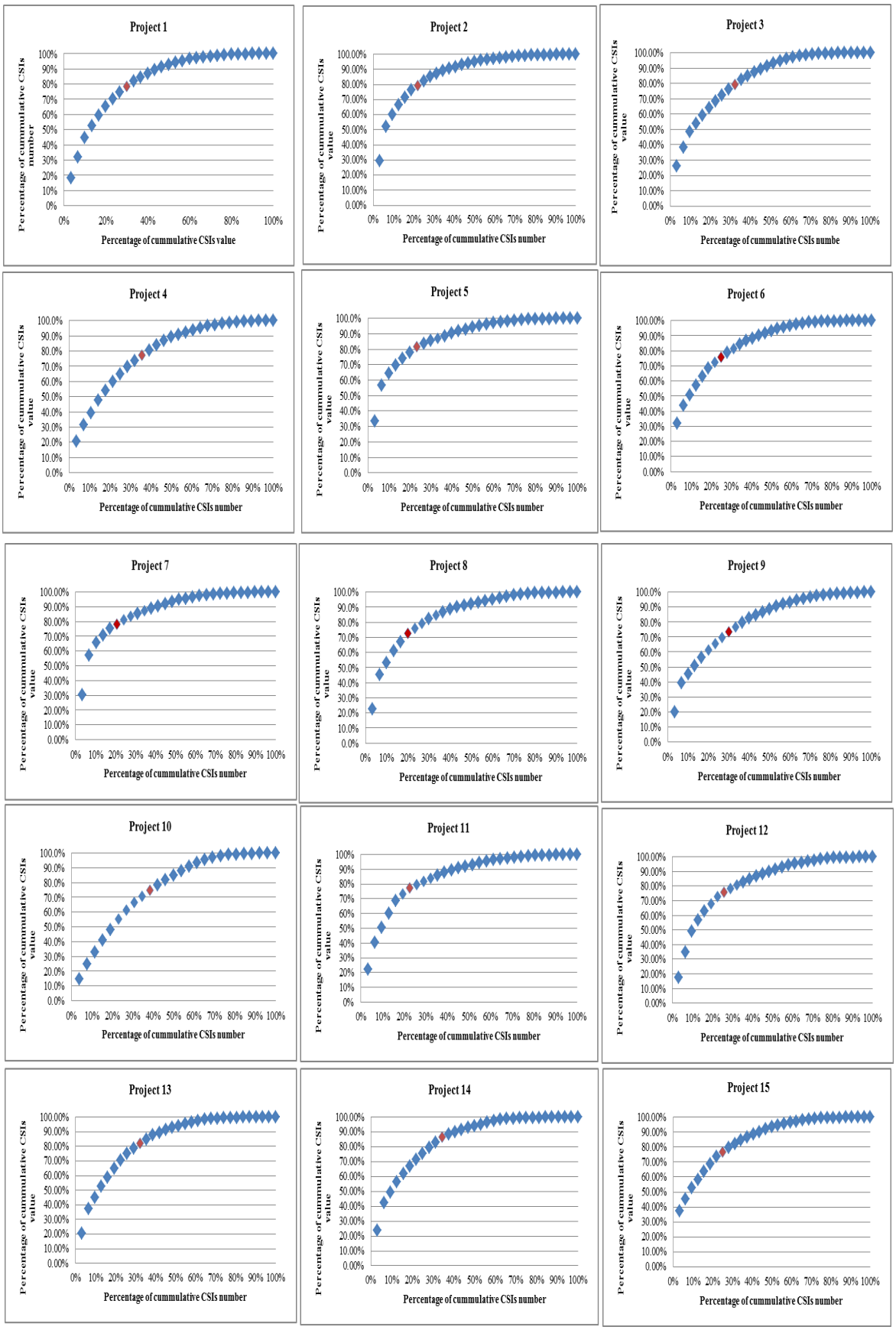


Figure 7. 13 The plots of cumulative value versus cumulative number of items of all project (running cost)

Table 7. 11 Running Cost significant Items identification

	Project number														
Elements	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
2.4.5 Services	CSI	CSI	CSI	CSI	CSI	CSI	CSI		CSI		CSI	CSI	CSI	CSI	CSI
3.1.2. Internal cleaning	CSI	CSI	CSI	CSI	CSI	CSI	CSI	CSI			CSI	CSI	CSI	CSI	CSI
3.5.1 Rate and other local charges	CSI	CSI	CSI	CSI	CSI	CSI	CSI	CSI			CSI	CSI	CSI	CSI	CSI
3.3.2 Staff engaged in servicing the building	CSI		CSI	CSI					CSI	CSI	CSI	CSI	CSI	CSI	
2.1.5 Services	CSI	CSI	CSI			CSI	CSI	CSI	CSI	CSI			CSI	CSI	CSI
3.4.1 Property insurance	CSI	CSI		CSI	CSI	CSI	CSI		CSI	CSI			CSI	CSI	CSI
3.2.2 Fuel-Electricity	CSI		CSI	CSI		CSI						CSI	CSI	CSI	CSI
3.3.1 Property management	CSI	CSI		CSI	CSI	CSI		CSI	CSI	CSI					
2.3.3 Finishes									CSI	CSI	CSI	CSI		CSI	
2.6 External works			CSI		CSI			CSI	CSI						CSI
3.2.1 Fuel-gas	CSI	CSI	CSI	CSI										CSI	
2.4.8 External works										CSI	CSI	CSI	CSI		
3.2.3 Water and drainage			CSI	CSI									CSI	CSI	
2.1.3 Finishes				CSI		CSI								CSI	
2.1.8 External works					CSI			CSI		CSI					
2.4.2 Superstructure										CSI	CSI	CSI			
3.1.1 Windows and external surfaces									CSI	CSI			CSI		
2.1.4 Fittings									CSI						

2.3.2 Superstructure										CSI					
3.1.3 Specialist cleaning															CSI
3.1.4 External works cleaning			CSI												

7.4.5. Identification of Cost-Significant Items for LCC

The SMLCC was used to classify the format of the elements of the project. The project was analysed based on the element level, as mentioned in chapter 5, Table 5.3 and 5.4. This stage consists of 32 elements used in the calculations. Each project was analysed separately.

The summary of the results for all projects is also shown in Table 7.12. These results indicate that on average, CSIs account for 77% of the total LCC of the projects, representing, on average, 30% of the total number of measured items.

The resulting coefficients of variation (CVs) of both the CSI values and the numbers are 20% and 7%, respectively. These results show that the data seem to be homogenous. Figure 7.14 below shows the plots of cumulative value versus the cumulative number of items for all 15 projects.

Each of the elements identified as being a CSI and accepted for inclusion into the next phase, according to the decision rules defined in the beginning of this phase, was tabulated according to the categories of buildings.

This information is presented in Table 7.13 below, which reveals that some elements appear as CSIs in all projects. However, some elements may occur less consistently than others but still have a greater effect on the total capital costs.

Table 7. 12 Cumulative value, quantity and number of items for all projects (life cycle cost)

Project Number	Total cost (£)	Mean	CSIs Number	CSIs Value	Percentage total number of items (%)	Percentage total value (%)
1	1619459.6	30555.8	17	1293503	32.08	79.87
2	2115661	40685.8	13	1551263.4	25	73.32
3	2922202.6	58444.1	17	2359039.6	34	80.73
4	2403266.4	48065.3	20	1892287.2	40	78.74
5	7875647.8	145845.3	14	6336195.2	25.93	80.45
6	4421775.8	83429.7	16	3277192	30.19	74.11
7	25494867.2	481035.2	13	18416978	24.53	72.24
8	10342948.8	178326.7	17	8149626.2	29.31	78.79
9	3714483	74289.7	14	3264361	28	87.88
10	1691497	36771.7	17	1313685	36.96	77.66
11	5591152	103540	10	3790574	18.52	67.8
12	7960407.74	137248.4	14	5564585.63	24.14	69.9
13	3091520	60618	18	2503560.2	35.29	80.98
14	6214164.8	121846.4	19	4892760.4	37.25	78.74
15	6182954	108472.9	16	4696669	28.07	75.96
Average	6109467.18	113945.00	15.67	4620151.99	29.95	77.14
Coefficient of variance (%)					19.86	6.56

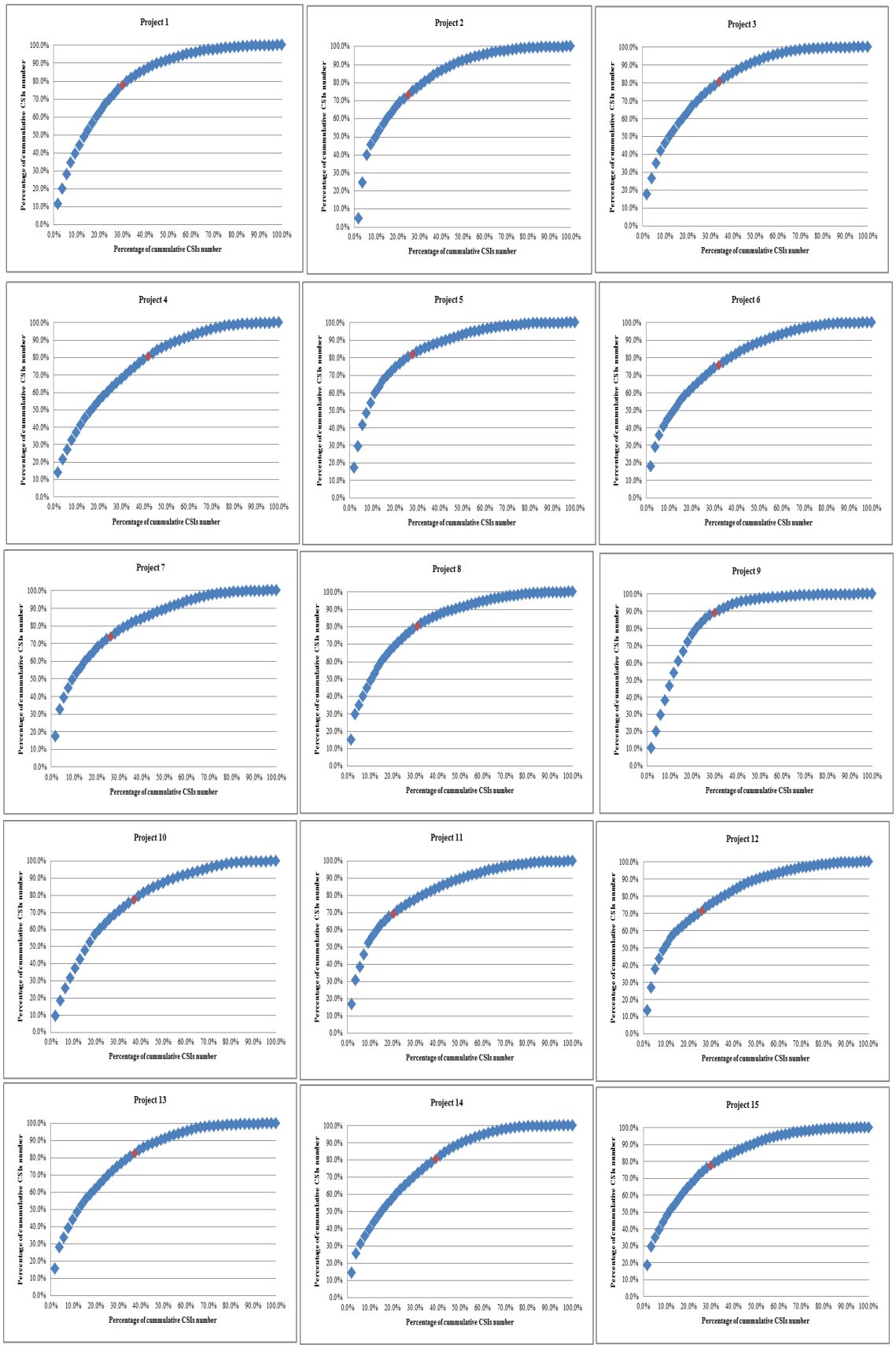


Figure 7. 14 The plots of cumulative value versus cumulative number of items of all project (life cycle cost)

Table 7. 13 Life cycle Cost significant Items identification

	Project number														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
2E External walls	CSI		CSI	CSI	CSI	CSI	CSI	CSI	CSI	CSI	CSI	CSI	CSI	CSI	CSI
2.4.5 Services	CSI	CSI	CSI	CSI	CSI	CSI	CSI	CSI			CSI	CSI	CSI	CSI	CSI
3.1.2. Internal cleaning	CSI	CSI	CSI	CSI	CSI	CSI	CSI	CSI			CSI	CSI	CSI	CSI	CSI
3.5.1 Rate and other local charges	CSI	CSI	CSI	CSI	CSI	CSI	CSI	CSI			CSI	CSI	CSI	CSI	CSI
2C Roof	CSI	CSI		CSI	CSI	CSI	CSI	CSI	CSI	CSI		CSI		CSI	CSI
5H Electrical installations			CSI		CSI	CSI	CSI	CSI	CSI	CSI	CSI	CSI	CSI	CSI	CSI
6A Site works	CSI	CSI	CSI	CSI	CSI				CSI	CSI	CSI	CSI	CSI	CSI	CSI
3.4.1 Property insurance	CSI	CSI	CSI	CSI	CSI	CSI	CSI			CSI		CSI	CSI	CSI	CSI
1 Substructure	CSI	CSI	CSI	CSI	CSI	CSI	CSI	CSI	CSI	CSI			CSI		
2A Frame	CSI	CSI		CSI		CSI	CSI	CSI	CSI	CSI			CSI	CSI	CSI
5F Space Heating and Air Conditioning			CSI	CSI	CSI	CSI	CSI		CSI	CSI			CSI	CSI	CSI
2.1.5 Services	CSI	CSI	CSI			CSI	CSI	CSI		CSI			CSI	CSI	CSI
3.2.2 Fuel-Electricity	CSI	CSI	CSI	CSI		CSI		CSI				CSI	CSI	CSI	CSI
3.3.1 Propartey management	CSI	CSI	CSI	CSI	CSI	CSI		CSI		CSI			CSI		
2F External Windows and Doors	CSI	CSI	CSI	CSI	CSI	CSI			CSI	CSI					
3.3.2 Staff engaged in servicing the building	CSI		CSI	CSI							CSI	CSI	CSI	CSI	
2.1.3 Finishes			CSI	CSI		CSI		CSI						CSI	
3.2.1 Fuel-gas	CSI	CSI	CSI	CSI										CSI	
2G Internal walls and partitions						CSI	CSI	CSI	CSI						
3B Floor finishes				CSI			CSI		CSI	CSI					
4 Fitting									CSI	CSI				CSI	CSI
2.3.3 Finishes										CSI	CSI	CSI		CSI	
2.6 External works			CSI		CSI			CSI							CSI
2.1.8 External works					CSI			CSI		CSI					
2.4.2 Superstructure				CSI							CSI	CSI			
2.4.8 External works											CSI	CSI	CSI		
3.2.3 Water and drainage				CSI									CSI	CSI	
3A Wall finishes									CSI	CSI					
6B Drainage										CSI					CSI
2.3.2 Superstructure	CSI											CSI			
3.1.4 External works cleaning				CSI									CSI		
2H Internal doors									CSI						
3C Ceiling finishes									CSI						
5G Ventilating systems								CSI							
5J Lift and conveyor installations	CSI														

5L Communications installations								CSI							
5N Builder's work in connection														CSI	
6C External services															CSI
3.1.1 Windows and external surfaces													CSI		

As the sample represents five types of building, an ANOVA test was conducted to examine the results of both the percentages of CSI value, and the number is no different between these types of building, at a significance level of a=0.05.

The normality test and Levene's statistic were conducted, and the sample data was likely drawn from a normally distributed population and the assumption of homogeneity of variance was not violated. Appendix II provides more detail with respect to these test results. Table 7.14 shows the main results of the ANOVA test, which indicate that there is no difference between the groups regarding the results of both the percentage CSI values and the number, at a significance level of a=0.05 and F-critical=3.6.

At the end of this phase, CSIs had been identified for all stages of building life. At each stage of the building life cycle, a group of very similar items were consistently identified as cost significant. However, a few items show a tendency towards a lack of consistency in terms of being CSIs or not. These cases may occur because some components are utilised more often in some types of buildings than in others.

For example, plumbing is used more often in residential buildings than in education buildings; therefore, it needs more care in the former than in the latter. In addition, some components existed in a few buildings but not in others. Therefore, all these CSIs at each stage of building life were further analysed in phase 2 in order to determine whether a CSI has a significant effect on the total costs for all types of buildings, including in the final model.

Table 7. 14 ANOVA results of both the percentage CSIs value and number of 15 projects.

		Test of Homogeneity of Variances		ANOVA	
		Levene Statistic	P-value	F	P-value
Capital costs	% of CSI's Value	2.586	0.106	0.719	0.561
	% of CSI's Number	0.634	0.608	1.099	0.39
Maintenance costs	% of CSI's Value	2.75	0.093	0.22	0.881
	% of CSI's Number	0.359	0.784	2.43	0.12
Operation costs	% of CSI's Value	3.467	0.054	0.518	0.678
	% of CSI's Number	1.053	0.408	1.296	0.325
Running costs	% of CSI's Value	1.316	0.318	3.389	0.058
	% of CSI's Number	1.039	0.412	1.205	0.366
LCC	% of CSI's Value	1.006	0.427	2.451	0.118
	% of CSI's Number	0.228	0.875	1.516	0.265

7.5.Phase 2: Selecting Cost Significant-Items

After identifying CSIs, the next step was to select the CSIs for use in the ANN modelling of costs, applying the mean value of identified CSIs at each stage of building life across all 15 projects.

This was considered to be too many for optimal efficiency. In order to further reduce the number of CSIs for a cost estimating model, a method is used which considerably reduces the number of items. This method applies the mean value method to the importance rate (IR) rank, so that the number of CSIs can be reduced efficiently.

7.5.1. Determine the importance rate

The factor used to measure the contribution of cost items is the IR, which is the percentage contribution of a cost item's value to the total value of the 15 projects.

$$\boldsymbol{IR} = \frac{\sum_{j=1}^{15} \boldsymbol{Ci}}{\sum_{j=1}^{15} \boldsymbol{Ct}} \ldots\ldots\ldots\ldots (\mathbf{7.1})$$

where: $\boldsymbol{Ci}$: The value of a cost item in each project; and $\boldsymbol{Ct}$: the total costs of each project .

The final CSIs included in the ANN model were identified on the basis of this rank, which indicated the contribution of each item to the overall value of all 15 projects at each stage of the building life cycle.

Correlation analysis was also applied to study the relationship between the importance rate result for each item and the item's frequency as a CSI.

Since the importance rate rank reveals the degree of significance of the cost items in descending order, the top-ranked significant items are the most important significant items; the last-ranked item is the least important significant item to the sample.

The CSIs in the upper part of the importance rank are more likely to be selected as the model CSIs than the items at the lower end of the rank.

According to the mean value method, the efficient way to handle the total of the CSIs is to focus on the items which are bigger than the average. Therefore, the items exceeding the average of the IR result at each stage were deemed the CSIs for the ANN model. The results of the implementation of the IR method at each stage of building life are outlined in the following sections.

7.5.2. Selecting CSIs for ANNs models of capital cost

In Table 7.5, 19 items have been identified as CSIs affecting the capital costs. The 19 items were ranked by the importance rate, as shown in Table 7.15. The plot of two factors, the contribution of each item (importance rate) and its frequency as a CSI in the sample, is shown in Figure 7.15.

Correlation analysis of the data gives a correlation coefficient of r=0.92. Since this is again higher than the value of r at the 0.05 level of significance, it can be concluded that there is a strong positive linear relationship between the contribution of each item and its frequency as a CSI.

The items on the top of the importance rate rank contribute more to the total value of the sample and appear more often as CSIs in the bills; therefore, they are more likely to represent the model CSIs which represent a consistent proportion of the sample.

The average importance rate of the 19 significant items is 3.78%. The items whose importance rates exceed the average are the top 7 items in the importance rate rank. Therefore, they are the CSIs of the 19 items. These items are:

1) External walls
2) Electrical installation
3) Roof
4) Space heating and air condition
5) Site work
6) Frame
7) Substructure

These items appear to be CSIs in the sample more than 84% of the time, and they occurred as CSIs in all five types of buildings in the sample. The contribution of the items to the total capital cost is between 10.27% and 5.77%, with an average contribution of 8.2%. The cumulative contribution of the items to the total maintenance cost is about 60%.

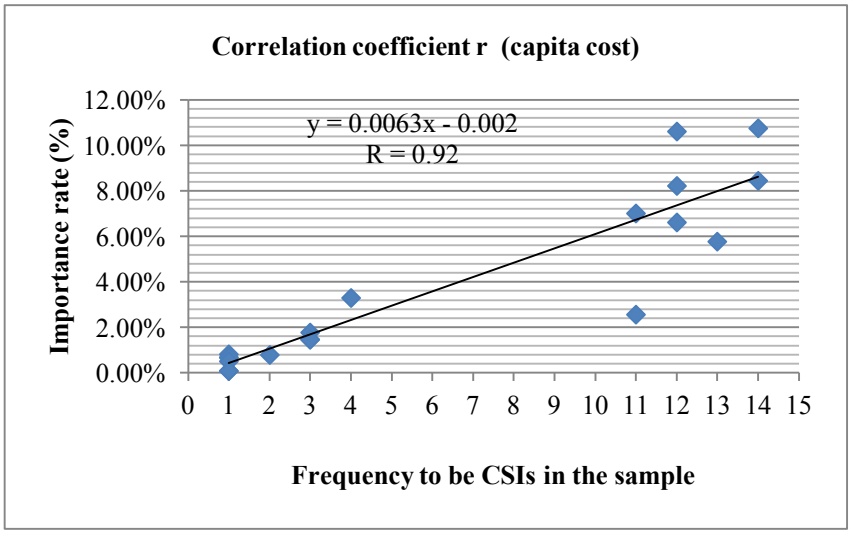


Figure 7. 15 Plot of importance rate of the 19 items and frequency to be CSIs (capital costs)

Table 7. 15 Importance rate rank and frequency of the CSIs for capital cost

Element	Frequency to be CSIs in the sample	Contribution of item to the sample (IR)	Cumulative contribution of the items
2E External walls	14	10.77%	10.77%
5H Electrical installations	12	10.61%	21.38%
2C Roof	14	8.46%	29.84%
5F Space Heating and Air Conditioning	12	8.23%	38.07%
6A Site works	11	7.01%	45.08%
2A Frame	12	6.62%	51.70%
1 Substructure	13	5.77%	57.47%
2G Internal walls and partitions	4	3.31%	60.78%
2F External Windows and Doors	11	2.58%	63.36%
3B Floor finishes	3	1.77%	65.13%
5J Lift and conveyor installations	3	1.48%	66.61%
4 Fitting	3	1.46%	68.07%
2H Internal doors	1	0.82%	68.89%
5L Communications installations	2	0.80%	69.69%
5G Ventilating systems	1	0.68%	70.37%
6C External services	1	0.68%	71.05%
5N Builder's work in connection	1	0.51%	71.56%
3A Wall finishes	1	0.10%	71.66%
6B Drainage	1	0.10%	71.76%
Average		3.78%	

7.5.3. Selecting CSIs for ANNs models of maintenance cost

In Table 7.7, 10 items have been identified as CSIs affecting the maintenance costs. The 10 items were ranked by the importance rate, as shown in Table 7.16. The plot of two factors, the contribution of each item (importance rate) and its frequency as a CSI in the sample, is shown in Figure 7.16. Correlation analysis of the data gives a correlation coefficient of r=0.68. Since this is again higher than the value of r at the 0.05 level of significance, it can be concluded that there is a strong positive linear relationship between the contribution of each item and its frequency as a CSI. The items on the top of the importance rate rank contribute more to the total value of the sample and appear more often as CSIs in the bills; therefore, they are more likely to represent the model CSIs which represent a consistent proportion of the sample.

The average importance rate of the 10 significant items is 7.88%. The items whose importance rates exceed the average are the top 5 items in the importance rate rank. Therefore, they are the CSIs of the 10 items. These items are:

1) Minor maintenance service (2.4.5 service)
2) Grounds Maintenance (2. 6 external works)
3) Minor maintenance external works (2.4.6 external works)
4) Minor maintenance superstructure (2.4.2 Superstructure)
5) Major maintenance service (2.1.5 service)

These items appear to be CSIs in the sample more than 84% of the time, and they occurred as CSIs in all five types of buildings in the sample. The contribution of the items to the total maintenace cost is between 16.69% to 9.27% with the average contribution of 12.6%.. The cumulative contribution of the items to the total maintenance cost is about 63%.

Minor maintenance costs are the most expensive element in CSIs and account for 38.15% of the total maintenance costs; they represent 60% of the total number of CSIs of maintenance costs. The reason is that the majority of the building's elements

require major maintenance every 15 years and some of them every 20 years. The major maintenance service accounts for 9.27% of the total maintenance.

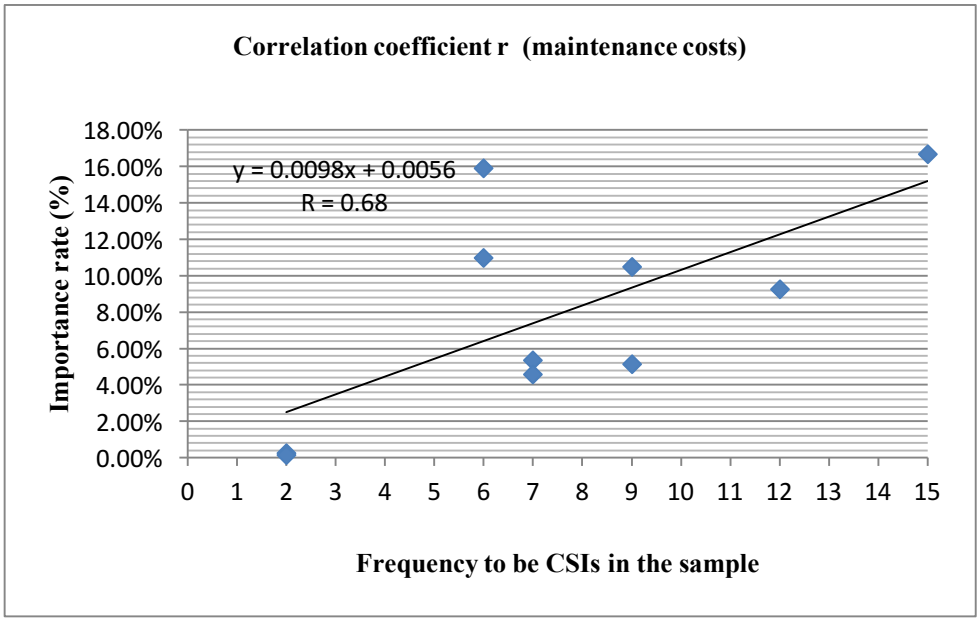


Figure 7. 16 Plot of importance rate of the 10 items and frequency to be CSIs (maintenance costs)

Table 7. 16 Importance rate rank and frequency of the CSIs for maintenance costs

Element	Frequency to be CSIs in the sample	Contribution of item to the sample (IR)	Cumulative contribution of the items
2.4.5 Services	15	16.69%	16.69%
2.6 External works	6	15.90%	32.59%
2.4.6 External works	6	10.97%	43.56%
2.4.2 Superstructure	9	10.49%	54.05%
2.1.5 Services	12	9.27%	63.32%
2.1.3 Finishes	7	5.36%	68.68%
2.3.3 Finishes	9	5.14%	73.82%
2.1.6 External works	7	4.56%	78.38%
2.3.2 Superstructure	2	0.27%	78.65%
2.1.4 Fittings	2	0.13%	78.78%
Average		7.88%	

7.5.4. Selecting CSIs for ANNs models of operation cost:

In Table 7.9, 8 items have been identified as CSIs affecting the operation costs. The 8 items were ranked by the importance rate, as shown in Table 7.17. The plot of two factors, the contribution of each item (importance rate) and its frequency as a CSI in the sample, is shown in Figure 7.18.

Correlation analysis of the data gives a correlation coefficient of r=0.97. Since this is again higher than the value of r at the 0.05 level of significance, it can be concluded that there is a strong positive linear relationship between the contribution of each item and its frequency as a CSI.

The items on the top of the importance rate rank contribute more to the total value of the sample and appear more often as CSIs in the bills; therefore, they are more likely to represent the model CSIs which represent a consistent proportion of the sample.

The average importance rate of the 8 significant items is 9.3%. The items whose importance rates exceed the average are the top 2 items in the importance rate rank. Therefore, they are the CSIs of the 8 items. These items are:

1) Internal cleaning
2) Rate and other local charges

These items appear to be CSIs in the sample more than 86.70% and they occurred as CSIs in all 5 types of building in the sample. The contribution of items to the total operation cost is 33.87% for internal cleaning and 27.63% for rate and other local charges with the average contribution of 30.75%. The cumulative contribution of items to the total operation cost is about 62%.

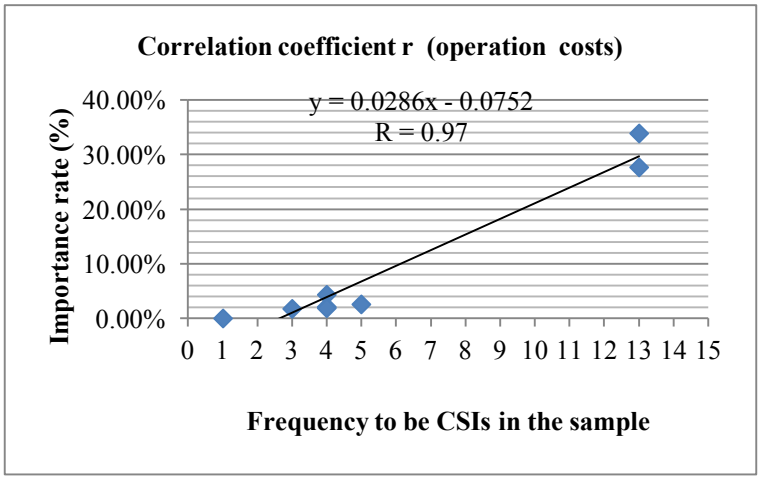


Figure 7. 17 Plot of importance rate of the 8 items and frequency to be CSIs (operation costs)

Table 7. 17 Importance rate rank and frequency of the CSIs for operation costs

Element	Frequency to be CSIs in the sample	Contribution of item to the sample (IR)	Cumulative contribution of the items
3.1.2. Internal cleaning	13	33.87%	33.87%
3.5.1 Rate and other local charges	13	27.63%	61.50%
3.4.1 Property insurance	4	4.43%	65.93%
3.3.1 Property management	5	2.59%	68.52%
3.2.2 Fuel-Electricity	4	2.14%	70.66%
3.3.2 Staff engaged in servicing the building	4	1.95%	72.61%
3.2.1 Fuel-gas	3	1.76%	74.37%
3.1.1 Windows and external surfaces	1	0.03%	74.40%
Average		9.30%	

7.5.5. Selecting CSIs for ANNs models of running costs

In Table 7.11, 21 items have been identified as CSIs affecting the running costs. The 21 items were ranked by the importance rate, as shown in Table 7.18. The plot of two factors, the contribution of each item (importance rate) and its frequency as a CSI in

the sample, is shown in Figure 7.19. Correlation analysis of the data gives a correlation coefficient of r=0.67. Since this is again higher than the value of r at the 0.05 level of significance, it can be concluded that there is a strong positive linear relationship between the contribution of each item and its frequency as a CSI.

The items on the top of the importance rate rank contribute more to the total value of the sample and appear more often as CSIs in the bills; therefore, they are more likely to represent the model CSIs which represent a consistent proportion of the sample.

The average importance rate of the 21 significant items is 3.68%. The items whose importance rates exceed the average are the top 6 items in the importance rate rank. Therefore, they are the CSIs of the 21 items. These items are:

1) Internal cleaning
2) Rate and other local charges
3) Grounds Maintenance (2. 6 external works)
4) Minor maintenance service (2.4.5 service)
5) Property insurance
6) Minor maintenance external works (2.4.6 external works)

These items appear to be CSIs in the sample more than 65.50% and they occurred as CSIs in all 5 types of building in the sample. The contribution of items to the total running cost is between 21.15% to 4.03% with the average contribution of 9.70%. The cumulative contribution of items to the total running cost is about 60%.

The operation costs elements in CSIs of running cost are account for 42.56% of the total running costs; they represent 50% of the total number of CSIs in running cost. The maintenance costs elements in CSIs of running cost are account for 15.76% of the total running costs. These maintenance costs only represent minor and ground maintenance and they represent 50% of the total number of CSIs in running cost.

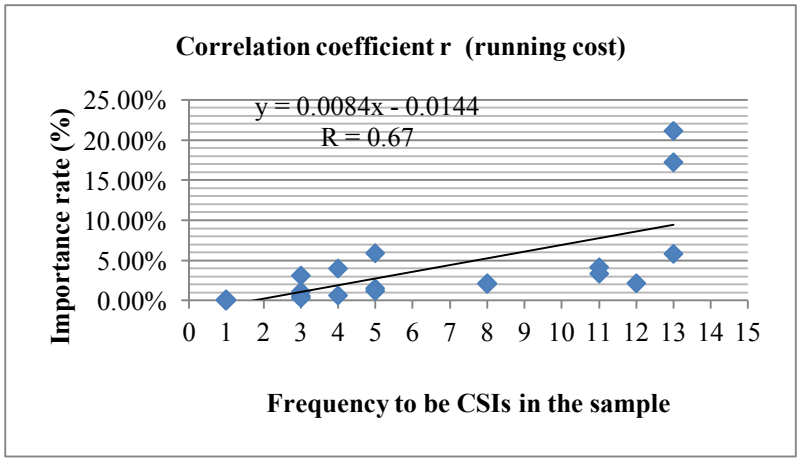


Figure 7. 18 Plot of importance rate of the 21 items and frequency to be CSIs (running costs)

Table 7. 18 Importance rate rank and frequency of the CSIs for running costs

Element	Frequency to be CSIs in the sample	Contribution of item to the sample (IR)	Cumulative contribution of the items
3.1.2. Internal cleaning	13	21.15%	21.15%
3.5.1 Rate and other local charges	13	17.25%	38.40%
2.6 External works	5	5.90%	44.30%
2.4.5 Services	13	5.83%	50.13%
3.4.1 Property insurance	11	4.16%	54.29%
2.4.8 External works	4	4.03%	58.32%
2.1.5 Services	11	3.40%	61.72%
2.4.2 Superstructure	3	3.13%	64.85%
3.3.1 Property management	8	2.18%	67.03%
3.3.2 Staff engaged in servicing the building	12	2.16%	69.19%
3.2.2 Fuel-Electricity	8	2.07%	71.26%
3.2.1 Fuel-gas	5	1.57%	72.83%
2.3.3 Finishes	5	1.22%	74.05%
2.1.8 External works	3	1.15%	75.20%
3.2.3 Water and drainage	4	0.68%	75.88%
2.1.3 Finishes	3	0.63%	76.51%
3.1.1 Windows and external surfaces	3	0.32%	76.83%
3.1.3 Specialist cleaning	1	0.18%	77.01%
3.1.4 External works cleaning	1	0.14%	77.15%
2.3.2 Superstructure	1	0.04%	77.19%
2.1.4 Fittings	1	0.02%	77.21%
Average		3.68%	

7.5.6. Selecting CSIs for ANNs models of LCC:

In Table 7.13, 39 items have been identified as CSIs affecting the LCC. The 39 items were ranked by the importance rate, as shown in Table 7.19. The plot of two factors, the contribution of each item (importance rate) and its frequency as a CSI in the sample, is shown in Figure 7.20.

Correlation analysis of the data gives a correlation coefficient of r=0.70. Since this is again higher than the value of r at the 0.05 level of significance, it can be concluded that there is a strong positive linear relationship between the contribution of each item and its frequency as a CSI. The items on the top of the importance rate rank contribute more to the total value of the sample and appear more often as CSIs in the bills; therefore, they are more likely to represent the model CSIs which represent a consistent proportion of the sample.

The average importance rate of the 39 significant items is 1.94 %. The items whose importance rates exceed the average are the top 14 items in the importance rate rank. Therefore, they are the CSIs of the 39 items. These items are:

1) Internal cleaning
2) Rate and other local charges
3) External walls
4) Electrical installations
5) Minor maintenance services
6) Ground maintenance works
7) Space Heating and Air Conditioning
8) Roof
9) Site works
10) Property insurance
11) Frame
12) Minor maintenance of external works
13) Substructure
14) Major maintenance of service

These items appear to be CSIs in the sample more than 66.67% and they occurred as CSIs in all 5 types of building in the sample. The contribution of items to the total life cost is between 12.54% to 2.0% with the average contribution of 4.29%. The cumulative contribution of items to the total running cost is about 60%.

The capital costs elements in CSIs of LCC are account for 23.15 % of the total LCC and the represent of 50% of the total number of CSIs of LCC. All of these items have also been identified as CSIs of capital costs.

The operation costs elements in CSIs of LCC are account for 25.47% of the total LCC and the represent of 21% of the total number of CSIs of LCC. Two of these three items have also been identified as CSIs of operation costs.

The maintenance costs elements in CSIs of LCC are account for 11.49% of the total LCC and the represent of 29% of the total number of CSIs of LCC. These items have also been identified as CSIs of maintenance costs. Table 7.20 below summaries the CSIs at each stage of building lifecycle.

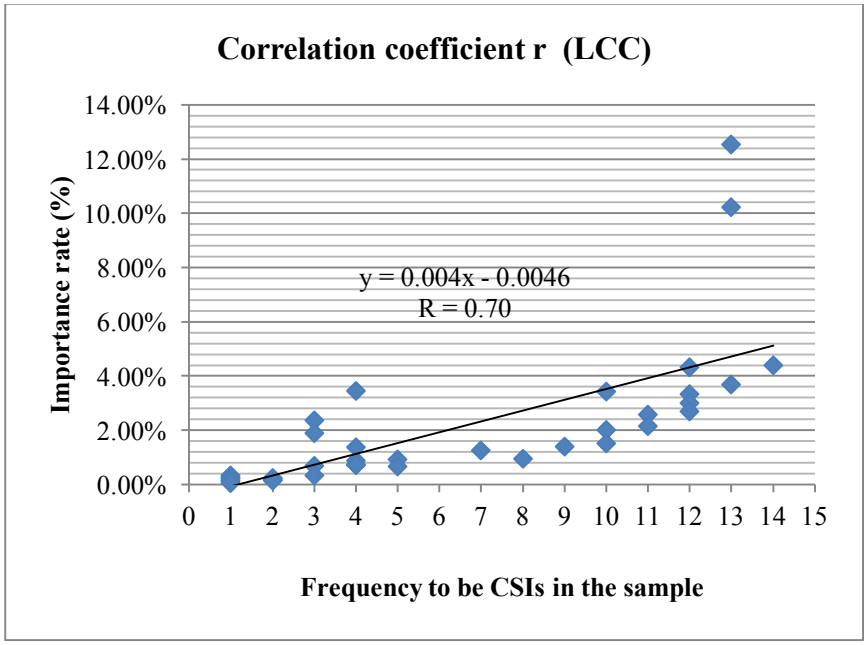


Figure 7. 19 Plot of importance rate of the 39 items and frequency to be CSIs (life cycle costs)

Table 7. 19 Importance rate rank and frequency of the CSIs for life cycle costs

Element	Frequency to	Contribution of item to the sample (IR)	Cumulative contribution of the items
3.1.2. Internal cleaning	13	12.54%	12.54%
3.5.1 Rate and other local charges	13	10.23%	22.77%
2E External walls	14	4.39%	27.16%
5H Electrical installations	12	4.31%	31.47%
2.4.5 Services	13	3.69%	35.16%
2.6 External works	4	3.45%	38.61%
5F Space Heating and Air Conditioning	10	3.41%	42.02%
2C Roof	12	3.32%	45.34%
6A Site works	12	3.00%	48.34%
3.4.1 Property insurance	12	2.70%	51.04%
2A Frame	11	2.57%	53.61%
2.4.8 External works	3	2.35%	55.96%
1 Substructure	11	2.15%	58.11%
2.1.5 Services	10	2.00%	60.11%
2.4.2 Superstructure	3	1.89%	62.00%
3.2.2 Fuel-Electricity	10	1.52%	63.52%
3.3.1 Property management	9	1.38%	64.90%
2G Internal walls and partitions	4	1.36%	66.26%
3.3.2 Staff engaged in servicing the	7	1.24%	67.50%
2F External Windows and Doors	8	0.94%	68.44%
3.2.1 Fuel-gas	5	0.93%	69.37%
3B Floor finishes	4	0.87%	70.24%
4 Fitting	4	0.73%	70.97%
2.3.3 Finishes	4	0.71%	71.68%
2.1.8 External works	3	0.68%	72.36%
2.1.3 Finishes	5	0.66%	73.02%
2H Internal doors	1	0.33%	73.35%
3.2.3 Water and drainage	3	0.33%	73.68%
5G Ventilating systems	1	0.28%	73.96%
6C External services	1	0.24%	74.20%
3A Wall finishes	2	0.23%	74.43%
5N Builder's work in connection	1	0.21%	74.64%
5L Communications installations	1	0.20%	74.84%
2.3.2 Superstructure	2	0.20%	75.04%
6B Drainage	2	0.17%	75.21%
3.1.1 Windows and external surfaces	1	0.15%	75.36%
3.1.4 External works cleaning	2	0.13%	75.49%
3C Ceiling finishes	1	0.11%	75.60%
5J Lift and conveyor installations	1	0.05%	75.65%
Average		1.94%	

Table 7. 20 Cost significant-items of all ANNs model of each stage of building life

The final CSI of all ANNs model of each stage of building life				
CSI of capital cost	CSI of maintenance cost	CSI of operation cost	CSI of running cost	CSI of LCC
1) External walls. 2) Electrical installation. 3) Roof. 4) Space heating and air condition. 5) Site work. 6) Frame. 7) Substructure	1) Minor maintenance service 2) Grounds Maintenance work 3) Minor maintenance external works 4) Minor maintenance superstructure 5) Major maintenance service	1) Internal cleaning 2) Rate and other local charges	1) Internal cleaning 2) Rate and other local charges 3) Grounds Maintenance work 4) Minor maintenance service 5) Property insurance 6) Minor maintenance external works	1) Internal cleaning 2) Rate and other local charges 3) External walls 4) Electrical installations 5) Minor maintenance services 6) Ground maintenance works 7) Space Heating and Air Conditioning 8) Roof 9) Site works 10) Property insurance 11) Frame 12) Minor maintenance of external works 13) Substructure 14) Major maintenance of service

7.6. Summary of this chapter

The concept of Pareto analysis was applied in this chapter order to simplify the data collection and analysis process.

The data from 15 projects has been used to identify the most important factors affecting the total cost at each stage of building's life cycle.

The analysis of this data was achieved by breaking the data-set down into two distinct phases in order to achieve the objective of this chapter.

In the first phase, the cost items that are significant in at least one project are identified. This step has been applied at each stage of building life cycle.
The result of this phase indicated that 19, 10, 8, 21, 39 items has been identified as CSIs affecting the capital , maintenance ,operation, running and life cycle costs, respectively.

In the second phase, important rate method has been applied to reduce and select the final CSIs at each stage. The result of this phase indicated that 7, 5, 2, 6, 14 items has been selected as the final CSIs affecting the capital , maintenance ,operation, running and life cycle costs, respectively.

8. CHAPTER EIGHT: DEVLOPING A NEURAL NETWORK MODEL TO PREDICT LIFE CYCLE COST

8.1. Introduction

This chapter describes the development of ANNs models of estimation of costs at each stage of building life cycle. Five models of ANNs have been developed to improve the current cost estimation processes. The most important factors affecting cost estimation at each stage of building life cycle were identified as outlined in chapter six and seven. These important factors were considered as input variables for each neural network models, whereas the total cost considered as the output variable to each models.

MATLAB Software version R2014a was utilized to train and test the neural networks models. These models were developed based on the feed forward back-propagation learning algorithm.

Traditional parametric (trial and error) has been performed to select the number of hidden layers and the number of hidden nodes. As a result, a number of alternative neural network structures were examined to obtain the best artificial neural network model to give the minimum value for the Mean Square Error (MSE).

After the best ANNs model was selected, a user interface has been developed on Microsoft Excel to make an application of the final model easier to use.

The following sections clarify the steps conducted to design the neural network model.

8.2. Design the Neural Networks Model

Neural networks model can be developed by the following five basic steps:

1. Identify the purpose of estimation. Decide what information to use and what the network will do.
2. Decide how to collect the data.
3. Define the network. Select network inputs and specify the outputs.
4. Train the network.
5. Test the trained network. This involves presenting new inputs to the network and comparing the network's results to reality. Fig.8.1 illustrates these five main steps.

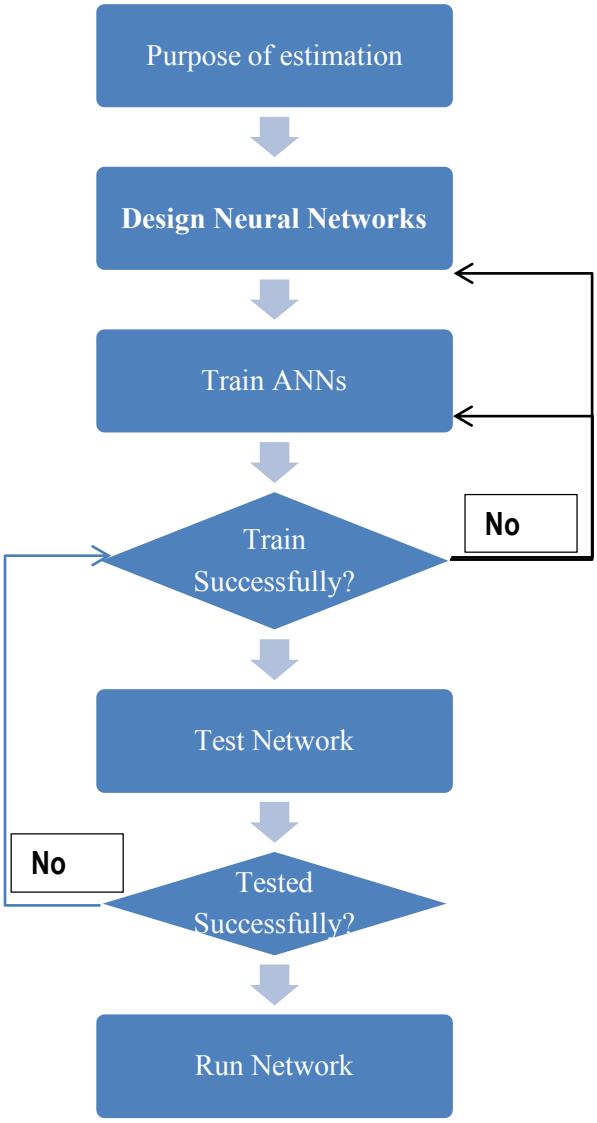


Figure 8.1 Design Neural Networks

8.2.1. The purpose of estimation

This study aims to estimate the total costs each stage of building life cycle. Therefore, five models of ANNs have been developed to different purpose.
These models are described in the table (8.1) below.

Table 8.1 Five ANNs models

Model number	**Objective**
Model 1	This model focuses in construction stage and aims to estimate the total capital costs.
Model 2	This model focus in operation stage and aims to estimate the total operation costs.
Model 3	This model focus in maintenance stage and aims to estimate the total maintenance costs.
Model 4	This model focus in running stage (maintenance + operation) and aims to estimate the total running costs.
Model 5	This model focus in all building stages (construction+ maintenance+ operation) and aims to estimate the total life cycle costs.

8.2.2. Design of Neural Networks

This step covers points to be considered to create and develop a neural network, including: selection, data-collection, and determination

8.2.2.1. Selection of NNs software/simulation

Many software designs are used to create neural network (NN) models. In this study, MATLAB software (2014 b) was used to develop the neural network model. This program is easier for the users, and its predictive accuracy is higher than that of other software. MATLAB consists of several options for modelling complex nonlinear systems in which it is difficult to find the relationship between variables. A neural

network is one of these options, and MATLAB provides a toolbox for neural networks to support supervised learning with feedforward, radial basis and dynamic networks. It also supports unsupervised learning with self-organising maps and competitive layers. Neural networks can be easily designed, trained on and tested by using this toolbox. It can be used for different purposes such as data fitting, pattern recognition, clustering, time-series prediction and dynamic system modelling and control.

8.2.2.2. Data collection

The second step in the design of neural network modelling is selecting, collecting and preparing suitable data. The accuracy of the NN model results depends on a clear identification and selection of the inputs and outputs of the model. In estimation cost modelling, there are two types of data needed to create a neural network model:

- ***Input data***: data identified as important affecting the result of the cost estimation model at each stage of building life cycle (chapter six and seven) representing CSIs and the important non-cost factors.
    - The roof type factor was excluded, as the majority of projects studied used more than one type.
    - In addition, the building life and inflation rate factors were excluded from first model, as they only affecting the future costs and the estimation of capital cost dependent on the actual cost of completing projects.
    - Maintenance and operation costs have been calculated based on the inflation rate and time period of the analysis.
    - As a result of survey, foundation type has been included in the estimation of capital cost model only.
- ***Output data***: the data collected from the BCIS representing the actual value of total costs at each stage of previous projects. Table 8.2 below illustrates the input and output data for each model.

Table 8.2 Input and output variables of each model

	the input and output data for each model				
	Model 1	Model 2	Model 3	Model 4	Model 5
Input variable		♦	♦	♦	♦
Project life		♦	♦	♦	♦
Inflation rate	♦	♦	♦	♦	♦
Type of building	♦	♦	♦	♦	♦
Type of structure	♦	♦	♦	♦	♦
Foundation type	♦				♦
Location	♦	♦	♦	♦	♦
Gross floor area	♦	♦	♦	♦	♦
Number of stories	♦	♦	♦	♦	♦
Number of elevator	♦	♦	♦	♦	♦
Total value of CSIs of life cycle costs	♦	♦	♦	♦	♦
Output variable					
Capital costs	♦				
Operation costs		♦			
Maintenance costs			♦		
Running costs				♦	
Life cycle costs					♦

The design of inputs and outputs in neural network are as figure (8.2) below:

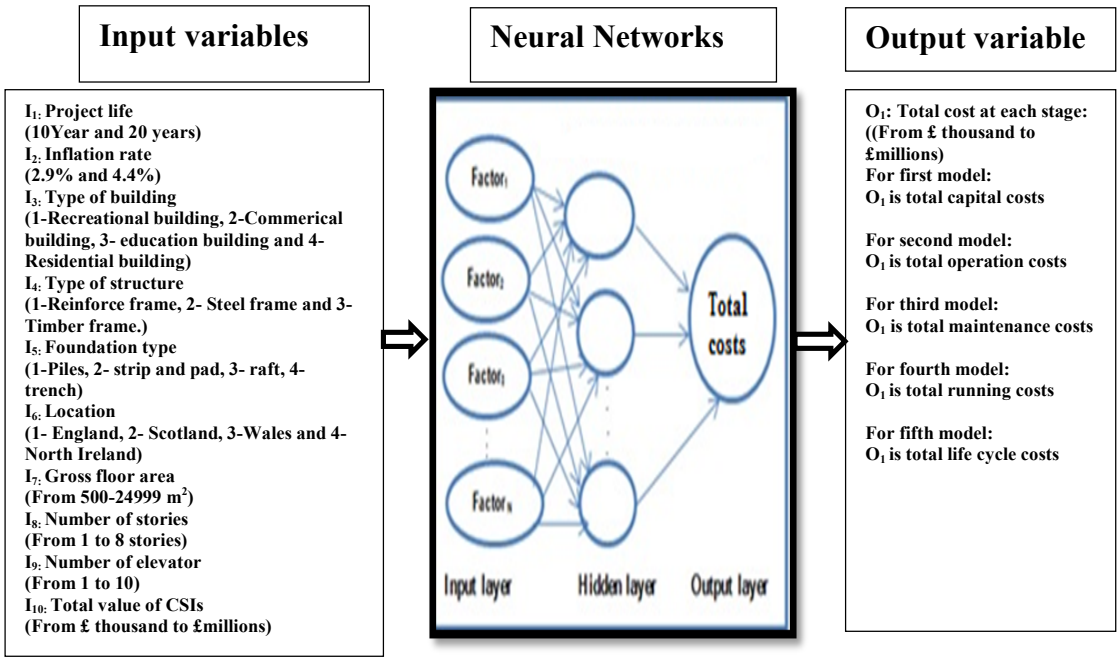


Figure 8.2 Description of neural network input and output variables

After identifying the important input and output variables to be included in the neural network model, these data can then be documented and collected for each project. Collecting the historical data from the completion of a project is a difficult step, because this kind of data is the property of each construction company. Most construction companies prefer not to share their cost data with other competing construction companies, as they usually believe that this information enhances their own chance to keep ahead of the competition. As a result, personal contacts were made with several construction companies.

The Building Cost Information Service (BCIS) database of the Royal Institution of Chartered Surveyors (RICS) indicated interest in providing such information, as mentioned in chapter 3. The cost data of one hander and 38 building projects were mostly collected and included in this research, including project documents containing cost and non-cost data describing the individual characteristics of each building.

Element	Description	Total cost (£)	Cost per m^2 (£)
Substructure	Concrete strip and pad foundations and bed. RC retaining walls	**107,565**	**125**
Frame	Laminated timber portal frame. Part steel frame.	278,545	324
Upper floors	RC upper floors. Timber decking	66,213	77
Roof	Softwood flat roof with sedum blanket on membrane.	287,527	334
Stairs and ramps	Timber stairs	0	0
External walls	Block walls with stone and timber cladding with lime render on wood-fibre boards. Curtain walls.	312,855	363
Windows and external doors	Double-glazed aluminium windows. Hardwood doors	67,645	79
Internal walls and partitions	Metal stud, timber stud and WC cubicle partitions.	37,011	43
Internal doors	Flush doors	19,005	22
Superstructure – Total		**1,068,801**	**1,241**
Wall finishes	Plasterboard and softwood boarding	33,583	39
Floor finishes	Vinyl, carpet, tile and softwood.	59,284	69
Ceiling finishes	Softwood boarding. Plasterboard suspended ceilings.	57,596	67
Internal Finishes – Total		**150,463**	**175**
Fittings		**197,533**	**229**
Sanitary appliances	Vitreous china, generally. 13Nr WCs, 12Nr	17,024	20

	YEAR 1	YEAR 2	YEAR 3	YEAR 4	YEAR 5	YEAR 6	YEAR 7	YEAR 8	YEAR 9	YEAR 10
Maintenance costs										
2.1 Major replacement										
Substructure										
2.1.1 Substructure										
2.1.1 Substructure total	0	0	0	0	0	0	0	0	0	0
Superstructure										
2.1.2.1 Frame										
2.1.2.2 Upper floors										
2.1.2.3 Roof										
2.1.2.4 Stairs and Ramps										
2.1.2.5 External walls										
2.1.2.6 Windows and external doors										
2.1.2.7 Internal walls and partitions										
2.1.2.8 Internal doors										
2.1.2 Superstructure total	0									
Finishes										
2.1.3.1 Wall finishes										

	YEAR 1	YEAR 2	YEAR 3	YEAR 4	YEAR 5	YEAR 6	YEAR 7	Y
Maintenance costs (continued)								
2.3 Redecorations								
Substructure								
2.3.1 Substructure								
2.3.1 Substructure total	0	0	0	0	0	0	0	
Superstructure								
2.3.2.1 Frame						3057		
2.3.2.2 Upper floors								
2.3.2.3 Roof						1099		
2.3.2.4 Stairs and ramps						1423		
2.3.2.5 External walls						5821		
2.3.2.6 Windows and external doors						284		
2.3.2.7 Internal walls and partitions								
2.3.2.8 Internal doors						1138		
2.3.2 Superstructure total	0	0	0	0	0	**12823**	0	
Finishes								
2.3.3.1 Wall finishes						11967		
2.3.3.2 Floor finishes						8467		
2.3.3.3 Ceiling finishes						3057		
2.3.3 Finishes total	0	0	0	0	0	**23492**	0	
Fittings								
2.3.4.1 Fittings, furnishings and equipment						53		
2.3.4 Fittings total	0	0	0	0	0	**53**	0	
Services								
2.3.5.1 Sanitary appliances								
2.3.5.2 Services equipment								
2.3.5.3 Disposal installations								
2.3.5.4 Water installations						281		
2.3.5.5 Heat source								
2.3.5.6 Space heating and air conditioning								
2.3.5.7 Ventilation systems								
2.3.5.8 Electrical installations								
2.3.5.9 Fuel installations								
2.3.5.10 Lift and conveyor installations								
2.3.5.11 Fire and lightning protection								
2.3.5.12 Communication, security and control systems								
2.3.5.13 Specialist installations								
2.3.5 Services total	0	0	0	0	0	**281**	0	
External Works								
2.3.8.1 Site preparation works								
2.3.8.2 Roads, paths, pavings and surfacings								
2.3.8.3 Soft landscaping, planting and irrigation systems								
2.3.8.4 Fencing, railings and walls						399		
2.3.8.5 External fixtures								
2.3.8.6 External services								

Element	Specification
1 Substructure	RC strip foundations and basement with bitumen tanking. 215mm common brick wall.
2A Frame	88.32t steel frame including trusses.
2B Upper floors	433m2 hollow section PCC floor.
2C Roof	Steel purlins and cladding rails with 0.7gauge 1770m2 zinc sheet. Aluminium louvres. Latc

Figure 8.3 Examples of project documents

Figure 8.3 exhibits an example of the collected documents, where it is clear that the data was collected and presented in different formats. The data requires special care to extract records and transfer them in suitable forms.

The Microsoft Excel program was used to enter the data included in the neural network models for all projects. The variables used in the development of the neural network models were quantitative and qualitative. Therefore, the data was further transformed into numerical values according to the representation of Figure. 8.1.

The values for the 'Type of building' variable, for example, have been transformed into integers from 1 to 4: 1-Recreational building, 2-Commercial building, 3-Education building and 4-Residential building.

After the data was transformed in the Excel program, it needed to be normalised before being presenting to the network, because using variables with both big magnitudes and small magnitudes would confuse the learning algorithm (Tymvios et al. 2008).

The input and output data can be normalized and scaled to a range (-1 to 1) to suit neural networks process; normalizing the data using the following formula (Arafa and Alqedra 2011):

$$\boldsymbol{Pi^{norm}} = \left[\frac{2(\boldsymbol{Pi} - \boldsymbol{P^{min}})}{\boldsymbol{P^{max}} - \boldsymbol{P^{min}}}\right] - \mathbf{1} \ldots\ldots\ldots\ldots (\mathbf{8.1})$$

Where $\mathbf{Pi^{norm}}$: Normal value, $\mathbf{Pi}$: Original data set, $\mathbf{P^{min}}$: the minimum value of data, $\mathbf{P^{max}}$: the maximum value of data. Figure (8.4) below exhibits example of the final a data entry sheet.

A	B	C	D	E	F	G	H	I	J	K	L
Project number	Type of building	Number of stories	Gross floor area m2	Location	Foundation type	Type of structure	Number of elevators	Discount rate	Project life	CSIs of Maintenan	Maintenance costs
1	-1	-0.75	0.666667	1	-1	-1	-1	-1	-1	-0.97660856	-0.96507384
2	-1	-0.5	0.666667	-1	-0.33333	0	-1	-1	-1	-0.9674984	-0.9588655
3	-1	-0.5	0.333333	-1	-1	0	-0.66667	-1	-1	-0.9551453	-0.95240097
4	-1	-0.75	1	-1	-0.33333	0	-1	-1	-1	-0.98522099	-0.98647199
5	-1	-0.75	1	-1	-0.33333	0	-1	-1	-1	-0.98643701	-0.98613797
6	-1	-0.75	1	-1	-0.33333	0	-0.66667	-1	-1	-0.99025283	-0.9848031
7	-1	-0.5	0.333333	-1	-0.33333	0	-0.33333	-1	-1	-0.9231309	-0.9195967
8	-1	-0.5	0.666667	-1	-0.33333	0	-1	-1	-1	-0.98365555	-0.973414
9	-1	-0.75	1	-1	-0.33333	0	-1	-1	-1	-0.99564757	-0.99641977
10	-1	-0.75	1	-1	0.333333	0	-1	-1	-1	-0.99980337	-0.99975115
11	-1	-0.75	1	-1	-0.33333	0	-1	-1	-1	-0.99172557	-0.99026607
12	-1	-0.75	1	-1	-0.33333	0	-1	-1	-1	-0.99107958	-0.98476904
13	-1	-0.75	1	-1	-0.33333	0	-1	-1	-1	-0.9854055	-0.98733966
14	-1	-0.5	1	-1	-0.33333	0	-1	-1	-1	-0.99637375	-0.99658251
15	-0.33333	-0.5	0.333333	-0.33333	-0.33333	0	-0.66667	-1	-1	-0.93885823	-0.93380504
16	-0.33333	-0.75	1	0.333333	1	0	-1	-1	-1	-0.98677896	-0.98726326
17	-0.33333	-0.5	0	-1	-0.33333	0	-0.66667	-1	-1	-0.8836045	-0.86132107
18	-0.33333	-0.75	1	-1	1	0	-1	-1	-1	-0.9904998	-0.98670097
19	-0.33333	-0.5	0.333333	-1	-0.33333	0	-1	-1	-1	-0.91258968	-0.88701904
20	-0.33333	-0.25	0.666667	-1	-0.33333	0	-0.66667	-1	-1	-0.96825668	-0.9598252
21	-0.33333	0	0.333333	-1	-1	0	-0.66667	-1	-1	-0.87932617	-0.87133319
22	-0.33333	-0.5	0.333333	-1	-0.33333	-1	-0.66667	-1	-1	-0.9167789	-0.92117285
23	-0.33333	-0.5	0.666667	-1	-0.33333	0	-0.66667	-1	-1	-0.96527693	-0.96254816

Figure 8.4 Example of the final entry sheet

8.2.2.3. Determining the Best Network Architecture

At this stage, the designer specifies the number of hidden layers, neurons in each layer, and training function. Previous research argues that having and selecting too many hidden layers and nodes can cause the network to 'memorise' which means the model performs well throughout training but tests poorly (Ismaail et al. 2011). Some studies suggest that the number of hidden layer nodes can be selected as one-half of the total input and output data as appropriate for the most models (Hegazy et al. 1994).

In this study, traditional parametric (trial and error) has been performed to select the number of hidden layers and the number of hidden nodes. During the training process, the number of hidden layers and hidden nodes has been adjusted to find the best artificial neural network model to gives the minimum value for the Mean Square Error (MSE). As mentioned in chapter three, tangent Sigmoid can be used when the required output range between (-1 and 1) so Tangent Sigmoid was used as a transfer function of NNs model for all methods.

Regarding to training function, Trainlm function was used in this research to updates weight and bias values according to Levenberg-Marquardt optimization. This function is able to gain lower MSE than any of the other algorithms tested and the storage requirements of this function are large than other algorithms.

8.2.3. Training the Networks

There are several methods for training neural networks. Most fall into one of two categories:

a) Supervised training methods: the teacher or trainer tells the model if its result was correct. This method requires two input and output vectors.

b) Unsupervised training method: there is no teacher or trainer during training tells the network whether its output was correct. This method does not require output vectors.

The back-propagation method, the 'weights' which aim to connect nodes and biases are changed utilising a number of inputs and the desired output value. The difference between the network output and actual output, become network error sets, after which the network error is back propagated from the output layer to adjust the weights and biases. The network's weights are continuously modified until the difference between model's outputs and the actually output converges to an acceptable level as shown in figure 8.5 below. The training process is stopped when a minimum mean square error in equation 8.2 is reached.

$$\boldsymbol{MSE = \frac{1}{n}\sum_{ni=1}^{n}(Oi - Pi)^2} \ldots\ldots\ldots\ldots (\mathbf{8.2})$$

where: MSR: mean square error, n: number of sample using in the training stage, O_i: the actual output. P_i: The model output.

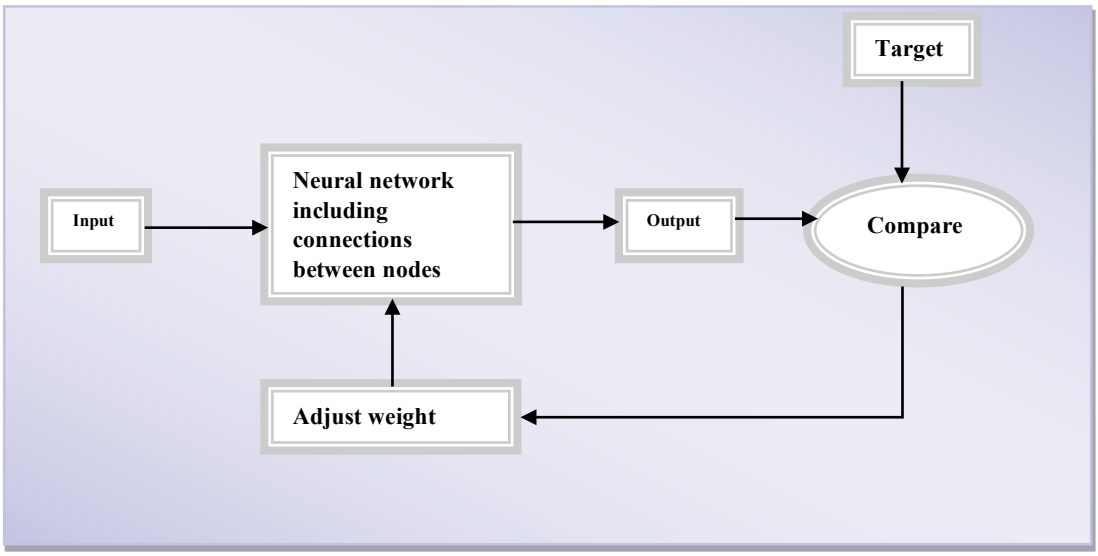


Figure 8.5 Training process

Over-fitting is one of the major problems in the process of neural network training. It occurs when an error in the training process is very small, but the value of the error for new data is very large. This means that the network is unable to generalise the form of the relationship between input and output data in the model. The early stopping method was performed in this study to avoid over-fitting. During the initial phase of training, the error calculated on the validation set normally decreases. However, when the network begins to over-fit the data, the validation error will begin to rise. If this situation occurs, the training process is stopped, and the neural network weights at the minimum validation are maintained for the next steps.

In this research, training stops when any of these conditions occur:

1- The maximum number of epochs (a number of times the training vectors are used to update the weights) is reached.
2- The maximum amount of time of the training process has been exceeded.
3- Performance has been reduced to the goal.
4- The performance of gradient drops below min_grad.
5- The validation error has rise more than max_fail times since the last time it decreased. The details of training function (trainlm) parameters used in this research are given in table 8.3.

Table 8.3 Training function (trainlm) parameters

Maximum number of epochs to train	1000
Performance goal	0
Maximum validation failures	6
Minimum performance gradient	1.00E-07
Maximum time to train in seconds	inf

Moreover, the historical data from completed projects are also generally divided into three sets in order to prevent the model from overfitting and to memorise the situation. The training data set is utilised for model parameter adjustment. The validation data set is utilised to control the training process and indicate when to stop training. The test data set is utilised to verify the performance of the proposed model with new data. There is no definite ratio for dividing the data into subsets, but in general, 20–30% of the available data is suggested to be utilised as a validation and test set and 70–80% for a training set. Different methods can be used for data division; the random selection method of data sets is a popular method which is used in this research.

8.2.4. Testing the Networks

Testing the model process is fundamentally the same as a training process, but the model will use sample data never seen before, and no corrections are made. If the results of a testing process are at an acceptable level, then the model is suitable to use. If the results are inappropriate, then a redesign of the model is required. The acceptable level of the result of the model will be evaluated based on the value of MSR (equation 8.2). Once the model is built, it can be utilised to predict the cost of new construction projects. It should be noted that the estimator is able to use the final model to estimate new projects without performing changes to the design structures of the ANN model, such as the transfer function, the number of inputs (important cost and non-cost factors) and hidden nodes, which had been selected at an initial stage. The following section shows the results for each model.

8.3. Capital cost model result

In the capital cost model, the 113 projects were divided into three sets. One set consisted of 79 projects (70%) used for training the model, 17 projects (15%) were used for model validation and the remaining 17 projects (15%) were used to test the procedure. The data used in the training of the network is shown in Table 8.2.

Eight parameters (inputs) were used in the design and training of this neural network model. These parameters were gross floor area, total value of cost-significant items of LCC, type of building, type of structure, number of stories, type of foundation and location, and they are considered significant in estimating the capital costs of the building projects.

The 11 network trial and errors were applied to identify the number of hidden nodes in hidden layers. It was clear that increasing the number of hidden nodes in hidden layers leads to changing the value of MSE. The network with six hidden nodes presented a better performance and provided the lowest MSE value of 2.85e-05, as shown in Figure 8.6 below. Table 8.4 below illustrates the configuration the 11 (eleven) networks.

Table 8.4 Training network of capital cost model

	N-1	N-2	N-3	N-4	N-5	N-6	N-7	N-8	N-9	N-10	N-11
Input node	8	8	8	8	8	8	8	8	8	8	8
Hidden node	5	6	7	8	9	10	11	12	13	14	15
Output node	1	1	1	1	1	1	1	1	1	1	1

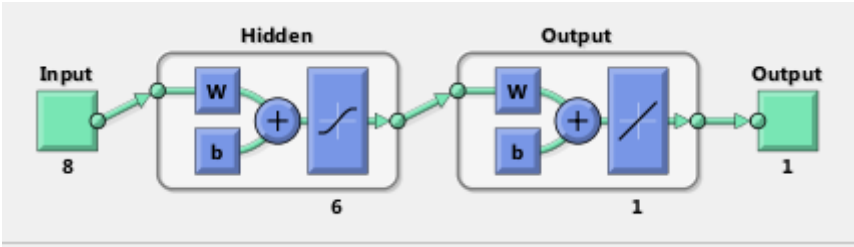


Figure 8.6 Structure of the best network of capital cost model

The MSE associated with the test set was 3.4e-04. The training continued for 13 more epochs before it stopped. Figure 8.7 below does not indicate any major problems with the training performance. Both the curves of the validation and the test are very similar.

The neural network model results from the training, validation and testing stages and the actual value of the capital costs for the best model were passed to regression analysis in order to investigate the model response in more detail.

The result of linearly regression of capital cost model is presented graphically in figure (8.8) below. Liner regression analysis consists of two parameters (as equation).

$$\boldsymbol{Y(actual\ cost) = m * X(estimation\ cost) + b} \ldots\ldots\ldots\ldots (\mathbf{8.3})$$

Where m & b, are represent the slope and the y-intercept of the best regression relating the actual value of running costs to the neural network model. If there is a good fit, the slope would be close to 1, and the y-intercept would be close to 0.

For best model, in training, validation and testing stages, the slope is close to1 and the y-intercept is close to 0. In addition, regression analysis is able to provide the value of the correlation coefficient (R^2) between the actual value of running cost and the model output. This variable measures the variation between the actual value and the model's result. If R^2 is equal or close to 1, then there is good correlation between the actual value and the estimation model output. For best model of capital cost, in training, validation and testing tests, R^2 is close to 1, indicating a good fit and linear

correlation between the actual capital cost and the neural network result at training and testing stage.

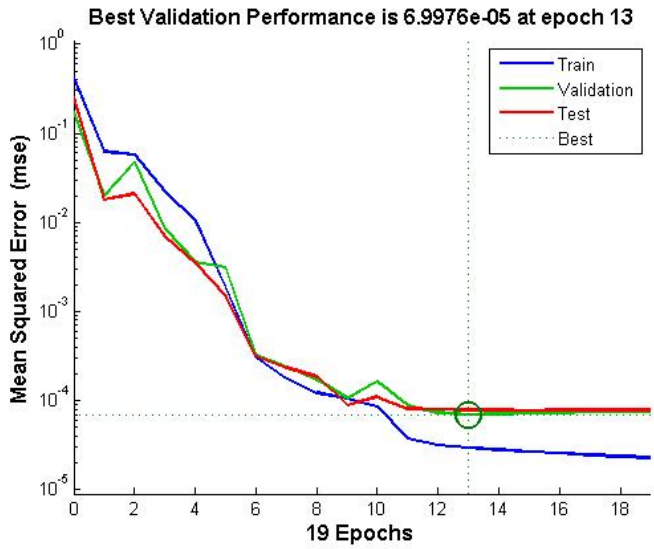


Figure 8.7 Structure of the best network of capital cost model

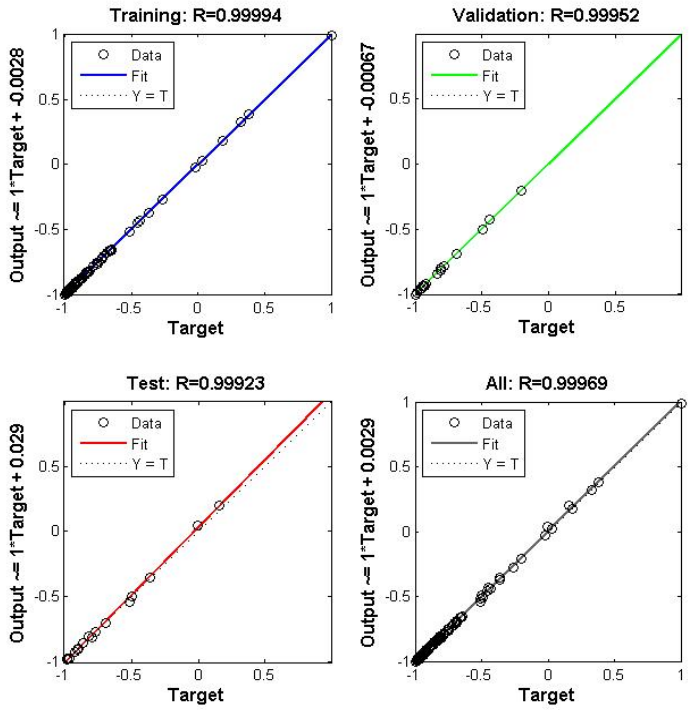


Figure 8.8 Linearly regression of capital cost model

8.4. Maintenance cost model result

The total maintenance, operation, running and life cycle cost of 113 projects was calculated four times based on different project life and different discount rate in order to examine the effect of these factors to the estimation of total cost:

1. Case1 : LCC at 10 years and inflation rate =2.9%
2. Case2: LCC at 20 years and inflation rate =2.9%
3. Case3 : LCC at 10 years and inflation rate =4.4%
4. Case4: LCC at 20 years and inflation rate =4.4%%

Therefore, the total sample including in the maintenance cost was 452 samples. These samples were divided into three sets. One set consisted of 362 projects (80%) used for training the model, 45 projects (10%) were used for model validation and the remaining 45 projects (10%) were used to test the procedure. The data used in the training of the network is shown in Table 8.2.

Nine parameters (inputs) were used in the design and training of this neural network model. These parameters were gross floor area, total value of cost significant items of LCC, type of building, type of structure, number of stories, project life, inflation rate, number of elevators, and location, and they are considered significant in estimating the maintenance costs of the building projects.

The 11 network trial and errors were applied to identify the number of hidden nodes in hidden layers. It was clear that increasing the number of hidden nodes in hidden layers leads to changing the value of MSE.

The network with nine hidden nodes presented a better performance and provided the lowest MSE value of 2.77e-05, as shown in Figure 8.9 below. Table 8.5 below illustrates the configuration the 11 (eleven) networks

Table 8.5 Training network of maintenance cost model

	N-1	N-2	N-3	N-4	N-5	N-6	N-7	N-8	N-9	N-10	N-11
Input node	9	9	9	9	9	9	9	9	9	9	9
Hidden node	5	6	7	8	9	10	11	12	13	14	15
Output node	1	1	1	1	1	1	1	1	1	1	1

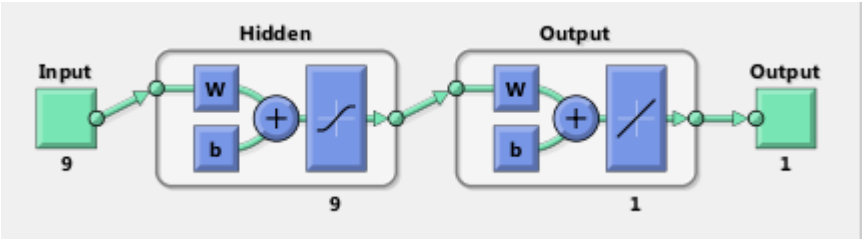


Figure 8.9 Structure of the best network of maintenance cost model

The MSE associated with the test set was 9.61e-05. The training continued for 61 more epochs before it stopped. Figure 8.10 below does not indicate any major problems with the training performance. Both the curves of the validation and the test are very similar.

The result of linearly regression of maintenance cost model is presented graphically in Figure 8.11 below. For best model, in training, validation and testing stages, the slope of regression is close to1 and the y-intercept is close to 0. For best model of maintenance cost, in training, validation and testing tests, R^2 is close to 1, indicating a good fit and linear correlation between the actual maintenance cost and the neural network result at training and testing stage.

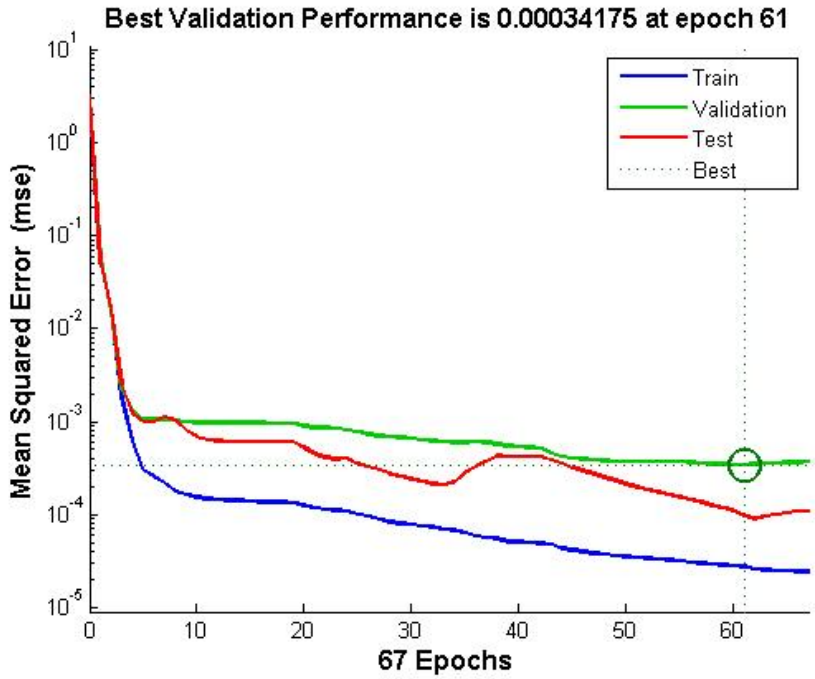


Figure 8.10 Training performance of maintenance cost model

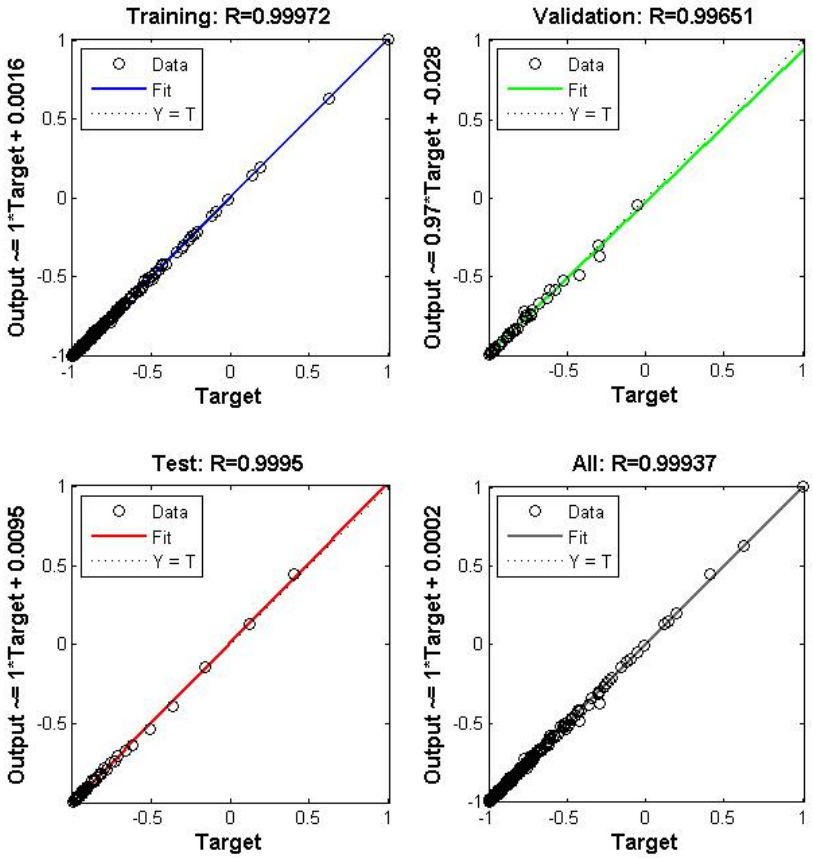


Figure 8.11 Linearly regression of maintenance cost model

8.5. Operation cost model result

The total sample including in the operation cost was 452 samples. These samples were divided into three sets. One set consisted of 362 projects (80%) used for training the model, 45 projects (10%) were used for model validation and the remaining 45 projects (10%) were used to test the procedure. The data used in the training of the network is shown in Table 8.2.

Nine parameters (inputs) were used in the design and training of this neural network model. These parameters were gross floor area, total value of cost significant items of LCC, type of building, type of structure, number of stories, project life, inflation rate, number of elevators, and location, and they are considered significant in estimating the operation costs of the building projects.

The 11 network trial and errors were applied to identify the number of hidden nodes in hidden layers. It was clear that increasing the number of hidden nodes in hidden layers leads to changing the value of MSE.

The network with ten hidden nodes presented a better performance and provided the lowest MSE value of 9.72e-05, as shown in Figure 8.12 below. Table 8.6 below illustrates the configuration the 11 (eleven) networks

Table 8.6 Training network of operation model

	N-1	**N-2**	**N-3**	**N-4**	**N-5**	**N-6**	**N-7**	**N-8**	**N-9**	**N-10**	**N-11**
Input node	9	9	9	9	9	9	9	9	9	9	9
Hidden node	5	6	7	8	9	10	11	12	13	14	15
Output node	1	1	1	1	1	1	1	1	1	1	1

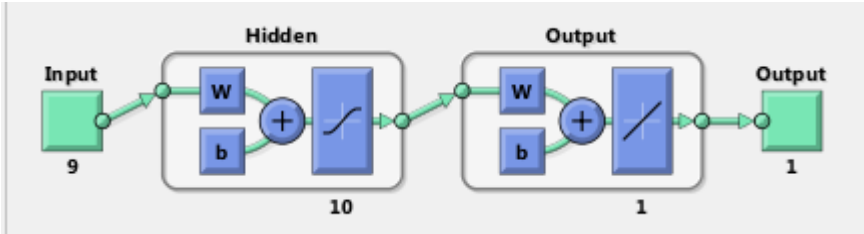


Figure 8.12 Structure of the best network of operation cost model

The MSE associated with the test set was 9.53e-05. The training continued for 11 more epochs before it stopped. Figure 8.13 below does not indicate any major problems with the training performance. Both the curves of the validation and the test are very similar.

The result of linearly regression of operation cost model is presented graphically in Figure 8.14 below. For best model, in training, validation and testing stages, the slope of regression is close to1 and the y-intercept is close to 0.

For best model of maintenance cost, in training, validation and testing tests, R^2 is close to 1, indicating a good fit and linear correlation between the actual operation cost and the neural network result at training and testing stage.

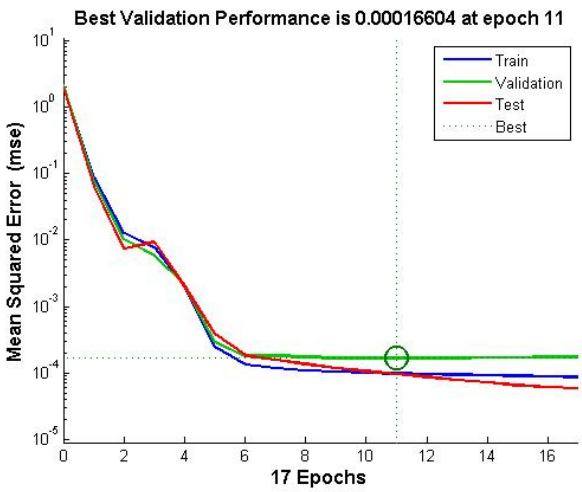


Figure 8.13 Training performance of operation cost model

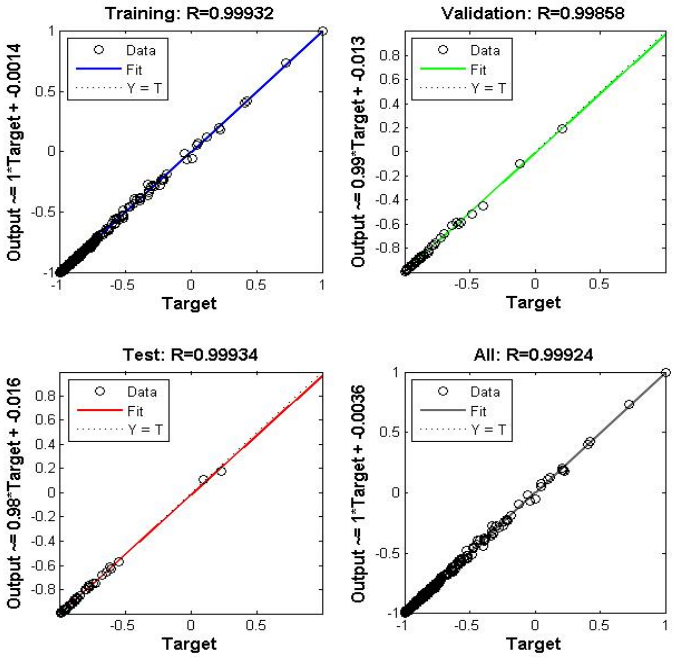


Figure 8.14 Linearly regression of operation cost model

8.6. Running cost model result

The total sample including in the running cost was 452 and it was divided to three sets. One set consist of 362 projects (80%) used for training the model and 45 projects (10%) are used towards model validation and the remaining 45projects (10%) used to test the procedure.

Nine parameters (inputs) were used in the design and training of this neural network model. These parameters were gross floor area, total value of cost significant items of LCC, type of building, type of structure, number of stories, project life, inflation rate, number of elevators, and location, they are considered significant in estimating the running costs of the building projects.

The 11 network trial and errors were applied to identify the number of hidden nodes in hidden layers. It was clear that increasing the number of hidden nodes in hidden layers leads to changing the value of MSE. The network with thirteen hidden nodes presented a better performance and provided the lowest MSE value of 6.31e-05, as

shown in Figure 8.15 below. Table 8.7 below illustrates the configuration the 11 (eleven) networks

Table 8.7 Training network of running cost model

	N-1	N-2	N-3	N-4	N-5	N-6	N-7	N-8	N-9	N-10	N-11
Input node	9	9	9	9	9	9	9	9	9	9	9
Hidden node	5	6	7	8	9	10	11	12	13	14	15
Output node	1	1	1	1	1	1	1	1	1	1	1

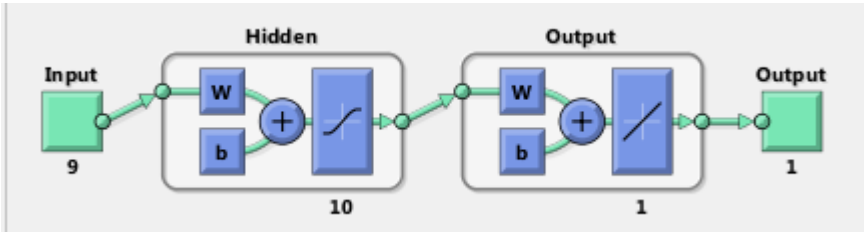


Figure 8.15 Structure of the best network of running cost model

The MSE associated with the test set was 7.18e-05. The training continued for 10 more epochs before it stopped. Figure 8.16 below does not indicate any major problems with the training performance. Both the curves of the validation and the test are very similar.

The result of linearly regression of running cost model is presented graphically in Figure 8.17 below. For best model, in training, validation and testing stages, the slope of regression is close to1 and the y-intercept is close to 0. For best model of maintenance cost, in training, validation and testing tests, R^2 is close to 1, indicating a good fit and linear correlation between the actual running cost and the neural network result at training and testing stage.

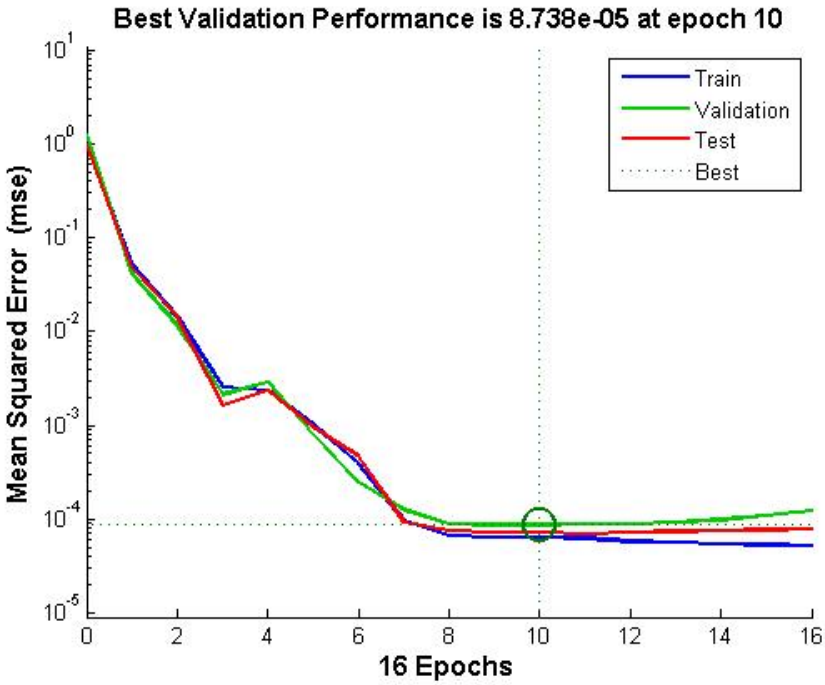


Figure 8.16 Training performance of running cost model

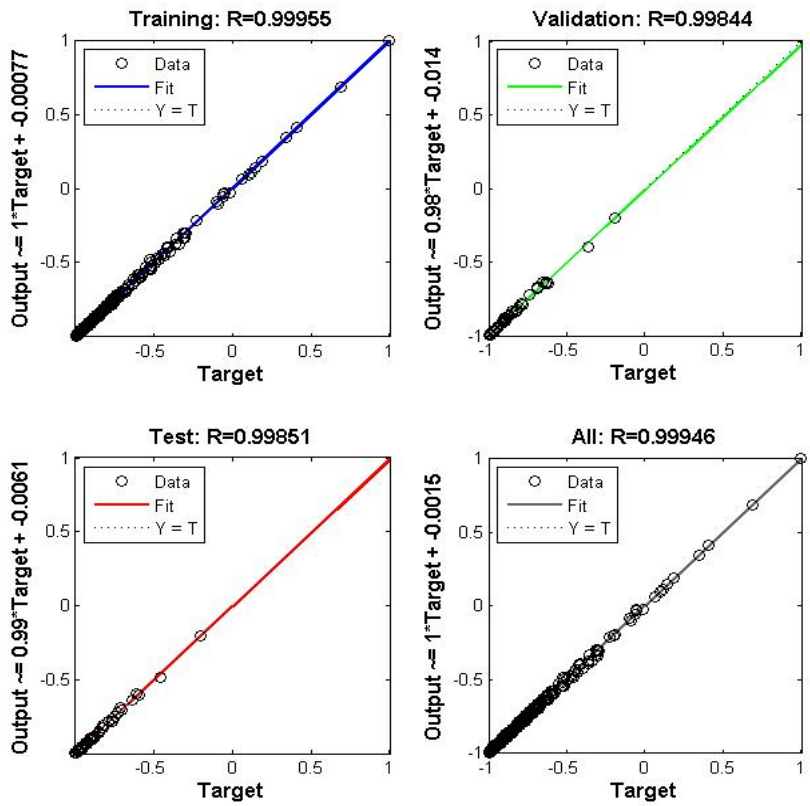


Figure 8.17 Linearly regression of running cost model

8.7. Life cycle cost model result

The total sample including in the LCC was 452 and it was divided to three sets. One set consist of 362 projects (80%) used for training the model and 45 projects (10%) are used towards model validation and the remaining 45projects (10%) used to test the procedure.

In the beginning, nine parameters (inputs) were used in the design and training of this neural network model. The performance of the model was poor and several trial and error models was developed with change the parameters of network.

The result of trial and error model indicated that the performance of network with eight parameters was very good. These parameters were gross floor area, total value of cost significant items of LCC, type of building, type of structure, number of stories, project life, inflation rate and number of elevators, they are considered significant in estimating the LCC of the building projects.

The 11 network trial and errors were applied to identify the number of hidden nodes in hidden layers. It was clear that increasing the number of hidden nodes in hidden layers leads to changing the value of MSE. The network with ten hidden nodes presented a better performance and provided the lowest MSE value of 4.24e-05, as shown in Figure 8.18 below. Table 8.8 below illustrates the configuration the 11 (eleven) networks

Table 8.8 Training network of life cycle cost model

	N-1	**N-2**	**N-3**	**N-4**	**N-5**	**N-6**	**N-7**	**N-8**	**N-9**	**N-10**	**N-11**
Input node	8	8	8	8	8	8	8	8	8	8	8
Hidden node	5	6	7	8	9	10	11	12	13	14	15
Output node	1	1	1	1	1	1	1	1	1	1	1

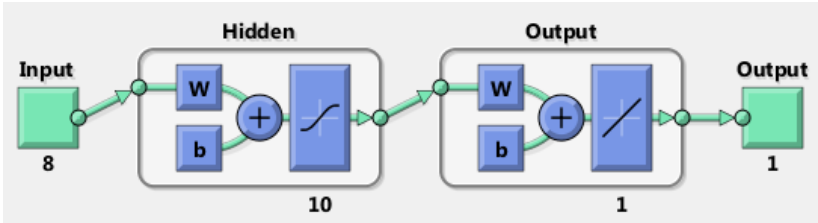


Figure 8.18 Structure of the best network of life cycle cost model

The MSE associated with the test set was 6.93e-05. The training continued for 7 more epochs before it stopped. Figure 8.19 below does not indicate any major problems with the training performance. Both the curves of the validation and the test are very similar.

The result of linearly regression of LCC model is presented graphically in Figure 8.20 below. For best model, in training, validation and testing stages, the slope of regression is close to1 and the y-intercept is close to 0. For best model of maintenance cost, in training, validation and testing tests, R^2 is close to 1, indicating a good fit and linear correlation between the actual LCC cost and the neural network result at training and testing stage.

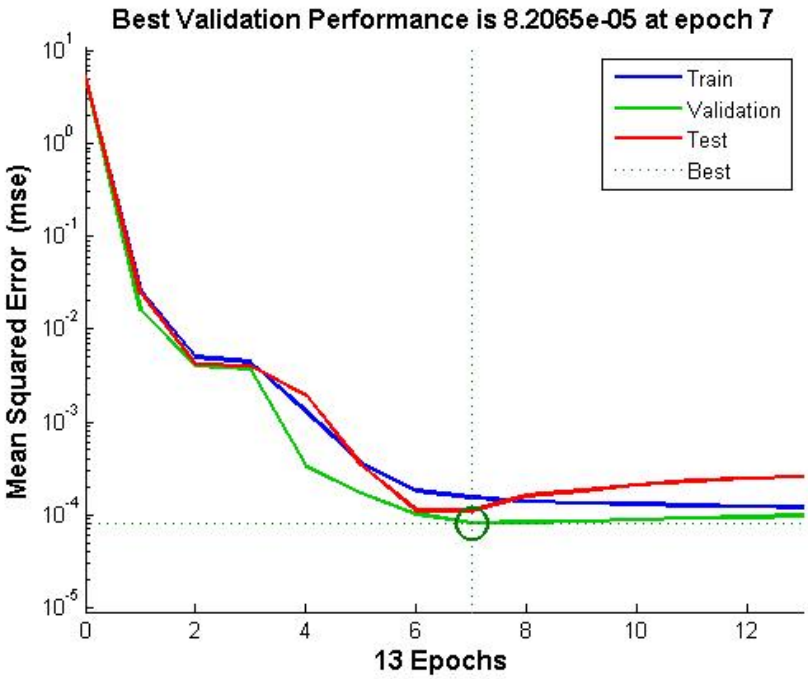


Figure 8.19 Training performance of life cycle cost model

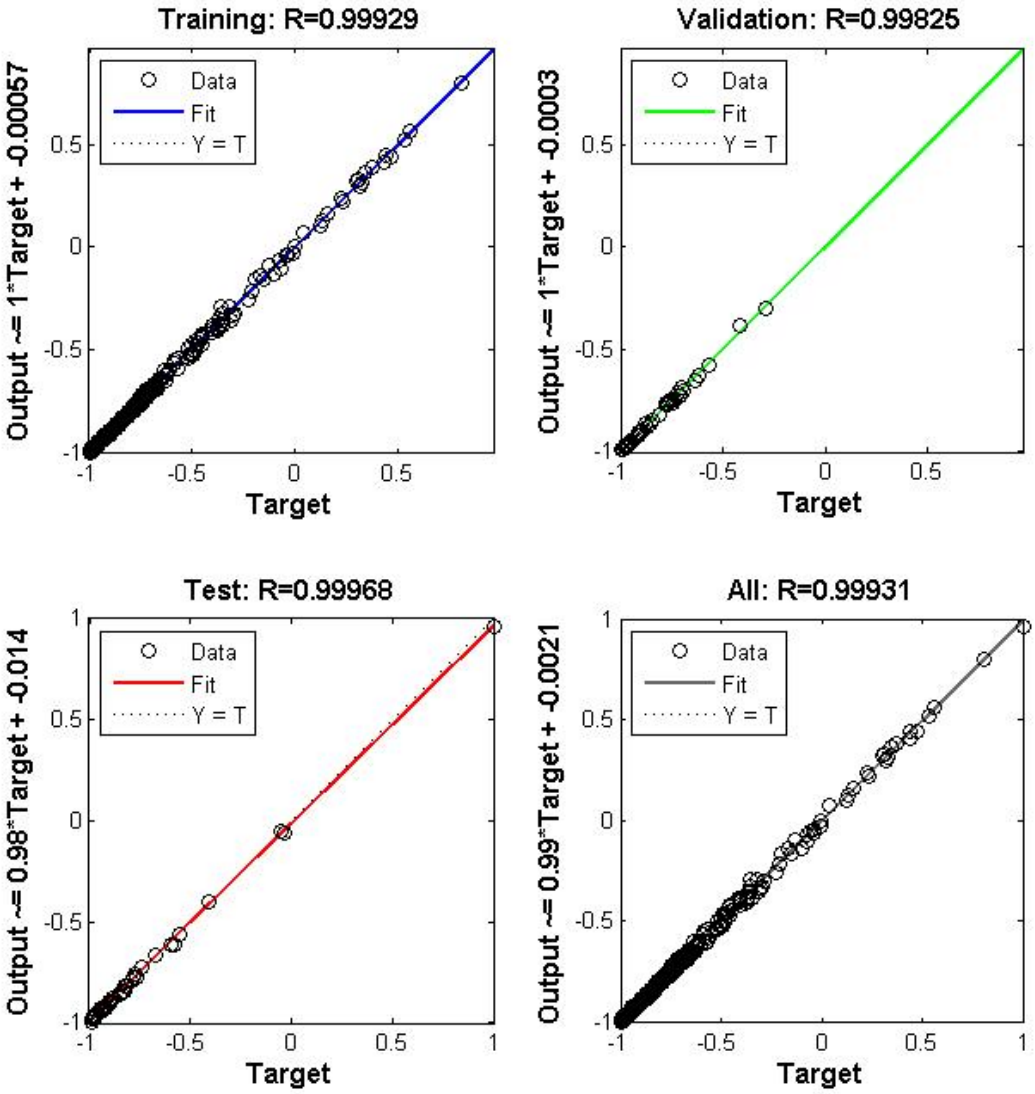


Figure 8.20 Linearly regression of life cycle cost model

8.8. Accuracy of a Cost Model

This step aims to demonstrate the performance of the developed network by a comparison between the prediction cost and actual cost of projects.

It should be noted that the sample in the test set for each model was used in this comparison. As mentioned before, these samples have never been exposed to the neural network during the training stage.

The total accuracy of the model can be calculated *as* shown below:

$$A = E \pm Standar\ devation\ of\ E \ldots\ldots\ldots\ldots\ldots (8.4)$$

$$E = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{Pi - AC}{AC}\right) * 100\% \ldots\ldots\ldots\ldots\ldots (8.5)$$

Where:

E= Average percentage error; A=Accuracy of cos model; P= Prediction cost of the NNs model; AC = Actual cost; If A is equal or closes to 0, then the accuracy of the model is very high. For each Model, percentage differences between actual and predicted costs were calculated and an error figure was presented for each model.

8.8.1. Accuracy of capital cost model

The ability of the capital cost model to predict the total capital costs was calculated based on the 17 projects of the test set. The accuracy of each project is summarised in Table 8.9, whilst an error histogram of prediction costs is presented in Figure 8.21.

Table 8.9 Accuracy of capital cost model

Project number	Actual capital cost (£)	Prediction capital cost (£) (ANNs)	Different error %
1	2088258	2257610	7.50
2	518591	515942.6	-0.51
3	2345011	2212030	-6.01
4	1301571	1312276	0.82
5	5384507	5092581	-5.73
6	3485044	3354817	-3.88
7	393255	431738	8.91
8	2666232	2614407	-1.98
9	12565080	13015530	3.46
10	3086685	3072208	-0.47
11	1690722	1775833	4.79
12	10816905	11354807	4.74
13	1051669	1009130	-4.22
14	1185531	1189702	0.35
15	841138	861935.9	2.41
16	982007	1004412	2.23
17	377861	374952.1	-0.78
Average different error			0.68
Standard deviation of different error			4.36

The results of the comparison between actual costs and prediction costs indicate that the capital cost models performed extremely well.

As can be noted from Table 8.9, the neural network model is able to estimate the total capital cost with an average accuracy of approximately 95%. The histogram indicated that the most different percentage error falls between -4% and 4%.

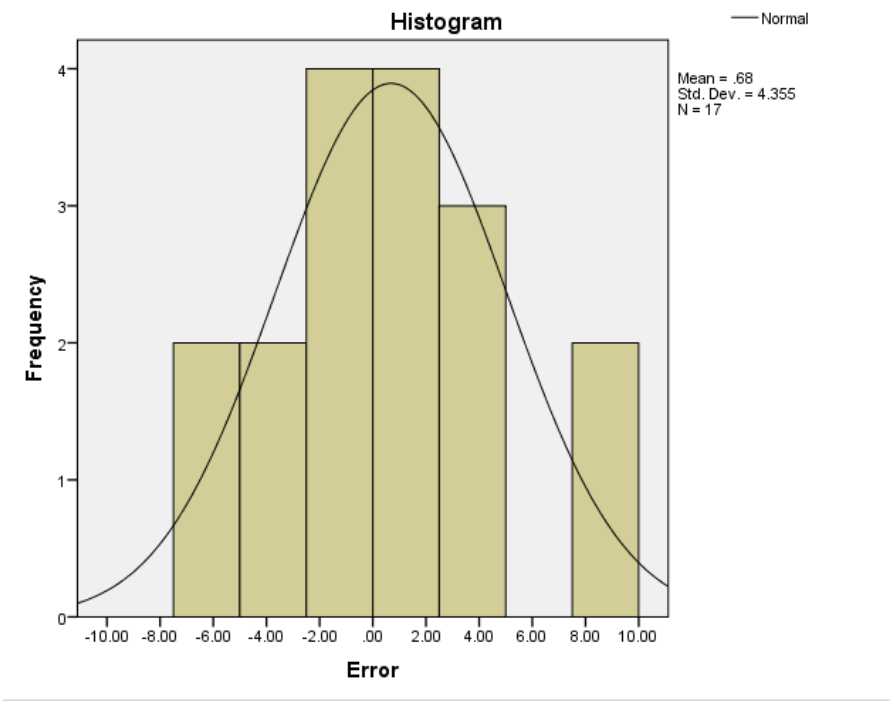


Figure 8.21 Error histogram of capital cost model

8.8.2. Accuracy of maintenance cost model

The ability of the maintenance cost model to predict the total maintenance costs was calculated based on the 45 projects of the test set. The accuracy of each project is summarised in Table 8.10, whilst an error histogram of prediction costs is presented in Figure 8.22.

Table 8.10 Accuracy of maintenance cost model

Project number	Actual maintenance cost (£)	Prediction maintenance cost (ANNs) (£)	Error at test
1	63349	66409.31	4.61
2	63672	78601.18	18.99
3	168152	167905.7	-0.15
4	74560	61596.19	-21.05
5	71319	60282.03	-18.31
6	429206	426163.5	-0.71
7	402007	373462.3	-7.64
8	284636	272130.2	-4.60
9	594565	583858.9	-1.83
10	196042	190118.8	-3.12
11	84763	75012.79	-13.00
12	798419	793264.4	-0.65
13	622465	628117.5	0.90
14	327736	333382.5	1.69
15	3581801	3630742	1.35
16	5953609	6119121	2.70
17	4738789	4780047	0.86
18	752273	776598	3.13
19	265927	237289.3	-12.07
20	1223640	1251379	2.22
21	866547	915982.6	5.40
22	190741	177489.3	-7.47
23	1614831	1542583	-4.68
24	289060	310967.6	7.04
25	370247	362762.5	-2.06
26	1046212	1061988	1.49
27	94461	88625.53	-6.58
28	101772	96108.33	-5.89
29	1431202	1397132	-2.44
30	921449	899939	-2.39
31	260017	268545.9	3.18
32	56178	51681.96	-8.70
33	384843	343602.1	-12.00
34	766189	740067.5	-3.53
35	535085	607489.6	11.92
36	138133	139815	1.20
37	2088441	1981017	-5.42

38	1147291	1095321	-4.74
39	387720	417629.4	7.16
40	151944	164844.1	7.83
41	690730	685431.8	-0.77
42	325099	341268.6	4.74
43	2692756	2605155	-3.36
44	610224	619515.3	1.50
45	147078	127988.5	-14.91
Average different error			-1.78
Standard deviation of different error			7.56

The results of the comparison between actual costs and prediction costs indicate that the maintenance cost models performed extremely well.

As can be noted from Table 8.10, the neural network model is able to estimate the total maintenance cost with an average accuracy of approximately 91%. The histogram indicated that the most different percentage error falls between -9% and 9%.

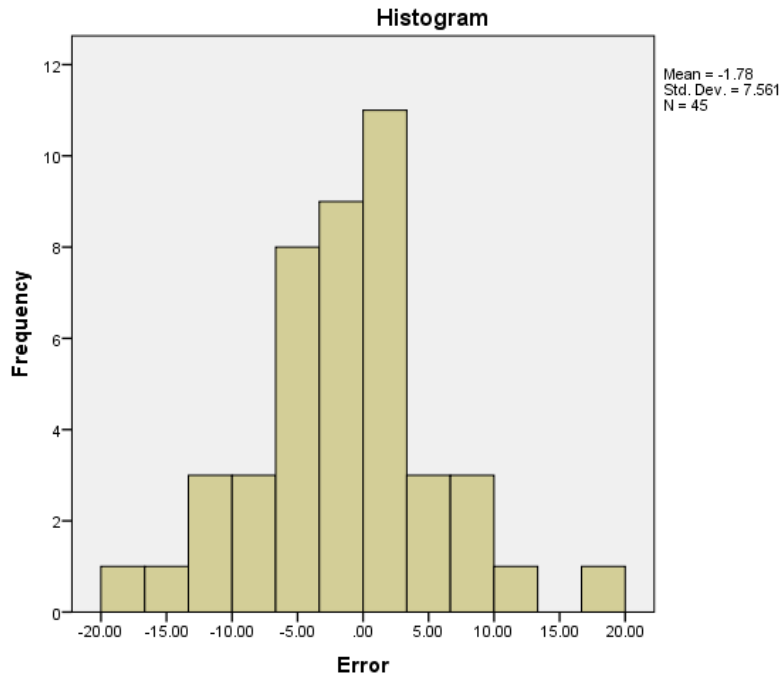


Figure 8.22 Error histogram of maintenance cost model

8.8.3. Accuracy of operation cost model

The ability of the operation cost model to predict the total operation costs was calculated based on the 45 projects of the test set. The accuracy of each project is summarised in Table 8.11, whilst an error histogram of prediction costs is presented in Figure 8.23.

Table 8.11 Accuracy of operation cost model

Project number	Actual operation cost (£)	Prediction operation cost (ANNs) (£)	Error at test
1	382017	363139.9	-5.20
2	66176	67632.5	2.15
3	1596878	1572396	-1.56
4	2100598	2016278	-4.18
5	1090975	1066907	-2.26
6	880762	904634.7	2.64
7	3003040	3032629	0.98
8	8590722	8721937	1.50
9	236088	234484.4	-0.68
10	1171017	1201554	2.54
11	655053	611155.5	-7.18
12	557873	537057.4	-3.88
13	181156	180192.5	-0.53
14	107461	98097.48	-9.55
15	553384	545980.7	-1.36
16	904157	909772.3	0.62
17	1799376	1784959	-0.81
18	278017	309960.5	10.31
19	1982380	2005559	1.16
20	903768	854994.6	-5.70
21	1005538	993603.3	-1.20
22	243406	265260.6	8.24
23	89178	105437.5	15.42
24	834867	864268.9	3.40
25	3503399	3360170	-4.26
26	385108	401184.2	4.01

27	811719	761075.8	-6.65
28	2767004	2744025	-0.84
29	221137	224347.7	1.43
30	324726	317374.5	-2.32
31	609525	606236.6	-0.54
32	166529	178361.8	6.63
33	1713525	1696281	-1.02
34	2500815	2531691	1.22
35	1760071	1827315	3.68
36	1550814	1626707	4.67
37	157752	126699.6	-24.51
38	522201	498527.4	-4.75
39	762689	743335.1	-2.60
40	298892	257613	-16.02
41	3063922	2921169	-4.89
42	375996	403619.1	6.84
43	1024020	1064101	3.77
44	777395	741856	-4.79
45	9648220	9244716	-4.36
Average different error			-0.90
Standard deviation of different error			6.47

The results of the comparison between actual costs and prediction costs indicate that the operation cost models performed extremely well.

As can be noted from Table 8.11, the neural network model is able to estimate the total operation cost with an average accuracy of approximately 93%. The histogram indicated that the most different percentage error falls between -7% and 7%.

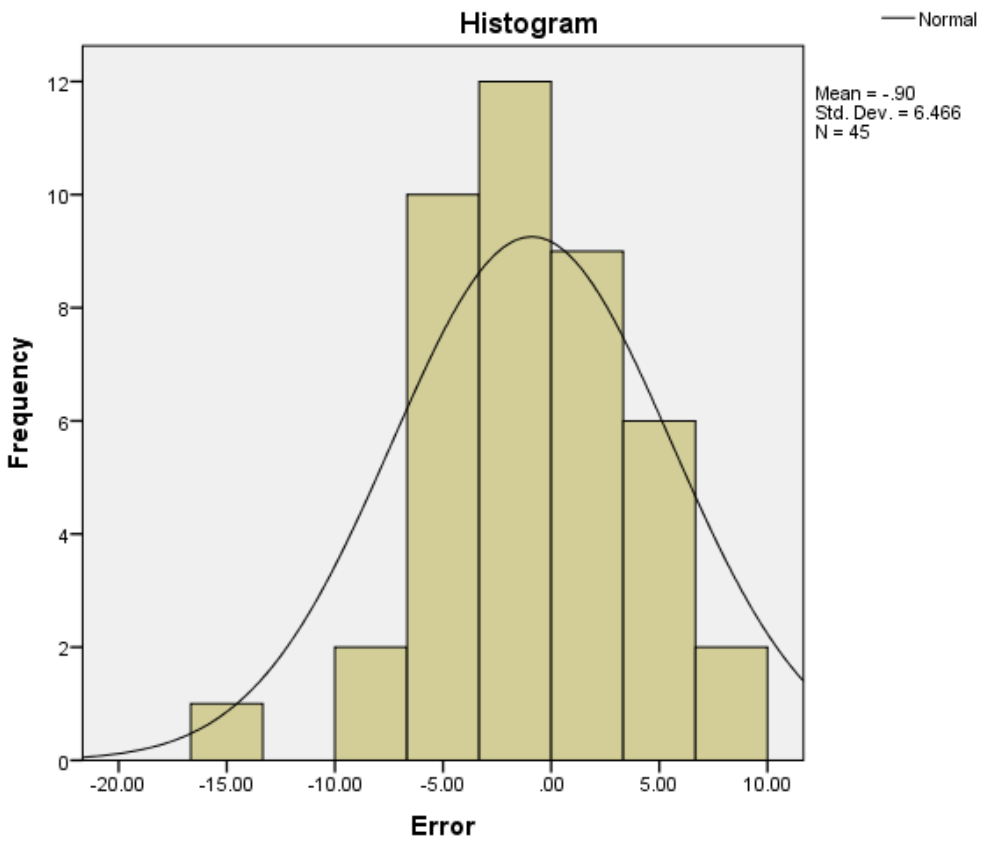


Figure 8.23 Error histogram of operation cost model

8.8.4. Accuracy of running cost model

The ability of the running cost model to predict the total running costs was calculated based on the 45 projects of the test set. The accuracy of each project is summarised in Table 8.12, whilst an error histogram of prediction costs is presented in Figure 8.24.

Table 8.12 Accuracy of running cost model

Project number	Actual running cost (£)	Prediction running cost (ANNs) (£)	Error at test
1	839833	903393.6	7.04
2	39727	51329.78	22.60
3	327368	343332.9	4.65
4	4417943	4357384	-1.39
5	1795434	1851485	3.03
6	217669	256489	15.14
7	149730	174953.5	14.42
8	542396	534443.6	-1.49
9	666435	699882.5	4.78
10	2814388	2849584	1.24
11	1221667	1289418	5.25
12	2521827	2689514	6.23
13	3545923	3545325	-0.02
14	3454371	3758299	8.09
15	1019853	1003491	-1.63
16	576869	552449.9	-4.42
17	1399903	1373691	-1.91
18	3227284	3406082	5.25
19	3112494	3074726	-1.23
20	1269390	1220298	-4.02
21	83495	87125.43	4.17
22	2173064	2114754	-2.76

23	1168526	1241782	5.90
24	2815533	2846113	1.07
25	470319	431654.6	-8.96
26	208415	235011.1	11.32
27	1508442	1421488	-6.12
28	2174767	2347848	7.37
29	1428700	1323647	-7.94
30	1795390	1704311	-5.34
31	549279	654145.6	16.03
32	1152886	1184862	2.70
33	611349	639224.8	4.36
34	1235936	1160538	-6.50
35	2048415	2091146	2.04
36	4908542	4766731	-2.98
37	9672759	9641243	-0.33
38	6565762	6267910	-4.75
39	2833997	2656705	-6.67
40	1195529	1225729	2.46
41	788221	764824.5	-3.06
42	4678029	4880775	4.15
43	1271021	1191514	-6.67
44	875882	787597.1	-11.21
45	315700	379748.7	16.87
Average different error			1.93
Standard deviation of different error			7.44

The results of the comparison between actual costs and prediction costs indicate that the running cost models performed extremely well.

As can be noted from Table 8.12, the neural network model is able to estimate the total running cost with an average accuracy of approximately 91%. The histogram indicated that the most different percentage error falls between -9% and 9%.

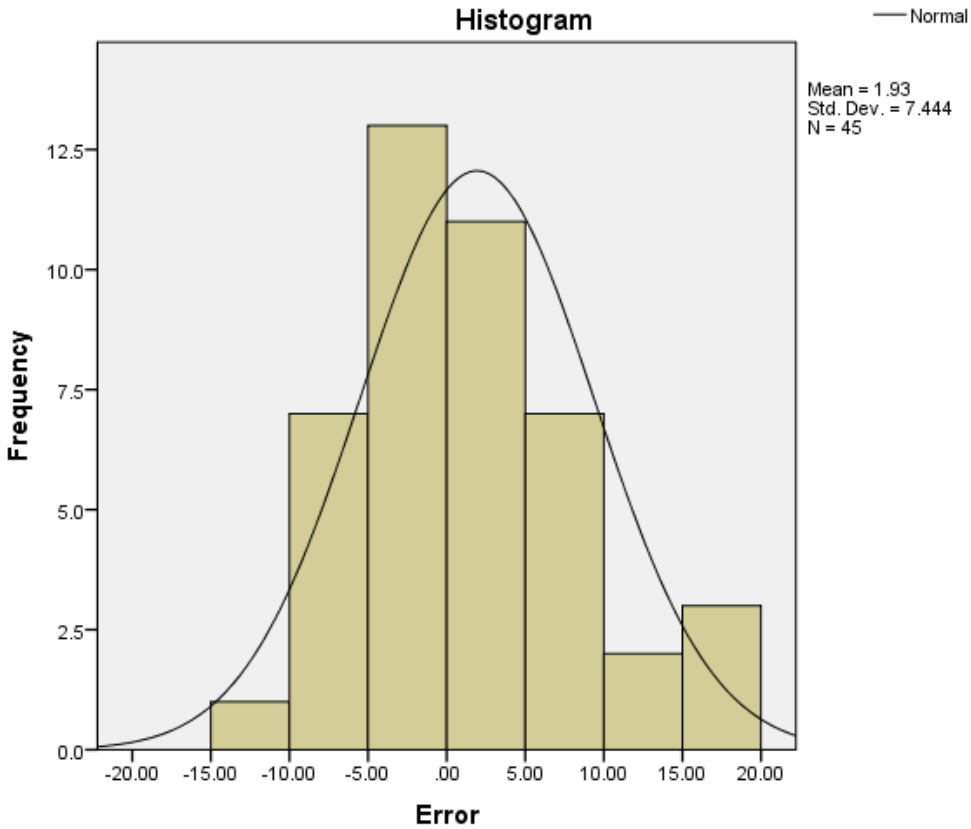


Figure 8.24 Error histogram of running cost model

8.8.5. Accuracy of life cycle cost model

The ability of the LCC model to predict the total LCC was calculated based on the 45 projects of the test set. The accuracy of each project is summarised in Table 8.13, whilst an error histogram of prediction costs is presented in Figure 8.25.

Table 8.13 Accuracy of life cycle cost model

Project number	Actual capital cost (£)	Prediction life cycle cost (ANNs) (£)	Error at test
1	3531112	3758246	6.04
2	403973	378720	-6.67
3	597497	604485.6	1.16
4	3626810	3744666	3.15
5	2053162	2137837	3.96
6	811437	831234.6	2.38
7	8893132	8693875	-2.29
8	3240424	3108075	-4.26
9	2067586	2249948	8.11
10	731895	831468.5	11.98
11	2025521	1994495	-1.56
12	1301097	1672961	22.23
13	18667103	18627732	-0.21
14	2112827	2072763	-1.93
15	1601900	1599164	-0.17
16	4638162	4879600	4.95
17	39111527	38439033	-1.75
18	1339923	1261782	-6.19
19	4201138	4330431	2.99
20	3090625	2950611	-4.75
21	5278677	5542910	4.77
22	1728090	1706308	-1.28
23	487381	566105.1	13.91
24	2264294	2364375	4.23
25	11704489	11912880	1.75
26	6523145	6735185	3.15
27	1520909	1569637	3.10
28	8009477	7779153	-2.96
29	632927	722698.4	12.42
30	3709470	3752634	1.15
31	8403607	7802150	-7.71
32	3415598	3272149	-4.38
33	18941860	18488536	-2.45
34	1333976	1355926	1.62
35	1300228	1365230	4.76
36	473368	586267.5	19.26
37	4750337	4581493	-3.69
38	1882047	1940574	3.02

39	871178	950836.6	8.38
40	1365469	1365226	-0.02
41	2499914	2580241	3.11
42	3572241	3345027	-6.79
43	1628970	1740350	6.40
44	4381415	4551230	3.73
45	1348520	1356633	0.60
Average different error			2.29
Standard deviation of different error			6.42

The results of the comparison between actual costs and prediction costs indicate that the LCC models performed extremely well.

As can be noted from Table 8.13, the neural network model is able to estimate the total LCC with an average accuracy of approximately 91%. The histogram indicated that the most different percentage error falls between -9% and 9%.

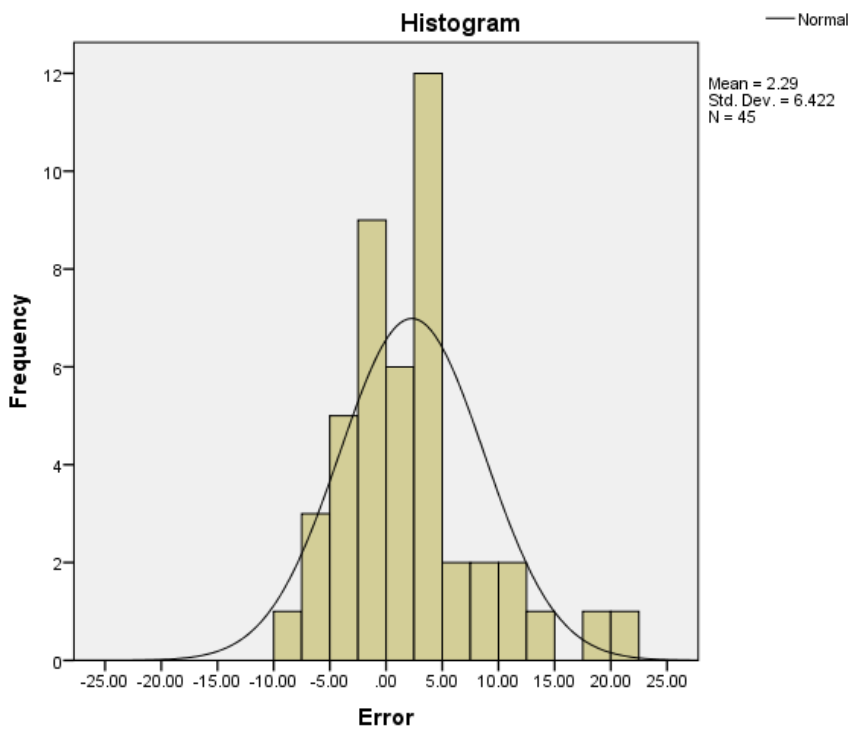


Figure 8.25 Error histogram of life cycle cost model

8.9. Connection weight method (CW)

As mentioned one disadvantage of ANNs modelling is the (black-box) lack of illustration for the relative importance affecting the independent variables. However, the connection weight(ed) method was applied in order to rank the importance of input variables in predicting the output variables for each models.

This method (Olden et al. 2004)) calculates the sum of products of weights of the connection from input nodes to the hidden nodes and the weight(ing) of the connection from hidden nodes to the output node for all input variables.

The larger the sum of the connection weight(ing), the more important is the corresponding input variable.
The relative importance of input variable i can be defined as:

$$\boldsymbol{RIi = \sum_{N=1}^{n}(Wi_N * WN_O)} \ldots\ldots\ldots\ldots(8.6)$$

Where:
$RI_{i:}$ the relative importance of input variable I;
N: is the total number of hidden neuron;
$\mathbf{Wi_N}$: The weight of connection from input neuron I and hidden neuron N; and,
$\mathbf{WN_O}$: The weight of the connection between hidden neuron N and output neuron.

From table 8.14 below, it is clear that
'CSIs' are most important variable(s) influencing estimation cost for all five models;
gross floor area is the second most important variable,
followed by type of building; inflation rate;
number of storeys and project life,
with number of elevator and foundation type of lesser importance.

Table 8.14 The result of CW method

	Final rank for all factors					
Factors	Model1 (capita)	Model2 (M)	Model3(O)	Model4(R)	Model5(LCC)	**Overall rank**
CSI	1	2	1	1	1	**1**
Gross floor area m2	6	1	3	8	2	**2**
Type of building	4	4	6	2	5	**3**
Inflation rate	0	9	2	5	3	**4**
Number of stories	2	6	4	3	6	**5**
Project life	0	3	7	6	7	**6**
Type of structure	7	7	8	4	4	**7**
Location	3	8	5	7	9	**8**
Number of elevators	8	5	9	9	8	**9**
Foundation	5					**10**

8.10. Summary of this chapter

In this chapter, the data of 113 building projects were used to develop five neural networks models.

These models were developed to predict the cost of each stage of building life. Issues regarding the design approach of Neural Networks were discussed, including selecting software, data collection, network configuration and training and testing methods.

To examine the accuracy of developed models, a comparison was conducted between the results of each neural network model and the actual cost of new data set.
The results indicate that neural network models were able to estimate the cost at each stage of building life with an average accuracy between 91%- 95%.

The neural-network model results from both training and testing stages and the actual value of running-costs were passed to regression analysis in order to investigate the model response in more detail.
In training and testing stages, the R^2 is close to 1, indicating a good-fit and linear correlation between the actual running-cost and the neural network models results at training and testing stages.

The connection weight method was applied to discover the relative importance affecting independent variable(s) (input-data) to predicting the output variables for each model.

CSIs are most important variable(s) influencing estimation cost for all five models, with number of elevator and foundation type of lesser importance.

9. CHAPTER NINE: CONCLUSION

9.1. Introduction

In the early chapters review was made of the application of LCC in building projects. It was discovered that industrial application of life-cycle cost analysis (LCCA) remains somewhat limited, with techniques (still) deemed overly theoretical, resulting in a reluctance to realise (and pass onto the client) the advantages to be gained from objective (LCCA) comparison of (sub) component material specifications.

To address the need for a user-friendly structured approach to facilitate complex processing, the work described here develops a new, accessible framework for LCCA of construction projects; it acknowledges Artificial Neural Networks (ANN_s) to compute the whole-cost(s) of construction.

The aim of the research work was to use artificial neural networks to accurately estimate the life-cycle cost of construction projects. Towards this goal, artificial network(s) applications were selected for incorporation due to their capability to address complex problems such as estimating LCC.

In order to attain the most accurate LCC estimation, this research focused upon the contribution of the different input factors that represent the main variables that affect the LCC and analysis of the techniques used to measure them.

As result, objectives were defined as:

- Review literature to investigate the limitation of the current practice of LCC.

- Review literature to identify non-cost factors (variables) which are significantly affecting accurate estimation of cost estimation in building projects.

- Conduct qualitative survey research to rank non-factors and provide the views of cost practitioners about how these factors can affect the accuracy estimation of LCC.

- Analyse the existing data (building projects) to clarify the relationship between capital cost and running costs.

- Utilisation of the principle of cost-significance items (CSIs) in order to simplify the process of estimating and identify the most important cost factors affecting the total cost at each stage of LCC.

- Utilisation of artificial neural networks to be employed to develop a new model for LCC; the validation of which to be a testing phase, using actual LCC values from number of previous completed construction projects to compare with model results.

The conclusions made in this section address these research objectives and are summarized in terms of the contributions to academic and industrial practice that arise from this study. This chapter also discusses the limitations of this research alongside areas for future research in the field.

9.2.The limitation of the current practice of LCC.

In this study, life-cycle cost (LCC) analysis has been defined and discussed in terms of its historical application in the construction industry. LCC utilisation in building projects has been described in the early chapters of this work, alongside estimating methodology and LCC components and basic economic principles. Past studies indicate that a wider use of LCC methodology in construction projects is still a being hampered by several factors such as:

- There is an absence of a systematic methodology currently in construction, which in turn, makes the LCC process more riskily complex to practitioners.
- The implementation of LCC currently may be difficult to apply at the early stages of the project life-cycle due to a lack of information.

- The current methods of LCC are deemed inaccurate especially when applied on a systems level.
- The current models of LCC are somewhat time consuming and costly with very limited explicit consideration of the non-cost factors affecting the estimation of projects.

9.3. Identification of non-cost factors affecting LCC

This research critically reviewed and identified the applicability of previous studies towards cataloguing the full range of non-cost factors affecting the estimation of costs at all phases of building's life-cycle. Previous literature reviewed found that the most significant non-cost factors varied based on the different objectives' weightings when research/study is conducted.

This research identified a total of 64 variables influencing cost estimation. Of these, 10 variables were deemed key, across a significant number of researchers, and are therefore seen as most greatly influencing total cost estimation. These factors are:

1- Number of stories
2- Type of building
3- Gross floor area
4- Project life
5- Location
6- Roof type
7- Foundation type
8- Inflation rate
9- Number of elevators
10- Type of structure

It must be recognized that each of these factors separately or in combination can affect the accuracy of an estimation of (whole) costs. Variations in these non-cost factors from one project to another were seen to cause vagaries and variations in the total cost, when differently configured.

9.4. Rank non- factors affecting the estimation of LCC

A survey research was conducted and used to rank the non-cost factors and provide the views of cost practitioners about how the factors could affect the accuracy estimation of LCC. The piloting study was conducted by interviewing the expert-individuals in charge of estimating. They were tested for appropriateness of the tool, namely: language and wording of questions, clarification of any ambiguous questions and ultimately provided proof that that (future expert) respondents were able to answer the question which assisted in the achievement of the objective of the research; the questionnaire (tool) generated, validated the questions and clarified and modified terms as appropriate.

A sample, covering quantity surveyors, cost estimators, cost engineers, and project managers who were involved in the construction industry, was selected for the survey (*203 potential participants were identified and contacted*). The first section of the questionnaire provided general information about the participation of the respondents. This part was aimed at reflecting the strength of the respondents' characteristics, and consequently to show the degree of reliability of the information provided by them. The second part of the questionnaire aimed to study the perspectives of the expert-sample across essential factors affecting the accuracy of LCC estimation in construction and building projects.

The respondents were asked to rate the finalised 10 factors deemed most influential in life-cycle costs, and considered key to the accuracy of the estimation of LCC.; they were asked to rank the importance of each factor on a 5-point Likert scale. The main survey was distributed to 203 professionals who are charged to deal with cost issues in the construction industry.

After distributing the survey, 124 (61%) was returned by the respondents within a standardised period of time. Cronbach's alpha was used to measure the reliability of the questionnaire, which could be defined as the degree to which the method of data gathering produces consistent results when the measurement was repeated. It was calculated as 0.862 for the questionnaire, which indicates a solid reliability across the survey responses.

The relative importance index computed for each factor ranged between 0.80 and 0.63. ANOVA testing revealed that a strong agreement between (those who termed themselves to be either) quantity surveyors, cost estimators, project managers & cost engineers; strong agreement existed in the ranking of the cost factors with no significant variation in the ranking of each factor by role. In terms of the factors themselves deemed (most) important to LCC, the *project life span* was ranked top followed by *inflation rate*. The third and fourth ranks were *type of building* and *structure* with the *foundation type* occupying the lowermost rank. *Gross floor area* and number of *elevators* have significant impact in the estimation of all costs at each stage of building's life cycle.

The result of this research-project-work's initial qualitative aspect of the current study was mostly consistent with the literature reviewed. However, this work found that the *foundation type* factor was deemed an insignificant factor for all-in costs across four sensitivities conducted; this factor affects the estimation of costs when considered as cost factor (where foundation is considered relative to the costs of the other elements) rather than as a non-cost factors (where the *type* of foundation from a range of options is considered).

9.5. Clarification of the relationship between capital cost and running costs

In order to achieve this objective, data were collected from the files of 113 construction building projects completed in the UK. The data were obtained from the Building Cost Information Service (BCIS) database of The Royal Institution of Chartered Surveyors (RICS). This data covered all the main costs of the principal sub-components of the building projects. Information obtained in respect of each project included number of storeys, type of building, gross floor area, location, number of elevator, type of structure, roof type, foundation type and project life and inflation rate. The data were used to clarify the relationship between capital costs and running costs.

The LCC was calculated four times, based on different project life and different discount rate:

- Case 1 : LCC at 10 years and Discount rate =2%.
- Case 2: LCC at 20 years and Discount rate =2%.
- Case 3 : LCC at 10 years and Discount rate =3.5.
- Case 4: LCC at 20 years and Discount rate =3.5%.

Both the capital costs and running costs (maintenance and operation costs) for each building type have been considered. In most cases running costs are over 50% of the total LCC of the (113) buildings assessed.

The pattern of running costs varies between building types. In the commercial building, the running costs are between 60-74% of the LCC in most projects, while for residential building running costs they are between 40%- 55% of the LCC in most projects.

9.6. Identification of the most important cost factors affecting LCC

The concept of Pareto analysis was implemented in this study in order to simplify the methodology of data gathering and estimation process. The data from 15 specific projects has been utilized to identify the most important factors affecting the total cost at each stage of building's life cycle. Two main steps were conducted in order to achieve this objective.

In the *first step*, the most important cost items were identified.
The result of this step indicated that 19, 10, 8, 21, & 39 items has been identified as cost-significant-items (CSIs) affecting the capital , maintenance ,operation, running and life cycle costs, respectively.

In the *second step*, important rate method has been applied to decrease and select the final CSIs at each stage. The result of this step indicated that 7, 5, 2, 6, 14 items has been selected as the final CSIs affecting the capital , maintenance ,operation, running and life cycle costs, respectively.

9.7. Development of a new model for LCC using ANNs

Data from BCIS was used to develop five neural networks model*s*. These models were developed to estimate the cost of each stage of building's life cycle.
The design of ANNs was discussed and then the five models were developed.

The accuracy of developed models was examined and the results indicated that neural network models were able to estimate the cost at each stage of building life with an average accuracy between 91%- 95%. Moreover, the result indicated that there was a good-fit and linear correlation between the actual running-cost and the neural network models results at the *training* and the *testing* stages.

Finally, the connection weighting method was applied to find out the relative importance affecting independent variable(s) (input-data), to predicting the output variables for each model. The result shown that identifiable cost-significant-items (CSIs) are the most important variable(s) influencing estimation cost for all five models, (with the number of elevators and foundation type of lesser importance).

9.8. Contribution to the knowledge

9.8.1. Academic perspective

One limitation of cost estimation/prediction modelling is the current typical reliance only on those factors that can be readily quantified and come easily to hand. In general, the factors affecting cost-estimation can be classified under two categories; cost factors (represented by quantitative factors such as all cost items; foundation cost, elevator cost, cleaning costs &etc.) and non-cost factors (represented by qualitative factors such as project type, project size and the like).

While estimation of the cost of the most common labour, material and plant resources receive consideration because of their high visibility factor, there are several non-cost factors (low visibility factors) affecting the estimate that are often overlooked and, it is argued here, require equal consideration in estimation processes that seek optimum accuracy. Unfortunately, such (low-visibility) factors are neglected or ignored by current prediction models. Identification of these non-cost

factors (low visibility factors) affects LCC estimate accuracy and can improve estimation process confidence.

The first contribution to knowledge of this research is that it identified the main cost and non-cost factors at each phase of construction project and can in-turn be proven to be a valuable method towards the improvement of estimation cost practices. The most significant aspects of this research are founded in taking the advantage of some technique such as CSIs theory, by integrating it with ANNs to improve the accuracy of estimation process towards saving project assessment time and cost.

The value of this research is in the method used, which involves analysis of both cost and non-cost factors affecting the accuracy of estimates in building projects. The results provide a plausible description of these factors affecting the accuracy of estimates. It is noted that stakeholders give greater consideration to these factors as being of greater importance in order to attain more accurate estimates.

The second contribution of this research is that knowledge gaps in research in the area of importance of the application of LCC, to help understand the relationship between initial cost and running cost, especially for the building and construction industry, and empirical study of the impact of cost and non-cost factors to cost estimation, has been addressed. Analysis of the existing data (building projects) was used to clarify the relationship between capital cost and running costs. Connection weight methods in an ANNs model was also used to conduct an empirical study that can now clarify the relationship between capital cost, running cost, LCC and input variables of the models.

The third contribution of this research is that the ANNs model has been developed based on the adequate historical project data collected, the usage of the proposed ANNs model is suitable to any type of building with any range of the value of the both input and output variables.

9.8.2. Practical perspective

One of the key barriers facing the estimator is the absent of standard method of data collecting. Several pieces of information are needed to carry out a cost estimation approach of each stage of building life such as, each building's component lives, physical data (e.g. type of building and gross floor area) and occupancy data, frequency of maintenance and replacement of building's components. Currently, information of building life cycle cost is recorded only for a relatively short period of time because of storage issues. Individuals believe that there is no benefit to retain this data. Only very few construction companies and organisations; such as those mentioned in this research, have attained consistent detailed data on total cost at each building life cycle for long period of time.

The fourth contribution of this research is that the new approach (the newly developed ANNs model) to improve cost-estimation suggested here, has provided a framework for an estimation process involving a data collection step, which includes relatively few categories of factors. In this research, it is clear that the ANNs models are capable of being utilized to estimate the total cost of construction projects at different phases of project's life cycle. This is not to revolutionize the estimation cost method; rather, it is improve upon the traditional approach of estimation process. Pervious data of completed building project has significant influence towards an understanding of the future behaviour of construction building projects, and also to estimate future costs. The new approach proposed in this research has presented data in a constant way and in a clear form. This has addressed the issue of insufficient data storage. The data collection process in this new approach becomes more flexible and easy to obtain and use. Moreover, it will also motivate estimators to reduce the time required for data collection withy resultantly less storage needed.

The fifth contribution to now knowledge of this study is the successful determination of the importance for utilising LCC in building projects. This research bridges the gap between the design stage of building project and the running stage, towards clarifying the relationships that may exist between each stage of building life cycle. This will assist the project management teams with choosing the best alternative from options based on economic criteria. This will enable increased owners'

satisfaction and a more useful approach to procurement. Stakeholders will be able to identify cost drivers, predict future budget requirements and control programmes and minimise total cost. Moreover, they can make a decision about whether to continue or abort the project by analysing all the costs of it. They can also make a comparison between components with similar function, or several design of building, to select the best one based on the most economic criteria. LCC can be used to create a significant decisions policy, design trade-offs and select a contractor when the project is placed for tender.

The sixth major contribution to knowledge is that identification of important factors affecting cost estimation at each stage will enable the designer to focus and give attention to these factors in order to select the best design solutions for the building project to achieve more efficient building costs for both capital and running costs. For example, electrical installation has been identified as one cost factors affecting capital and running cost. Therefore designers may give more attention to this component during design towards building with less cost incurred subsequently.

Finally, it can be argued that the data used to develop this framework of an ANNs model, in this work, consists of several domains of building types. Therefore, generalising the framework model developed to any type of buildings or to other location may be readily feasible. In addition, the steps used in this framework can be followed to perform and develop similar ANNs model based on relevant data from any country.

The main differences between the properties of current life-cycle costing, and the LCC (ANNs) estimation method developed here might be summarised in terms of:

- Consisting of few components and thus saving in the analysis of whole-cost estimation;
- This new LCC (ANNs) model allows a clear data collection rationale and methodology and is argued to be therefore represent a simplified process;
- The approach is easy to implement and includes an appraisal of key non-cost factors; and finally that,
- The LCC (ANNs) model developed here provides an accurate prediction of LCC.

9.9. Future work

To build upon the current research described here, future work is envisaged, namely:

- Further research is deemed necessary to measure the performance of the model developed across homogeneous building types, allowing further comparisons with the results of this research.
    - Further work is of use to break down the key cost factors of non-structural elements (such as mechanical and electrical services, water installation and the like) of such homogeneous types to better understand the total cost implications of these items, by type.
- This research considers only the life-cycle cost of design and material specifications of applicable building elements and sub-elements and construction-options; further research is necessary to include external softer (humanistic application) variables more explicitly within developed model application.
- More work is recommended towards incorporation of this research (and it's ANNs models) translated into existing off-the-shelf cost-estimation software.

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11.APPENDIX

11.1. Appendix I: Questionnaire form

This research will be focused upon the contribution of the different cost and non-cost factors that represent the main variables that affect the LCC and analysis of the techniques used to measure them. The researcher intention is to attempt to industrial assistance to support this research. We thank you very much in advance for any help received related to this matter.

The researcher thank you very much in advance for any help received related to this matter.Where appreciate any and all information deem sensitive including data regarding name, places, dates and value shell (upon request by your good-selves and through the necessary action by the candidate) remain confidential.

Part I : General Information

PLEASE ANSWER THE FOLLOWINGS QUESTIONS. INDICATE WITH A TICK (X) AGAINST THE OPTION :

1) WHAT IS YOUR COMPANY TYPE?

- ☐ QUANTITY SURVEYOR
- ☐ PROPERTY ENGINEER
- ☐ COST ESTIMATOR
- ☐ PROJECT MANAGER
- ☐ COST ENGINEER
- ☐ OTHERS, PLEASE SPECIFY : _____

2) WHICH SECTOR DO YOU HAVE THE MOST EXPERIENCE IN?

- ☐ Education building (school, university.etc)
- ☐ Residential building
- ☐ Office building
- ☐ Industrial building
- ☐ Commercial building
- ☐ Hospital
- ☐ Other : _____

3) HOW MANY YEARS DO YOU HAVE IN THIS SECTOR?

- ☐ 1-3 YEARS.
- ☐ 3 - 5 YEARS.
- ☐ 5-10 YEARS.
- ☐ 10 + YEARS
- ☐ OTHERS, PLEASE SPECIFY : _____

4) WHAT IS YOUR HIGHEST FORMAL EDUCATION QUALIFICATION?

- ☐ EXPERIENCE, SPECIFY: _____
- ☐ ENGINEERING DEGREE, SPECIFY: _____
- ☐ NONE ACADEMIC DEGREE, SPECIFY : _____
- ☐ ON-JOB TRAINING: _____
- ☐ OTHERS, PLEASE SPECIFY : _____

5) Do you know the concept of Life Cycle Costing?

- ☐ Very well
- ☐ Well
- ☐ Somehow
- ☐ Little
- ☐ None

6) What is the best define of the LCC?

- ☐ The total cost of a system, building, or other product, computed over its useful life.
- ☐ A technique that allows the assessment of a given solution or choice among alternate solutions.
- ☐ An economic valuation of system or an item that takes into account all important costs of ownership over the economic life of an item or system.
- ☐ Other:_____

7) Is Life Cycle Costing presently applied in your company?

- ☐ Always
- ☐ Often
- ☐ Sometimes
- ☐ Little
- ☐ Never

8) What is the method your firm applies to calculate the LCC?

- ☐ Net Present value
- ☐ Equivalent annual cost
- ☐ Internal rate of return
- ☐ Simple payback method
- ☐ Discounted payback
- ☐ Others ,specify :_____

9) What are the overall objectives to apply the LCC?

a) As part of V.E. (value engineering) program.
b) Choose between alternatives.
c) Predicting future running cost
d) As a means for budgeting for future expenditures.
e) Others, please specify_____ .

10) What are most important problems of application of Life Cycle Costing in your firm. You can select more than one (but rank them):

- ☐ Lack of Knowledge of the concept
- ☐ Unknown relation between initial cost and running cost
- ☐ Unknown the best method to calculate LCC
- ☐ Unavailability of data
- ☐ Unavailability of standard method for collecting and recording of data
- ☐ Unclear benefits of LCC to stakeholders.
- ☐ Difficulties in identifying cost components
- ☐ Others, please specify:_____

Part II: Rate non-cost factors affection estimation processes

11) Please rate the non-cost factors affecting the estimation of LCC:

1= not at all important 2= not very important 3=somewhat important 4=very important 5=extremely important

No.	Factors	1	2	3	4	5
1	Number of stories (affecting the estimation of LCC)					
How does the number of stories affecting design and construction cost estimation? Please explain and rate:						
How does the number of stories affecting operation and maintenance cost estimation? Please explain and rate:						
2	Type of building (affecting the estimation of LCC)					
How does the type of building affecting design and construction cost estimation? Please explain and rate:						
How does the type of building affecting operation and maintenance cost estimation? Please explain and rate:						
3	Gross floor area(affecting the estimation of LCC)					
How does the gross floor area affecting design and construction cost estimation? Please explain and rate:						
How does the gross floor area affecting operation and maintenance cost estimation? Please explain and rate:						
4	Project life (affecting the estimation of LCC)					
How does the project's life affecting design and construction cost estimation? Please explain and rate:						

How does the project's life affecting operation and maintenance cost estimation? Please explain and rate:						
5	Location (affecting the estimation of LCC)					
How does the location affecting design and construction cost estimation? Please explain and rate:						
How does the location affecting operation and maintenance cost estimation? Please explain and rate:						
6	Roof types(affecting the estimation of LCC)					
How does the roof type affecting design and construction cost estimation? Please explain and rate:						
How does the location affecting operation and maintenance cost estimation? Please explain and rate:						
7	Foundation types(affecting the estimation of LCC)					
How does the foundation type affecting design and construction cost estimation? Please explain and rate:						
How does the foundation type affecting operation and maintenance cost estimation? Please explain and rate:						
8	Number of elevators (affecting the estimation of LCC)					
How does the foundation type affecting design and construction cost estimation? Please explain and rate:						

How does the foundation type affecting operation and maintenance cost estimation? Please explain and rate:						
9	Type of structure(affecting the estimation of LCC)					
How does the type of structure affecting design and construction cost estimation? Please explain and rate:						
How does the foundation type affecting operation and maintenance cost estimation? Please explain and rate:						
10	Inflation rate (affecting the estimation of LCC)					
How does the inflation rate affecting design and construction cost estimation? Please explain and rate:						
How does the inflation rate affecting operation and maintenance cost estimation? Please explain and rate:						

11.2. Appendix II: Normality test

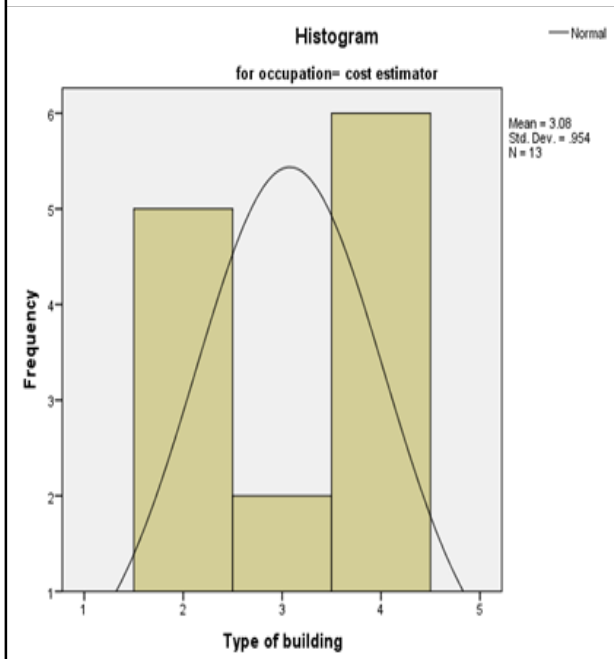
a) Survey research : Skewness and Kurtosis test; Normal distribution histogram

	1- Number of Stories									
	quantity surveyors		Cost estimators		Project mangers		cost engineers		Others	
	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis
Statistic	-0.34	-1.31	0.68	-0.61	-0.46	-0.55	-0.21	-0.01	-0.13	-0.08
Standard Error	0.46	0.89	0.62	1.19	0.5	0.97	0.4	0.78	0.43	0.85
Z (score) = Statistic/ Standard Error	-0.74	-1.47	1.1	-0.51	-0.92	-0.57	-0.53	-0.01	-0.29	-0.09
	2- Type of building									
	quantity surveyors		Cost estimators		Project mangers		cost engineers		Others	
	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis
Statistic	-0.32	-1.17	-0.17	-2.08	-0.61	-0.11	-0.33	-0.7	-0.67	-0.5
Standard Error	0.46	0.89	0.62	1.19	0.5	0.97	0.4	0.78	0.43	0.85
Z (score) = Statistic/ Standard Error	-0.7	-1.32	-0.28	-1.75	-1.22	-0.11	-0.84	-0.9	-1.54	-0.59
	3- Gross floor area									

	quantity surveyors		Cost estimators		Project mangers		cost engineers		Others	
	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis
Statistic	-0.72	0.17	-0.02	-1.36	0.06	-0.65	-0.5	-0.45	-0.58	0.15
Standard Error	0.46	0.89	0.62	1.19	0.5	0.97	0.4	0.78	0.43	0.85
Z (score) = Statistic/ Standard Error	-1.57	0.19	-0.04	-1.14	0.11	-0.67	-1.25	-0.58	-1.33	0.18
	4- Project life									
	quantity surveyors		Cost estimators		Project mangers		cost engineers		Others	
	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis
Statistic	-0.22	-1.45	0.19	-1.33	-0.25	-0.64	0	-1.44	-1.27	3.76
Standard Error	0.46	0.89	0.62	1.19	0.5	0.97	0.4	0.78	0.43	0.85
Z (score) = Statistic/ Standard Error	-0.49	-1.64	0.32	-1.12	-0.5	-0.66	0	-1.85	-2.92	4.45
	5- Location									
	quantity surveyors		Cost estimators		Project mangers		cost engineers		Others	
	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis
Statistic	-0.44	-0.99	-0.23	-1.27	-0.37	-0.72	-0.32	-0.97	-0.5	0.39
Standard Error	0.46	0.89	0.62	1.19	0.5	0.97	0.4	0.78	0.43	0.85

Z (score) = Statistic/ Standard Error	-0.96	-1.11	-0.38	-1.06	-0.74	-0.74	-0.81	-1.25	-1.16	0.47
	6- Roof type									
	quantity surveyors		Cost estimators		Project mangers		cost engineers		Others	
	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis
Statistic	-0.79	-0.16	-0.53	-0.95	-0.62	0.46	-0.42	-0.68	0.19	-0.56
Standard Error	0.46	0.89	0.62	1.19	0.5	0.97	0.4	0.78	0.43	0.85
Z (score) = Statistic/ Standard Error	-1.73	-0.18	-0.86	-0.79	-1.24	0.48	-1.07	-0.88	0.45	-0.67
	7- Foundation type									
	quantity surveyors		Cost estimators		Project mangers		cost engineers		Others	
	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis
Statistic	-0.28	-0.83	-0.15	-1.05	-1.18	1.23	-0.45	-0.57	-0.07	-1.25
Standard Error	0.46	0.89	0.62	1.19	0.7	0.97	0.4	0.78	0.43	0.85
Z (score) = Statistic/ Standard Error	-0.62	-0.94	-0.25	-0.88	-1.68	1.27	-1.12	-0.73	-0.16	-1.48
	8- Number of elevators									
	quantity surveyors		Cost estimators		Project mangers		cost engineers		Others	
	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis

Statistic	**-0.22**	**-0.36**	**0.05**	**0.05**	**-0.42**	**0.2**	**0.15**	**-0.14**	**-0.36**	**-0.83**
Standard Error	**0.46**	**0.89**	**0.62**	**1.19**	**0.5**	**0.97**	**0.4**	**0.78**	**0.43**	**0.85**
Z (score) = Statistic/ Standard Error	**-0.47**	**-0.41**	**0.08**	**0.04**	**-0.83**	**0.2**	**0.37**	**-0.18**	**-0.82**	**-0.99**
	9- Type of structure									
	quantity surveyors		**Cost estimators**		**Project mangers**		**cost engineers**		**Others**	
	Skewness	**Kurtosis**	**Skewness**	**Kurtosis**	**Skewness**	**Kurtosis**	**Skewness**	**Kurtosis**	**Skewness**	**Kurtosis**
Statistic	**-0.42**	**-0.43**	**-0.37**	**-1.33**	**-0.53**	**-0.31**	**-0.43**	**-1.13**	**-0.5**	**-0.83**
Standard Error	**0.46**	**0.89**	**0.62**	**1.19**	**0.5**	**0.97**	**0.4**	**0.78**	**0.43**	**0.85**
Z (score) = Statistic/ Standard Error	**-0.91**	**-0.48**	**-0.59**	**-1.12**	**-1.06**	**-0.31**	**-1.07**	**-1.46**	**-1.15**	**-0.98**
	10- Inflation rate									
	quantity surveyors		**Cost estimators**		**Project mangers**		**cost engineers**		**Others**	
	Skewness	**Kurtosis**	**Skewness**	**Kurtosis**	**Skewness**	**Kurtosis**	**Skewness**	**Kurtosis**	**Skewness**	**Kurtosis**
Statistic	**-0.39**	**-0.29**	**-0.7**	**-0.72**	**-0.84**	**0.26**	**-0.34**	**-0.79**	**0.05**	**-1.16**
Standard Error	**0.46**	**0.89**	**0.62**	**1.19**	**0.5**	**0.97**	**0.4**	**0.78**	**0.43**	**0.85**
Z (score) = Statistic/ Standard Error	**-0.86**	**-0.33**	**-1.14**	**-0.6**	**-1.68**	**0.27**	**-0.85**	**-1.01**	**0.11**	**-1.37**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Mean = 3.08
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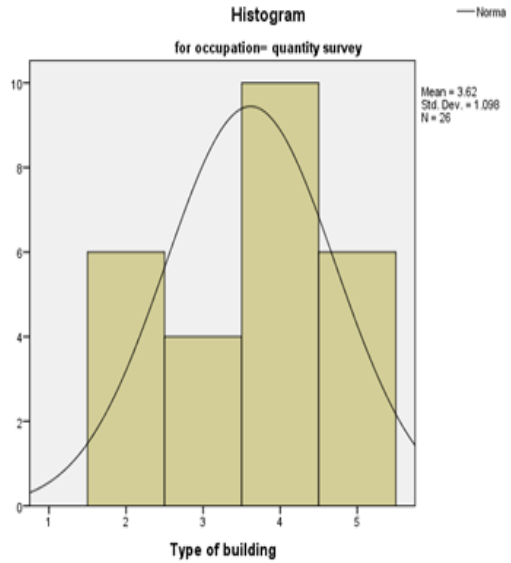
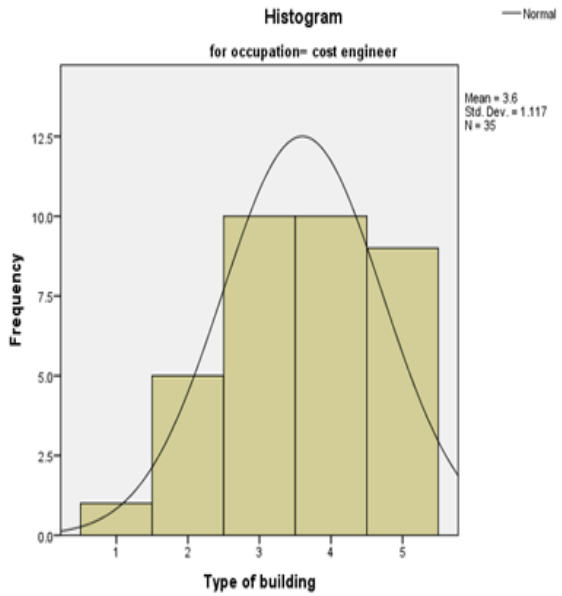
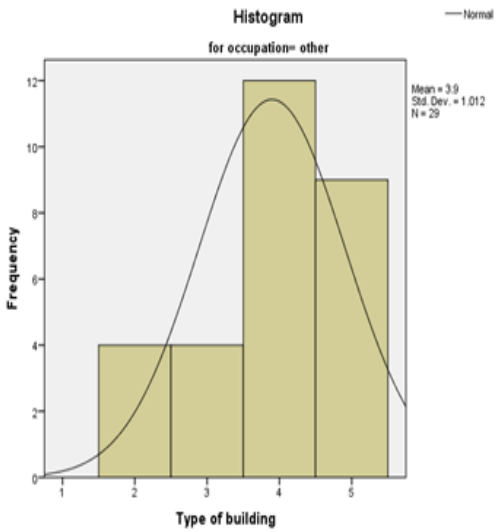
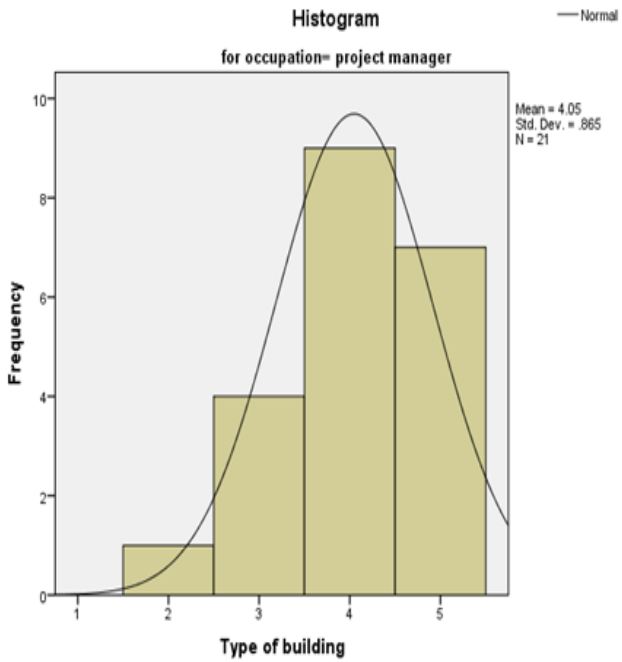
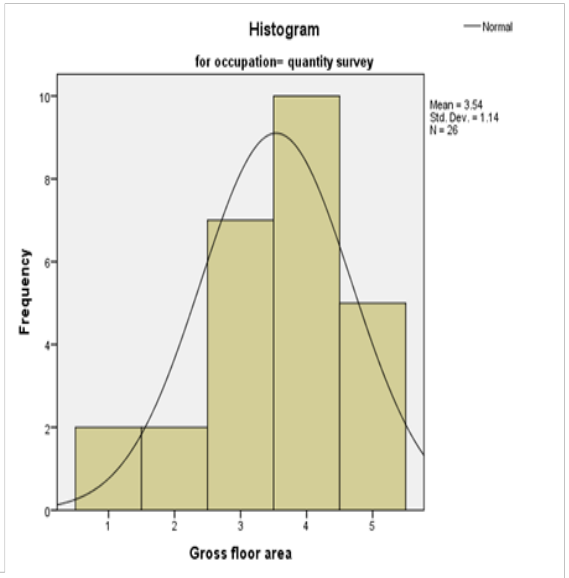
N = 13
Frequency
Type of building

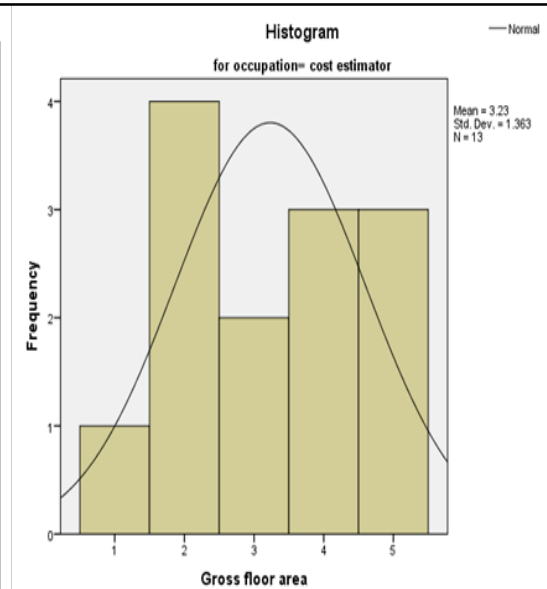

Histogram
Norma
for occupation= quantity survey
Mean = 3.62
Std. Dev. = 1.098
N = 26
Type of building


Histogram
Normal
for occupation= cost engineer
Mean = 3.6
Std. Dev. = 1.117
N = 35
Frequency
Type of building


Histogram
Normal
for occupation= other
Mean = 3.9
Std. Dev. = 1.012
N = 29
Frequency
Type of building


Histogram
Normal
for occupation= project manager
Mean = 4.05
Std. Dev. = .865
N = 21
Frequency
Type of building


Histogram
Normal
for occupation= quantity survey
Mean = 3.54
Std. Dev. = 1.14
N = 26
Frequency
Gross floor area


Histogram
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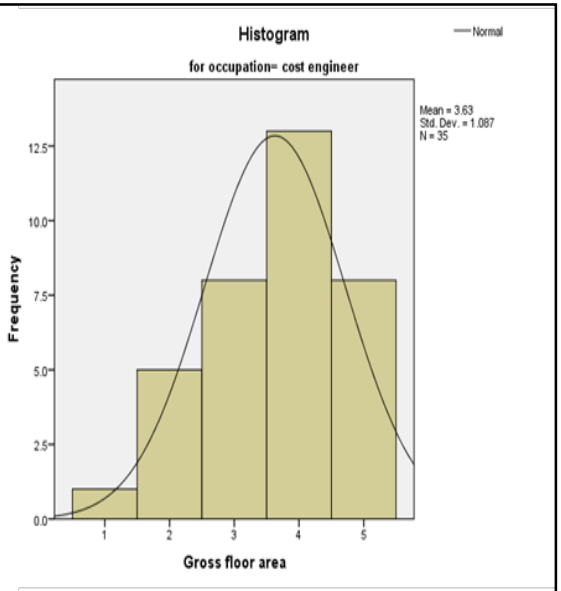
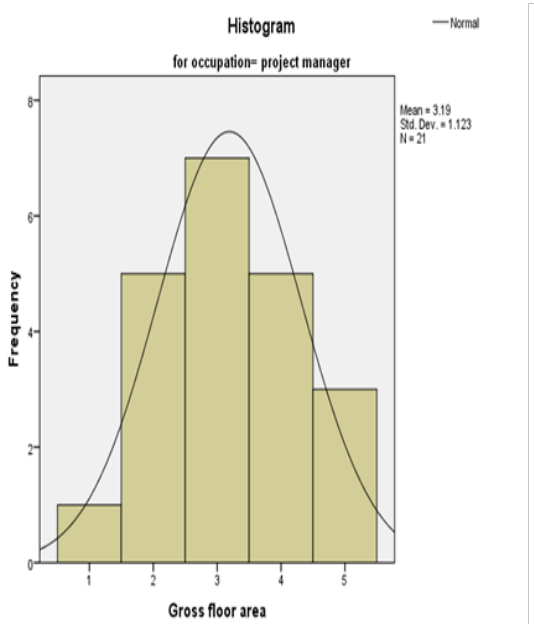
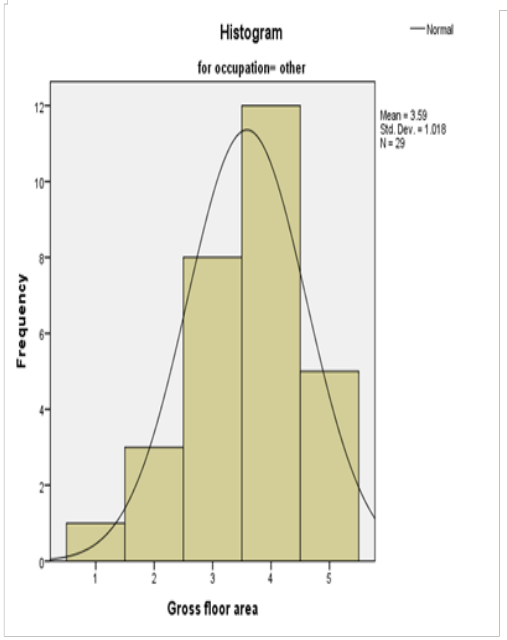
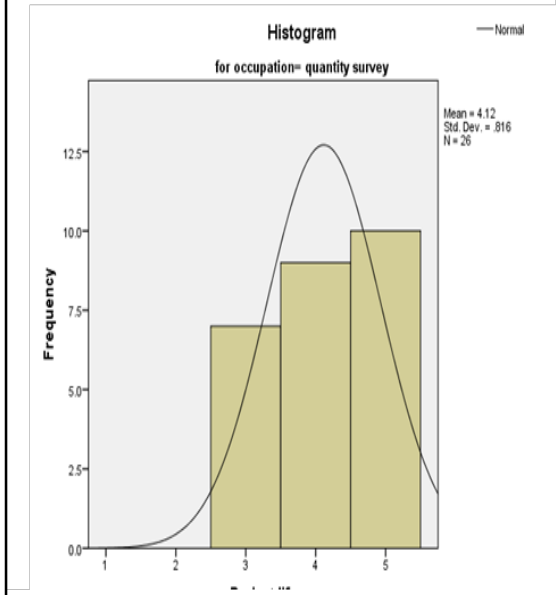
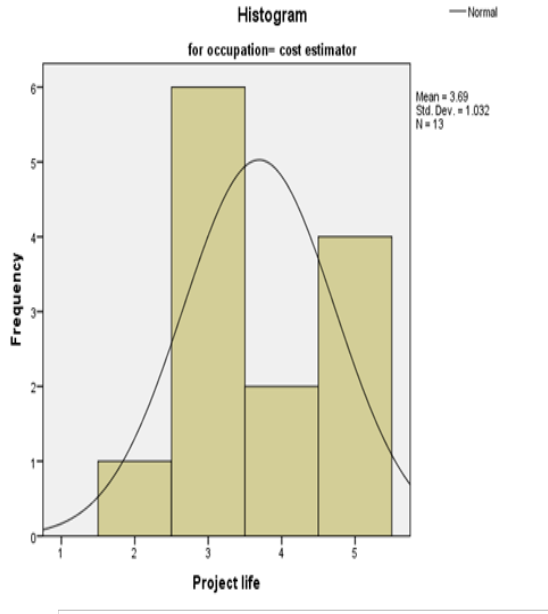
for occupation= cost estimator
Mean = 3.23
Std. Dev. = 1.363
N = 13
Frequency
Gross floor area

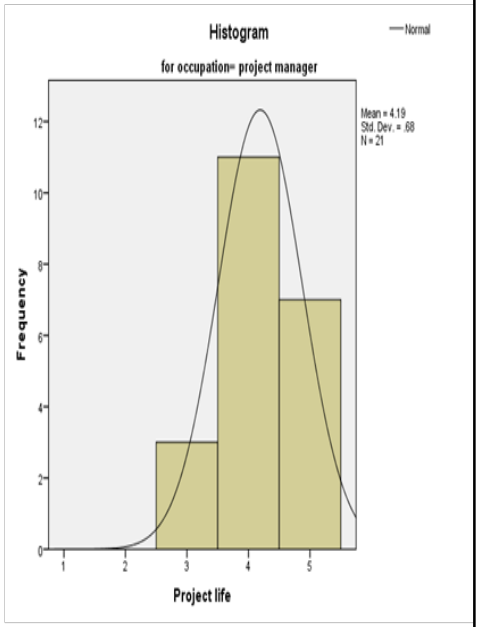

Histogram
Normal
for occupation= cost engineer
Mean = 3.63
Std. Dev. = 1.087
N = 35
Frequency
Gross floor area

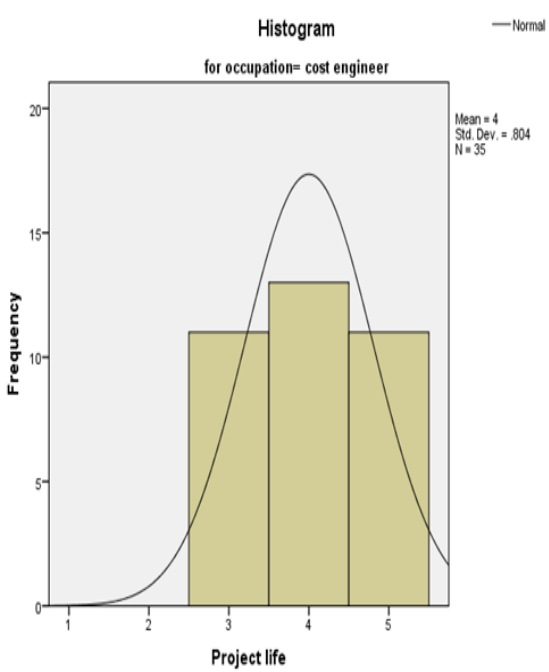

Histogram
Normal
for occupation= project manager
Mean = 3.19
Std. Dev. = 1.123
N = 21
Frequency
Gross floor area

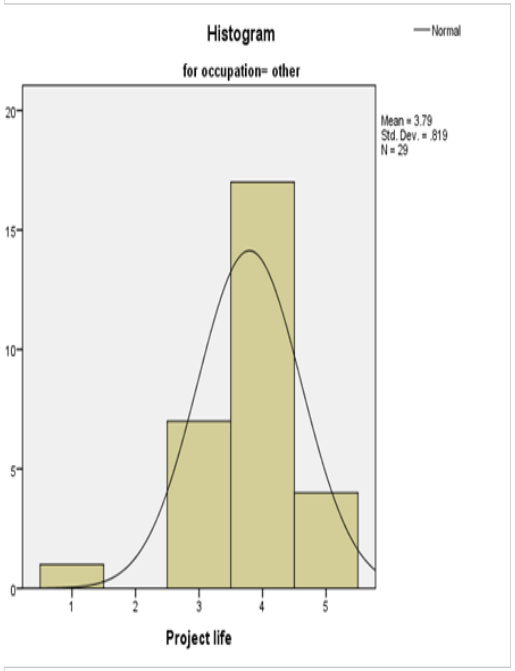

Histogram
Normal
for occupation= other
Mean = 3.59
Std. Dev. = 1.018
N = 29
Frequency
Gross floor area

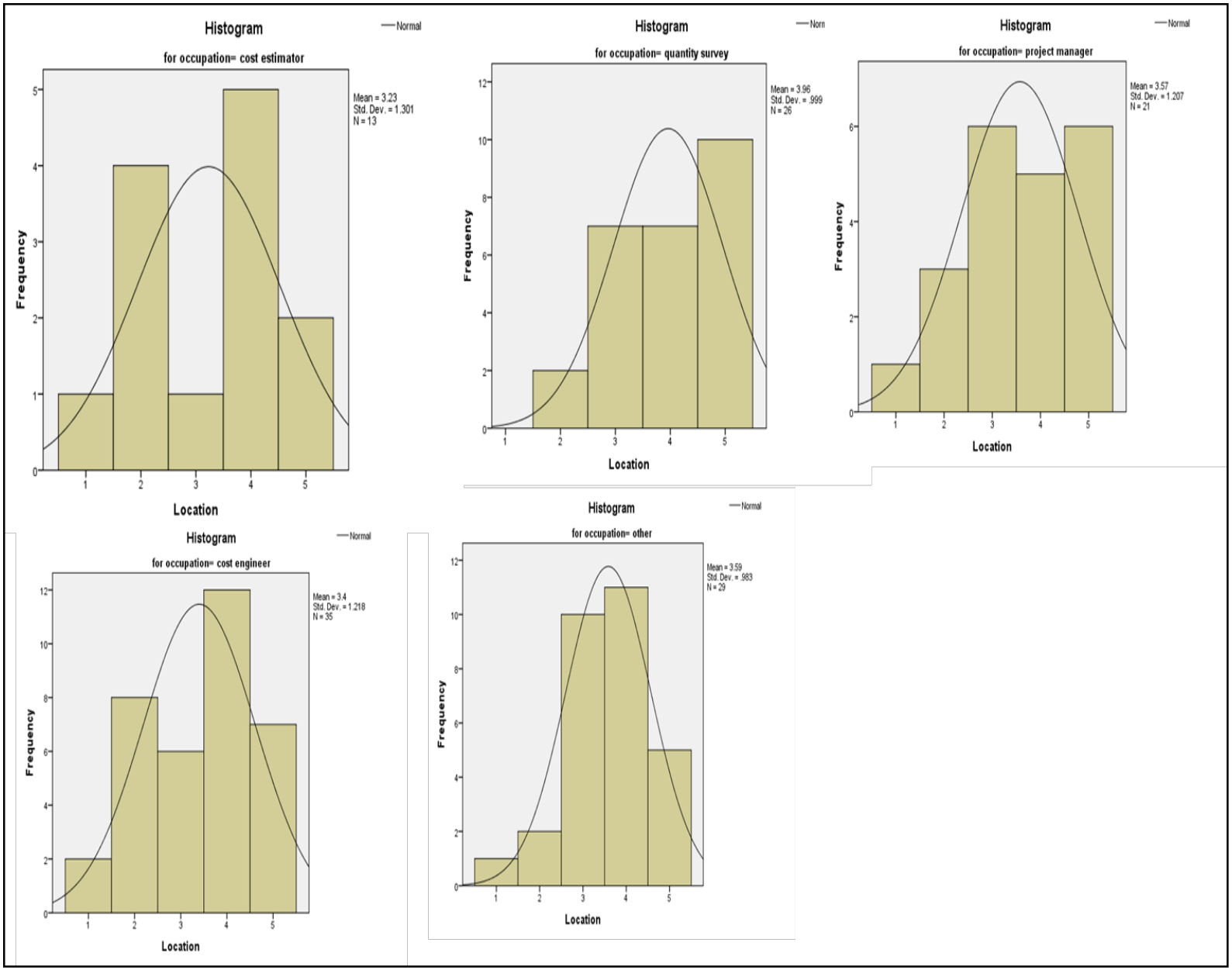

Histogram
Normal
for occupation= quantity survey
Mean = 4.12
Std. Dev. = .816
N = 26
Frequency
Project life

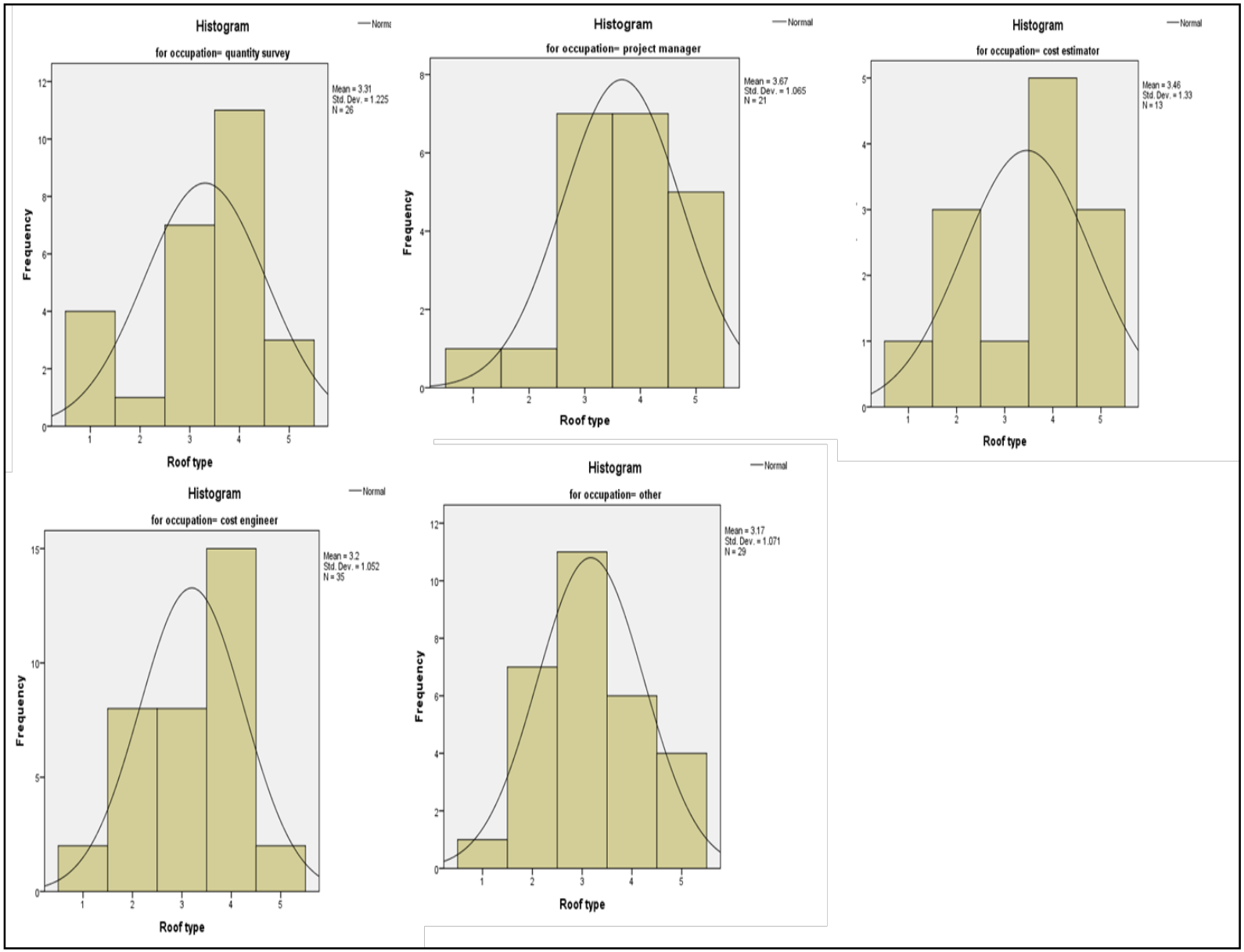

Histogram
Normal
for occupation= cost estimator
Mean = 3.69
Std. Dev. = 1.032
N = 13
Frequency
Project life

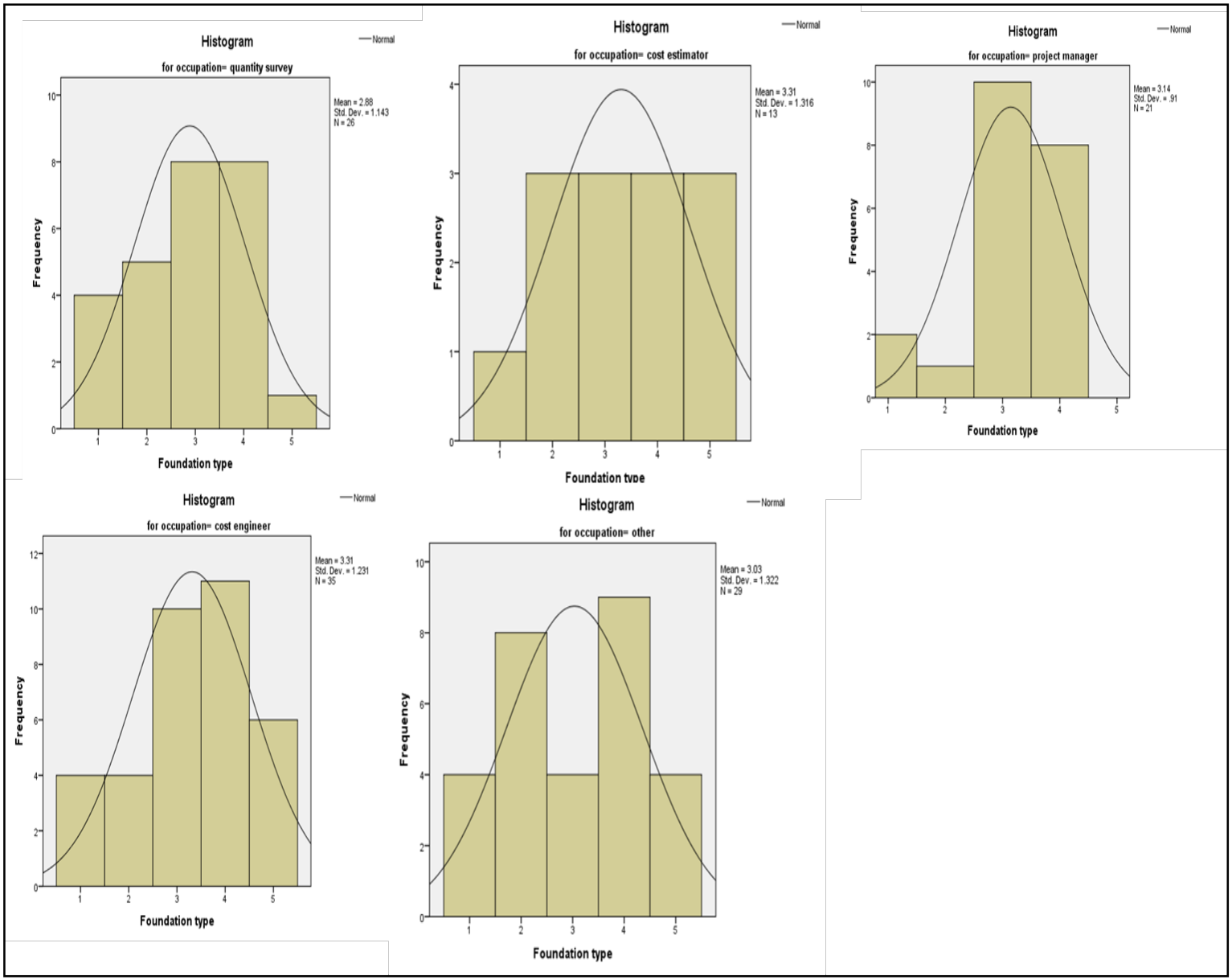

Histogram
Normal
for occupation= project manager
Mean = 4.19
Std. Dev. = .68
N = 21
Frequency
Project life

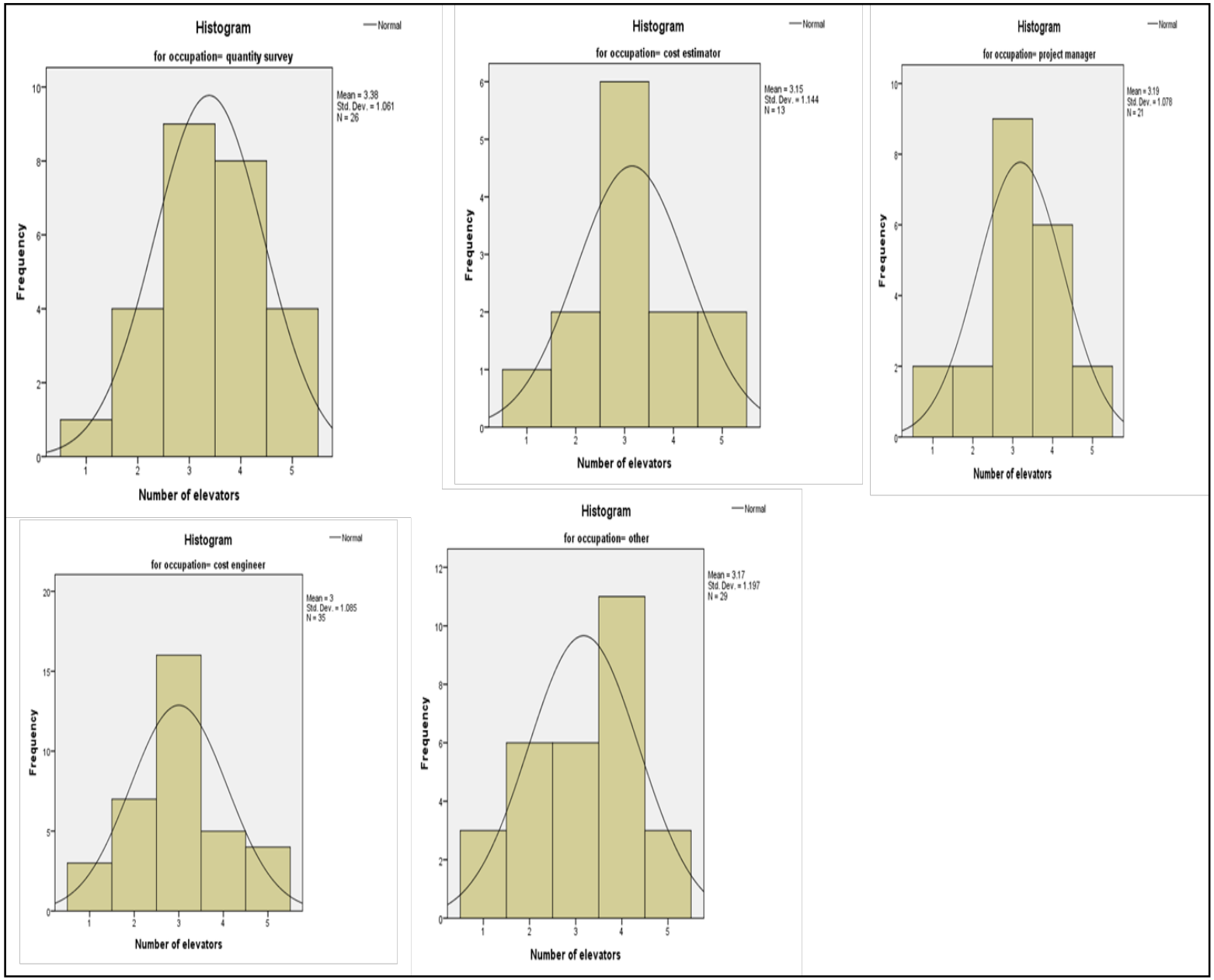

Histogram
Normal
for occupation= cost engineer
Mean = 4
Std. Dev. = .804
N = 35
Frequency
Project life

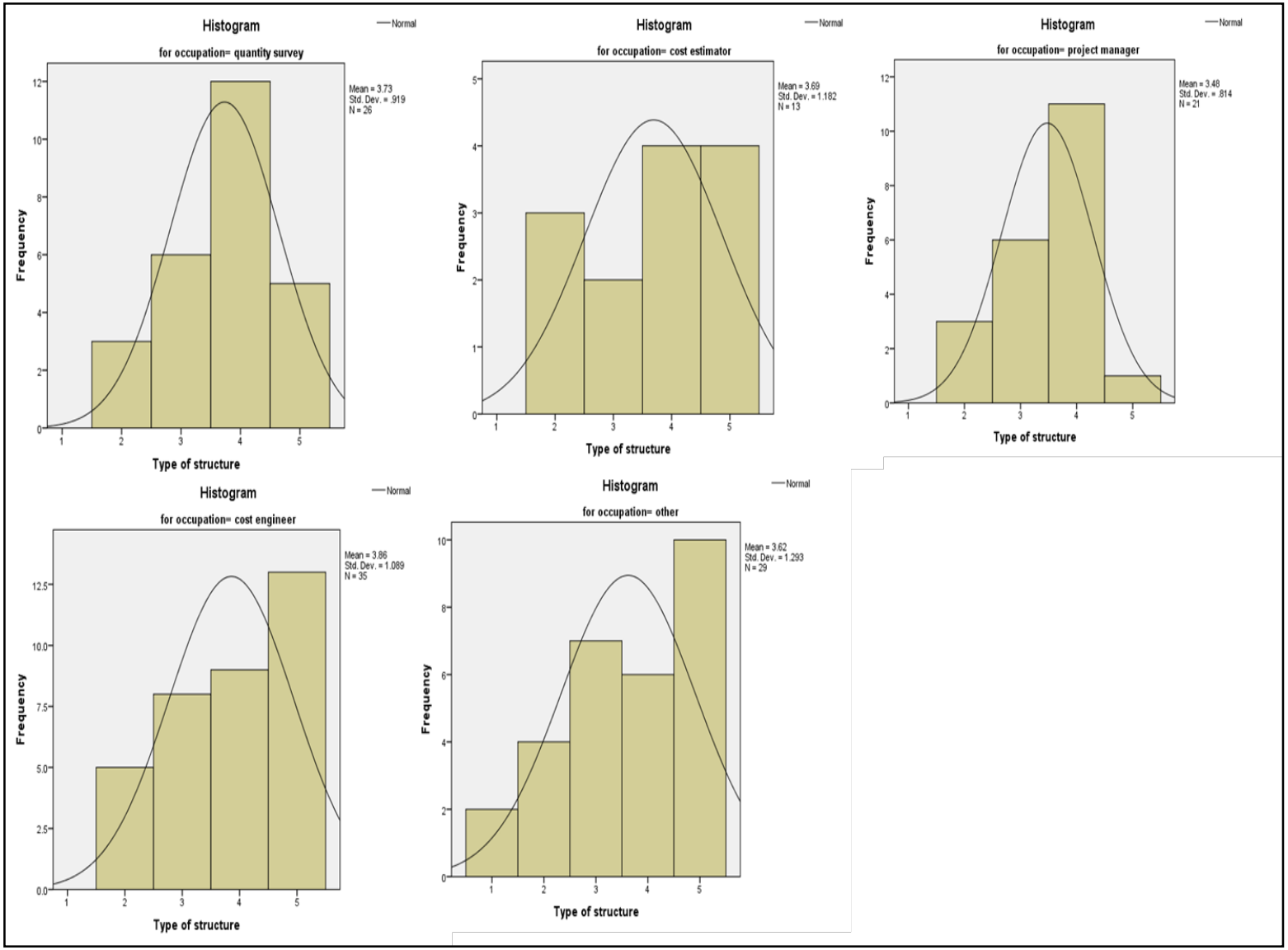

Histogram
Normal
for occupation= other
Mean = 3.79
Std. Dev. = .819
N = 29
Frequency
Project life

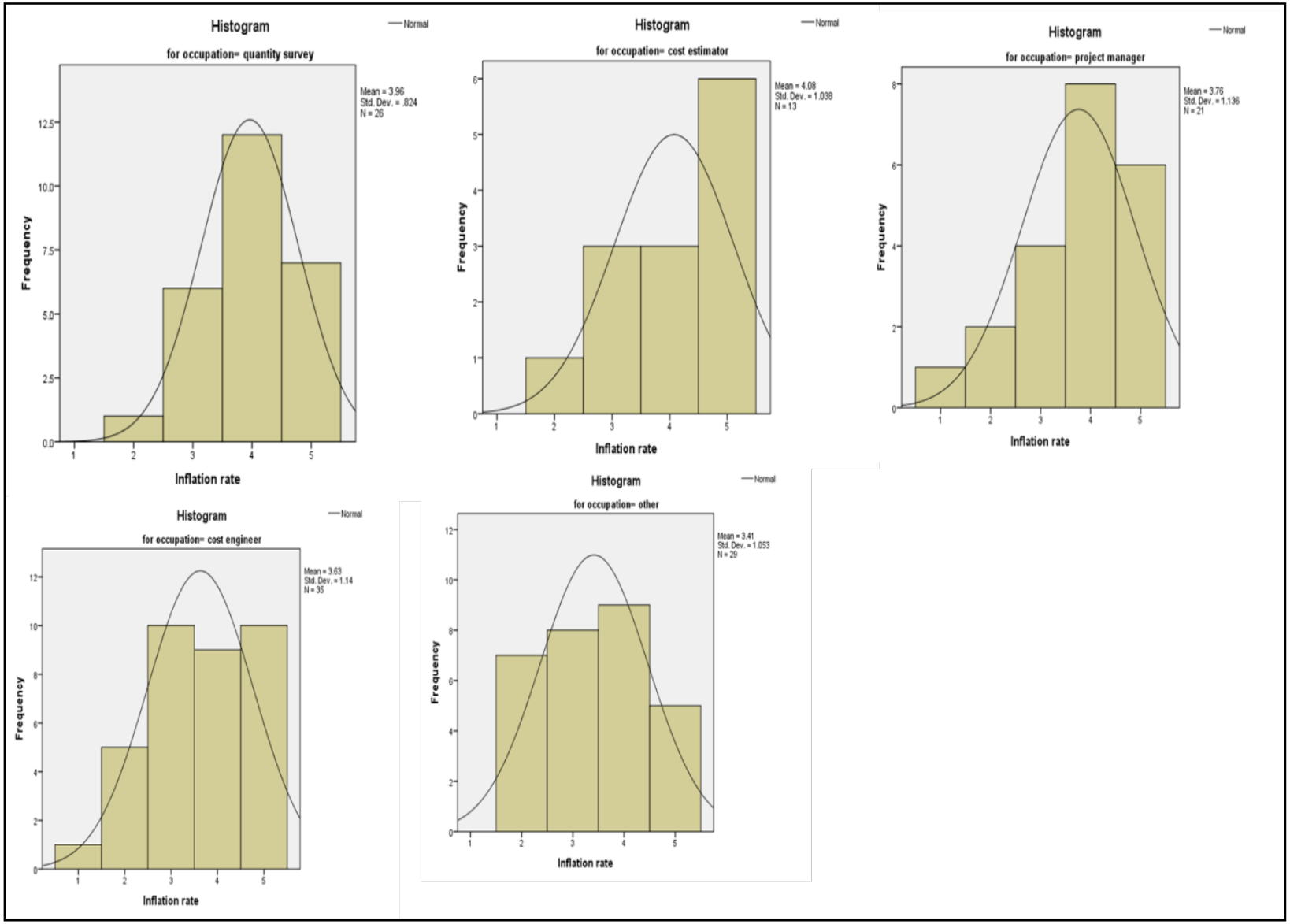

Histogram
Normal
for occupation= cost estimator
Mean = 3.23
Std. Dev. = 1.301
N = 13
Frequency
Location
Histogram
Norn
for occupation= quantity survey
Mean = 3.96
Std. Dev. = .999
N = 26
Frequency
Location
Histogram
Normal
for occupation= project manager
Mean = 3.57
Std. Dev. = 1.207
N = 21
Frequency
Location
Histogram
Normal
for occupation= cost engineer
Mean = 3.4
Std. Dev. = 1.218
N = 35
Frequency
Location
Histogram
Normal
for occupation= other
Mean = 3.59
Std. Dev. = .983
N = 29
Frequency
Location

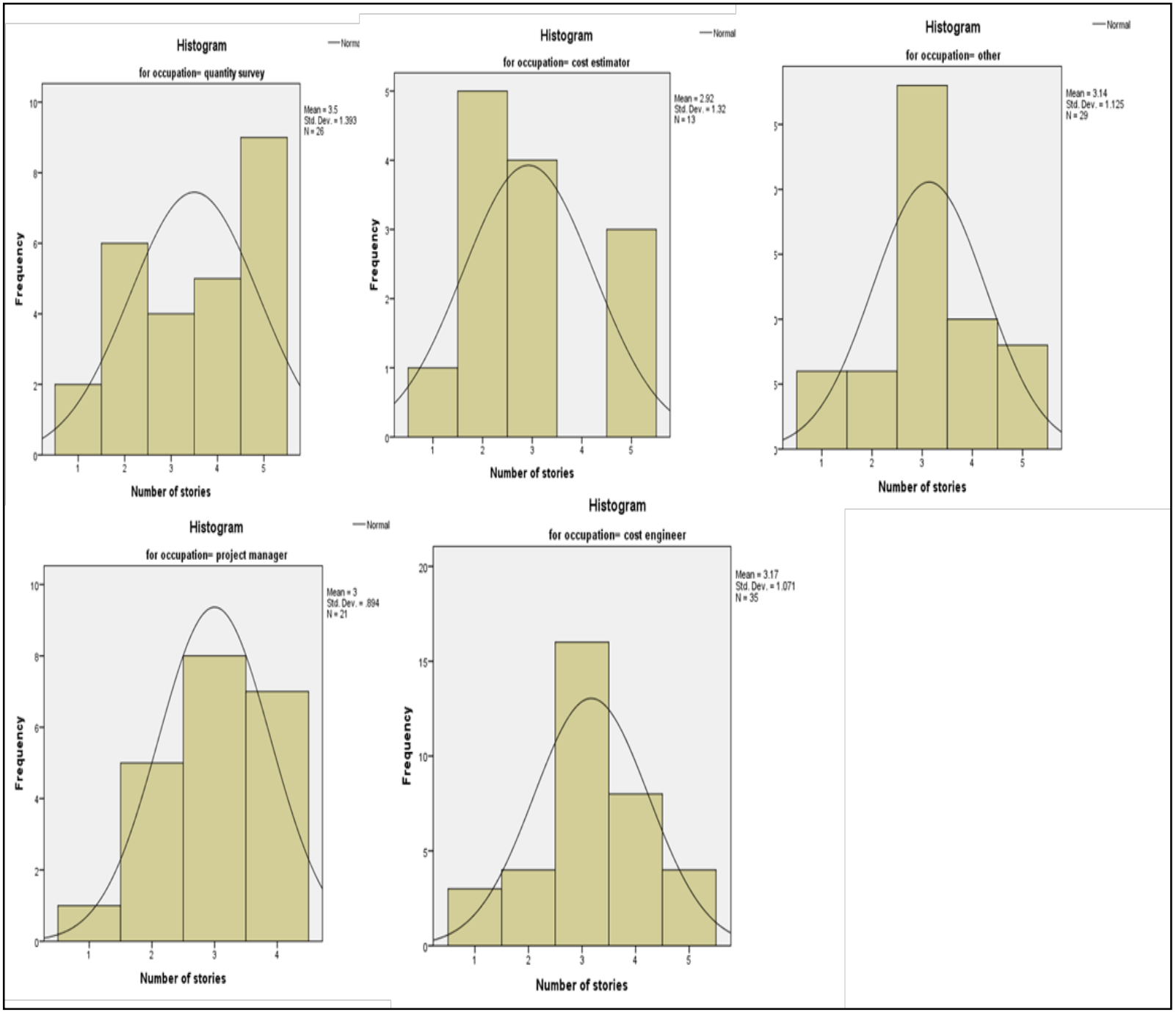

Histogram
for occupation= quantity survey
Mean = 3.31
Std. Dev. = 1.225
N = 26
Frequency
Roof type
Histogram
for occupation= project manager
Mean = 3.67
Std. Dev. = 1.065
N = 21
Frequency
Roof type
Histogram
for occupation= cost estimator
Mean = 3.46
Std. Dev. = 1.33
N = 13
Roof type
Histogram
for occupation= cost engineer
Mean = 3.2
Std. Dev. = 1.052
N = 35
Frequency
Roof type
Histogram
for occupation= other
Mean = 3.17
Std. Dev. = 1.071
N = 29
Frequency
Roof type


Histogram
Normal
for occupation= quantity survey
Mean = 2.88
Std. Dev. = 1.143
N = 26
Frequency
Foundation type
Histogram
Normal
for occupation= cost estimator
Mean = 3.31
Std. Dev. = 1.316
N = 13
Frequency
Foundation type
Histogram
Normal
for occupation= project manager
Mean = 3.14
Std. Dev. = .91
N = 21
Frequency
Foundation type
Histogram
Normal
for occupation= cost engineer
Mean = 3.31
Std. Dev. = 1.231
N = 35
Frequency
Foundation type
Histogram
Normal
for occupation= other
Mean = 3.03
Std. Dev. = 1.322
N = 29
Frequency
Foundation type


Histogram
Normal
for occupation= quantity survey
Mean = 3.38
Std. Dev. = 1.061
N = 26
Frequency
Number of elevators
Histogram
Normal
for occupation= cost estimator
Mean = 3.15
Std. Dev. = 1.144
N = 13
Frequency
Number of elevators
Histogram
Normal
for occupation= project manager
Mean = 3.19
Std. Dev. = 1.078
N = 21
Frequency
Number of elevators
Histogram
Normal
for occupation= cost engineer
Mean = 3
Std. Dev. = 1.085
N = 35
Frequency
Number of elevators
Histogram
Normal
for occupation= other
Mean = 3.17
Std. Dev. = 1.197
N = 29
Frequency
Number of elevators


Histogram
Normal
for occupation= quantity survey
Mean = 3.73
Std. Dev. = .919
N = 26
Frequency
Type of structure
Histogram
Normal
for occupation= cost estimator
Mean = 3.69
Std. Dev. = 1.182
N = 13
Frequency
Type of structure
Histogram
Normal
for occupation= project manager
Mean = 3.48
Std. Dev. = .814
N = 21
Frequency
Type of structure
Histogram
Normal
for occupation= cost engineer
Mean = 3.86
Std. Dev. = 1.089
N = 35
Frequency
Type of structure
Histogram
Normal
for occupation= other
Mean = 3.62
Std. Dev. = 1.293
N = 29
Frequency
Type of structure


Histogram
for occupation= quantity survey
Normal
Mean = 3.96
Std. Dev. = .824
N = 26
Frequency
Inflation rate
Histogram
for occupation= cost estimator
Normal
Mean = 4.08
Std. Dev. = 1.038
N = 13
Frequency
Inflation rate
Histogram
for occupation= project manager
Normal
Mean = 3.76
Std. Dev. = 1.136
N = 21
Frequency
Inflation rate
Histogram
for occupation= cost engineer
Normal
Mean = 3.63
Std. Dev. = 1.14
N = 35
Frequency
Inflation rate
Histogram
for occupation= other
Normal
Mean = 3.41
Std. Dev. = 1.053
N = 29
Frequency
Inflation rate


Histogram
for occupation= quantity survey
Mean = 3.5
Std. Dev. = 1.393
N = 26
Frequency
Number of stories
Histogram
for occupation= cost estimator
Mean = 2.92
Std. Dev. = 1.32
N = 13
Frequency
Number of stories
Histogram
for occupation= other
Mean = 3.14
Std. Dev. = 1.125
N = 29
Number of stories
Histogram
for occupation= project manager
Mean = 3
Std. Dev. = .894
N = 21
Frequency
Number of stories
Histogram
for occupation= cost engineer
Mean = 3.17
Std. Dev. = 1.071
N = 35
Frequency
Number of stories

b) **Normality test of % CSIs value and number at each stage:**

	Capital costs			
	% CSIs Number		% CSIs value	
	Skewness	Kurtosis	Skewness	Kurtosis
Statistic	-1.033	-0.521	-0.291	-0.356
Standard Error	0.580	1.104	0.580	1.121
Z (score) = Statistic/ Standard Error	-1.781	-0.472	-0.502	-0.318
	Maintenance costs			
	% CSIs Number		% CSIs value	
	Skewness	Kurtosis	Skewness	Kurtosis
Statistic	0.377	0.580	0.311	-0.620
Standard Error	-0.465	1.121	0.580	1.121
Z (score) = Statistic/ Standard Error	-0.811	0.517	0.536	-0.553
	Operation costs			
	% CSIs Number		% CSIs value	
	Skewness	Kurtosis	Skewness	Kurtosis
Statistic	0.692	0.501	-0.081	-0.161
Standard Error	0.580	1.121	0.580	1.121
Z (score) = Statistic/ Standard Error	1.193	0.447	-0.140	-0.144
	Running costs			
	% CSIs Number		% CSIs value	
	Skewness	Kurtosis	Skewness	Kurtosis
Statistic	0.334	-1.162	0.951	1.004
Standard Error	0.580	1.121	0.580	1.121
Z (score) = Statistic/ Standard Error	0.576	-1.037	1.640	0.896
	LCC			
	% CSIs Number		% CSIs value	
	Skewness	Kurtosis	Skewness	Kurtosis
Statistic	0.006	0.444	-0.029	0.580
Standard Error	0.580	1.121	0.580	1.121
Z (score) = Statistic/ Standard Error	0.010	0.396	-0.050	0.517