DEVELOPMENT OF AN ARTIFICIAL NEURAL NETWORK MODEL FOR PREDICTING THE IMPACT OF RISK ON COST OF BUILDING PROJECTS

BY

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PhD/SET/2013/530

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A THESIS SUBMITTED TO THE POSTGRADUATE SCHOOL, FEDERAL UNIVERSITY OF TECHNOLOGY MINNA, IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE AWARD OF THE DEGREE OF DOCTOR OF PHILOSOPHY (Ph.D) IN QUANTITY SURVEYING

JULY 2018

DECLARATION

I hereby declare that this thesis titled "Development of an Artificial Neural Network model for predicting the impact of risk on cost of building projects" is a collection of my original research work and it has not been presented for any other qualification anywhere. Information from other sources (published and unpublished) has been duly acknowledged.

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CERTIFICATION

This thesis titled “Development of an Artificial Neural Network model for predicting the impact of risk on cost of building projects” by OKE, Abdulganiyu Adebayo (Ph.D/SET/2013/530) meets the regulations governing the award of degree of Doctor of Philosophy (Ph.D) of the Federal University of Technology, Minna and it is approved for its contribution to scientific knowledge and literary presentation.

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DEAN, POSTGRADUATE SCHOOL Signature & Date

DEDICATION

I dedicate this work to the memory of my late father, Alh. AbdulSalaam A. Oke and my late mother, Alhaja Aminat A. Oke. May Allah (SWT) grant them *Al-Jannatul Firdaus*. Ameen.

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ABSTRACT

The use of construction project features (CPFs) to predict the impact of risk on costs of building projects is severely limited by the necessity to gather a homogeneous sample of projects. This limitation of the use of CPFs for risk prediction is the problem addressed by the study. The study aimed to develop artificial neural networks for predicting the occurrence, type and degree of impact of risk on costs of building projects by using selected CPFs. Data on 69 building projects was collected through the use of questionnaires from Quantity Surveyors in Abuja who were purposively sampled. The study found that costs of building projects are impacted by eight risks, which include variation, scope and design changes; error/omission in design/estimates, and unforeseen economic, site and social conditions. Project consultants are responsible for 69% of risks occurrence, while 52% of the cost impacts of risks result from the actions of clients. ANN1, an MLP artificial neural network with 2:31:1:1 structure was developed to predict variance between initial and final contract values by using five of the eight risks in two groups of client and consultant risks. A validation MSE of 0.0026 established ANN1's superiority over a conventional MLR statistical model *(Final cost variance = -4.834 + 1.056Consultant Risks + 1.058Client Risks)* which had an MSE of 10.22. ANN2, an 8:19:7 MLP network was developed to predict risk effect on building costs by using 8 CPFs including gross floor area and costs of building elements. ANN2 used binarization to normalize data, with a resultant MSE of 0.2109, although lower MSE of 0.09 and higher specificity were obtained when risks were predicted one at a time. Optimum network settings for activation function, number of neurons and threshold were also derived for ANN2. The study concluded that using the derived network settings optimized network sensitivity, enabling ANN2 to correctly predict 9 out of 10 occurrences of risk, with a minimal false alarm rate of 2 out of 10. This is considered very satisfactory because clients are more interested in the occurrence of risk, which usually results in more money being needed to achieve ongoing projects. It was recommended that the developed networks ANN1 and ANN2 could be applied in the estimation of cost variance and risk effect on building costs, early in the construction phase when designs have been finalized but construction is yet to commence.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF APPENDICES

ABBREVIATIONS, GLOSSARIES AND SYMBOLS

ANN	Artificial Neural Network
ANN1	Artificial Neural Network Approach 1
ANN2	Artificial Neural Network Approach 2
BOQ	Bills Of Quantities
CPF	Construction Project Features
FA	Final Account
FAV	Final Account Value
FCV	Final Contract Value / Final Cost Variance
ICV	Initial Contract value
MLR	Multiple Linear Regression
NIQS	Nigeria Institute of Quantity Surveyors
SPSS	Statistical Package for Social Sciences

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Construction risk has traditionally been perceived as the variance of cost or duration estimation, although, there has been a gradual shift in perception towards seeing it as a project attribute (Taroun, 2014). This might be in part because no single methodology satisfies risk assessment in all situations (Kokangül *et al.*, 2017). As a project attribute, risk is mainly modelled as a multiplication of 'Probability of occurrence' and 'Impact on the project' (P – I). The P–I risk model dominates the literature on construction risk (Taroun, 2014), and has been subjected to a lot of criticism from researchers who have discussed potential improvements in it. Moreover, researchers have investigated different theories, tools and techniques for aiding risk assessment. In this wise, Laryea and Hughes (2008) identified a paradigm shift in risk assessment from "classicalism"; using Probability Theory (PT)-based and simulation tools, towards "conceptualism"; using analytical tools. However, maybe as a result of the complexity of the available tools, the paradigm shift did not result in a greater adoption of the analytical tools by professionals (Laryea and Hughes, 2008).

When risks occur, changes to construction projects are observed. Such changes may be in terms of cost, time or quality performance (Larkin *et al.*, 2012) of the project; theoretically however, all of these changes can be expressed in monetary values, such as additional costs due to poor quality e.g. rework, additional cost of extensions to planned completion times (Jha and Chockalingam, 2009). A variety of approaches have been employed in predicting the changes that occur in project costs. These approaches range from classic statistical analysis techniques (Choudhury and Rajan, 2003; Wang and Gibson Jr., 2010; Perrenoud *et al.*, 2016), to fuzzy logic (e.g. Ibrahim, 2008; Jaśkowski *et al.*, 2010), genetic algorithms (e.g. Rogalska *et al.*, 2008) and neural networks (Amusan *et al.*, 2013; Larkin, *et al*., 2012).

Research attention in the construction industry has turned to neural networks as a means of predicting construction costs within ever-narrowing bounds of accuracy. In expert systems and traditional modelling methods, explicit knowledge is provided by rules which impose limitations on both the data that is required for modelling, and the accuracy of derived models. Neural networks avoid these limitations by generating their own rules through learning from examples (Gallant, 1993). Evidence from the research literature reveals that Odeyinka *et al*. (2012) neural model for predicting variability between contract sum and final account was based on five significant risk factors and exhibited a maximum absolute percentage error of 6.5%. Ahiaga-Dagbui and Smith (2012) also developed a neural network model that achieved a mean absolute percentage error (MAPE) of 3.67%.

1.2 Statement of the Problem

The prediction of the impact that risks will have on a project is usually required in order to facilitate accurate estimation of the future cost of a construction project. Risk prediction at the early stages of a project is a difficult task, because cost estimates have to be finalized before project designers and clients become aware of the risks posed by the many factors that influence the project's cost. Risk prediction with artificial neural network uses estimates of the impact of risks encountered on projects to estimate the variance between initial and final contract values of projects. The use of construction project features (CPFs) to directly predict project risk impact was not found in the literature. This might be because of the difficulty of collecting a homogenous sample of projects for development of a workable model.

One of the most popular ways of assessing risk effect on the change in project costs derived the impact of risk factors through Likert-type scaled questionnaires (Larkin *et al.,* 2012; Odeyinka *et al.,* 2012). Gill and Johnson (2002) have however pointed out that questionnaire survey results may lack ecological validity, reflecting what people claim to be the case, rather than what is in actual reality the case. The adoption of risk registers may be a way out of this situation. Registers of the impact of risks are built up as the project progresses (Perrenoud *et al*, 2016), or from final accounts at practical completion of the project (Ibrahim, 2008).

The prediction of risk impact through the use of CPFs holds tremendous promise because risk impact can be estimated from the very early stages of a project. At present, disparity of projects in terms of CPFs limits the use of CPFs for prediction of risk impact. Prediction only works where a homogenous sample of projects has been collected. The possibility of treating CPF data in ways that allow the use of hetorogenous samples to achieve accurate predictions was the research problem addressed in this study. This study combined the risk register approach with data binarization as a normalization technique in order to facilitate the use of construction project features (CPF) as predictors in an artificial neural network for estimating the impact of risk on final cost of building projects.

1.3 Aim and Objectives of the Study

1.3.1 Aim

The aim of the study is to develop an artificial neural network to predict the occurrence, type and degree of impact of risk on costs of building projects through the use of selected construction project features.

1.3.2 Objectives of the study

To achieve the above stated aim, the research has five objectives, which are: -

1. To determine the risks that can be used to predict the effect of risks in the costs of building projects.
2. To determine the Construction Project Features (CPFs) that can be used to predict the effect of risks in the costs of building projects.
3. To determine the effect of risks in the costs of building projects.
4. To develop an artificial neural network for the prediction of risk effect in costs of building projects.
5. To carry out a performance analysis of artificial neural network developed for the prediction of risk effect in costs of building projects.

1.4 Research Questions

This study addressed the following research questions:

1. What risks can be used to predict the effect of risks on final costs of building projects?
2. What Construction Project Features (CPFs) can be used to predict the effect of risk on final costs of building projects?
3. How can the effects of risks be determined in the final costs of building projects?

4. How can an artificial neural network be developed to predict the effects of risks in the final costs of building projects?
5. How can artificial neural network be analysed in terms of its performance in the prediction of risk effect in the final costs of building projects?

1.5 Justification for the Study

Risk has been modelled as an estimation variance using the Probability–Impact (P–I) risk model for almost as long as risk awareness has existed; the (P–I) model enabled researchers to assess risk through its probability of occurrence and impact. As reported by Edwards and Bowen (1998), the (P–I) risk model lent itself initially to the use of statistical methods, then later on more complex analysis involving Monte-Carlo Simulation (MCS) during the 1970s. Some researchers (for example Charette, 1989; Williams, 1996; Ward, 1999) have criticized the P–I risk model and recommended potential improvements that could be made to it. Other researchers such as Kokangül *et al.* (2017) believe that there exists no risk assessment methodology that is convenient for all situations. Over time, researchers have discovered that risk prediction can only be carried out successfully for homogenous samples of projects. Wide disparities in the features of projects severely limit the ability to model the impact of risk on the costs of such projects.

The core value of this study lies in its use of novel techniques to treat the data collected for the prediction of risk impact on costs of buildings. This study made use of project final account data because final accounts have the advantage of being regarded as the true representation of a project's financial history for both practical and contractual purposes. Both the risk and CPF data were normalized through binarization before being used to develop the ANN. It is the submission of this study that the process of binarization reduces the heterogeneity present in the data and that the binarized data functions as a homogeneous sample. This allows data containing wide disparities of project features to be used successfully in accurately predicting the impact of risk on building projects.

The use of artificial neural networks as the prediction tool in this study was because of its robustness, ability to adapt to unknown data sets, and good learning capability (Ling and Liu, 2004; Jha and Chockalingam, 2009). There are other cost modelling techniques available which include Linear/Dynamic Programming, Regression Analysis, Simulation/Risk Analysis, and Expert Systems (ES). These cost modelling techniques have however been said to be unable to deal with problems such as: (i) Imprecision and uncertainty of data and variables affecting costs of construction projects; (ii) Unknown combined effects and inter-relationships of cost-influencing factors, and (iii) Complex and vagueness of input-output relationships which cannot fit nicely and successfully into a quantitative description.

ANN effectively copes with the situations itemized above, as it is able to learn, generalize and represent general knowledge, through the extraction of information from existing data, a process known as inductive learning. The use of neural networks in construction management research goes back more than two decades. Starting with Boussabaine's (1996) review, artificial neural networks (ANN) techniques have been applied to cost estimation models of school buildings (Elhag and Boussabaine, 1998), influence of rework causes on project performance indicators (Palaneeswaran, *et al.* (2008), pre-project planning (Wang and Gibson Jr., 2010); prediction of actual project cost and time (Abu Hammad *et al.*, 2010) and risk factors impact on cost variability in design and build projects (Larkin *et al.*, 2012).

1.6 Scope of the Study

This study was carried out in Abuja which is located within the Federal Capital Territory of Nigeria. The choice of Abuja was influenced by the assertion by the Real Estate Developer Association of Nigeria (REDAN) that majority of construction firms that have on-going building projects are located in Abuja. This means that Abuja is presently the focus of the nation in terms of building development. Another factor in the choice of Abuja as study area, apart from the fact that mass building construction is an established and ongoing feature of Abuja, was the discovery that 22% of quantity surveying consulting firms in Nigeria are located in Abuja (NIQS Members Diary, 2015). These firms represent potential sources of information for this study.

The units of analysis of the study are **building projects** that were characterized by the following features: (i) the use of **in-situ concrete** as the material for structural framing of the buildings; and (ii) the **number of floors** in the buildings was between 1 and 5 floors; (iii) the project were either **new** or **refurbishment** projects for the public sector that were commercial, institutional or residential in nature; relevant data was available for extraction from final accounts. The use of project closure documentation (final accounts) was justified in the light of the assertion by Adinyira, Botchway and Kwofie (2012) that assessment of success takes place at the completion stage of projects. The implication of this was that scope of application of the prediction models developed does not extend to civil and heavy engineering projects or private-sector building projects.

Only projects that were completed within the **13-year period of 2003 - 2015** were considered. This timeframe was adopted to ensure that respondents are able to retrieve pertinent project information and that a large enough sample of projects can be collected for the development of artificial neural networks. Although the study accessed information on risks at project closure (after final account preparation), yet the action of the risks took place during the construction phase of projects, as observed by Goh and Abdul-Rahman (2013) that the construction phase of projects has the highest risk occurrence.

1.7 Assumptions of the Study

Building projects are subjected to different types and levels of risk that are associated with their specific features such as location, height, and size. In this study it was assumed that heterogeneity in the characteristics of risk faced by projects that were sampled did not vitiate the ability of artificial neural networks to accurately predict the impact of risk on project costs based on the data binarization technique that was adopted.

1.8 Limitations of the Study

In order for the study to be practicable and the results to be valid and applicable, the following limitations have been identified: -

1) There existed a lack of uniformity in the formats adopted for preparation and presentation of final accounts amongst the building projects that were sampled. This necessitated some form of adjustment of the content of some of the final accounts. A common format was obtained from the Nigeria Institute

of Quantity Surveyors (NIQS). All final accounts were then recast into the NIQS format. None of the data in the original final accounts was discarded; data was either re-assigned or combined under a different heading. This situation represented a limitation arising from the fact that the final accounts employed as sources of data were not prepared exclusively for the use of this study. Some additional work was necessary before the data in the final account could be conveniently compared.

2) The CPFs employed in this study were purposively selected based on their relevance to the prediction of risk impact on building projects as perceived by the researcher. Purposive selection of CPFs might represent a limitation of the study; different results might be obtained where CPFs are selected based on other criteria.

1.9 Operational Definition of Terms

Artificial Neural Network (ANN): This is an information processing system that is inspired by biological neural networks of animals, in particular the brain. An ANN consists of a pattern of connections between neurons, which solve multi-attribute problems better than conventional methods by generating its own rules through learning from examples (Masters, 1993).

Cost variability: This is the difference between the initial contract value (ICV) in the project bill of quantities (BOQs), and the final contract value (FCV) in the final account (FA) (Odeyinka *et al.,* 2012).

Impact of risk: Impact of risk is the value of an increase or decrease in cost as inserted in a final account that is attributable to a specific risk(s). Impact of risk, consequence and severity are used interchangeably to describe the resultant effect of risk on project objectives, which some researchers have termed 'risk cost' (Franke, 1987).

Probability of risk occurrence: Probability of risk occurrence is a measure of how likely it is that a risk event will occur. Probability of risk occurrence is used interchangeably with likelihood of risk occurrence.

Project characteristics: Project characteristics are variables that are used in defining a project. The variables are client type, the project type, tendering method, procurement method, type of contract, project location, project size, project cost (or value), project duration, and project complexity among others. The term 'project characteristics' is used interchangeably with 'project specific factors' (Doyle and Hughes, 2000).

Project Performance: Project performance is considered as the productivity of a project. It is a comparison of inputs (set objectives or targets for cost, time, quality, dispute and safety) with outputs (actual achievements in terms of cost, time, quality, dispute and safety) (Pocock *et al.*, 1996).

Risk: Risk is an uncertain condition or set of circumstances that may occur within a project life cycle, the exact impact of which was neither foreseen in the project description nor in the contract. Such impact may be positive or negative, desirable or undesirable, in terms of the planned objective(s) of the project (Project Management Institute (PMI), 2012).

CHAPTER TWO

2.0 LITERATURE REVIEW

2.1 Construction Costs

The main concerns of the construction client are projects constructed within budget, on time, of the expected quality and with no surprises. Setting a budget at the pre-contract stage of any construction project requires the estimation of the likely cost of the proposed works. Westney (1992) defined cost estimation as the determination of quantity and cost required to construct a facility. The developed estimate forms the basis of the contract sum for the project and normally it is not expected to be exceeded. Cost estimation can be carried out from the early strategic phase of a project to the construction phase; the approach selected usually depends on the level of accuracy required, how quickly the estimate is required, experience level of the estimator and the level of information available at the time of estimate (Ahiaga-Dagbui and Smith 2012).

Owing to the complexity of the construction industry and bespoke nature of every project undertaking, the overall project cost is determined by a number of key items, such as the structural, architectural, sanitary, electrical and air-conditioning systems. Olotuah (2002) posited that the supply and fixing of building materials accounts for about 60% of residential buildings costs; Gould and Joyce, (2000) on their own part estimated that 25% of total construction cost in multistorey reinforced concrete residential buildings is spent on the structural frame. To improve the cost certainty of projects, in traditional procurement, a contingency sum is included to cover unforeseen circumstances. However, despite this precaution, there are evidences in construction management literature indicating that it is very difficult to find many projects where the initial contract sums are not exceeded at completion (Winch, 2010; Wolstenholme, 2009). Accurate estimation of the future cost of a construction project is a difficult task, because of the fact that it must be completed before the project designers and even the client are aware of many of the factors that influence the cost of the project (Adafin *et al.*, 2016).

The reliability of estimates of construction cost are important for a variety of reasons – to enhance the budgeting process of organizations, to set loan or equity funding thresholds in the case of credit facilities or equity participation, for estimating project feasibility or viability in commercial terms. Ahiaga-Dagbui and Smith (2012) have identified the following as part of the complex web of cost influencing factors that make it extremely difficult to estimate the final cost of construction projects: type of project, material costs, likely design and scope changes, ground conditions, duration, size of project, type of client, and tendering method. Jennings (2012) noted that a high level of uncertainty surrounds most of these factors at the initial stages of the project; yet ignoring the risk they pose to the successful completion of the project is akin to an invitation to cost overruns, disputes, law suits and even project termination in extreme cases.

2.2 Cost Performance of Construction Projects

The success of a construction project undertaking is generally expressed in terms of price certainty, completion time certainty and satisfactory level of quality (Chan and Kumaraswamy, 2002). Aside from these three criteria which have been termed the iron triangle, client satisfaction and satisfaction of other stakeholders have been proposed as workable frameworks for measuring project performance (Bryde and Robinson, 2005; Toor and Ogunlana, 2008). Notwithstanding all other criteria that have been adopted, cost performance on a construction project remains one of the main measures of the success of a construction project (Ogunsemi and Jagboro, 2006).

The construction client is mainly concerned with realizing a project constructed within budget, on time, to the expected level of quality and with no (usually unpleasant) surprises. These concerns are encapsulated in the contract drawn up for the project, of which bills of quantities (BOQ) form an important part. As an additional hedge against the unforeseen, a contingency sum is normally included to ensure the completion of the project within the budget. However, notwithstanding this precaution, on many projects the initial contract values are exceeded at completion (Adafin *et al.*, 2016). The findings in Odeyinka *et al*. (2009) study suggests that the more complex the nature of a construction project, the more likely is the tendency of deviation between the contract sum and final account.

Although a decline in the number of contracts based on BOQ has been observed in the UK and Australia over the past 20 years (Davis *et al.*, 2009), there is little evidence to show that this trend applies in Nigeria as well. Within the Commonwealth the bill of quantities remains unsurpassed as a preferred model of contract cost documentation, (Cartlidge, 2013). While it has been established that the BOQ lacks precision in predicting building cost (Brewer, 1998), it has also been asserted that this is not totally due to inherent shortcomings of the BOQ. Rather events that occur between the point at which the project was commenced and the point at which it was completed are to blame. These events have been termed pathogens (Love *et al*., 2009).

Cost overruns are a major and recurring problem of construction industries globally; there is however a variation of the degree of the severity from country to country (Doloi, 2013). In Nigeria, additional costs of between 2.7% - 62.4% of the planned construction cost were incurred as cost overruns (Radujkovic, 1999). Similarly, more than 33% of sample projects in Kuwait required additional budgets to complete (Koushki *et al.*, 2005). Asiedu and Alfen (2015) confirmed that payment defaults were a principal cause of cost overruns in Ghana.

No two projects are totally alike; a project is after all, a temporary undertaking (PMI, 2000). To aid comparison of projects, researchers have used some attributes or characteristics present in all projects. Such characteristics or attributes include client type, location, complexity, type of procurement adopted, number of floors, total or gross floor area and project value among others (Chan and Park, 2005). The interdependence of the factors affecting the performance of construction projects is established in literature, and is the reason why Ogunsemi (2002) suggested that for accuracy of predictive models, homogeneity of data is very important.

Modeling of project cost performance has followed a mathematical/statistical approach from the earliest times. Hudson (1978) developed an expenditure-forecasting model for hospital buildings in the UK that utilizes mathematical equations to forecast value S-curves. For the next decade and half researchers were preoccupied with this model (Sidwell and Rumball, 1982; Berny and Howe, 1983;

Skitmore, 1992; Skitmore 1993). To avoid the inaccuracies observed in previous efforts, Evans and Kaka (1998) based their work on historical data of 20 food retail building projects. They however failed to obtain an accurate standard S-curve even when projects were subjected to further more detailed sub-classification. Kenley and Wilson (1986) analyzed 72 commercial and industrial building projects in two groups of data and developed a value S-curve for each individual project and an average one for each of the two groups. They concluded that cost models for groups of projects represent both functional as well as conceptual error. Khosrowshahi (1991) developed a computerized model that simulated the periodic expenditure pattern of projects. Although its forecasting accuracy has yet to be documented, the model has been converted into a professional computer-based forecasting system (Khosrowshahi, 2000).

Computer-based artificial intelligence techniques have also been applied by researchers such as Lowe *et al.* (1993) (expert system), Boussabaine and Kaka (1998) (neural network), Boussabaine *et al*. (1999) (neural network), and Boussabaine and Elhag (1999) (fuzzy technique). None of the developed models dealt with the issue of risk impacting on cost of construction projects.

2.3 Final Account Procedure for Building Projects

Generally, under traditional method of procurement, payment from clients to contractors in respect of the construction works is a process that begins from the start of construction until the project is completed. Different types of payment can be identified, such as advance payment, progress payment and final payment, which represents the final cost of a construction project (Zakaria *et al.*, 2012b). Zakaria *et al*.

(2013a) classified the procurement of construction projects into five stages: initiation/planning, design, tender, construction and final account/defect liability stage. After practical completion of the project, the preparation and settlement of the final account is the only outstanding task that is linked to the design/construction team, in most instances. Standard forms of contracts for construction projects usually contain provisions relating to a specified period of time within which the final account should be settled.

Final accounts for construction projects are prepared in order to arrive at a definitive final cost of a project that has been completed by the contractor. Final accounts conventionally include all costs arising from additions, alterations, deductions resulting from project changes and other related payment as stated in the contract (Zakaria *et al.*, 2013b). Although most standard forms of contract specify that final accounts should be prepared immediately after the projects are completed, and settled after defects liability periods have elapsed, Ho (2012) research showed that on the average, main contractors in Hong Kong experience up to 12 months delay in the settlement of final accounts for completed projects.

Final accounts are important in many ways; at times, a final account could refer to the calculation and agreement of the final construction cost between the employers and contractors (Ashworth and Hogg, 2002). The historical importance of the final account can be seen from the assertion that the final account amount includes all additions, alterations and deductions resulting from changes made to the project (Baloi and Price, 2003). Another facet of its importance was expressed by Baccarini (1999) and Khang and Moe (2008), that the final settlement of financial obligations effected through a final account implies that the project is satisfactory to all key stakeholders (including contractors), an indication that the project has been successfully procured.

2.3.1 Variations in the final account

Giwa (1988) stated that standard forms of contracts for construction projects always contain provisions under which changes can be effected to the contract sum of a construction project. The adjustment of the initial or adjusted contract sum to obtain the final account sum is usually effected through computation of the net costs involved in variations to the works, re-measurement of provisional quantities, adjustment of provisional and prime cost sums, fluctuation, and claims as a result of errors in contract document and loss and expense.

The Standard Form of Building Contract in Nigeria (SFBCN) formally defined variation as the modification of design or quantity of work as shown upon the contract drawings and described by or referred to in the contact bills. Variations include addition, omission or substitution of any part of the works. Only the Architect is empowered to issue variation orders, even though the client, designers, contractors and statutory authorities could also be sources of variations. Under clause 11.2 of the 1990 Edition of the SFBCN, variations may arise under:

a. circumstances that could not have been reasonably foreseen before signing the contract.
b. additional requirement by the employer.
c. compliance with new government orders or legislation.
d. correction of errors or omission in the contract drawings and contract bills.

e. non-availability of materials and goods specified in the contract.

f. substitution of materials, goods and workmanship specified in the contract.

Under normal circumstances, the major factors that cause variations were identified by Agbo (1993) to include inadequate brief, design inconclusiveness, inadequate pre-contact planning, indiscipline on the part of consultants, non-availability of materials labour specified for the work, unforeseen conditions and discrepancy between two or more contract documents and client's intentions.

2.3.2 Re-Measurement of provisional quantities

Provisional quantities are essentially educated guesses of the amount of work that will be required to construct a building or facility. Actual quantities of work obtained on the site might deviate substantially from the quantities in the contract bill, a situation which necessitates adjustment of the original contract sum to reflect the reality of the site works. Olabopo (1991) defined provisional quantities as measured items in the contract bill whose exact quantity cannot be ascertained at the time of preparing the bill. Re-measurement of substructure works generates about 58 percent of the overall increases according to Giwa (1988); concrete work accounts for 22 percent while external works contributes 15 percent.

2.3.3 Adjustment of provisional and prime cost sums

The Building and Engineering Standard Method of Measurement 3 defined Prime cost sums as a sum provided for works or services to be executed by a nominated sub-contractor, a statutory authority or public undertaking or for materials or goods to be obtained from a nominated supplier. It is usual for the actual costs of the items for which prime cost sums were allowed in contract bills to be much higher than the provisional sums. This is because at the time of preparing the contract bills, the parties to execute the works covered by provisional sums have neither been specified, nor have quotations been received in respect of such works.

Ogunsemi (2002) posited that provisional sums represent a high degree of imprecision in the pricing of construction works. The higher the proportion of provisional sums inserted into contract bills, the less precise and realistic the initial contract sum will be with respect to the final cost of the project.

2.3.4 Adjustment for inflation

Onyechi (1990) described increases in contract sum attributable to inflation (called fluctuations) as usual occurrences in non-fixed price contracts. Fluctuations arise because there is usually an appreciable length of time between the submission of tender by contractors, and actual purchase of construction resources consequent upon award of contract by clients. Prices of construction resources change from time to time. Giwa (1988) reported that fluctuation is one of the most misunderstood sections of the conditions of contract. Fluctuation has not only led to increases in the final cost of construction, it often leads to complete abandonment of projects.

2.3.5 Adjustment for claims

Contractual claims have been defined as additional cost or time that a contractor is entitled to, based on the support of specific clauses of the conditions of contract (Alli 1998). Ofoma (1990) listed seven basic requirements that a genuine claim must meet, which included compliance with all the detailed requirements of the contract, how and why the causal event or instruction leading to the loss being claimed occurred, and an evaluation of the direct reasonable loss or expense that can be claimed.

Clause 24 of the SFBCN deals with loss and expense caused by disturbance of regular progress of work, which results into claims and identified the situations that can generate claims. Such situations include delayed transmission of drawings/details from designers to the contractor, failure of clients to pay as at when due, and compensation to landowners, the absence of which might interfere with the works proceeding according to plan. Ogunsemi (2002) posited that the causes of loss and expense are matters for which the client is responsible in the sense that they are either his or his Architect's acts of omission. Some of them included improperly timed changes to the work, incorrect information, failure to provide information on time, and postponement of work.

2.4 Risk and Uncertainty in Construction

The construction process moves from initiation/conception to practical completion/final account stages, a progression characterized by increase in the complexity and number of uncertainties that can influence the project negatively (Boateng *et al.,* 2015). It has been asserted that construction can be structurally impacted by a large number of risks (Ball, 2014). The risks that can potentially affect a project are many and varied, almost limitless; as changes occur in technologies, methodologies and lifestyles, so also are changes likely to occur in the specific risks experienced on construction projects.

Almost all projects are carried out in open conditions that are exposed to uncertain and to some extent unpredictable weather (Mentis, 2015). The large number of stakeholders on every construction project also exposes the client to delays on the part of subcontractors and suppliers (Eizakshiri *et al*., 2015; Diab and Nassar, 2012). With the rise of citizen awareness about Corporate Social Responsibility (CSR), social unrest or community resistance also ranks as a risk factor for construction projects (Jordhus-Lier, 2015). Research has also documented the fact that construction is one of the most regulated spheres of human activity (Mbachu, 2012); in many cases this constitutes undue influence from governments/legislative authorities (Kennedy, 2015). One of the most well known risks that construction projects always have to contend with has to do with the suitability of ground and subsurface conditions on project sites (Adam *et al*., 2014; Boateng *et al*., 2012).

The New Rules of Measurement 1 of the Royal Institution of Chartered Surveyors (RICS) in the UK specified that an elemental cost plan must have a contingency provision that provides for some or all of the risks associated with design development, construction, employer driven changes, and other employer restrictive concerns (RICS NRM 1, 2012). Design development risks are defined to include changes in estimating data, planning restrictions, legal requirements, covenants, environmental concerns, pressure groups, statutory requirements, procurement methodology, and delays in tendering.

Risks that manifest during the construction stage were referred to as Construction risks, a phrase which covers site conditions, ground conditions, existing services, and delays by statutory undertakers. The impact of employers/clients on the type, scope and number of risks faced by construction projects was highlighted in the following risks that were defined as Employer risks. These include changes in brief, changes in scope of work, changes in quality of work, and changes in time; other risks are early handover, postponement, acceleration, funds availability, and liquidated damages (Adafin *et al.*, 2013).

Zhao *et al.* (2014) noted that a typical construction project may involve several forms of risks such as contractual, financial, operational, political and technical risks. The unique temporary 'one-off' nature of construction as well as the fact that the many stakeholders of any project usually have a varied and sometimes conflicting understanding of risks, might also constitute sources of risks. Bala *et al.* (2014) opined that traditional cost estimating methods have failed to cope with the problems of uncertainties and accuracy. Lowe *et al*. (2006) and Cheng *et al*. (2009) have therefore stressed the need to develop more accurate and robust construction cost forecast techniques.

2.4.1 Definitions of some risk and uncertainty terms

Definitions of risk by some researchers in the past tended to focus on the negative impacts alone (Mason, 1973; Moavenzadeh and Rossow, 1976). According to Wideman (1986) project risk "is the chance of certain occurrences adversely affecting project objectives''. Carter *et al.* (1994) viewed risk as the presence of potential or actual constraints which could cause failure of a project. In a similar vein, Fong (1987) defined the impact of risk as the likelihood of a specific unwanted event and its unwanted consequences. To reconcile this negative view of risk with definition offered by the PMI and APM, Winch (2010) opined that risk is only used to refer to the probability of a detrimental effect, while reward signifies the probability of occurrence of a beneficial event. However, when risk occurrence and detrimental impacts are minimized, the benefit of positive impacts, whether passive or active, will be realized.

Risk in construction is an abstract concept; it is very difficult to define and almost impossible to measure with any precision. Risk is defined by the UK based Association for Project Management (APM) (2006) as "an uncertain event or set of circumstances that, should it occur, will have an effect on the achievement of one or more project objectives." The US based Project Management Institute (PMI) (2008) definition of risk is "an uncertain event or condition that, if it occurs will have either a positive or negative effect on one or more of the project's objectives".

Odeyinka *et al.* (2006), regarded risk as a variable in the process of construction, the occurrence of which results in uncertainty in the final cost, duration and quality of the project. Risk is used interchangeably with uncertainty in some cases (Baloi and Price, 2003), however Smith (1999) considered that uncertainty should be separated from risk because the two terms are distinctly different. He defines uncertainty as a state of having limited knowledge which makes it impossible to describe an existing situation or a future outcome. According to Odeyinka (2000) risk is measured by an objective probability while uncertainty is measured by a subjective probability.

The nomenclature used to describe risk and uncertainty is wide and varied. Some terms are used loosely and interchangeably. Generally however, 'Project risk' is an uncertain event that, if it occurs, affects the achievement of the project's objectives positively or negatively (Hillson, 2009). Past research has defined ‘risk event’ as the time (in relation to the project timeline) in which a risk occurs (Yoon *et al*., 2015). Although Project Management Institute (2010) specified when and how often risk management tasks should be performed, there is little information about when certain risks occur (Zou *et al*., 2007). Perrenoud *et al.*, (2016) defined ‘risk encounter’ as the percentage of the project time that has elapsed at the time a risk is identified and communicated to all project stakeholders. ‘Risk distribution’ was defined as the frequency and timing of risk encounters during the construction phase. They found that 70% of the risk encounters documented by them occurred before the original completion date.

2.4.2 Some perspectives of risk and uncertainty in construction

It is possible to identify four schools of thought on the relationship between risk and probability (Winch, 2010). These are: (i) the Objectivist school – future events are predicted from known data about risk sources, using the science of statistics, with varying degrees of accuracy; (ii) the Logical school – studies the probability of a failure event in closed engineered systems, using the scientific properties on which the design is based; (iii) the Subjectivist school - the risk as it is perceived by an individual: the degree of belief held by the decision maker in the probability of an event is used to predict risk in future projects and (iv) the Behavioural school - focuses on the actual behaviour of a decision maker under conditions of uncertainty.

Within the objectivist school four compartments of ‘risk space’ can be identified based on where the occurrence of any event falls between the two extremes of certain and impossible. The four compartments are: (i) known knowns – a risk source has been identified and a probability can be assigned to the occurrence of a risk event; (ii) known unknowns - a risk source has been identified but a probability cannot be assigned to the occurrence of a risk event; (iii) unknown knowns - the risk source and the associated probabilities are known to someone who is keeping the information private; and finally (iv) unknown unknowns - a risk source has not been identified and therefore the risk event is not known, (Winch, 2010).

2.4.3 Historical development of risk modelling

It is debatable whether risk was studied as a branch of academic endeavour before the 1960s, (Edwards and Bowen, 1998). It was apparent however that Hertz (1964) is credited with being the first to use the term "risk analysis", while working on computer-generated probability distributions of rates of return for investment projects (Baker *et al*., 1999). Risk assessment during the two decades from 1960 to 1980 was carried using the Probability-Impact (P–I) risk model; Probability Theory (PT) and Monte Carlo Simulation (MCS) were thus the main analytical tools available at that time.

The next two decades (from 1980 to 2000) witnessed a flurry of research into construction risk modelling and assessment, which was theoretically driven by PT, Fuzzy Sets Theory (FST) and Analytical Hierarchy Process (AHP). Within this period Franke (1987) recommended the assessment of risk impact using financial measures such as "risk cost" as a common measure of all risks within the P–I risk model. This brought to limelight the thinking that risk has impact on specific project objectives. Williams (1995) found that risk assessment research focused almost entirely on cost and duration related risks, to the detriment of quality related risks.

The last two decades (from the year 2000 to the present time – 2017) have come to be associated with a major shift in how risk is perceived. From being viewed as a variance in the estimating process, risk was now considered to be a project attribute, rather like physical project characteristics such as height, size and shape. Risk was still modelled as a multiplication of Probability of occurrence and Impact upon occurrence, and to all appearances, the dominance of the P–I risk model was established in the literature (Taroun, 2014).

However there have been a considerable number of recommendations for improvement of the P–I risk model. Chronologically, these recommendations include the proposal by Charette (1989) to add ‘predictability’ as a third dimension to the P–I risk model. A decade and half later Jannadi and Almishari (2003) suggested adding ‘extent of exposure’ to risk as a third dimension to the P–I model. Cervone (2006) advocated ‘discrimination’ to cater for the interdependencies between risks in the P–I model. The notion that some risks are more manageable than others was advanced by Aven *et al*. (2007) and supported by Dikmen *et al*. (2007), who considered risk manageability in terms of its influence on the overall project risk level.

‘Risk controllability’ was defined by Cagno *et al*. (2007) as a ratio between the expected risk impacts before and after applying specific mitigation actions. The work by Zeng *et al.* (2007) considered that the environment in which projects are carried out influences the level of severity and interdependencies between risks. They proposed incorporating the factor index (FI) as a third dimension in the P–I risk model. The effect of project environment on risk impact was incorporated into project risk analysis process by Zhang (2007); project vulnerability was also the focus of the argument by Vidal and Marle (2012) that project risks analysis could be enhanced by focusing on the weaknesses of project organizations. Han *et al*. (2008) proposed ‘risk significance’ as a third dimension to the P–I model in order to capture the unique nature of risks as estimated through the intuition of risk analysts.

2.5 Risk Factors affecting Construction Cost Performance

Studies on risk factors in construction projects have occupied researchers for at least the last three decades in different parts of the world. In Nigeria, price fluctuation, financing and payment of completed work, additional work, design changes, inaccurate estimates, imported materials and plant items among others were identified by Mansfield *et al.* (1994) as significant factors impacting on project cost. Other researchers in the same area found that financial, design and construction risks have significant impact on cost of construction projects in Nigeria (Odeyinka, *et al.*, 2006; Dada and Jagboro, 2007).

A summary of the most important risk factors discovered by different researchers is provided in Table 2.1a and Table 2.1b. This summary was built up by taking the top five most important risks as ranked by each researcher. Only research that was carried within the last ten years (2006 – 2015) was considered, to enhance comparability of the risk rankings.

Table 2.1a: Summary of risks in literature (Risk1 – 40)

S/Nr	Year	Risks	Location	Sources
1	2006	Change in the design by the Architect	Australia	Omoregie and Radford (2006); Zou *et al.* (2006)
2		Delay due to excessive approval procedures	Australia	
3		High performance/quality expectations	Australia	
4		Inadequate program scheduling	Australia	
5		Changes in site conditions	Nigeria	
6		Cash flow difficulties	Nigeria	
7		Delay due to excessive approval procedures	Nigeria	
8		Inflation	Nigeria	
9		Poor contract management	Nigeria	
10	2008	Client's Cash flow difficulties	Nigeria	Aibinu (2008)
11		Contractor's cash-flow problems	Nigeria	
12		Incomplete drawings	Nigeria	
13		Equipment breakdown/ maintenance	Nigeria	
14		Nominated suppliers cash flow problems	Nigeria	
15	2010	Acts of God	Nigeria	Windapo and Martins (2010)
16		Cash flow difficulties	Nigeria	
17		Consultant competence	Nigeria	
18		Contractor competence	Nigeria	
19		Social issues/area boys, original land owners	Nigeria	
20	2011	Unforeseeable design development risks at tender	China	Chan *et al.* (2011); Chileshe and Yirenkyi-Fianko (2011)
21		Cash flow difficulties	Ghana	
22		Inflation	Ghana	
23		Poor financial market	Ghana	
24		Quality and performance control	Ghana	
25		Change in scope of work	Hong Kong	
26		Error/omission in design/estimates	Hong Kong	
27		Exchange rate variations	Hong Kong	
28	2012	Cash flow difficulties	Malaysia	Karim *et al.* (2012); Odeyinka *et al.* (2012)
29		Equipment breakdown/ maintenance	Malaysia	
30		Late deliveries / shortage of material	Malaysia	
31		Poor quality of workmanship	Malaysia	
32		Change in design / variations by the client	UK	
33		Change in scope of work	UK	
34		Change in the design by the Architect	UK	
35		Changes in site conditions	UK	
36	2013	Change in design / variations by the client	UK	Odeyinka *et al.* (2013)
37		Change in the design by the Architect	UK	
38		Inclement weather	UK	
39		Labour shortage	UK	
40		Production target slippage	UK	

Source: Researcher's summary.

Table 2.1b: Summary of risks in literature (Risks 41 - 70)

S/Nr	Year	Risks	Location	Sources
41	2014	Absence of professional project pre-planning studies	Saudi Arabia	Taylan *et al.* (2014); Perera, *et al.* (2014); Tran and Molenaar (2014)
42		Cash flow difficulties	Saudi Arabia	
43		Delay due to excessive approval procedures	Saudi Arabia	
44		Delays (lack of coordination between participants)	Saudi Arabia	
45		Inadequate program scheduling	Saudi Arabia	
46		Cash flow difficulties	Sri Lanka	
47		Contractor’s cash-flow problems	Sri Lanka	
48		Delays in shifting utility lines by authorities	Sri Lanka	
49		Design errors made by designers	Sri Lanka	
50		Labour shortage	Sri Lanka	
51		Change in scope of work	USA	
52		Construction risk	USA	
53		Level of design and contract risk	USA	
54		Third-party and complexity risk	USA	
55		Utility and right-of-way (ROW) risk	USA	
56	2015	Changes in site conditions	Saudi Arabia	Albogamy and Dawood (2015)
57		Client’s lack of experience in construction	Saudi Arabia	
58		Design errors made by designers	Saudi Arabia	
59		Difficulties in obtaining work permits	Saudi Arabia	
60		Land acquisition	Saudi Arabia	
61	2016	Host government–related risk	China	Liu, *et al.* (2016); Perrenoud, *et al.* (2016)
62		Inflation	China	
63		Legal risk	China	
64		Macroeconomic risk	China	
65		Social risk	China	
66		Change in scope of work	USA	
67		Client codes/permits	USA	
68		Contractor/subcontractor/supplier issues	USA	
69		Error/omission in design	USA	
70		Unforeseen unknown conditions	USA	

Source: Researcher’s summary

In the UAE, inflation/sudden changes in price, changes in design required by owners, owners' improper intervention during construction, and owners' delayed payment to contractors among others were identified as significant risk factors (El-Sayegh, 2008). In the case of Malaysia, financial, time, design and technical, physical, contractual, political and regulation, personnel and safety risks were found to be cost-significant factors by Goh and Abdul-Rahman, (2013). Toor and Ogunlana (2008) in investigating factors causing delay in Thailand, revealed problems related to client, designers, project management/consultants and contractors as significant delay factors.

Similar trends have been found in Jordan, Hong Kong and Saudi Arabia that varying combinations of client-related, contractor-related and consultant-related factors contribute significantly to delay in construction projects in these countries (Odeh and Battaineh, 2002; Wang *et al.,* 2003; Al-Karashi and Skitmore, 2009). In the Kuwaiti construction industry the delay-significant risk factors identified included financial failure, delayed payment on contract, labour, material and equipment availability, defective design, coordination with subcontractors, productivity of labour and equipment, contractor competency, actual quantities of work, quality of work and third party delay, (Kartam and Kartam, 2001).

2.5.1 Characteristics of risks in construction projects

Most of the time risk is assessed based on certain characteristics that can be identified and associated with the risk. Although a consistent method for characterizing risk has yet to be established (Chapman and Ward, 2007), the following characteristics of risk were considered in this study: (i) the magnitude of the impact on the total project cost, (ii) the source of the risk and (iii) the nature of the risk. Items (ii) and (iii) together make up the risk category.

The source is the agitator or the party responsible for creating the project risk; for example, the source may be the client, architects and engineers, contractors, subcontractors, suppliers, or government agencies (Zou *et al*., 2007; Perry and Hayes, 1985). Risk sources are generally agreed to be tied to project stakeholders. The nature of the risk is most often defined by pigeon-holing the risk into one of the following categories: financial, strategic, operational, project, or hazardous (AIRMIC and IRM, 2002; Chapman, 2001; Shen *et al*., 2001). Broadly, these categories are aligned with project objectives such as cost, quality, time, and health and safety. Specific examples that can be found in most construction projects include tight project schedules, design variations, inadequate site information, inaccurate cost estimates, unavailability of managers and skilled laborers, and government interference (Zou *et al*., 2007).

The magnitude of the impact that risks will have on project objectives is another useful characteristic of risk which was used by Flanagan and Norman (1993) where they grouped risk impacts to measure the magnitude of the effect on project costs and project schedule. Financial business theories (such as Portfolio theory and capital market theory) define total risk as being comprised of systematic risk and unsystematic risk (Fischer and Jordan, 1995). In project management terminology, risk is divided into internal risk and external risk, which is not really different from the earlier categorization (Tah *et al.,* 1993).

Systematic or external risks affect all organizations and are prevalent in the external environment of a project and are relatively uncontrollable. These external risks are those due to inflation, currency exchange rate fluctuations, technology change, major client induced changes, politics, and major accidents or disasters. Unsystematic or internal risks are relatively more controllable, are organization specific and relate to the management of internal resources within a firm. Internal risks can further be grouped under local and global risks (Tah *et al.,* 1993). Local risks affect individual work packages of a project, resulting from uncertainties in labour, plant, materials and subcontractor resources. Global risks affect the entire project, and mainly have to do with performance, contractual, location, and financial aspects of a project, (Laryea *et al.,* 2007).

2.5.2 Risk assessment

Risk assessment and risk analysis are two interchangeable terms that both refer to risk quantification, which might be qualitative or quantitative, (Edwards and Bowen, 1998; the Project Management Body of Knowledge (PMBOK Guide) PMI, 2004). Qualitative methods of risk assessment employ graduated semantic scales to describe the probability of risk occurrence and the impact such occurrence would have on project objectives (Mootanah, 1997). The quantitative assessment of risk requires empirical data about similar events in the past, (Dawson, 1997).

The qualitative method of assessing risks based on the probability of occurrence and impact employs the use of simple semantic scales such: as high, medium, low. This is much like the graduated responses in questionnaires developed by Likert and has been used by researchers such Carbone and Tippett (2004), El-Sayegh (2008) among others. Inconsistent use of scales terminology might reduce the value of the method, (Carbone and Tippett, 2004). Although qualitative risk assessment is inherently subjective in nature, since what is assessed and how it is assessed depends entirely on the assessor (Dawson, 1997), it finds wide application within fuzzy logic theory.

There are also some qualitative methods of risk assessment that form the basis for quantitative methods, such as risk probability and impact assessment, probability/impact risk rating matrix, risk categorization and risk urgency assessment, (PMI, 2004; Shah, 2004).

Under quantitative methods of risk assessment, the use of empirical data about past similar events obtained from either participants or observers helps to overcome the shortcomings of the qualitative method of risk assessment. Quantitative risk analysis methods include sensitivity analysis, probabilistic analysis, decision trees and Monte Carlo simulation, event and fault trees, fuzzy logic, system dynamics, expected value tables among others (Dikmen *et al.*, 2007).

To obtain the benefit of both methods of assessing risk, Shah (2004) recommended the use of a combination of qualitative and quantitative risk assessment in identifying the risks associated with the control of the project cost, time, and resources. An example of this recommendation in action can be seen in Dada and Jagboro (2007) simple model for evaluating the impact of risk on project cost overrun, using as inputs both qualitative and quantitative data. This was applied in this study as well; risk assessment was assessed both qualitatively (through expert knowledge, participant experience and intuitive judgment) and quantitatively (using increases/decreases in project cost attributable to particular risks) for sampled completed building projects.

2.6 Features of Building Projects Employed in Cost Prediction

An overview of previous studies suggests that a large number of project features may be used to predict the variance observed in final costs of building projects. Such features have been termed ‘construction project features’ (CPF). A detailed review of previous studies has been carried out by Gunner and Skitmore (1999); they identified these features as including: building function, type of contract, conditions of contract, contract sum, price intensity, contract period, number of bidders, good/bad years, procurement basis, project sector (public, private or joint), number of priced items and number of drawings. According to Aibinu *et al.* (2011) previous studies suggest that there are a large number of variables that may substantially influence the accuracy of estimates of building project costs.

2.6.1 Construction project features employed as inputs in cost prediction

Identification of the features of construction projects that had been employed in recent research for the prediction of the costs of the projects began with the identification of studies located within the construction industry and which employed artificial neural network (ANN) as the prediction tool. Forty of such studies were found and reduced to thirteen when those studies that did not specifically address the forecasting of costs using ANN were discarded. It was found that only one feature, gross floor area, was employed in 4 studies. The number of stories and the type of project were employed as input in 3 studies each.

.In their work, Elhag and Boussabaine (1998) extracted data on 30 school projects from the Building Cost Information Service (BCIS) database. The data covered 14 CPFs and represented the complete range of project-related cost variables in the BCIS database. These CPFs included Type of project, Type of contract, Market conditions, Number of tenderers, Site slope, Start conditions, Ground conditions, Excavation conditions, Site access, Work space in site, Number of stories, Gross floor area, Duration, and Lowest tender price.

Aibinu *et al.* (2011) worked on prediction of estimate bias of projects; their work employed 9 CPFs, which included Gross Floor Area (GFA), Principal structural material, Procurement route, Type of work, Location, Sector, Estimating method, Number of storey, Estimated Sum. Arafa and Alqedra (2011) attempted to predict early-stage structural costs of building projects using 7 CPFs. These were Area of ground floor, area of typical floor, number of stories, nr of columns, type of foundation, number of elevators, numberr of rooms. Ahiaga-Dagbui and Smith (2012) also employed 9 CPFs for modeling the total cost of projects. The data included Project Frequency, Tendering Strategy, Need for Project, Ground Condition, Project Type, Duration, Location, Soil Type, Site Access. In dealing with categorical variables such as type of Project and need for project, one-of-N coding system was employed, resulting in multiple sub-variables being generated from a single initial CPF.

Kim *et al.* (2013) researched the costs of school buildings; their data consisted of 11 CPFs that included the following: Year, Budget, School Levels, Land Acquisition, Class Number, Building Area, Gross Floor Area, Storey, Basement Floor, and Floor Height. The structural cost of buildings in the Phillipines was the focus of the study by Roxas and Ongpeng (2014). Their study utilized six variables namely: number of storeys, number of basements, floor area, volume of concrete, area of formworks, and weight of reinforcing steel.

2.6.2 Construction project features derived as outputs in cost prediction

The literature on building cost forecasting was also analyzed in order to characterize the different types of output adopted for the neural networks that were developed in the studies. It was found and presented in Table 2.2 that studies focusing on building cost forecasting employed four main types of outputs. These were (i) the variability between initial and final contract values, (ii) initial contract values, (iii) structural costs of buildings and (iv) final contract values. Variability between initial and final contract values was the prediction outcome in 5 studies, while 3 studies each adopted initial contract values and structural costs of buildings as the network targets respectively.

Table 2.2: ANN outputs for cost prediction in literature

S/n	Authors	Location of study	FCV-ICV	ICV	Structural cost	FCV
1	Elhag and Boussabaine (1998)	UK		x		
2	Palaneeswaran *et al.* (2008)	Hong Kong	x			
3	Wang and Gibson (2010)	USA	x			
4	Aibinu *et al.* (2011)	Malaysia	x			
5	Arafa and Alqedra (2011)	Palestine			x	
6	Ahiaga-Dagbui and Smith (2012)	Scotland		x		
7	Odeyinka *et al.* (2012)	UK	x			
8	Ahiaga-Dagbui and Smith (2013)	UK				x
9	Gulcicek *et al.* (2013)	Turkey			x	
10	Amusan *et al.* (2013)	Nigeria				x
11	Kim *et al.* (2013)	Korea		x		
12	Odeyinka *et al.* (2013)	UK	x			
13	Roxas and Ongpeng (2014)	Phillipines			x	

Source: Researcher's summary
Note: FCV = Final Contract Value; ICV = Initial Contract Value.

Two very important findings from the review of literature included the discovery that the use of costs of building elements as predictors in the forecasting of changes in costs of building projects was not found to be widespread in the literature. No attempt to predict risk impact on the costs of building projects through the use of construction project features as inputs to neural network was found in the literature.

2.7 Use of Artificial Neural Networks (ANN) in Construction

Construction project costs have been modelled successfully with the aid of techniques such as (i) Linear/Dynamic Programming, (ii) Regression Analysis, (iii) Simulation/Risk Analysis, and (iv) Expert Systems (ES). These techniques have been in use for decades, and can be said to have been performing tolerably well. However, the complexities of modern construction coupled with financial pressures on the construction industry have necessitated a revisiting of the levels of accuracy required from existing cost modelling techniques (Bala *et al.*, 2014). Researchers have stressed the need to develop more accurate and robust construction cost forecast techniques (Cheng *et al*., 2009). Partially in response to these calls, artificial neural network (ANN), which is an inductive machine learning methodology, has been applied to construction management research since the early 1990s.

The wide-ranging interest generated by the application of ANN techniques to construction is due in part to the drawbacks associated with the use of the cost modelling techniques mentioned earlier. These are said to be unable to effectively handle situations involving (a) imprecise and uncertain data; (b) unknown effects of combining variables; (c) unknown inter-relationships of cost-influencing factors; (d) complex and vague input-output relationships. Artificial neural networks are able to learn, generalize and represent general knowledge through the extraction of information from existing data, even where knowledge about rules and relationships are not available (Hecht-Nielson, 1990).

The use of mathematical formulae to perform cost modelling in construction was popularized by Bromilow (1969) with the use of parameters for forecasting time performance of construction projects, which represented groundbreaking work at that time. This well-known model was developed using the contract cost and time variability of 329 projects constructed within the preceding half decade. Several researchers have attempted to adapt this model to projects within their own localities, with varying degrees of success, (Kaka and Price, 1991; Kumaraswamy and Chan, 1995; Chan, 2001; Yousef and Baccarini, 2001; Choudhury and Rajan, 2003; Ogunsemi and Jagboro, 2006; Hoffman *et al.,* 2007).

The search for an adaptable tool for predicting cost variability has thus continued with Boussabaine (1996) review of artificial neural networks (ANN) techniques that are applicable in construction management, specifically in predicting project cash flow, costs and risk analysis. The use of new techniques gained ground with Elhag and Boussabaine (1998) work on development of models for cost estimation of school buildings using artificial neural networks. In Palaneeswaran *et al.* (2008), ANN was also applied to the influence of rework causes on the various project performance indicators such as cost overrun, time overrun, and contractual claims.

The quest for cost variability prediction has not been limited to the western world alone. Abu Hammad *et al.* (2010) attempted to predict the actual project cost and time in Jordan with acceptable accuracy using the following independent variables: project type; project size; contract scope; time interval and homogeneity of region of study. In Palestine Arafa and Alqedra (2011) constructed, trained and tested an ANN model that estimated building structural system cost at early (pre-design) stage. ElSawy *et al.* (2011) developed a neural network model that assessed site overhead costs for building projects in Egypt.

In what represents a paradigm shift in construction cost overrun thinking, Odeyinka *et al.* (2012) applied ANN to model risk impacts on the variability between contract sum and final account. Using 5 risk factors on a sample of nineteen projects and a back-propagation neural network, they predicted the deviation of the final account sum from the initial contract sum to within 2 - 6.5 % (mean absolute percentage deviation). This highpoint in research thinking that views variability of cost and time on construction projects as being due to the impact of risk factors over the construction phase of projects was sustained with the work of Larkin *et al.* (2012), which extended knowledge on how risk factors impact on the variability between the contract sum and final account on design and build projects. Ahiaga-Dagbui and Smith (2012) advocated the use of Artificial Neural Networks (ANN) as a data mining technique for developing cost forecast models of construction projects; they tested their technique on water projects in the UK where the final cost was predicted using several physical, organizational and contractual characteristics of the projects.

The ANN technique has also been applied to cost variability in civil engineering; Lin *et al.* (2012) established a model based on Taiwan practices for the prediction of price tenders on roadway construction. In Nigeria, Amusan *et al.* (2013) carried out an exploratory study of cost modeling of reinforced office building projects. Abiola and

Kupolati (2014) used Artificial Neural Network to explore the relationship between Present Serviceability Rating (PSR) and Present Serviceability Index (PSI) for highways in South-Eastern Nigeria.

Table 2.3a and Table 2.3b presented a compilation of the different ways in which the ANN methodology has been applied. It was possible to observe that the number of studies that utilized ANN had increased over time. The diverse ways in which ANN has been used becomes apparent, as well as the wide variation in sample sizes of the different studies; this demonstrated the incredibly versatile nature of ANN. A brief examination of the results of the artificial neural networks developed in some of the works in Table 2.3a and Table 2.3b was undertaken. Wang and Gibson Jr (2010) in the USA utilized ANN and regression to investigate the relationship between level of pre-project planning carried out and the subsequent performance of projects. Although the exact architecture of the ANN model was not provided, the findings proved the superiority of the ANN model over that of the simple linear regression model.

Tu and Huang (2013) ANN model also outperformed a regression analysis model, although the exact architecture of the ANN model was not provided. Their results showed that the ANN model had maximum absolute error of 16.7% as against 48.1% for the regression model. Turning to the prediction of construction costs, Kim *et al.* (2013) worked in Korea with three estimating techniques. Their findings revealed that Mean Absolute Error Rates (MAERs) were 5.68, 5.27 and 7.48 for the Regression, Neural Network and Support Vector Machine models respectively. As in the two previous studies examined, the exact architecture of the ANN model was not provided.

Table 2.3a: Artificial neural networks in construction literature (Nos 1 – 19)

S/n	Year	Research aim	Study Area	Analysis Unit/Sample	Examples of data	Authors
1	1997	Forecast exchange rate of currencies	USA	exchange rate / 321	Euro rate on US dollar deposits.	El Shazly and El Shazly (1997)
2	1998	Model school building costs.	UK	Projects / 30	Market conditions; Lowest tender price (£);	Elhag and Boussabaine (1998)
3	2008	Influence of rework on cost/time and claims.	Hong Kong	/ 112	87 rework parameters; 18 data sets	Palaneeswaran *et al.* (2008)
4	2009	Model quality performance of projects.	India	Projects / 91		Jha and Chockalingam (2009)
5		Predict hourly cooling load.	China	Building / 154	Relative humidity and solar radiation intensity.	Li *et al.* (2009)
6		Predict heating loads of buildings.	Turkey	Building / 3	Building transparency ratio (%), orientation (^{o}).	Ekici and Aksoy (2009)
7	2010	Model preproject planning and project performance	USA	Projects / 140	Project Definition Rating Index; cost growth	Wang and Gibson Jr (2010)
8		Predict rate of return of time deposit (mudharabah)	Indonesia	exchange rate / 108	exchange rate USD to Indonesian Rupiah;	Anwar *et al.* (2010)
9	2011	Predict winning teams at next stage games.	Taiwan	Matches / 64	Goals For (GF), Shots (S), Comer Kicks (CK)	Huang and Chang (2010)
10		Predict accuracy of pretender cost forecasts.	Malaysia	Projects / 100	Gross Floor Area; Principal Material;	Aibinu *et al.* (2011)
11		Model structural cost at early (pre-design) stage	Palestine	buildings / 71	nr of cols, gross floor area, typical floor area	Arafa and Alqedra (2011)
12		Model site overhead costs for building projects	Egypt	Projects / 52	Size; Duration; Type; Extra-man Power.	ElSawy *et al.* (2011)
13		Model project time contingency.	Egypt	Projects / 54	No. of change orders; delay in payment	Yahia *et al.* (2011)
14		Predict project schedule performance	India		Project manager's competence;	Jha and Chockalingam (2011)
15		Model cooling load of a building.	Hong Kong		physical properties; occupants behavior	Kwok *et al.* (2011)
16		Forecast short time building energy.	China	buildings / 2	temperature, solar radiation, humidity ratio	Li *et al.* (2011)
17		Predict price of crude oil.	USA	Price /barrel / 1252	Seasonal Demand; events impact factor (WEIF);	Khashman and Nwulu (2011)
18	2012	Cost forecast models of construction projects.	Scotland	Projects / 98	cost; procurement/client type, fluctuation	Ahiaga-Dagbui and Smith (2012)
19		Model risk impacts on final account variability.	UK	Projects / 19	Risk probability; Risk impact; Final account	Odeyinka *et al.* (2012)

Source: Author (2017).

Table 2.3b: Artificial neural networks in construction literature (Nos 20 – 38)

S/n	Year	Research aim	Study Area	Analysis Unit/Sample	Examples of data	Authors
20	2013	Improve construction cost estimation accuracy	UK	Projects / 1600	Delivery Partners; Target cost; Duration.;	Ahiaga-Dagbui and Smith (2013)
21		Model cost of building loadbearing system	Turkey	Projects / 384	soil types; importance factor; number of stories;	Gulcicek *et al*. (2013)
22		Model reinforced office building project costs	Nigeria	Buildings / 100	Initial and final cost of sampled projects	Amusan *et al*. (2013)
23		Predict future Operating and Maintenance costs.	Taiwan	Buildings / 65	Building age; Nr of units; Common facility area.	Tu and Huang. (2013)
24		Comparative modelling of building cost	Korea	Projects / 217	Budget; Gross Floor Area; Storey; Basement.	Kim *et al*. (2013)
25		Model project time performance	Vietnam	Projects / 75	project factors and risks; client; contract selection	Le-Hoai *et al*. (2013)
26		Model variability between forecast and out-turn cost	UK	Projects / 55	Risk probability/impact; forecast/actual cost flow	Odeyinka *et al*. (2013)
27		Model recyclable concrete and reinforcement volume	Serbia	Buildings / 110	building complexity; gross area; height	Mučenski *et al*. (2013)
28		Model operation /maintenance costs	UK	Buildings / 20	decoration; Roof repair; cleaning; Insurance	Alqahtani and Whyte (2013)
29		Predict compressive strength of CDW concrete.	Brazil	datasets / 1178	Water/Cement Ratio; Cement Content; Age	Adriana *et al*. (2013)
30	2014	Model structural cost of buildings	Philippines	Projects / 30	nr of storeys, floor area, concrete volume	Roxas and Ongpeng (2014)
31		Model road quality parameters relationship	Nigeria	Road / 247	pavement condition, Roughness;	Abiola and Kupolati (2014)
32		Predict rate of accidents	Nigeria	Years / 12.5	persons killed/injured; vehicles/day; road length	Ogwueleka *et al*. (2014)
33		Model project costs in construction disputes	India		Tender price; Inflation; ADR Cost	Asra Fatima *et al*. (2014)
34	2015	Model expected level of project selection success.	Italy	Projects / 150	Project schedule/plan; Personnel;	Costantino *et al*. (2015)
35		Model project variation claims performance.	India	Variation claims / 204	Contract condition; owner ordered variation;	Chaphalkar *et al*. (2015)
36		Predict impact of expected claims.	Egypt	Projects / 32	project type, duration, cost, contract type,	Ossama *et al*. (2015)
37			India	Projects / 2	Preliminaries; Site Clearance; Earthwork;	Gopal and Shiva (2015)
38		Model severity of occupational injuries.	Iran	Accidents / 980	Age; training; Working experience; PPE;	Mohammadfam *et al*. (2015)

Source: Author (2017).

Odeyinka *et al.* (2013) model of the significant risk factors that impact on the variability between baseline forecast and out-turn cost flow developed an 11-11-11-6 back propagation architecture ANN model. The relative mean absolute deviation (RMAD) was found to be 0.166 at 100% completion, while the standard deviation of Y (SDY) ranged between 0.69 and 12.04. The results compared favourably with earlier researches which had SDYs of 3.1% - 11.5% (Kenley and Wilson, 1986; Kaka and Price, 1993). In the application of ANN to modelling of road quality, Abiola and Kupolati (2014) study obtained R^2 values of 0.335 and 0.901 for regression and ANN respectively; the ANN Model had a 4-18-1 architecture.

2.7.1 Basic architecture of artificial neural networks

ANN modeling is usually chosen because of its robustness, ability to adapt to unknown data sets, and good learning capability (Ling and Liu, 2004; Jha and Chockalingam, 2009). An ANN is an information processing system that is essentially a mathematical model made up of a number of simple elements called neurons (nodes); signals move between neurons through connection links that possess varying weights. The transfer of the signal by each neuron involves an activation function that determines what the output will be. A model of an artificial neuron as proposed by McCulloch and Pitts is shown in Figure 2.1 (Zurada, 1992).

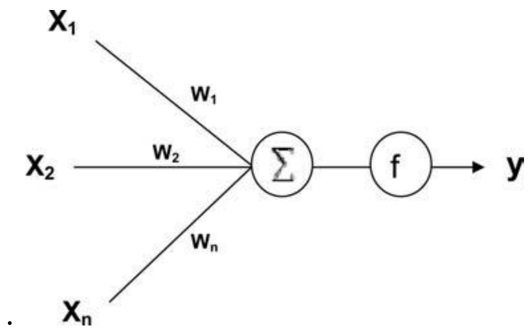


Figure 2.1: McCulloch–Pitts model of a neuron
Source: Zurada (1992)

A neuron compares the computed weighted sum of its *n* input signals Xj = 1, 2, . . . , *n* with certain preset thresholds. An output of 1 is generated if the threshold is exceeded, otherwise the output is simply 0 (Zurada, 1992). The activation functions that determine the comparison thresholds include linear, sigmoid, and Gaussian functions; the sigmoid is however the most commonly used function (Jain *et al*., 1996).

Mathematically, the sum of the weighted input of a neuron *j* is expressed as follows:

$$\mathrm{net}_j = \sum_{j=1}^{n} w_j \, x_j$$ ……………… Equation 2.1

While the neuron's output, y which is a function of its weighted input is expressed as follows:

$$y = f(\mathrm{net}_j)$$ ……………… Equation 2.2

Feed forward neural network architecture consists of an input layer, output layer and hidden layers if required. The network is fed input data through the input layer; the numbers of neurons (nodes) which make up the input layer are representative of the independent variables from which the dependent variable will be determined. Where hidden layers are used, the number of nodes embedded in the hidden layer is usually decided by trial and error. Hidden nodes receive input values; calculate the input values' weighted sum and then, based on the transfer function selected, squeezes the values into a limited range (Edwards, 2007). The squeezed values then serve as input to the output nodes where the same process is again repeated. Figure 2.2 presented a simplistic model of an ANN.

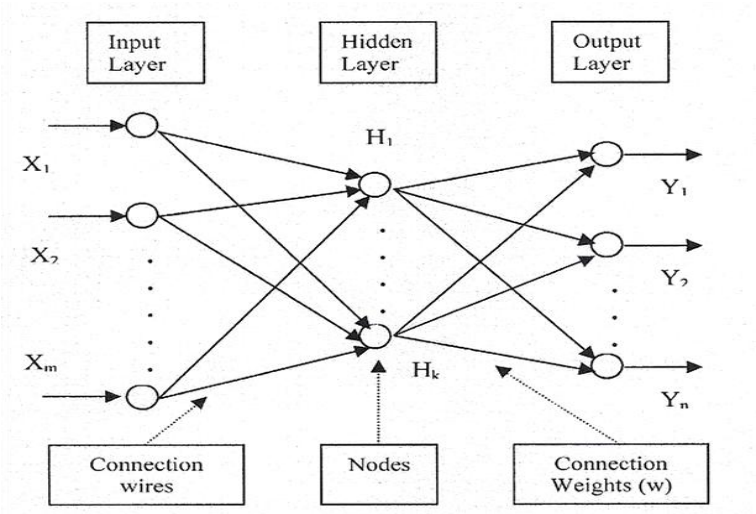


Figure 2.2: A simple artificial neural network structure
Source: Elhag and Boussabaine (1998)

The descriptions of the sigmoid and linear transfer functions used in MATLAB software are given in Table 2.3.

Table 2.4: Description of transfer functions

Transfer function	Input range	Output range	Function
Log sigmoid	Plus and minus infinity	0 and 1	$f(x) = \frac{1}{1 = e^{-x}}$
Hyperbolic tangent sigmoid	Plus and minus infinity	−1 and +1	$f(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}}$
Linear function	Plus and minus infinity	Plus and minus infinity	$f(x) = x$

Source: Jha and Chockalingam (2009)

A neural network is trained to minimize output error by adjusting network weights and biases. This it does by using one of several learning algorithms. The back propagation learning algorithm with feed forward network architecture is considered most suited for predictions (Jain *et al*., 1996). Inputs are sent forward to hidden and output nodes while errors are propagated backwards through the network. Using the back propagation algorithm, a network is trained with an input and its corresponding output to a point where a function and an input becomes associated with a specific output. Where properly trained, back propagation networks usually give reasonably accurate responses when presented with new inputs. The training of the network through adjustment of weights is usually a trial by error process, since no single algorithm suits all applications.

A neural network model can be trained and tested using either the hold-out method or a re-sampling method called random sub-sampling (Edwards, 2007). The hold-out method splits the data sets into two groups. The design (training set) is usually two-thirds of the sample, while the testing and validation set makes up the balance of one-third, and is used for the estimating the true performance of the model on data not yet known to the network. The random sub-sampling method performs multiple random train and test experiments on training and testing samples.

Neural networks are trained continuously until the mean squared error (MSE) is acceptable, and then validation is carried out. Once the mean absolute percentage deviation (MAPD) is found to be within acceptable limits, the prediction model is considered as validated. During validation predicted values derived from the models are compared with actual values obtained from sampling. Some of the performance measures used to validate prediction models are presented in Table 2.4.

Table 2.5: Performance measures for model validation

Performance measure	Formula
Percentage deviation (PD)	$\mathrm{PD} = \frac{\text{Actual performance- predicted performance}}{\text{Actual performance}} \times 100\%$
MAPD	$\mathrm{MAPD} = \frac{\sum_{i=1}^{n} \lvert \mathrm{PD} \rvert}{n}$
MSE	$\mathrm{MSE} = \frac{\sum_{i=1}^{n} (\text{Actual performance} - \text{predicted performance})^2}{n}$
Root mean square error (RMSE)	$\mathrm{RMSE} = \sqrt{\mathrm{MSE}}$

Source: Jha and Chockalingam (2009)

2.7.2 Performance analysis of tools for cost variability prediction

There are a wide variety of methodologies that can be utilized in performance analysis and prediction. To begin with, the modelling approach selected depends on a number of factors; this usually includes the type and quantity of available data, what use the developed model would be put to, and the quality of the predictive performance required (StatSoft Inc, 2011). Some of the available modelling techniques include case-based reasoning, principal component analysis, regression, decision trees, machine learning, genetic algorithm, fuzzy logic, as well as artificial neural networks.

Regression is used to model the distribution of a variable, which is dependent upon variations in the distribution of one or more predictor variables (also known as independent variables). Simple regression analysis is also known as the least squares regression, where the best fitting line is chosen under the criteria that the sum of the squares of the residuals is minimized. The application of "fuzzy techniques" has been gaining popularity to the research area of construction management over the past decade. Fuzzy techniques refer to all fuzzy concepts, which include fuzzy set and logic; hybrid fuzzy techniques are those that combine fuzzy set and/or logic with other techniques, such as neural network, evidential reasoning, expert system and clustering (Lin *et al.*, 2012).

ANN models are based on a number of simple elements called neurons (nodes); which are linked by connections that possess varying weights. The transfer of the signal by each neuron involves an activation function that determines what the output will be. ANN is usually robust, adapts to unknown data sets easily, and has good learning capability (Jha and Chockalingam, 2009). Based on a review of relevant literature where the different analytical tools and techniques were applied and the results obtained in such research works, Table 2.6 was drawn up.

Table 2.6: Performance Analysis Table for prediction tools

S/Nr	Criteria	ANN	FL	GA	R	Tentative Choice	References
1	Prediction accuracy	Good	Fair	Poor	Fair	**ANN**	Tu and Huang (2013); Hornik *et al.* (1989); Czarnigowska and Sobotka (2013);
2	Learning ability	Good	Poor	Good	None	**ANN/GA**	Aibinu *et al.* (2011); Flood and Kartam (1994); Francesco *et al*. (2015); Bansal *et al*. (1993);
3	Tolerance of non-completeness of data	Good	Poor	Good	Poor	**ANN/GA**	Emsley *et al*. (2002); Flood and Kartam (1994); Chua *et al*. (1997);
4	Data structure detection capability	Good	Fair	Good	Poor	**ANN/GA**	Aibinu *et al*. (2011); Anderson and McNeill (1992); Dvir *et al*. (2006); Arafa and Alqedra (2011)
5	Speed	Fair	Fair	Good	Fair	**GA**	
6	Non-linear capability	Good	Fair	Good	Poor	**ANN/GA**	Arafa and Alqedra (2011); Cho *et al.* (2013);
7	Multi-attribute problem handling capability	Good	Fair	Good	Poor	**ANN/GA**	Masters (1993); Deng and Yeh (2010);
8	Freedom from assumptions (functional form, probability distribution and smoothness)	Good	Poor	Good	Poor	**ANN/GA**	Camargo *et al.* (2003); Adeli (2001);
9	Applicability / Customizability	Good	Fair	Good	Poor	**ANN/GA**	Francesco *et al.* (2015); Czarnigowska and Sobotka (2013);
10	Tendency for over-fitting	Low	-	High	-	**ANN**	
	Number of characteristics that favour use of tool	**9**	**0**	**8**	**0**		

Source: Author (2017)

Notes: ANN= Artificial Neural Networks; FL= Fuzzy Logic; GA= Genetic Algorithms; R= Regression

In the Table 2.6, ten (10) key characteristics of four prediction and modelling tools were examined. The results presented in the table revealed that two characteristics make ANN preferable above other tools, while genetic algorithms (GA) have a single characteristic that gives them an edge over other tools. In the case of the rest 7 characteristics, the choice would lie equally between ANN and GA. With ANN featuring favourably in 9 out of 10 characteristics, it was easy to see why the use of ANN decided upon in this study.

2.8 Theoretical Frameworks of Risk Impact on Construction Cost

This study was built on the theoretical models of risk assessment and modelling. The method employed in assessing and modelling of risk depends to a large extent on the way the risk is perceived. Thus Odeyinka *et al*. (2012) remarked in their study on risk impact on cost variability, that there are many theories regarding risk perception and risk measurement. To Elseth and Hamann (1999), risk is the probability of failure in the cost, schedule or technical performance of a system as well as the consequences of such failure. Gamez (2009) also shared this view of risk assessment as a function of probability of occurrence and the consequence.

Some researchers have tended to view risk assessment as a controversial issue (Baloi and Price, 2003), which by tradition focused on the assessment of risk quantitatively (Tah and Carr, 2001). This approach has persisted despite the difficulties encountered in deriving appropriate data. Quantitative risk assessment comes with the problem of ensuring the objectivity of probabilities and frequencies; the fact that projects in the construction industry are very often one-off enterprises is the main source of the problem (Flanagan and Norman, 1993). Researchers have circumvented this problem by relying on subjective probabilities (Winch 2003) or adding an approximate sum of money as a contingency allowance (Kangari and Riggs, 1989). Current research paradigms allow for subjectivity in data because adequate historic data can usually be obtained in linguistic but not numeric form (Al-Bahar and Crandall, 1990). This means that individual knowledge, experience, intuitive judgement and rules of thumb all serve as sources of data for risk assessment and should be collected in a structured manner so as to facilitate risk assessment (Dikmen *et al*., 2007).

A very narrow boundary exists between risk assessment and risk modelling, as can be observed in Figure 2.3. Risk is conventionally assessed through assessing its probability of occurrence and impact; for this reason the Probability–Impact (P–I) risk model has become the dominant risk model in literature. The P–I risk model has been criticized by some researchers who discussed the possibility of improving it. There however appears to be a wide gap between the theory and practice of risk modelling and assessment (Laryea and Hughes, 2008). The consequence of risk eventually manifests as a difference (which may be negative or positive) between the planned costs and the actual costs of construction projects.

When the cognitive model of Winch (2010), which subdivided risks and uncertainties on construction projects into four 'risk spaces' is applied to the effect of risks on building costs, it becomes apparent that although it is known that differences do occur between planned costs and actual costs, yet the magnitude of the difference usually remains unknown before the completion of the project. Thus the final costs of construction projects fall into the 'known unknown' risk space. The Project Management Institute (2012) concurs with this view and even goes further to provide descriptive aids to assist in measuring the degree of risk.

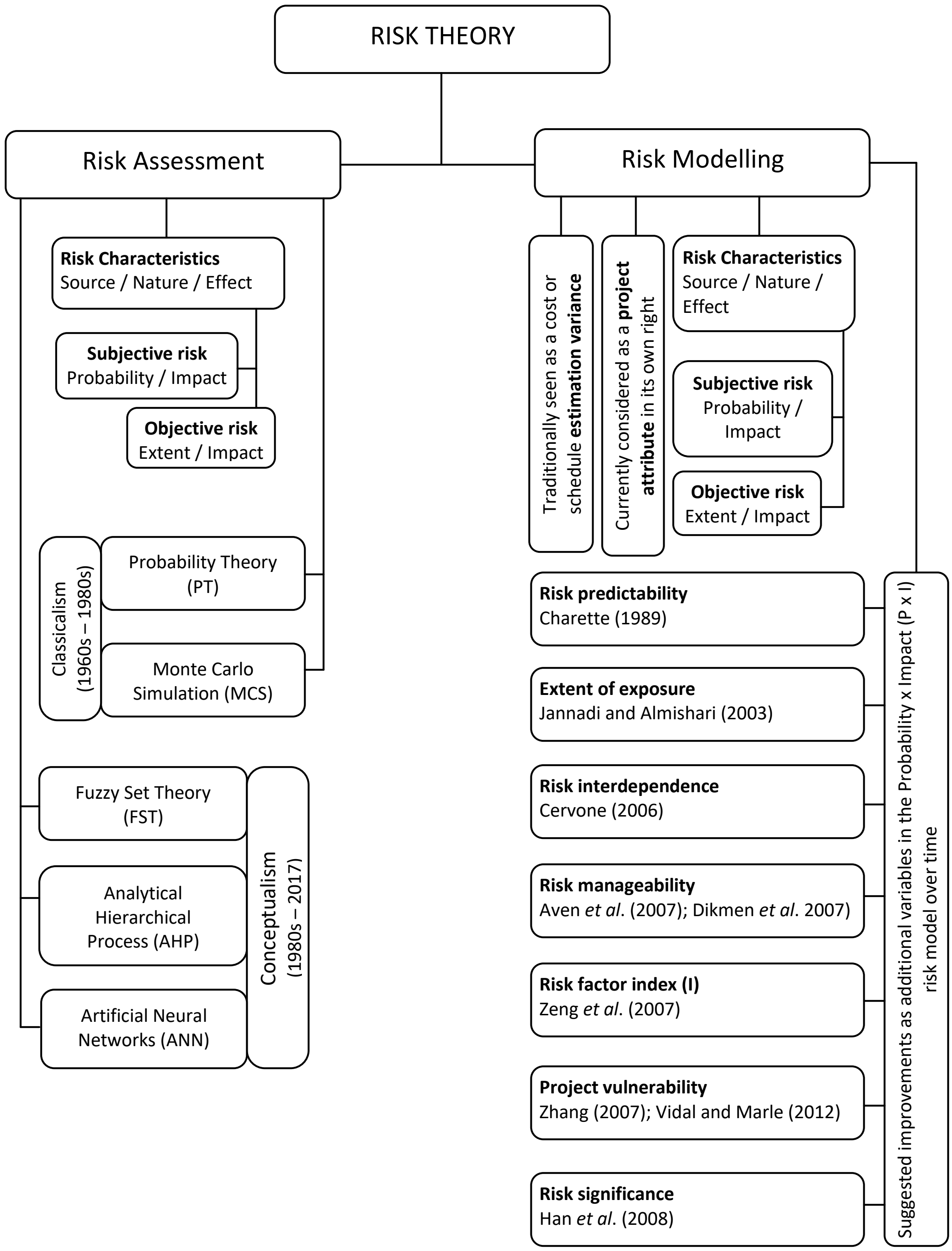


Figure 2.3: Historical summary of some key developments in risk assessment and modelling
Source: Researcher's summary

2.8.1 Theoretical works in the assessment of risks

Risk assessment has over time been enveloped in such complexity that it has always drawn huge research attention which has been reflected in the different approaches that have been adopted for assessing project risks. Research into the assessment of risks in construction has proceeded from purely quantitative statistical methods based on Probability Theory (PT) to mixed qualitative-quantitative techniques such as Fuzzy Set Theory (FST). From that point, progress has been made with the introduction of Analytical Hierarchical Process (AHP) in dealing with the ever increasing complexity in risk assessment due to the growing complexity in construction projects (Tah and Carr, 2000).

The initial reliance on PT for dealing with cost and schedule risks perceived risk as being simply an estimation variance, which can be assessed if objective probabilities and frequencies of the occurrence of the risks are known. The switch to FST showed that many researchers now believed that subjectivity in the form of human factors, intuition, professional experience and personal judgement were essential inputs in the risk assessment process. Currently, AHP appears to be the effective tool of choice for researchers to systematically handle the complexities in assessing construction risk by allocating importance weightings. At present, researchers are focused on attempting to represent the interdependencies between project risks to reflect the complexity of the project environment (Ackermann *et al*., 2007; Lazzerini and Mkrtchyan, 2011; Nieto-Morote and Ruz-Vila, 2011). In explaining the profusion of tools and techniques for risk assessment, Laryea and Hughes (2008) referred to the use of PT-based and simulation tools as "classicalism", while the use of analytical tools such as AHP was termed "conceptualism". Classicalism perceived risk as an estimation variance; conceptualism on the other hand regarded risk as a project attribute.

Researchers have identified two forms of risk; subjective risk is the probability of risk occurrence/impact of occurrence while objective risk is the extent of risk occurrence/the impact of occurrence, (Adams, 2006). Although the extent of risk occurrence is viewed as an objective estimate of risk, yet data on it still relies on linguistic rather than numeric approaches. This introduces the risk that perceptions regarding extent of risk occurrence might vary if project stakeholders are interviewed at different points in time. In contrast, the financial consequence of risk (the 'risk cost' first put forward by Franke (1987)) is documented in final accounts; hence this risk measure remains the same under varying conditions and at different points in time. If the financial consequence of risk were substituted for the extent / impact of risk, a relatively more stable measure of risk is obtained.

2.8.2 Theoretical works in the modelling of risks

Evidence from the literature showed that construction risk has been traditionally modelled as the variance of cost or duration estimation, using the P–I risk model that multiplies probability of occurrence with impact. In the present times however, newer tools and techniques have allowed researchers to model risk as a project attribute; however most researchers still base such tools and techniques on the P–I risk model. Thus it is evident that the P–I risk model still dominates the theory of risk modelling. Across the space of three decades however, researchers have put forward a lot of proposals for improving the existing dominant risk model. Taroun (2014) has very comprehensively summarized these improvement proposals.

The highlights of the suggested improvements to the P-I risk model includes Charette (1989) proposal that the 'predictability of risk' be added as a third dimension to the P–I risk model. This was followed by Jannadi and Almishari (2003) who suggested that instead of predictability, the extent of exposure to risk should be used as a third dimension to the P–I model. Attention was drawn to the role of the interdependencies between risks in the modelling of construction risk by Cervone (2006), who recommended that risks should be discriminated through reducing their independent scores generated by the P–I model. Still on the interdependence of risks, Aven *et al*. (2007) posited that some risks are more manageable than others; Dikmen *et al*. (2007) concurred by suggesting risk manageability as a mitigating factor for the overall project risk level. Zeng *et al*. (2007) also supported the notion that risks are interdependent, but by incorporating the factor index (I = influence of the surrounding environment and the interdependencies between the identified risks) as a third dimension in the P–I risk model. The project environment was also the focus of Zhang (2007), who incorporated project vulnerability as a measure of the mediating effect of project environment on risk impact. Risk analysts rely on their intuition to rank risks in terms of what applies to a project and what does not. This observation influenced Han *et al*. (2008) in adding 'risk significance' as a third dimension to the P–I model; this was to account for the subjectivity inherent in human assessment of risks as significant or not. The work by Zhang (2007) was adopted by Vidal and Marle (2012) in their assessment of project risks management systems.

2.9 Conceptual Framework for Assessing Risk Effect on Building Costs

The conceptual model for the study which showed how the effect of risk on project cost performance can be evaluated from changes to the initial contract values of projects was presented in Figure 2.4. The conceptual framework subscribed to Odeyinka *et al*. (2013) postulation of risk as the underlying reason why changes occur in the costs of construction projects between the start and completion of such projects.

Construction projects have been said to comprise five general stages: initiation/planning, design, tender, construction and final account/defect liability stage, each of which has influence on the project success. Some researchers believe that the importance of the final account stage in achieving successful closure of construction projects has always been neglected in construction management literature (Zakaria *et al*., 2012a; Zakaria *et al*., 2012b). This perception was partially remedied in this study. The conceptual framework was predicated on the belief that the financial changes documented in final accounts represented a stable and appropriate measure of the consequences of risk. This position taken by the study was not an isolated one; the association of final account values with specific risks was undertaken in line with the risk register methodology adopted in studies such as those of Perrenoud *et al.* (2016) and Ibrahim (2008).

The framework has been designed to avoid the two shortcomings of previous efforts at predicting risk effect on costs, which were (i) reliance on semantic scales to derive risk impact, and (ii) minimal or zero use of established sources of project historical data. For this reason, final accounts of building projects formed the major source of data for testing the framework. The derivation of risk impact was undertaken with the use of the risk register methodology; it reduced subjectivity in risk inpact estimation by requiring the use of a construction professional only to associate costs in the final accounts with risks whose action resulted in the cost.

2.9.1 Conceptualizing the effect of risks on costs of building projects

Right from the moment a project is started, changes begin to be observed in the values of the quantities of work, which were considered as provisional as at the time of commencement. Firm bids are obtained from subcontractors and suppliers that in many cases differ markedly from the monetary allowances that were made for goods and services to be purchased from subcontractors and suppliers. In addition, as the work progresses, the client or design team have cause to vary the scope of the works either by addition of new works, subtraction of some parts of the works planned to be done, or substitution of some part of the works with a different type of work.

Odeyinka *et al*. (2012) opined that the effect of risk manifests in the costs incurred on a construction project through differences in the project's planned cost at the pre-construction stage and out-turn cost at completion. This they blamed on risk factors eventuating during the in-progress phase of construction. In his own contribution, Love (2011) postulated that cost overruns were due to pathogens that reside latently within a system such as a construction project. They are activated by 'active failures', which are unsafe acts committed by people within the system. For example, the relatively common practice of commencing work using tentative information might be the source of active failures, such as non-provision of proper cost details for work sections. This then leads to an increased risk of cost changes for works included in the 'provisional sums' section of final accounts.

At project commencement, it is expected that the final contract value (FCV) that will be revealed in the final account (FA) will be lower than or at the most equal to the planned cost of the project that was encapsulated in the initial contract value (ICV). This expectation is based on the adequacy of the contingency allowances built into the ICV. Mathematically, this can be expressed as:

$$FA \leq ICV \quad \text{…………………….. } Eq\ 2.3$$

However, from the literature on cost performance of construction projects, the actual observation is better expressed by Equation 2.4

$$FA \neq ICV \quad \text{…………………….. } Eq\ 2.4$$

Relying on the perspectives of Perrenoud *et al.* (2016), Odeyinka *et al*. (2013), Odeyinka *et al*. (2012) and Ibrahim (2008), equation 2.4 could be re-written as

$$FA = ICV + RC \quad \text{…………………….. } Eq\ 2.5$$

where RC is the effect of risk on the project manifested in observed changes in the project costs.

The magnitude of the deviation of Final Accounts from Initial Contract Values served as the dependent variable. It must be remarked that equation 2.5 would also be valid for a situation where savings had been made in the project expenditure; in such a case, RC would be negative and would depress the value of FA. In a small minority of projects, deriving from the professed inevitability of risk (Latham, 1994), RC would be equal to zero.

The frequency and timing of the changes that are observed in the project costs are important and can be measured (Perrenoud *et al.*, 2016). This is because of the cumulative effect of risk; on a project several incidences are recorded and each has a small cost value, relative to the ICV of the project. However, when these individual incidences are aggregated cumulatively, the overall effect on cost of the project might be substantial. To identify the various costs that were incurred as a consequence of specific risks, 8 different risks were classified into three groups (client, consultant and unforeseen) in this study.

Using the risk register approach, costs were associated with specific risks (and thus specific risk groups) through interaction with project quantity surveyors (PQS). The result of this was expressed in equations 2.6 and 2.7:

$$RC_1 = (C1_1 * f1_1) + (C1_2 * f1_2) \ldots + (C1_n * f1_n) \qquad \ldots\ldots \text{ Eq 2.6}$$

$$RC_2 = (C2_1 * f2_1) + (C2_2 * f2_2) \ldots + (C2_n * f2_n) \qquad \ldots\ldots \text{ Eq 2.7}$$

where RC_1 was the aggregate cost effect of the client risk group and RC_2 referred to the aggregate cost effect of the consultant risk group; C1 and C2 were the individual cost increases due to Client and Consultant risks respectively; f1 and f2 were the frequencies of the cost increases due to Client and Consultant risks respectively.

The outcome of the data collection phase of the study would provide the values of *RC*, *C* and *f* as well as the value of *n* in equations 2.6 and 2.7.

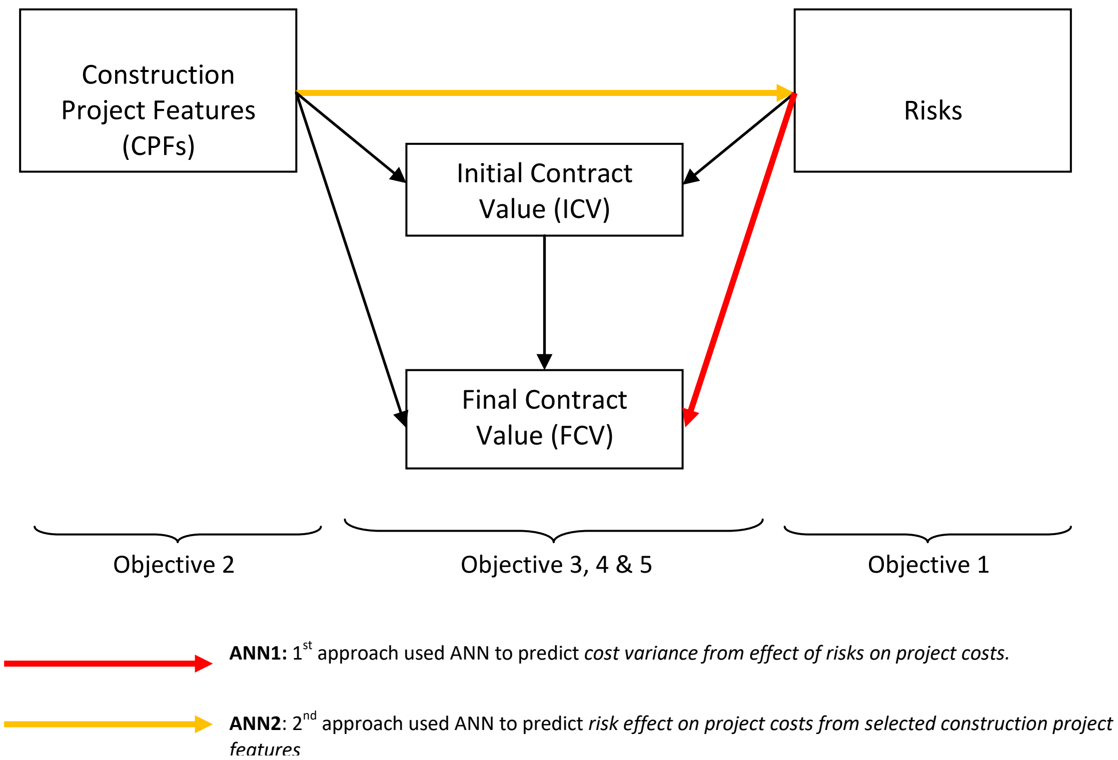


Figure 2.4: Conceptual framework for assessing risk effect on project costs

2.9.2 Conceptualizing the development of artificial neural network for prediction of risk effect in costs of building projects

Two separate approaches were employed in the deployment of ANN as tool of choice for prediction of risk effect on costs as required by Objective 4 of the study. Details of these two approaches were provided in the following sub-sections.

2.9.2.1 Prediction of cost variance using risk effect on project costs

The conceptual framework encompassed the modelling of the deviation between initial contract values and final accounts, which was indicated on the conceptual framework by a bold red arrow. This was achieved through the application of artificial neural network and multiple regression analysis (MRA) for purposes of comparison. The choice of the tool employed for modelling was informed by the nature of the data to be modelled as well as the need to derive a model having optimal performance in terms of accuracy and generalizability. At the end of the analysis with MRA, a linear equation would be obtained in the usual regression form of $y = a + bx$. As stated by Kumar and Phrommathed (2005), the two main types of variables (independent and dependent variables) can be identified in the conceptual framework. The expected actual form of the predictive model that would be developed was:

$$(FA\text{-}ICV) = a + (b_1 * RC_1) + (b_2 * RC_2) \qquad \text{…… Eq 2.8}$$

where b_1 and b_2 are the regression coefficients and a is a constant indicating the slope of the regression line.

2.9.2.2 Prediction of effect of risk on project costs using CPFs

Prediction of the effect of risk in the costs of the project was also captured in the conceptual framework of the study. The prediction of risk effect was carried out through the use of artificial neural network with CPFs as network inputs (indicated by the bold yellow arrow in Figure 2.4. It needs to be stated here that in the entire review of literature on the use of ANN in cost forecasting and prediction of risk effect in construction costs, no evidence was found that risk effect has ever been predicted through the agency of ANN with CPFs as network inputs. The closest to ANN2 that was found in literature were two studies where risk effect on costs was applied in the prediction of final cost variance (Odeyinka *et al*., 2012; Odeyinka *et al*., 2013).

The main differences between the two approaches applied include the adoption of risk grouping in ANN1, while in ANN2 the normalization of data was carried entirely through reduction to binary scale. The use of binarization enabled the application of engineering tools such as receiver operating characteristic (ROC) charts, 2 x 2 contingency tables and derived performance metrics to the network developed through Methodology 2, in order to caliberate its performance. This was in line with the requirements of Objective 5.

2.10 Outcome of the Review of Related Literature

The review of literature carried out in this study has revealed that the modeling of project cost performance has followed a mathematical/statistical approach from the earliest times; computer-based artificial intelligence techniques have also been applied, although prior to 2012 none of the developed models have dealt with the impact of risk on project costs. Risk has been defined in the literature as "an uncertain event or condition that, if it occurs will have either a positive or negative effect on one or more of the project's objectives". A typical construction project may involve several forms of risks such as contractual, financial, operational, political and technical risks. Researchers have opined that traditional cost estimating methods have failed to cope with the problems of uncertainties and accuracy, and have stressed the need to develop more accurate and robust construction cost forecast techniques.

The significant factors impacting on project cost in Nigeria that have been identified include price fluctuation, financing and payment of completed work, additional work, design changes, inaccurate estimates, imported materials and plant items; some other researchers found that financial, design and construction risks have significant impact on cost of construction projects in Nigeria. However it was also found from the literature review that a consistent, industry-wide method for characterizing construction risks does not exist. Risks have been assessed qualitatively through their probability of occurrence and impact using simple semantic scales such: as high, medium, low. There are also quantitative methods of assessing risk that use empirical data about past similar events obtained from either participants or observers. Experts however recommended that both qualitative and quantitative risk assessment methods should be combined in identifying the risks associated with the control of the project cost, time, and resources.

An artificial neural network (ANN) is an information processing system that is essentially a mathematical model made up of a number of simple elements called neurons (nodes); signals move between neurons through connection links that possess varying weights. The transfer of the signal by each neuron involves an activation function that determines what the output will be. ANN modeling is usually chosen because of its robustness, ability to adapt to unknown data sets, and good learning capability. Drawing on the reviewed literature, the evaluation of effect of risk on project cost performance from changes to the initial contract values of projects was encapsulated in the conceptual model for the study. The framework attempted to avoid the two shortcomings of previous efforts at predicting risk effect on costs, which were (i) reliance on semantic scales to derive risk impact, and (ii) minimal or zero use of established sources of project historical data. For this reason, the derivation of risk impact was undertaken with the use of the risk register methodology that had been adopted in some previous studies.

CHAPTER THREE

3.0 RESEARCH METHODOLOGY

3.1 Research Design

This study utilized two different approaches (ANN1 and ANN2) in applying ANN in the prediction of risk effect in final costs of building projects, as detailed under the conceptual framework of the study in Chapter Two. Both ANN prediction approaches utilized the same data collection procedures, and only differed in the way data was prepared and analyzed. This difference has been reflected in Section 3.3, which dealt with Analysis of Data on an objective-by-objective basis.

Construction research is often as a matter of necessity based on empiricism where conclusions are drawn on the basis of observed facts (Kenley, 2003); this is because a lot of what is being researched into in the construction industry is not underpinned by theories that have been tested and proved. This study adopted a positivist epistemological approach, through the extensive use of project historical records. This is based on the argument by Osei-Hwedie (2011) that in positivism, scientific knowledge is proven through the accrual of verified facts. Applying a positivist empirical approach represents an alignment with approaches applied in previous researches on risk effect on costs in building projects.

A combination of two research approaches (qualitative and quantitative) was employed sequentially in the study. Onwuegbuzie and Johnson (2006) describe sequential Mixed Method as a contextual overlaying strategy, where qualitative approaches are used to collect contextual information for facilitating the interpretation of quantitative data or reconciling findings. It has been argued that a characteristic of truly mixed method studies involves integration of the qualitative and quantitative findings at some stage of the research process, be that during data collection, analysis or at the interpretative stage of the research (Kroll and Neri, 2009 cited in Ostlund *et al.,* 2011). Yin (2003) observed that processes that employ quantitative approach are typically well structured and formalized; by contrast qualitative approaches are more flexible and suited to in-depth exploration.

Mixed method research designs are pursued largely based on the premise that they exploit the advantages of quantitative and qualitative methods, while neutralising the "costs" or "risks" associated with each method (Grafton *et al.*, 2011). Creswell (2009) describes the Mixed Method approach as one where the researcher may first explore generally in a qualitative manner to learn about which variables to study, and then study those variables with a large sample of individuals quantitatively. However, in studying the effect of risk on project costs, the use of only one approach will be limiting, as risks abound in large numbers and variety in the construction industry. It may be helpful if contextual knowledge of types and features of risks possessed by cost management professionals is assessed qualitatively before the effect of the risks is measured quantititatively.

Some of the advantages of the Mixed Method approach are that the techniques of qualitative and quantitative domains, when interlinked, help to maximize the knowledge yield of research outcomes (Teddlie and Tashakkori, 2009). Mixed Method also allows the researcher to discover and justify the model components within one study. In addition, qualitative techniques permit gathering of data that is robust in details, which will have a great influence on the research output.

When qualitative and quantitative methods are mixed in a single study, one method is usually given priority over the other. This is less challenging in sequential Mixed Method studies, where one approach clearly informs the other (Ostlund *et al.*, 2011). The proposed Sequential exploratory strategy for this research starts with in-depth reviews of literature (qualitative), to capture as much of the construction researchers' perspectives towards risk effect on project costs. Information obtained from this process is then fed into the development of a questionnaire survey (quantitative) to extract definitive data on risk effect on project costs from historical project records.

3.2 Data Collection

The process of acquiring data for determining the risks (Objective 1 of this study) and construction project features (Objective 2 of the study) that could be employed for the development of an artificial neural network for predicting risk effect on project costs began with a review of relevant literature. This exercise yielded a total of 70 risk factors and 33 CPFs that were then whittled down to more manageable numbers (see Section 3.3) before inclusion into the research instrument of the study.

Data employed for the determination of effect of risk on project costs (Objective 3) was obtained from the final account documentations as well as the bills of quantities of the sampled building projects. Project Quantity Surveyors (PQS) served as sources of experiential data by helping to identify the risks that had influenced the costs of the building projects. In some cases, apart from extraction of relevant information from final account documents, the PQS also provided project files for perusal of records of architect's instructions, variations and certificates, arising out of site meetings or other project communications. All of the foregoing kinds of data were thereafter employed in the development of artificial neural networks for predicting risk effect in final costs of building projects, which was Objective 4 of the study. Analysis of the performance of the neural networks thus developed (Objective 5 of the study) did not require any additional kind of data apart from what was used to develop the neural networks.

3.2.1 Population of the study

The unit of analysis of this study is building construction projects. The population of the study comprised building projects where final accounts had been prepared to mark the end of the construction phase. Final accounts are technical documents detailing the costs incurred on a construction project over the construction phase of the project. They are prepared by quantity surveyors, and are of a confidential nature. There was no organization, statutory, voluntary or otherwise, that was known to the researcher which kept complete lists of completed building projects for which final accounts had been prepared. Fragmented sets of the population of interest were maintained by some statutory organizations such as the Development Control Unit of the Federal Capital Development Agency (FCDA) as well as the various quantity surveying consultancy firms.

In order to improve the chances of obtaining as many final accounts as possible, it was decided to approach the QS consultancy firms directly. Purposive sampling was identified as the sampling technique that offered the best chance of accessing the most projects.

3.2.2 Sampling technique

Purposive sampling technique was employed in this study, because projects had to satisfy some criteria to qualify for inclusion in the study (building project; completed between 2004-2015; detailed final account prepared). The 2015 Diary of the Nigerian Institute of Quantity Surveyors (NIQS) was consulted to provide an indication of the population of QS consultancy firms that could be approached. There were a total of 230 firms registered with the NIQS nationwide, of which 48 were located in Abuja (NIQS, 2015). The NIQS, which is a trade association, was employed rather than the Quantity Surveyors Registration Board of Nigeria (QSRBN) which is a statutory body. This was because the NIQS publishes annual lists of members qualified to practice Quantity Surveying.

The choice of purposive sampling technique hinged on its ability to provide a representative sample (Patton 2001) of sample elements based on certain specified criteria, such as the possession of specific knowledge required by the study. An alternative non-probability sampling technique that could be employed is convenience sampling, where selection is based on willingness to participate in the study. Both of these two sampling techniques have been recognized as appropriate in situations when respondents are not randomly selected from the entire population Wilkins (2011). This study required input from PQS who had worked on projects that had been affected by risk; such effect must have manifested as change in the cost of the project.

3.2.3 Sample size and response rates

Information in final accounts of 77 completed projects was entered into the research instrument. This information included additions and omissions to projects costs as presented in BOQs. Detailed breakdown of the information collected is presented in Section 3.2.4. The inability to provide final accounts of completed building projects supervised by them limited the participation of most of the quantity surveying firms located within the study area. Eight final accounts were found to provide incomplete project financial information and were discarded, leaving 69 project final accounts for use in the study.

Based on the fact that the study population could not be defined accurately, response rates for the study could not be computed. However, the quantum of data collected and utilized for the development of the artificial neural network, 69 projects in all, compared favourably with precedents in the literature (see Table 2.2a and Table 2.2b in Chapter 2 for a detailed list of sample sizes for researches that have utilized ANN). Sample sizes for some studies that had building projects as unit of analysis include 55 datasets for Odeyinka *et al*. (2013) (obtained from a potential population of 370, representing a 14.86% response rate) and 19 datasets for Odeyinka *et al*, (2012) (obtained from a population of 62, representing a 30.65% response rate)..

3.2.4 Research instruments

Two kinds of questionnaires were used for data collection, to obtain information on the CPFs as well as the specific risks that affected project costs. The CPF questionnaire contained two sections, Section ‘A’ where ‘general demographic information about the respondents’ was requested; in Section ‘B’ information on the 8 construction project features was requested. A sample of the CPF questionnaire was included as Appendix A.

The Risks questionnaire was designed to accommodate cost information extracted from final accounts of projects, against which respondents filled in information on risks. All of the 5 classes of costs in final accounts were covered (provisional sums (PS), provisional quantities (PQ), variations that increase costs (Va), variations that decrease costs (Vo) and variations that substitute costs (Vs)). A sample of the Risk questionnaire was included as Appendix B.

3.2.5 Classification and measurement of research variables

<u>CPF Questionnaire – Section A</u>

The variables in Section A of the questionnaire were classified and measured as follows:

QV1 - Designation of respondents: On the designation of respondents, the respondents were asked to state their position in the organization.

QV2 - Construction experience: The construction experience of respondents were measured and assigned values as follows: Less than 11 years - 1; 11 - 20 years - 2; 21 - 30 years - 3; more than 30 years - 4.

QV3 - Highest academic qualification: For the academic qualification, values were assigned as follows: OND-1; HND-2; B.Sc-3; PGD-4; M.Sc-5; PhD-6; Others-7

<u>CPF Questionnaire – Section B</u>

The variables in Section B of the questionnaire were classified and measured as follows:

QV4 - Year: The year in which construction of the project commenced would be provided.

QV5 – Gross floor area: The area covered by the building being constructed, measured to the external faces of enclosing walls. Measurement was in square meters.

QV6 – Project type: The type of project was classified into 11 categories and values were assigned as follows: Carpark-1; Hospital-2; Hostel-3; Hotel-4; House-5; Library-6; Office-7; School-8; Warehouse-9; Workshop-10; Others-11.

QV7 – Project nature: The nature of project was classified into 2 categories and values were assigned as follows: New construction-1; Refurbishment-2.

QV8 – Cost of structural element: The Naira value of the structural element of the building (which encompassed the substructure, frames, external and internal walls and roof) would be provided.

QV9 – Cost of services element: The Naira value of the services element of the building (which encompassed the plumbing, mechanical and electrical engineering installations) would be provided.

QV10 – Cost of finishing element: The Naira value of the finishing element of the building (which encompassed the floor, wall and ceiling finishing, as well as painting and decoration) would be provided.

QV11 – Cost of external work element: The Naira value of the external work element of the building (which encompassed the fencing, roads, landscaping, external lighting, stormwater drainage, gate and generator houses) would be provided.

<u>Risks Questionnaire</u>

The variables in the Risks questionnaire were defined and measured as follows:

CV1 – Section of Final Account concerned: This column identified the information presented in each row as taken from either ‘Adjustments to Prime

Costs/Provisional Sums', or 'Re-measurements of Provisional Quantities', or 'Variations' section of Final Account.

CV2 - Brief Description of costs items in Final Account: Very brief description of individual items in Final Accounts are inserted here.

CV3 – Value of costs items in Final Account: The value in Naira of individual cost items in Final Accounts are inserted here under either an 'Addition' or 'Omission' column.

CV4 –**Risks**: the risk that was identified as responsible for changes in individual cost items in Final Accounts is identified here from a List of Risks: The risks to be selected were identified and assigned values as follows: Risk1 [Client scope change] – 1; Risk2 [Client variation/design change]– 2; Risk3 [Consultants' error/omission in design] – 3; Risk4 [Consultants' error/omission in estimates] – 4; Risk5 [Consultants' design change] – 5; Risk6 [Unforeseen economic conditions] – 6; Risk7 [Unforeseen site conditions] – 7; Risk8 [Unforeseen social disturbance] – 8.

3.2.6 Validity of the research instruments

This study adopted the classification and measurements of variables as employed in previous researches such as Odeyinka (2003); Aibinu and Jagboro (2002) and Ogunsemi (2002); this was to ensure the validity of the contents of the research instruments. The supervisors of this study and senior researchers who possessed experience in risk analysis were also consulted on the freedom from ambiguities and validity of the contents of the research instrument. The responses from these varied sources were used to design the version of the research instruments that was used in the fieldwork.

3.2.7 Reliability of the research instruments

In order to provide assurance that the research instruments for the study were reliable, a split-half test was done in order to provide evidence that the research instruments will be able to retrieve the same information every time from respondents. Pilot data was collected, split into two halves and analyzed using Spearman's Correlation. The results presented in Table 3.1 showed that the research instruments were reliable. Details of the analysis as performed with SPSS are included as Appendix C.

Table 3.1: Reliability of research instruments

Type of Research Instrument	**Spearman's '*rho*'**	**Coefficient of Determination (R^2 in %)**	**Remark**
CPF Questionnaire	0.887	78.68%	Highly reliable
Risks Questionnaire	0.911	82.99%	Highly reliable
Both Questionnaires	0.895	80.10%	Highly reliable

Source: Author (2016)

3.3 Method of Analysis of the Research Data

This section dealt with the manner in which the data collected for achieving the research objectives were analyzed, in order to provide meaningful information. The treatment of the data in this study was summarized in general terms in Table 3.2. A complete list of the projects that made up the study sample was included as Appendix D; the changes in project costs and the associated risks which were encountered in these projects were included as Appendix E.

Table 3.**2: Data analysis tools and decision criteria**

Research objectives		**Types of data**	**Types of analytical tools**	**Decision criteria**
Obj1	To determine the risks to use in predicting the effect of risks in the final costs of building projects.	Risks from previous studies *(client scope change, client variation/design change, consultants' error/omission in design, consultants' error/omission in estimates, consultants' design change, unforeseen economic conditions, unforeseen site conditions, unforeseen social disturbance)*	Literature search; purposive selection of risk based on relevance to study	Meet at least 1 of 3 criteria: Applied ANN; Predicted building costs;In Nigeria Risk is significant if it impacted >9 projects
Obj2	To determine the Construction Project Features (CPFs) to use in predicting the effect of risks in the final costs of building projects	Construction Project Features employed in multiple studies *(gross floor area, project type, project nature, year, elemental costs – structural, services, finishing, external work).*	Literature search; purposive selection of CPF based on relevance to study	Meet 4 criteria: Applied ANN; Forecasted building costs; Construction industry-based In more than 2 study
Obj3	To determine the effect of risks in the final costs of building projects.	Monetary values of 5 clasess of costs in final accounts *(provisional sums (PS), provisional quantities (PQ), variations that increase costs (Va), variations that decrease costs (Vo) and variations that substitute costs (Vs)*; Initial Contract Value; Final Contract Value	Tabulation using data filters; Correlation analysis; Bar charts; Pie charts;	Modal values of risk occurrence
Obj4	To develop an artificial neural network for the prediction of risk effect in final costs of building projects.	Numerical values of: Construction project features Effect of risks on project costs Initial Contract Value; Final Contract Value	Neural network toolbox of MATLAB 2015;	ANN was validated by MSE, SSE, SAE, MAPE values;
Obj5	To carry out a performance analysis of artificial neural network developed for the prediction of risk effect in final costs of building projects.	Simulation output of the developed neural network	Obj4	True positive values are > false positive values of simulation output.

Source: Author (2017)

Notes: MSE = Mean Square Error; SSE = Sum of Squared Errors; SAE = Sum of Absolute Error; MAPE = Mean Absolute Percentage Error;

3.3.1 Method of data analysis for determination of risks for predicting variance on costs of building projects

Seventy risks had earlier been identified from construction management literature (see Table 2.1a and Table 2.1b in Chapter Two). Risks to be included in the research instrument were purposively selected from this list by extracting risks that were considered relevant to this study. Relevance to the study was believed to be enhanced by use of the risks in ANN prediction studies and use of the risks as predictors in cost forecasting with statistical tools. Nineteen risks were obtained from the purposive selection phase as presented in Table 3.3; these risks were included in the research instrument.

Table 3.3: Result of purposive selection of risks

Risk Nr	Risks	Sources
1	Acts of God	Windapo and Martins (2010)
2	Cash flow difficulties	Omoregie and Radford (2006); Aibinu (2008); Windapo and Martins (2010)
3	change in design / variations by the client	Odeyinka *et al.* (2012); Odeyinka *et al.* (2013)
4	Change in scope of work	Odeyinka *et al.* (2012); Perrenoud *et al.* (2016)
5	change in the design by the Architect	Odeyinka *et al.* (2012); Odeyinka *et al.* (2013)
6	Changes in site conditions	Omoregie and Radford (2006); Odeyinka *et al.* (2012)
7	Consultant competence	Windapo and Martins (2010)
8	Contractor competence	Windapo and Martins (2010)
9	contractor/subcontractor/ supplier issues	Perrenoud *et al.* (2016); Aibinu (2008)
10	Incomplete drawings	Aibinu (2008)
11	Delay due to excessive approval procedures	Omoregie and Radford (2006)
12	Equipment breakdown/ maintenance	Aibinu (2008)
13	error/omission in design/estimates	Perrenoud *et al.* (2016); Aibinu (2008)
14	Inclement weather	Odeyinka *et al.* (2013)
15	Inflation	Omoregie and Radford (2006)
16	Labour shortage	Odeyinka *et al. (*2013)
17	Poor contract management	Omoregie and Radford (2006)
18	Production target slippage	Odeyinka *et al.* (2013)
19	Social issues/area boys, original land owners	Windapo and Martins (2010)

Source: Researcher’s summary

3.3.2 Method of data analysis for determination of Construction Project Features (CPFs) for predicting risk effect on costs of building projects

An extensive literature search yielded thirty-three CPFs which were presented in Table 3.4. All of the CPFs in the table were collated from studies carried out within the construction industry where artificial neural network (ANN) had been employed as the prediction tool. Only one CPF (gross floor area) had been used in 4 studies.

Table 3.4: Construction project features applied as ANN inputs

S/N	CPFs	a	b	c	d	e	f	g	h	i	j	k	l	m
1	Gross floor area	x			x	x				x				
2	Number of stories	x			x					x				
3	Type of project	x			x		x							
4	Duration	x							x					
5	Estimated Sum				x				x					
6	Initial contract sum							x			x			
7	Number of basements											x		x
8	Procurement Route;				x		x							
9	Risk probability							x					x	
10	Risk impact							x					x	
11	area of formworks													x
12	Estimating Method				x									
13	fluctuation measure						x							
14	Floor Height											x		
15	Ground conditions	x												
16	Land Acquisition											x		
17	Lowest tender price	x												
18	Location;				x									
19	Market conditions	x												
20	Number of tenderers	x												
21	Number of cols					x								
22	Structural Material				x									
23	payment method,						x							
24	Site slope	x												
25	Site access	x												
26	Scope of project								x					
27	Type of contract	x												
28	typical floor area					x								
29	type of client						x							
30	volume of concrete													x
31	weight of steel													x
32	Work space in site	x												
33	Year											x		

Source: Researcher's summary

Note: a = Elhag and Boussabaine (1998); b = Palaneeswaran *et al*. (2008); c = Wang and Gibson (2010); d = Aibinu *et al*. (2011); e = Arafa and Alqedra (2011); f = Ahiaga-Dagbui and Smith (2012); g = Odeyinka *et al*. (2012); h = Ahiaga-Dagbui and Smith (2013); i = Gulcicek *et al*. (2013); j = Amusan *et al*. (2013); k = Kim *et al*. (2013); l = Odeyinka *et al*. (2013); m = Roxas and Ongpeng (2014).

This was followed by two CPFs (number of stories and type of project) which had been used in 3 studies each. A further seven CPFs had been employed in 2 papers each (duration, estimated sum, initial contract sum, number of basements, procurement route, risk probability and risk impact). The balance of 23 CPFs had been employed in only one research study each.

Three CPFs were purposively selected from the thirty-three in Table 3.4 as being relevant to this study. The selection was done bearing in mind that the CPFs would be converted to binary scale. The 3 CPFs were gross floor area, type of project and year. The use of five additional CPFs as predictors in neural networks was explored in this study. The 5 CPFs were project nature and costs of structural, services, finishing and external works expressed as a percentage of the initial contract values of projects.

The 5 CPFs that were not taken directly from literature nevertheless shared similarities with those taken from literature. The costs of elements were related to the targets of the ANN employed in Arafa and Alqedra (2011), which was termed structural cost of building. A general elemental layout of building was followed, where elements are defined as groups of works that perform the similar notwithstanding their location or the materials used to construct them. The selection of CPFs in this study however emphasized elements that contributed heavier proportions of the project cost.

3.3.3 Method of data analysis for determination of risk effect in costs of building projects

This subsection of the study dealt, in general terms, with how the effect of risks on project costs was determined. More specifically, the subsection showed the effect on project costs of those risks that were employed as targets in neural networks. The ANN had to predict three attributes of those risks – occurrence, type and degree. The same data was employed for all 3 kinds of predictions. The effect of risks on projects was shown by a tabular listing of risks and (i) associated frequency of occurrence, (ii) arithmetical sign of the risk and (iii) impact of the risk expressed as a proportion of the project cost.

Piecharts were thereafter employed to summarize and compare the proportion of risk effect on project costs accounted for by the risks that were employed as targets in ANN. This process of summarizing and comparing the proportion of risk effect was repeated for the 3 classes of costs that can generally be found in a final account – provisional sums, provisional quantities and variations. Finally the proportion of risk effect was summarized and compared in piecharts for the three kinds of variations conventionally presented in final accounts – addition, omission and substitution.

3.3.4 Method of data analysis for development of artificial neural network for prediction of risk effect in costs of building projects

Two approaches were followed in developing the neural networks in this study. ANN Approach 1 (abbreviated as ANN1) is presented in Section 3.3.5, while ANN Approach 2 (abbreviated as ANN2) is the subject of Section 3.3.6. The key differences between ANN1 and ANN2 are presented in Table 3.5.

Table 3.5: Differences between approaches 1 and 2 for ANN development

Basis for contrast	ANN1	ANN2
network inputs	Risk effect	CPFs
network targets	Cost variance	Risk effect
Treatment of inputs	Grouping of risks	Conversion to binary scale

Source: Author (2017)

3.3.5 Method of data analysis for ANN1: prediction of variance in cost of building projects using ANN

Inputs for ANN1 were taken from the 19 risks that were presented to respondents in the research questionnaire. Modal values of risk occurrence were used to select risks to be used as ANN1 inputs. Using modal values of occurrence as opposed to modal values of impact ensured that the neural network was designed to predict project cost variance by employing the most frequently occurring risks. The ANN could thus be applied to a wider selection of projects than would be the case if modal values of impact had been employed.

Some of the forecasting techniques generate a multivariate error distribution; artificial neural network is not an exception. Clear and actionable information about this distribution can be provided by a suitable error measure (Murphy and Winkler, 1992). Researchers have thus employed various accuracy measures to evaluate the performance of forecasting techniques. This study also followed suit by applying the following error measures, which are among the most commonly used error measures in business (Co, 2007). These are the mean absolute error (MAE), mean absolute percentage error (MAPE), and mean squared error (MSE)

The overall sequential procedure taken in the development of ANN1 is presented in Figure 3.1. There were 6 main steps and a total of 22 secondary steps. Validation of the ANN model was provided in part by comparison with a multiple linear regression model which was developed concurrently. While the superior performance of ANN over conventional forecasting techniques such as regression has been acknowledged in literature (for example Kim *et al*., 2013), the exact circumstances in this study are different. in the literature Regression has not been used concurrently with ANN where the input data is risk impact on project costs obtained from project final accounts. Regression has also not been concurrently employed where risks have been grouped and their impact on project costs used to predict the cost variance of projects.

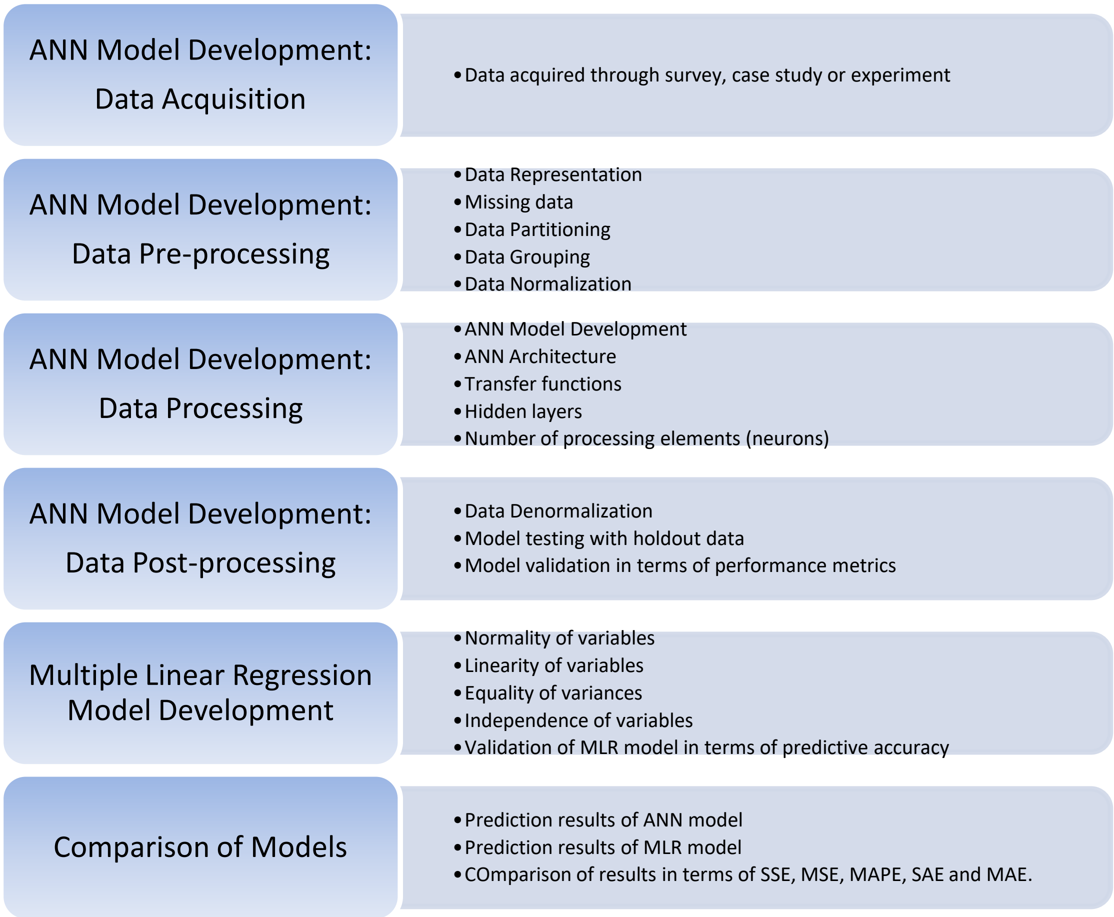


Fig 3.1: Overall sequential procedure for ANN1development

Tasks involved in the development of the neural network component of ANN1 were depicted in a flowchart in Figure 3.2. This procedure was adopted based on evidence from literature, such as Jha and Chockalingham (2009) and Jha and Chockalingham (2011).

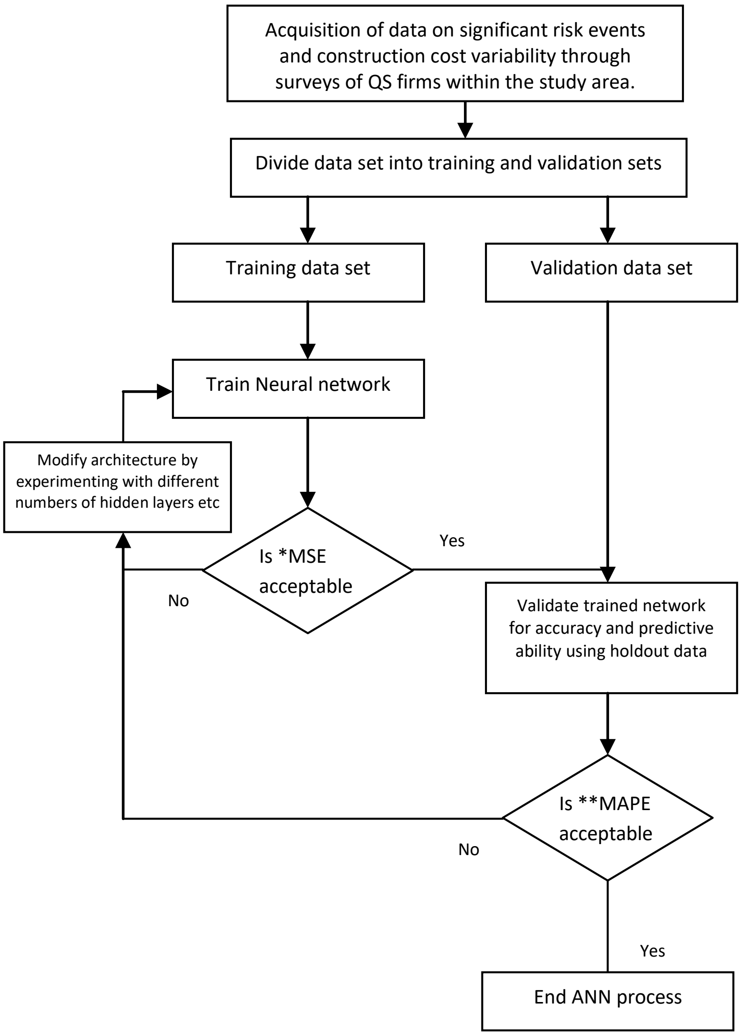


Fig. 3.2: Flowchart of ANN1

3.3.5.1 Data pre-processing (ANN1)

Pre-processing of data is carried out in order to achieve several objectives. These include reducing input space size, achieving smoother relationships, and normalizing data by forcing it into a narrower range of values (Kennedy *et al.*, 1998).

3.3.5.2 Handling of missing data (ANN1)

Each of the 69 projects in the dataset of the study had an average of only three risks identified as having some effect on construction costs. Only one project had cost consequences that were attributable to 6 risks. The risk register approach links individual events that affected project costs to a specific risk, or group of risks. The downside of such methodological approach is that not all risks will feature in all projects. Thus not all of the projects in a sample can be used to develop an ANN. This probably underscores why there have been so few researches on risk effect on construction cost that utilized the risk register methodology.

Grouping of risks according to some criteria of similarity was thus explored, in order to generate a dataset that will be complete, not having any instances of missing data, and which will be of sufficient size as to be adequate for ANN development. Grouping of risks into broad categories has featured in the literature on risk assessment and handling. For example, in Perera *et al.* (2014), risks were grouped according to the project stakeholder most fitted to handle them. Thus there were risks allocated to the client, the contractor and the consultants. The effects of risks on construction costs in Perrenoud *et al.* (2016) were also documented along project stakeholder lines (client, contractor and consultants); a fourth category covered risks that could not reasonably be foreseen by or attributed to any of the parties.

Against this backdrop, the 8 risks that had been determined as having impact on project costs were separated into three groups; these were the client, consultants and unforeseen risks groups. Within each group, the effects of risks were summed up for each project. This re-classification of risks into groups provided only three inputs for the ANN, but at the same time improved the likelihood of having an adequate dataset for the ANN model development. The re-classification of risks resulted in 46 projects impacted by two risk groups (clients and consultants).

3.3.5.3 Data representation (ANN1)

Data intended for use in the creation of an ANN could be represented in several ways; such data could be in the form of numbers, alphabets, symbols or a mixture of alphabets and numbers. The data employed in the ANN modelling process was entirely numeric in nature. Some of the salient aspects of the data employed for the development of the ANN were presented in Table 3.6.

Table 3.6: Description of the data employed for ANN development

Parameters for description	Description of ANN input	Description of ANN Output
Definition of the data	Cost consequences of risks	Deviation of final accounts (FA) from the initial contract values (ICV)
Measurement type	Ratio	Ratio
Measurement units	Percentages	Percentages
Numeral type	Non-integer percentages	Non-integer percentages
Decimal places	Two (2)	Two (2)
Bit length	8-bit (255 characters)	8-bit (255 characters)
Normalized data range	0 to +1	0 to +1

Source: Author (2017).

3.3.5.4 Data partitioning (ANN1)

Partitioning is the splitting of data into different subsets that will be applied to training, validating and testing of the developed network. Different researchers have partitioned their data into training and validation sets in different ways. Some previous research studies have established that using the larger portion of a research dataset for training gives better results (Arditi and Gunaydin, 1998; Chaphalkar and Sandbhor, 2014). Chaphalkar *et al*. (2015) in their own research favoured the randomization of input into the ANN; this was a position that this study also took. The actual process of randomization was however carried out by default settings in the MATLAB software employed. Since any model developed from the ANN would be applied to projects that will be completed in the future, the most recent portion of the dataset was kept for testing of the developed network.

The 46 projects that were impacted by the clients and consultants risks groups were spilt in the ratio 70:15:15 for training, validation and testing respectively. Forty projects were applied to the training and concurrent validation of the ANN model, while 6 projects were employed in validating and testing the developed model.

3.3.5.5 Data normalization (ANN1)

Normalization was done to constrain the data within a uniform and narrow scale, such as 0 to 1. This ensures that the network's energy is not dissipated in trying to learn all data combinations within a very wide scale, for example 0 to 10,000. Several standard data normalization techniques such as min-max, softmax, z-score, decimal scaling, and box-cox have been employed in previous researches (Kuźniar and Zając, 2015). Researchers need to consider whether a general guideline exists with respect to the appropriate technique for a particular application? The choice of activation functions (logsig [0, 1] or tansig [-1, 1] will also affect the selection of a normalization technique. Four types of normalization techniques were applied to the research data; these techniques were the (i) decimal scaling, (ii) Min-Max, (iii) Unitary, and (iv) Z-score normalization techniques. Some summary statistic measures of the resulting data were computed and presented in Table 3.7.

Trends that were observed in the normalized data included that all of the mean values for the three variables were now positive after Min-Max normalization. The unitary method of normalization resulted in smaller values for standard deviations and variance of the distribution. In addition the unitary technique has a fixed upper boundary (+1) and a floating lower boundary which depends on the values in the dataset. By comparison, only the Min-Max technique resulted in a dataset with minimum and maximum boundaries rigidly fixed at 0 and +1 respectively.

Table 3.7: Effect of different normalization techniques on research variables

Risk group	Normalization type	Mean	Std Dev	Variance	Min	Max	N
Client risks	Actual	5.21	11.05	122.05	-32.79	48.49	40
	Decimal scaling	0.05	0.11	0.01	-0.33	0.48	40
	Min-max	0.47	0.14	0.02	0.00	1.00	40
	Unitary	0.11	0.23	0.05	-0.68	1.00	40
	Z-score	0.00	1.00	1.00	-3.44	3.92	40
Consultant Risks	Actual	1.73	11.04	121.88	-16.51	46.37	40
	Decimal scaling	0.02	0.11	0.01	-0.17	0.46	40
	Min-max	0.29	0.18	0.03	0.00	1.00	40
	Unitary	0.04	0.24	0.06	-0.36	1.00	40
	Z-score	0.00	1.00	1.00	-1.65	4.04	40
FCV - ICV	Actual	2.47	15.18	230.56	-19.51	53.72	40
	Decimal scaling	0.02	0.15	0.02	-0.20	0.54	40
	Min-max	0.30	0.21	0.04	0.00	1.00	40
	Unitary	0.05	0.28	0.08	-0.36	1.00	40
	Z-score	0.00	1.00	1.00	-1.45	3.38	40

Source: Author (2017).

Notes: FCV = Final Contract Value; ICV = Initial Contract Value;
Decimal scaling = transforms data into decimal fractions (-0.99 to +0.99)
Min-Max = compressing all data into a range with a minimum of -1 and a maximum of +1.
Unitary = dividing through with the largest value;
Z-score = converts data to have mean = 0 and variance = 1

The Min-Max technique compressed the data and converted negative values to zero; this might enhance the ability of the ANN to produce better predictions. The actual extent of improvement in prediction would only be known after developing the ANN. This was why all four normalization methods were employed.

Decimal Scaling Normalization

Decimal scaling normalization is also a linear scaling algorithm. It transforms the original input range into a new data range that is now composed of decimal fractions (typically -0.99 to +0.99). It was given as: -

$$y_{new} = \frac{(y_{old})}{(10j)} \quad \text{.......Equation 3.1}$$

where j *= smallest integer such that* $(|y_{old}|) < 1$; y_{old} *is the original value of a variable before normalization;* y_{new} *is the value of the variable after normalization.*

Min-Max Normalization

Min-max normalization is a linear scaling algorithm. It transforms the original input range into a new data range (typically 0 -1). It was given as: -

$$y_{new} = \frac{(y_{old} - min1)}{(max1 - min1)} \quad \text{.......Equation 3.2}$$

Where:

y_{old} *is the old value;* y_{new} *is the new value; and minl and maxl are the minimum and maximum of the original data range,*

Another form of the min-max equation that compresses the data into any specified range (such as -1, +1; +0.1, +0.9 etc) was given as equation 3.3.

$$y_{new} = \frac{(y_{old} - min1)}{(max1 - min1)} (max2 - min2) + min2 \quad \text{.......Equation 3.3}$$

Where:

min2 and max2 are the minimum and maximum of the new data range.

Since the min-max normalization is a linear transformation, it can preserve all relationships of the data values exactly.

Unitary Normalization

Unitary normalization is carried out by dividing the entire data, column by column, by the largest value in each column. It has the effect of transforming all of the data into decimal fractions, with the exception of the largest value, which acquires a new transformed value of 1.0. The equation for z-score normalization was given as: -

$$y_{new} = \frac{(y_{old})}{(y_{max})} \quad \text{.......Equation 3.4}$$

Where y_{max} *is the largest value in each column.*

Z-Score Normalization

In Z-score normalization, the input variable data is converted into zero mean and unit variance. The mean and standard deviation of the input data should be calculated first. Z-score is often used when responses are on different magnitude scales. All of the mentioned techniques are sensitive to outliers in the data, although the effect is less felt in the case of Z-score. The equation for z-score normalization was given as: -

$$y_{new} = \frac{(y_{old} - y_{mean})}{(std)} \quad \text{.......Equation 3.5}$$

Where:

y_{old} *is the old value;* y_{mean} *is the mean of the range of values of y; std is the standard deviation of the original data range,*

3.3.5.6 Data processing (ANN1)

MATLAB 2015a software was used to design and train the ANN models. A feed forward neural network based on back propagation was applied in the ANN model training. Training algorithm and transfer functions were selected based on trial and error procedures. Work by other researchers had found that the Levenberg-Marquardt back propagation algorithm (*trainlm* in MATLAB) and the hyperbolic tangent transfer function (tansig in MATLAB) for the neurons in the hidden layers gave quicker convergence and better results during training and validation (Jha and Chockalingham, 2009).

3.3.5.7 Network architecture (ANN1)

Designing the network architecture involved selection of key parameters such as transfer functions, number of input and output nodes, number of hidden layers and the number of neurons in the hidden layer(s) (Costantino *et al.,* 2015), number of partitions of the data, number of cycles to be run to train the network and criteria for validating the performance of the trained network.

The partitioning of the data had been handled in an earlier section of this thesis (see subsection 3.3.5.4). In this study, twenty-seven training runs were initially preset to be carried out within each training cycle that was ordered. This was because 27 different numbers of hidden neurons were subjected to trial and error selection. The network was designed to allow training cycles to be requested and commenced manually. Each training run was continued for as many epochs as the software deemed necessary. Based on the early stopping criterion adopted however, this setting was modified such that where no decrease in validation parameter occurred for six (6) consecutive epochs, the training run was discontinued. The validation parameter adopted in this study was the mean square error (MSE). This network topology concurred with that of previous studies such as Costantino *et al.* (2015).

3.3.5.8 Transfer functions (ANN1)

Hyperbolic tangent sigmoid activation function has been employed in several studies such as Marzouk and Elkadi (2016) and Odeyinka *et al*. (2013) for the nodes in the hidden layer. This study employed the hyperbolic tangent sigmoid transfer function in the hidden layers; for the output layers of the network, a linear transfer function was used. This choice of transfer functions had also been used by Mučenski *et al.* (2013) when they modelled the recycling capacities of multistory structures.

3.3.5.9 Number of hidden layers (ANN1)

This study employed networks that had two hidden layers. The survey of literature carried out had shown that most researchers worked with networks that had either one or two hidden layers. This could be seen in their comparison of the performance of ANN and GA-ANFIS in forecasting short time building energy, where Li *et al.* (2011) used feed forward neural network with a single hidden layer of *tansig* neurons to predict hourly energy consumption. In the modelling of construction project time performance, Le-Hoai *et al*. (2013) also adopted one hidden layer for their perceptron model, based on minimal errors of both training and testing sets. There thus appeared to be a preponderance of research that employed only one hidden layer of neurons; however Mučenski *et al*. (2013) had employed neural networks that consisted of two hidden layers. They opined that having more than 2 hidden layers produces networks that are unstable in prediction and less accurate (Mučenski *et al.*, 2012).

3.3.5.10 Number of neurons (ANN1)

Three approaches towards the selection of number of neurons were found. Experimentation in a trial and error manner has been described as the 'art' aimed at identifying the optimal architecture, which gives the best performance outcomes. This approach was adopted by El Shazly and El Shazly (1997). They suggested that as a starting point of experimentation, researchers could apply the following formulae:

i. Number of hidden neurons = training facts x error tolerance;
ii. Number of hidden neurons = (sum of inputs + outputs)/2; or
iii. Number of hidden neurons = 5 - 10% of training facts.

Some researchers consider that as a rule of thumb, the number of neurons (nodes) in the hidden layer should be (i) less than twice the number of input neurons or (ii) in between the number of neurons in the input layer and the number of neurons in the output layer (Heaton, 2008). Based on this, Shrestha and Shrestha (2016) employed the following equation:

$N = (m + b + o) * 2/3;$

where N = the number of neurons in hidden layers; m = the number of neurons in the input layer; b = the number neurons as biased inputs and; o = the number of neurons in output layers.

The second approach for the selection of number of neurons involves the application of statistical tests. This approach was adopted by Li *et al*. (2011) for forecasting short time building energy, by using a methodology based on least squares estimation and statistical tests (Rivals and Personnaz, 2003; Karatasou *et al.*, 2006). In the third approach, the choice of the number of neurons is left to the software employed, based on the proviso that the eventual selection optimizes the performance of the network. Le-Hoai *et al*. (2013) in their study of project time performance adopted this approach. The number of neurons in the hidden layers of the network developed in this study was based on experimentation. However, the experimentation was restricted to a range between 5 and 60; only odd numbers of neurons were tested, based on trial and error results. The incremental rate was thus 2, resulting in a simple arithmetical series of the form 5, 7, 9, 11 …… 59. There could thus be a minimum of 5 and a maximum of 59 neurons in the first hidden layer; the second hidden layer contained only one neuron.

3.3.5.11 Code for design and validation of neural network (ANN1)

The neural network required in furtherance of Objective 4 of this study was developed with the use of the code provided below. All of the settings of the network architecture described in this subsection have been incorporated into the code.

Neural network code for prediction of risk effect in final cost variance

```
clear all
clc
%    [num,txt,raw]=xlsread('Modified_Data_P.xlsx');
%    Client=num(:,5);
%    Consultant=num(:,6);
%    FCV=num(:,7);
%
load 'New_data1.mat'
% Preprocessing effect.
% Decimal_Scaling_Normalization
% MinMax_Normalization
% Modified_MinMax_Normalization
% Z_Score_Normalization
% Unitary_Normalization
% N_Input_Data=[NCL';NCO'] data Set= client risks, consultant risks.
% Target =NFC'.
Input_1=[NCL NCO]
Input_data=Input_1';   %Input to the ANN

Target_1= [NFCV]
Target_data=Target_1';    % Target of the ANN

% ======================================================================
% ======================================================================
% To create multidimensional ANN to investigate the effect of different
% parameters on the effect of the prediction of the deviation of Final
% Contract Value (FCV) based on Client risks (CL), Consultant risks (CO).
%=======================================================================
% ======================================================================
counter=0;

for Hidden_Neuron =5:2:60   % 5:2:60 is the range of the data set.
% Changes for the number of Neurons in the Hidden Layer
```

```
            Cost_var=newff(Input_data,Target_data,[Hidden_Neuron,1], {'tansig','purelin'},'trainlm','learngdm');
% creating the network with Performance Features and selection for the ANN
            Cost_var.trainParam.showWindow= true  % Turning off the nntool GUI
            Cost_var.trainParam.showCommandLine=true %Turning off the commandline outputs
            Cost_var.trainParam.lr =0.01 % Sets the learning rate of the Network.
            Cost_var.trainParam.mc = 0.9 %Sets the Momentum of the Network
            Cost_var.trainParam.show= 2  % epoch between progress to show.
            Cost_var.trainParam.time=inf % maximum time to train network in seconds
            Cost_var.trainParam.goal=0 %Performance goal

% The training of the Network and its Simulation.
            Cost_var=train(Cost_var,Input_data,Target_data); % Training the network
            Cost_Output=sim(Cost_var,Input_data);%Simulation of the ntw with the training data

% Performance Analysis of the FCV_Network.

            Perf_2=mse(Cost_var, Target_data,Cost_Output); %MSE performance  (Mean Square Error)
            Perf_3=sse(Cost_var, Target_data,Cost_Output); %SSE Performance (Sum Square Error)
            Perf_4=sae(Cost_var, Target_data,Cost_Output); %SAE Performance (Sum Absolute Error)


            Cost_ANN_Display=['Cost_Result' num2str(counter)] %saving by coounter
            save(Cost_ANN_Display,'Hidden_Neuron','Cost_var','Cost_Output','Perf_2','Perf_3','Perf_4')
                  %saving by counter
            counter=counter+1; %counter for result (Load by Counter)
end

         Load_Results_Simulation
            % This would load the simulation result to give you the network with the best performance.

        Display_Prediction_Results
            % This would display in graph the performance of the Predicted Data Vs Actual Data.
```

3.3.5.12 Network performance (ANN1)

The performance of the trained networks was validated with the aid of three measures, which were obtained from review of relevant literature (Palaneeswaran *et al*., 2008; Kumar, 2005). These were the sum of squared error (SSE), sum of absolute error (SAE) and mean squared error (MSE). The squaring of the errors in the MSE measure achieves two ends: (1) positive or negative sign differences are neutralized, and (2) there is greater magnification of any errors present. The MSE measures the difference between the set of actual observations and corresponding predicted values of the neural network. The SSE is the sum of the difference between actual observations and corresponding predicted values. The sum of absolute errors (SAE) is a basic indicator of network performance being the sum of absolute values of the difference between actual observations and the corresponding network prediction values (Palaneeswaran *et al*., 2008).

A total of 540 training runs of the network were carried out spread across the different configurations of network design parameters as provided in Table 3.9. The networks were labeled based on the minimization techniques employed; decimal scaling networks were 'MIN1', min-max networks were 'MIN2', unitary networks were 'MIN3', and z-score networks were 'MIN4'. To further aid identification, each network carried a number suffix that denoted the particular training cycle concerned.

Table 3.8: Number of training runs of ANN carried out

S/No	Minimization techniques	Training and Validation cycles	Training runs per training cycle	Total number of training runs
1	Decimal scaling (MIN1)	5	27	135
2	Min-max (MIN2)	5	27	135
3	Unitary (MIN3)	5	27	135
4	Z-score (MIN4)	5	27	135
	Total	**-**	**-**	**540**

Source: Author (2017).

3.3.5.13 Regression model development

A Multiple Linear Regression (MLR) model of the influence of risk on the deviation of the final account from the initial contract value was also carried out in this study. This was done in order to provide information against which the predictive performance of the developed ANN model could be compared.

Linear Regression estimates the coefficients of the linear equation, involving one or more independent variables, which best predict the value of the dependent variable. There are four basic assumptions of linear regression, which must be met in order for the results obtained to be valid. These are assumptions are as follows:

1. For each value of the independent variable, the distribution of the dependent variable must be normal; (The error term should have a normal distribution with a mean of 0.)
2. The variance of the distribution of the dependent variable should be constant for all values of the independent variable; (The variance of the error term should be *homoscedastic,* meaning it is constant across cases and independent of the variables in the model.)

3. The relationship between the dependent variable and each independent variable should be linear, and
4. All observations should be independent.

In order to check whether these assumptions have either been met or violated, different types of graphical plots can aid in the validation of the assumptions of normality, linearity, and equality of variances. To determine which model to use, the research data should be plotted. If the research variables appear to be related linearly, a simple linear regression model should be used. When the variables are not linearly related, an attempt could be made to transform the data in order to apply curve estimation, (IBM SPSS 20, 2011)

3.3.5.14 Normality of variables

The skewness of a distribution is a good starting point for establishing the normality of a dataset. Skewness is a measure of the asymmetry of a distribution. The normal distribution is symmetric about the mean and has a skewness value of 0. A distribution that has a long right tail is said to exhibit significant positive skewness, while the opposite (a distribution that has a long left tail) displays significant negative skewness. It is generally taken that a distribution is said to be asymmetrical when its skewness value is more than twice the standard error of the skewness. From the statistics presented in Table 3.10, it appeared that 'client risks' was only variable that was normally distributed, since its skewness value was less than twice its standard error.

Table 3.9: Descriptive statistics of the variables for regression

Statistics		Client Risks	Consultant Risks	Final Cost Variance
N	Valid	34	34	34
	Missing	0	0	0
Mean		5.08	1.17	1.77
Std. Error of Mean		2.00	1.85	2.58
Median		3.58	-0.82	-0.83
Std. Deviation		11.69	10.81	15.02
Variance		136.60	116.92	225.55
Skewness		**0.73**	2.21	1.74
Std. Error of Skewness		**0.40**	0.40	0.40
Kurtosis		7.95	8.51	4.13
Std. Error of Kurtosis		0.79	0.79	0.79
Range		81.29	62.88	73.23
Minimum		-32.79	-16.51	-19.51
Maximum		48.49	46.37	53.72

Source: Author (2017).

A second measure of the shape of a distribution is known as kurtosis, which is a measure of the extent to which observations cluster around a central point. The value of the kurtosis statistic is zero for a normal distribution. All three variables exhibited leptokurtic distributions. This was because their kurtosis values were positive, which indicated that their observations were more clustered about the center of the distribution, resulting in thinner tails; the extreme ends of the tails were however thicker than those of a normal distribution. A platykurtic distribution would be the reverse of this observation. Graphical representation of the distributions of the three variables of the research relative to the normal distribution was presented in Figs3.3, 3.4 and 3.5.

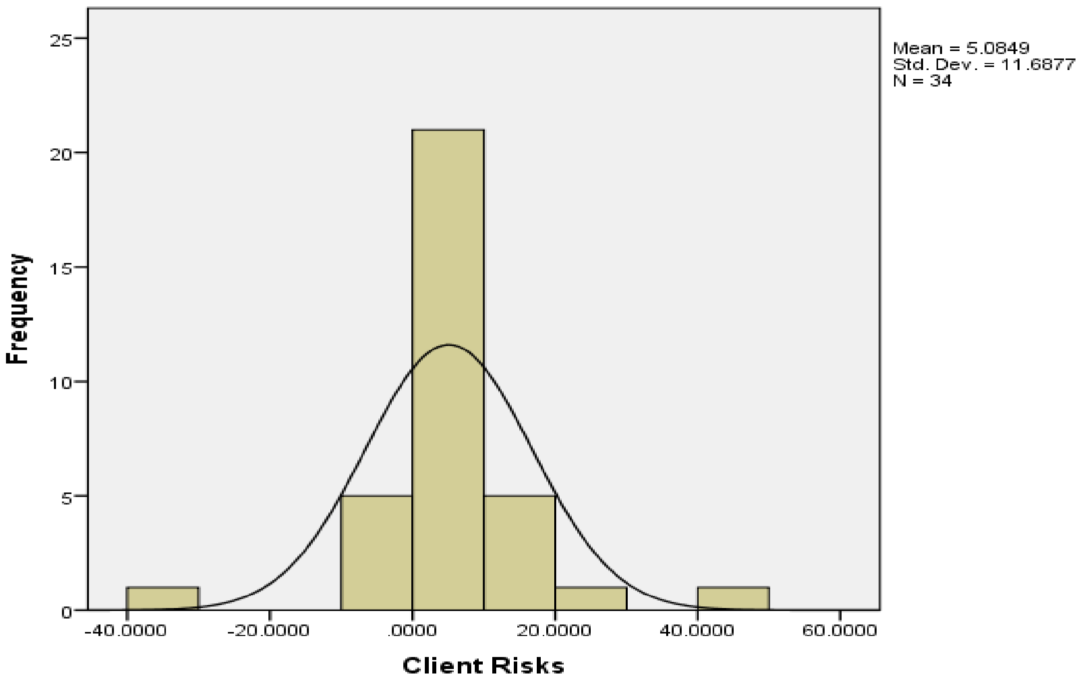


Fig. 3.3: Histogram of Client risks with superimposed normal distribution

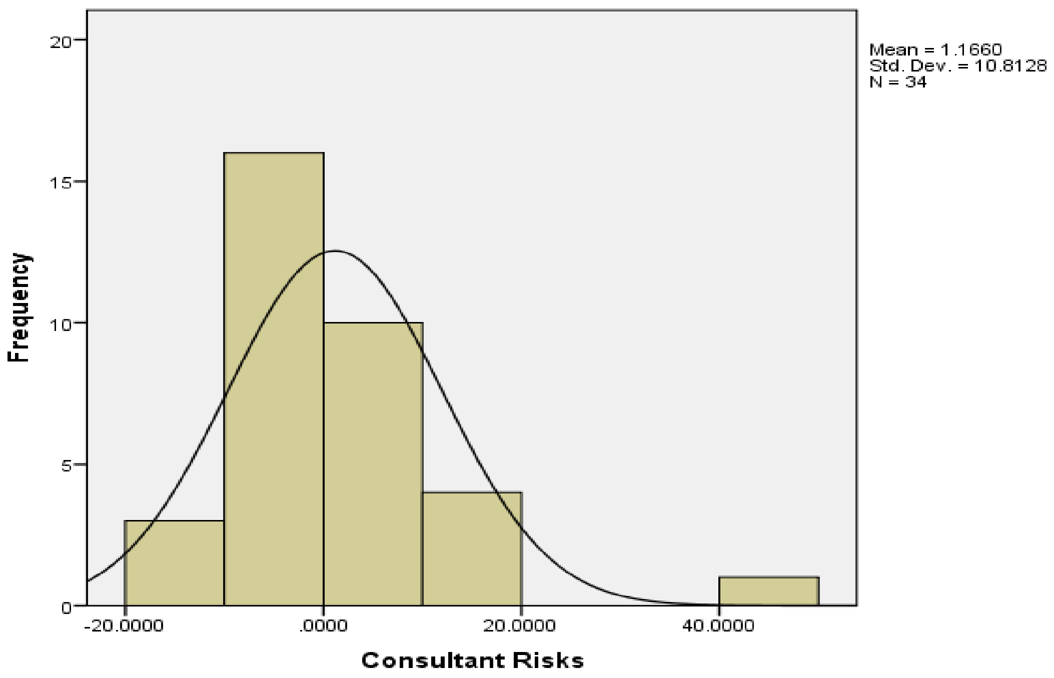


Fig. 3.4: Histogram of Consultant risks with superimposed normal distribution

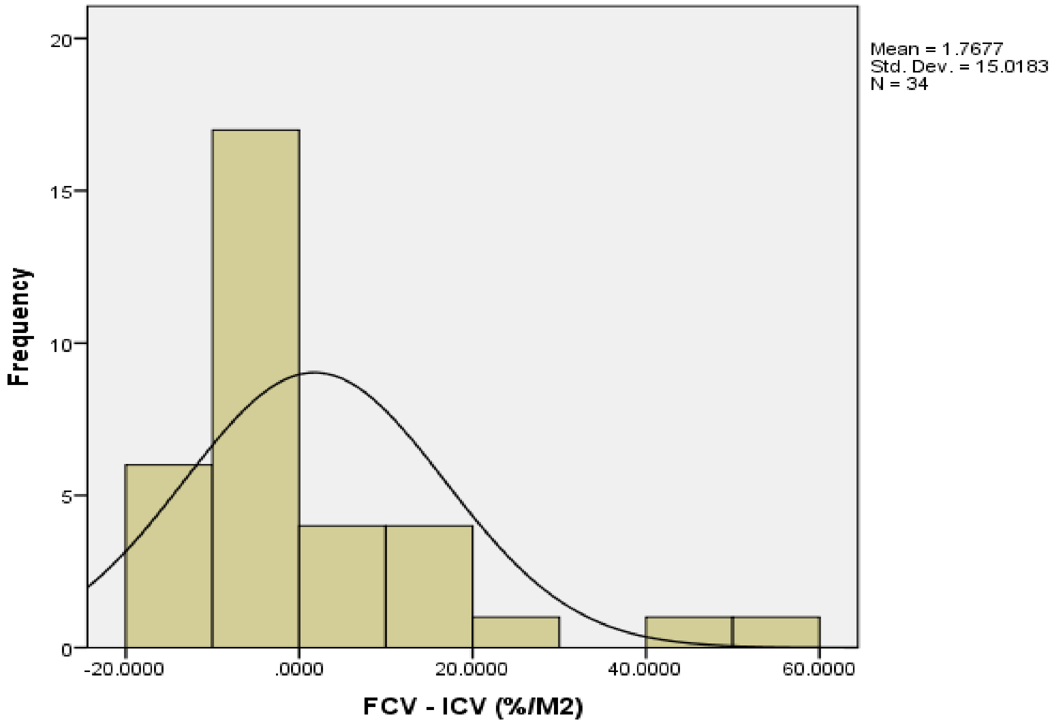


Fig. 3.5: Histogram of Final cost variance with superimposed normal distribution

3.3.5.15 Linearity of variables

The assumption of linearity of the relationship between the variables was explored with the aid of scatter plots using non-normalized data. Scatter plots are also useful for detecting outliers, unusual observations, and influential cases. A single point on a graph is recorded for each pair of observations from the two variables under study. The plots showed that the research data was mostly clustered around the point at which the x and y axes cross each other. In the case of consultant risks and cost deviation, however, a sizeable proportion of the observations fell within the negative region of both axes. All of these observations were presented in Figs. 3.6 and 3.7.

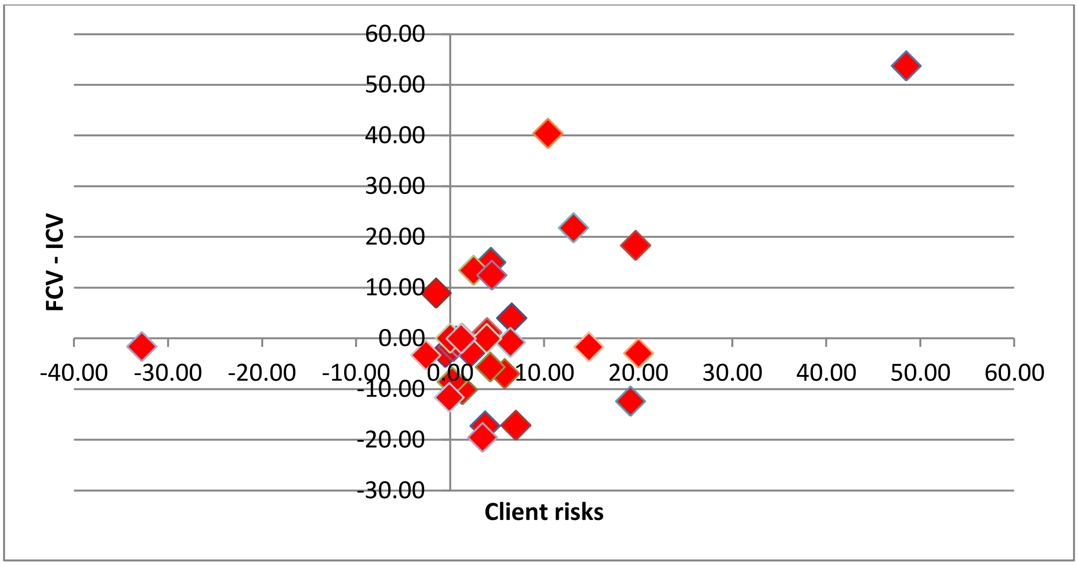


Fig. 3.6: Scatter plot of client risks and final account cost deviation

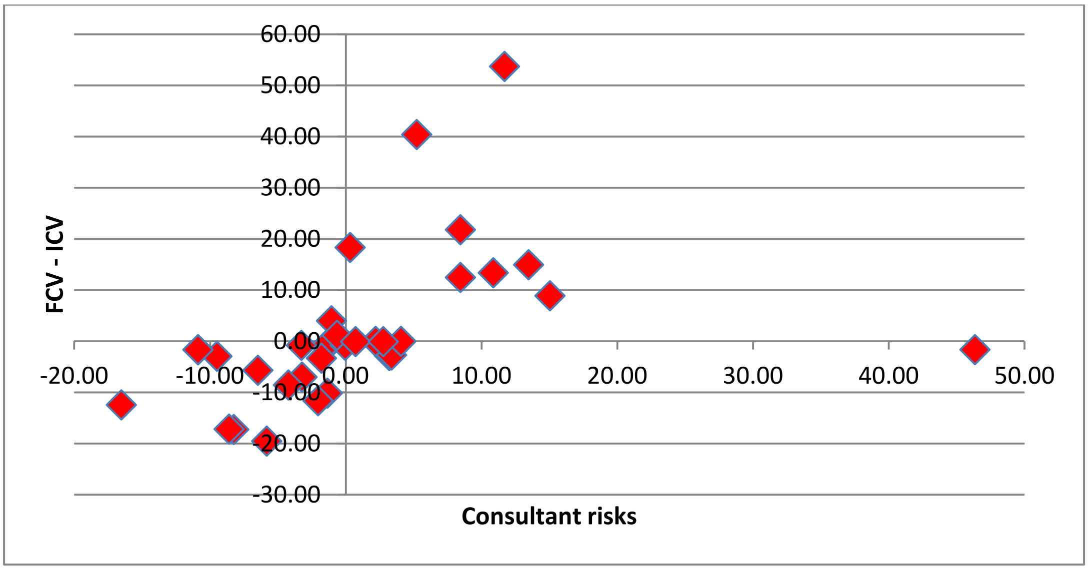


Fig. 3.7: Scatter plot of consultant risks and final account cost deviation

3.3.5.16 Equality of variances

Error bar charts summarize the distribution of one or more numeric variables, and help researchers visualize distributions and dispersion by indicating the variability of the measure being displayed. In Fig. 3.8, the means of the three variables in this study, which were ratio in terms of measurement scale, were plotted. The length of the error bars on either side of the mean value indicated the spread of 2 standard errors of the mean.

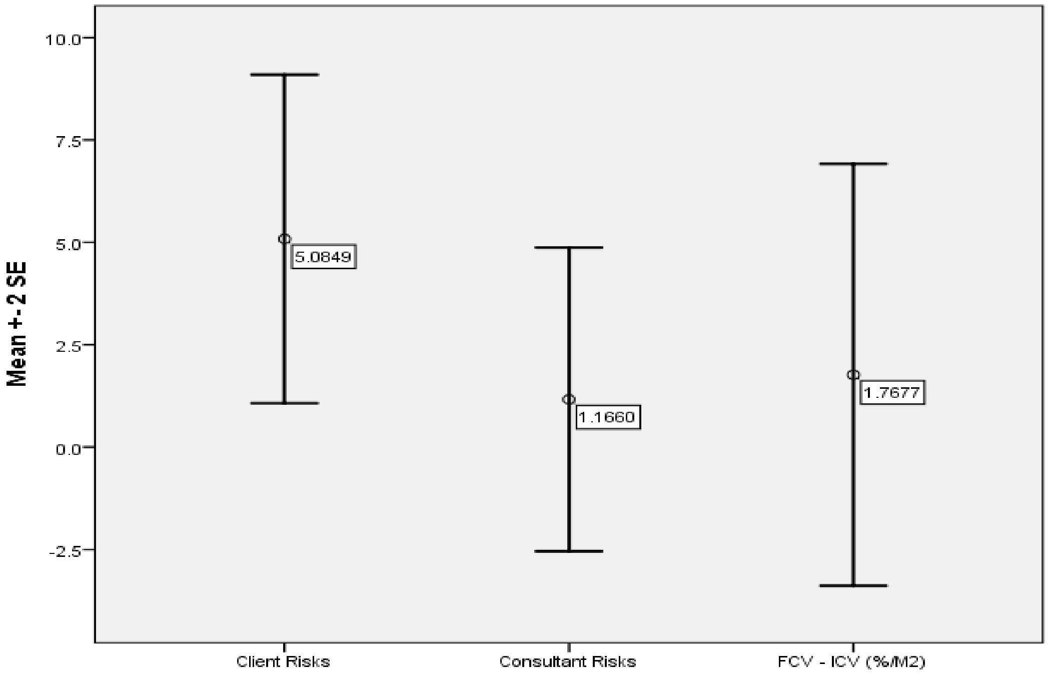


Fig. 3.8: Error bar chart of variables using non-normalized data

It was apparent that the two independent variables had similar variances; the variance of the dependent variable was however much longer than that of the other two variables.

3.3.5.17 Independence of variables

A starting point for determining whether or not the variables in this study are independent of each other is to compute the correlation coefficient (r) of pairs of the variables. Correlations measure how variables or rank orders are related. It is advisable to screen data for outliers before calculating the correlation coefficient; this is because outliers, which are unusually large or small values, relative to the generality of the data, can cause misleading results. Pearson's correlation coefficient is a measure of linear association, which uses symmetric quantitative variables and can provide evidence of a linear relationship, as presented in Table 3.11.

Table 3.10: Correlation coefficients of the research variables

		Client Risks	Consultant Risks	FCV - ICV
Client Risks	Pearson Correlation	---	-0.413*	0.507**
	Sig. (2-tailed)	---	0.015	.002
Consultant Risks	Pearson Correlation	-00.413*	---	0.422*
	Sig. (2-tailed)	0.015	---	0.013
FCV - ICV (%/M2)	Pearson Correlation	0.507**	0.422*	---
	Sig. (2-tailed)	0.002	0.013	---

Source: Author (2017).

Notes: *. Correlation is significant at the 0.05 level (2-tailed).
**. Correlation is significant at the 0.01 level (2-tailed); N = 34

It was observed from the information in Table 3.11 that both of the independent variables had relatively weak associations with the dependent variable; both correlations were however positive, indicating that increases in the costs due to any of the two groups of risks would be associated with an increase in the deviation between the final and initial contract values. The correlation between the two independent variables was also relatively weak and negative. However, there was still a need to establish if one of the independent variables was a linear function of the other. This undesirable situation is referred to as collinearity.

The collinearity diagnostics that were presented in Table 3.12 confirmed that there were no problems with multicollinearity in the dataset. None of the eigenvalues were close to 0; this indicated that the predictors were not intercorrelated, and that small changes in the data values would not lead to large changes in the estimates of the coefficients. Furthermore, condition indices were computed as the square roots of the ratios of the largest eigenvalue to each successive eigenvalue. Condition indices values that were greater than 15 would indicate a possible problem with collinearity; any value greater than 30 would be indicative of a serious problem. None of the indices obtained for the research dataset were larger than 2, confirming that there was no problem with collinearity.

Table 3.11 Collinearity Diagnostics of the independent variables

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions		
				(Constant)	Client Risks	Consultant Risks
1	1	1.472	1.000	.15	.26	.09
	2	1.107	1.154	.27	.00	.45
	3	.421	1.870	.57	.74	.46

Source: Author (2017).

3.3.6 Method of data analysis for ANN2: prediction of risk effect in cost of building projects using ANN

The different tasks involved in the manipulation of the data as part of the process for ANN2, which involved the development of a neural network for the prediction of risk effect on final costs of buildings, using CPFs as network inputs were depicted graphically in Figure 3.9.

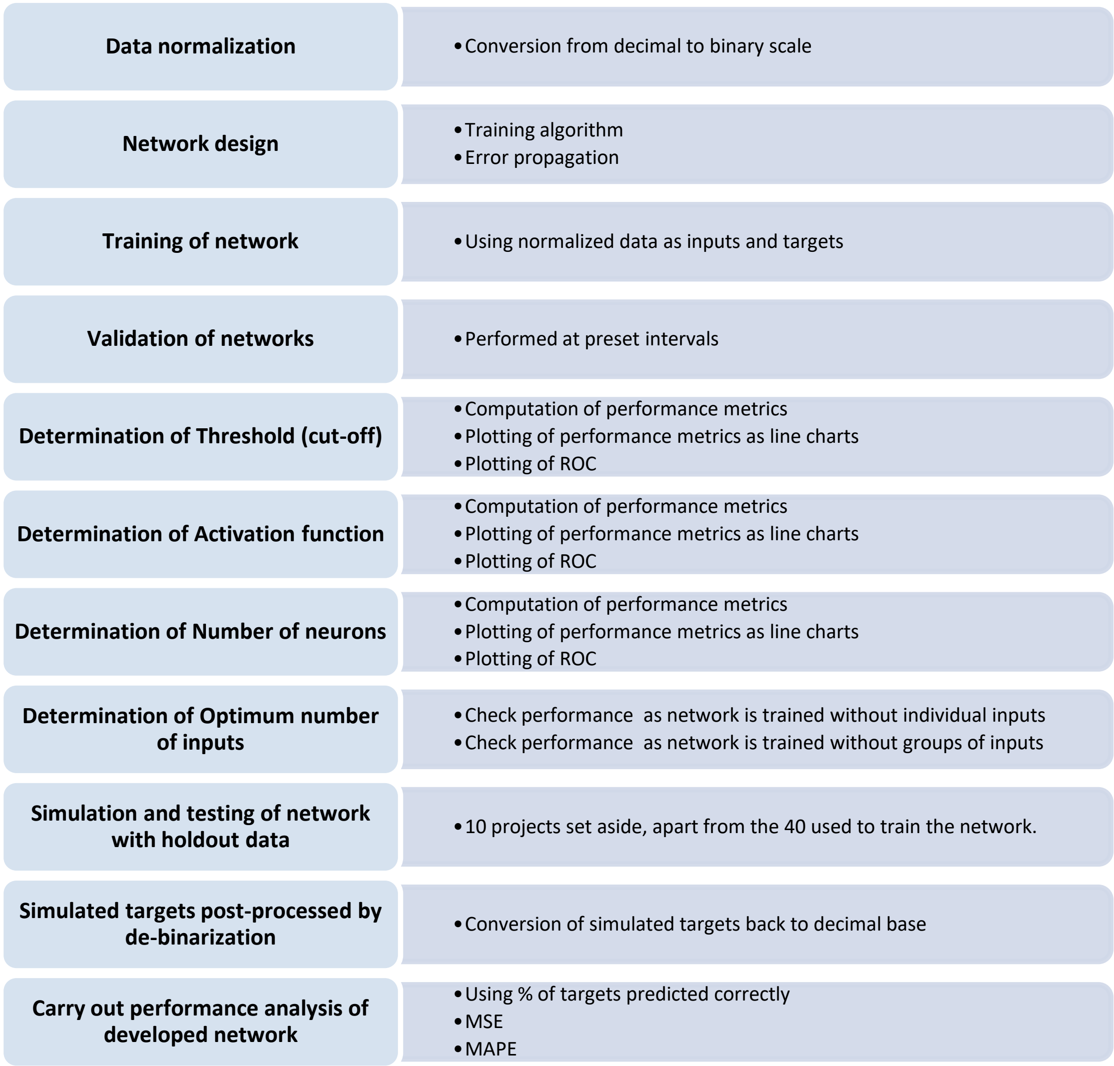


Figure 3.9: Network development process for ANN2

3.3.6.1 Data pre-processing (ANN2)

Pre-processing represented the first level in the preparation of data for use in neural network development. The objectives of data preprocessing are five: reduction of the input space size, smoother relationships, data normalization, noise reduction, and feature extraction (Kennedy *et al.*, 1998). Three activities were grouped under data pre-processing in this study; these were data representation, data partitioning and data normalization. Each of these activities contributed to adding value to the data, by improving the performance of the data in the developed neural network.

3.3.6.2 Data representation (ANN2)

Data intended for use in the creation of an ANN could be represented in several ways; such data could be in the form of numbers, alphabets, symbols or a mixture of alphabets and numbers. Numeric, alphabetic, symbolic and alphanumeric data might need to be converted or transformed in some manner before they could be suitable for neural network development.

The data employed in the neural network development process was entirely numeric in nature. The input data was comprised of selected construction project features (CPFs), which were expressed in various units such as square meters, percentages of initial contract values, and years. The output data employed was the cost consequences of risks, which were measured as percentages of the Initial Contract Value of the sampled projects.

The dataset comprised 8 input variables (the CPFs) and 8 output or target variables (the risks determined through a questionnaire survey). Only 6 of the 8 risks were however employed in the ANN. These were R3-CLV, R4-CLS, R5-CND, R6-UNS, R10-CNV and R13-CNE. One of the 6 risks (R13-CNE) was employed twice, for two different classes of cost (provisional quantities and variations). The ANN was thus developed with 7 targets (R3-CLV, R4-CLS, R5-CND, R6-UNS, R10-CNV, R13-CNE(pq) and R13-CNE(va). The details of the input and output variables were provided in Tables 3.12 and 3.13 under Section 3.3.6.4.

3.3.6.3 Data partitioning (ANN2)

Data partitioning involved the splitting of datasets into different subsets that were applied to different purposes during the development the neural network. Datasets are commonly split into three groups so that part of the data is used for training the developed network and for validating the trained network; the rest of the data is then introduced to the network in order to test its predictive ability.

Decisions on how to split the data into training and validation sets vary from researcher to researcher. Husin (2017) employed a dataset of 156 actual projects for training the neural network, and 15 simulated projects for validating the trained network. In their own case Juszczyk and Lesniak (2016) divided their data set in the ratio 60:20:20, for learning, validation and testing respectively. Chaphalkar *et al.* (2015) took cognizance of earlier research studies and divided their dataset into 70% for training, 15% for validation and 15% for testing purposes. They were able to achieve an MSE (mean square error) of 0.01 and a correlation coefficient (r) of 1.00.

In this study, the entire data employed for neural network development was 50 projects out of the total sample of 69 projects. This was spilt in the ratio 80:20 for training/validation and testing respectively. This meant 40 projects were applied to the training of the neural network, while 10 projects were employed in testing the developed network. The projects in the test group were purposively selected to reflect all of the different data combinations observed in the training group.

3.3.6.4 Data normalization (ANN2)

Normalization is done to map the data to a uniform scale. Knowledge of the domain is important in choosing preprocessing methods to highlight underlying features in the data, which can increase the network's ability to learn the association between inputs and outputs. To do this, several standard data normalization techniques such as min-max, softmax, z-score, decimal scaling, box-cox are available (this list is not exhaustive and many more techniques are in use) (Kuźniar and Zając, 2015).

There are several questions which must be answered when normalization is applied o a research data. Some of the questions include whether there is a general guideline to determine the appropriate technique for a particular application? Whether the normalization method should be solely determined by the range of input features (for removing scaling effect)? The influence of the choice of activation functions (logsig [0, 1] or tansig [-1, 1], etc.) has to be considered as well. Researchers must also consider what influence the type of the problem they are trying to solve (classification, function approximation, prediction, forecasting of time-series data, etc) will have on the type of normalization technique they adopt.

In this study, the normalization technique employed was binarization. All of the 8 inputs were binarized (see Table 3.12); the 7 outputs were however subjected to three different levels of binarization. The first level of binarization was simply to represent the occurrence or non-occurrence of risk. The second level of binarization employed 3 categories to represent the type of impact exerted by the risk where it occurred (negative, no impact and positive). The third level of binarization divided the level of severity of the risk into seven categories. Table 3.13 presented the output data both before and after binarization.

The midpoint of the data in terms of year of construction was 2010; the entire study period of 2003 – 2016 was however situated within a relatively uniform political climate. The data contained a preponderance of small sized projects since only 25% of the projects had gross floor areas in excess of 1000 square meters. Institutional projects included lecture rooms, offices, hostels and workshops; residential houses were the main type of non-institutional buildings. Classification of works as new construction or renovation was done in line with the practice in most Commonwealth countries, where separate information services were maintained for new and maintenance works. In the case of elemental costs, typical proportions of such elements were obtained for institutional and non-institutional buildings; an average value was computed and used as the cutoff point for the binarization.

Table 3.12: Binary equivalents of input variables

S/Nr	Description	Min	Max	Unit	Binary components
1	Year	2003	2016	Years	Before 2010 = 0; 2010 and after = 1
2	Gross floor area	33	6646	M^2	Less than $1000M^2$ = 0; $1000M^2$ and greater = 1
3	Project type	-	-	-	Non-institutional = 0; Institutional = 1
4	Project nature	-	-	-	Renovation = 0; New construction = 1
5	Structural costs	25	83	% of ICV	Less than 57% = 0; 57% or greater = 1
6	Services costs	6	21	% of ICV	Less than 17% = 0; 17% or greater = 1
7	Finishing costs	3	34	% of ICV	Less than 16% = 0; 16% or greater = 1
8	External works costs	0	41	% of ICV	Zero = 0; Greater than 0% = 1

Source: Author (2017)

Notes: Min = Minimum value; Max = Maximum value; ICV = Initial Contract Value;

Table 3.13: Binary equivalents of output variables

Risk code	Nature and source of risk	Min	Max	Unit	Binary equivalents of risk		
					Occur?	**Type?**	**Degree?**
CLSva	Additional costs arising from variation to scope by client	0	29.36	% of ICV	Yes = 1 ;	-ve = 01 ;	-22 to -11 = 000;
CLVva	Additional costs arising from variation to design by client	0	50.08	% of ICV	No = 0	Zero = 00 ;	-11 to 0 = 001;
CNDva	Additional costs arising from variation to design by consultants	0	49.08	% of ICV		+ve = 11	0 to 11 = 010;
CNEpq	Changes in Provisional Quantities arising from errors in estimates by consultants	-16.51	21.38	% of ICV			11 to 22 = 011;
CNEva	Additional cost variations arising from errors in estimates by consultants	0	3.42	% of ICV			22 to 33 = 100
CNVps	Changes in Provisional Sums arising from changes to design by consultants	-16.75	11.07	% of ICV			33 to 44 = 101
UNSpq	Changes in Provisional Quantities arising from unforeseen site conditions	-4.29	0.11	% of ICV			44 to 55 = 110

Author (2017)

Notes: Min = Minimum value; Max = Maximum value; ICV = Initial Contract Value;

3.3.6.5 Data processing (ANN2)

This section detailed how the artificial neural network was developed from its key components, with the aim of predicting the effect of risks on project costs, (as the output or target of the network) using selected features of building projects (as the input vectors).

MATLAB 2015a software was used to design and train the neural network. A feed forward neural network based on back propagation was employed. The Levenberg-Marquardt back propagation algorithm (*trainlm* in MATLAB) was used because of its quicker convergence and better results during training and validation (Jha and

Chockalingham, 2009). Transfer functions were selected based on trial and error experimentation.

3.3.6.6 Network architecture (ANN2)

The design of the architecture of the network involved the selection of the values of the key parameters of an artificial neural network such as transfer functions, number of input and output nodes, number of hidden layers and the number of neurons in the hidden layer(s) (Costantino *et al.*, 2015). There are some other considerations in neural network design such as number of partitions of the data, number of cycles to be run to train the network and criteria for validating the performance of the trained network.

The partitioning of the data had been handled in an earlier section of this thesis (see subsection 3.3.6.3). Most of the software that are employed in neural network development come with preset settings for either number of training cycles, time allotted for training the network, or the number of epochs to be completed by the network before validation is undertaken. In the case of this study, the following approach was employed. The networks were initially created with all 8 inputs and only 1 output; this was done to provide valuable insight into the predictability of a single risk, as a prelude to the prediction of groups of risks. The risk selected for this purpose was R10-CNVps (changes in provisional sums arising from changes to design by consultants), which, it was observed, occurred in 44 out of the 69 projects in the dataset. Three different activation functions were explored (*Logsig*, *Purelin* and *Tansig*).

Number of neurons and hidden layers were initially set at the lowest practicable levels (2 and 1 respectively). The survey of literature carried out had shown that most researchers worked with networks that had either one or two hidden layers. This could be seen in their comparison of the performance of ANN and GA-ANFIS in forecasting short time building energy, where Li *et al.* (2011) used feed forward neural network with a single hidden layer of *tansig* neurons to predict hourly energy consumption. In the modeling of construction project time performance, Le-Hoai *et al*. (2013) also adopted one hidden layer for their perceptron model, based on minimal errors of both training and testing sets. There thus appeared to be a preponderance of research that employed only one hidden layer of neurons; however Mučenski *et al*. (2013) had employed neural networks that consisted of two hidden layers. They opined that having more than 2 hidden layers produces networks that are unstable in prediction and less accurate (Mučenski *et al.,* 2012).

This created an 8:2:1 back-propagation multi-layer perceptron network, which was trained at the default settings of *nntool* (epochs 1000; target MSE 0.0; minimum gradient 10^{-7}; mu 0.001; mu_dec 0.1; mu_inc 10). Each training run was continued for as many epochs as the software deemed necessary. Based on the early stopping criterion adopted however, this setting was modified such that where no decrease in validation parameter occurred for six (6) consecutive epochs, the training run was discontinued. The validation parameter adopted in this study was the mean square error (MSE).

The default settings of *nntool* which were used to train the network initially were later modified in the light of unsatisfactory performance of the network. It was observed that overfitting of the data was occurring, a situation where training results are excellent, yet simulation results with fresh data are abysmally poor (MATLAB, 2015). The solution proposed in MATLAB (2015) was adopted and the *nntool* setting were adjusted accordingly (epochs 1000; target MSE 0.0; minimum gradient 10^{-7}; mu 1; mu_dec 0.7; mu_inc 1.3). This improved the performance of the network both in training and simulation appreciably.

3.3.7 Method of data analysis for performance analysis of artificial neural network for prediction of risk effect in costs of building projects

The performance analysis of the developed neural networks was carried out with the aid of performance metrics obtained from literature. To aid comparison of performance, five (5) measures of performance were computed, using the 2 x 2 contingency table approach. The performance metrics and the parameters employed in their computation were presented in Table 3.15.

Table 3.15: Formulae for common performance metrics

Performance parameter	**Formula**	*Where:*
Accuracy	(TP+TN)/(P+N)	*P = sum of positives (true positives and false negatives in output);* *N = sum of negatives (true negatives and false positives in output);* *TP = sum of true positives (with a value of 1 in both target and output);* *TN = sum of true negatives (with a value of 0 in both target and output);* *FP = sum of false positives (with a value of 0 in target and 1 in output);* *FN = sum of false negatives (with a value of 1 in target and 0 in output)*
False Positives Rate	FP/(FP+TN)	
Precision	TP/(TP+FP)	
Sensitivity	TP/(TP+FN)	
Specificity	TN/(FP+TN)	
True Positives Rate	TP/(TP+FN)	

Source: Hart (2016)

Receiver operating characteristics (ROC) charts were also plotted and used to decide on which network parameter (threshold, activation function and number of neurons) enabled the network to attain optimum performance in predicting the effect of risk on final costs of building project.

CHAPTER FOUR

4.0 RESULTS AND DISCUSSION

4.1 Arrangement of Results

The results of the five objectives set out in Chapter One are presented and discussed in this chapter. Sections 4.3, 4.4 and 4.5 dealt with Objectives 1, 2 and 3 respectively, while results for Objective 4 were presented in Sections 4.6 and 4.7. This was because of the two different procedures employed in predicting the effect of risk on the final costs of building projects. Thus Section 4.6 reported the results for ANN1 which developed a neural network for predicting final cost variance using risk effect as network input. Section 4.7 on the other hand reported the results for ANN2, which developed a neural network for predicting risk effect in final cost using construction project features (CPFs) as network input. Section 4.8 was concerned with results pertaining to Objective 5; a summary of all the findings made in the chapter was presented as Section 4.9.

4.2 Analysis of Respondent Demographics

This section presents relevant demographic information on the survey respondents for the 69 projects that were found suitable for development and validation of the artificial neural network model undertaken in the study. Table 4.1 presents data on some salient aspects of the projects that served as the sources of data for this research.

All of the respondents were quantity surveyors, at various stages in their careers. Two-thirds of the sample was made up of resident quantity surveyors (Resident QS), who are attached to specific projects; this class of construction professionals usually has dedicated offices on site. Their functions are identical to those of project quantity surveyors (Project QS). The different nomenclature reflected the particular party to the construction contract that the quantity surveying firms worked for. Resident QS work for the project owner, often referred to as the Employer; project QS on the other hand usually denote those QS professional who work for contractors, subcontractors or suppliers. Chief quantity surveyors (Chief QS) are senior professionals who supervise the resident quantity surveyors.

Table 4.1: Summary of respondents' demographic information

Parameter	Options	Frequency	Percent (%)
Designation	Chief QS	1	1.4
	Resident QS	49	71.0
	Project QS	19	27.5
		69	**100**
Experience	Less than 11 years	49	71.0
	11 - 20 years	20	29.0
		69	**100**
Qualification	MSc	3	4.3
	BSc	66	95.7
		69	**100**
Project Description	Car park	1	1.4
	Hospital	5	7.2
	Hostel	4	5.8
	Hotel	1	1.4
	House	26	37.7
	Library	1	1.4
	Office	9	13.0
	School	19	27.5
	Warehouse	2	2.9
	Workshop	1	1.4
		69	**100**

Source: Author (2017)

About three quarters of the sample (71%) had worked in construction for between 1 and 11 years; close to a third of the sample had however worked for between 11 and

20 years. Sixty-six of the respondents had Bachelor degrees while 3 respondents had acquired Masters Degrees.

The dominant use of the projects that were employed in the development of the artificial neural network model was institutional (39 out of 69 projects), while three projects were for commercial purposes. The physical size of the projects varied from 33 - 6646 square meters. Information on the effect of risk as was applicable to the projects was summarized descriptively in Table 4.2.

Table 4.2: Summary of project cost information

Category	**Sum**	**(%)**
Total ICV of all sampled projects	7,940,987,258.81	-
Mean ICV of all sampled projects	115,086,771.87	-
Standard Deviation of ICV of projects	170,124,024.89	-
Minimum ICV	1,472,635.50	-
Maximum ICV	1,046,041,530.38	-
Average increase in project costs	13,989,698.44	8.14
Total increases in project costs	965,289,192.63	12.16
Risk source		
Cost increases caused by Clients	431,134,033.79	5.43
Cost increases caused by Consultants	190,413,480.47	2.40
Cost increases due to Other Causes	343,741,678.37	4.33

Source: Author (2017)

Notes: ICV = Initial Contract Value

The mean difference between the final account and the contract value of the projects was 8.14%, which indicated cost overrun. Increases in project costs as a result of changes requested by clients were the major reason for the cost overrun (making up 44.7% of the cost overrun). This pattern of project stakeholder responsibility for cost increases, where client-caused increases were the dominant contributor to the overall difference between the initial contract sums and final accounts, has been documented in the literature by Perrenoud *et al.* (2016).

A summary of the risk information available about the projects that were sampled is provided in Table 4.3. A total of 1047 risk events that impacted on the costs of projects were identified from the sample of 69 projects. This meant that each individual project experienced an average of 15 risk events during the period of construction. About 64% of these risk events contributed to increases in the project costs; 35% of the risk events resulted in decreases in project costs, while in about 1% of the risk events no changes were recorded in the project costs.

Table 4.3: Summary of project risk information

Category	Sum	(%)
Number of Projects	69	-
Number of risk events	1047	-
Average number of risk events per project	15	-
Standard Deviation of risk events per project	14.55	-
Risk nature		
Increase	674	64.37
No change	10	0.96
Decrease	363	34.67

Source: Author (2017)

4.3 Results of Data Analysis for Objective 1: Risks Encountered in Building Projects

Review of relevant literature was carried out in order to generate a list of the risks that could be tested for significance of effect on the costs of building projects. A list of 70 risks was generated; purposive selection of risks that were considered relevant to the study reduced this number to 19. These 19 risks were then included in the research instrument, in order to determine which risks had impacted on the costs of the projects sampled in this study. This section presents the results of the questionnaire survey that was carried out with respect to the risks that had impacted on the costs of projects.

The 69 projects sampled in this study were examined for impact of risks and a tabular record of the examination is presented in Table 4.4a and 4.4b. All of the 19 risks in the research instrument served as column headings while the rows represented individual projects. A zero in the table meant that the risk at the head of the column in which the zero appeared did not occur on the project identified by the row number. The number 1 meant the reverse; the specific risk occurred on the specific project referred to by the row number. The prefix ‘A’ in the first column (which was labeled Proj Nr) identified multistory projects; a ‘B’ referred to single-story projects while ‘C’ denoted refurbishment projects.

It was observed from Table 4.4a and 4.4b that only 8 risks impacted on the costs of the 69 projects that were sampled. These 8 risks were labelled R3, R4, R5, R6, R10, R13, R15 and R19. Some of these 8 risks occurred very sparingly; for example it was only in two instances that R19 (Social issues/disturbance) was associated with changes in project costs. This risk had been identified by Windapo and Martins (2010); their study was located in the southern part of Nigeria, where tussles over the ownership of land were rife, as noted in their study (the *‘omo onile’* phenomenon, a euphemism for landlord). The other 11 risks did not have any impact on the costs of the projects.

Table 4.4a: Risks that impacted on costs of Projects 1 - 35

Proj Nr	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12	R13	R14	R15	R16	R17	R18	R19
A01	0	0	0	1	0	1	0	0	0	1	0	0	1	0	0	0	0	0	0
A02	0	0	0	1	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0
A03	0	0	1	1	1	1	0	0	0	1	0	0	1	0	0	0	0	0	0
A04	0	0	0	0	1	0	0	0	0	1	0	0	1	0	1	0	0	0	0
A05	0	0	0	0	1	1	0	0	0	1	0	0	1	0	0	0	0	0	0
A06	0	0	0	0	1	0	0	0	0	1	0	0	1	0	0	0	0	0	0
A07	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
A08	0	0	0	0	0	0	0	0	0	1	0	0	1	0	1	0	0	0	0
A09	0	0	1	1	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0
A10	0	0	1	0	1	0	0	0	0	1	0	0	1	0	0	0	0	0	0
A11	0	0	0	1	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0
A12	0	0	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
A13	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0
A14	0	0	1	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0
A15	0	0	0	1	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0
A16	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
B17	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
B18	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
B19	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
B20	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
B21	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
B22	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
B23	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
B24	0	0	1	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0
B25	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0
B26	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0
B27	0	0	0	0	0	1	0	0	0	1	0	0	1	0	0	0	0	0	0
B28	0	0	1	0	0	1	0	0	0	1	0	0	1	0	0	0	0	0	0
B29	0	0	0	0	0	1	0	0	0	1	0	0	1	0	0	0	0	0	0
B30	0	0	0	0	0	1	0	0	0	1	0	0	1	0	0	0	0	0	0
B31	0	0	0	0	0	1	0	0	0	1	0	0	1	0	0	0	0	0	0
B32	0	0	0	0	0	1	0	0	0	1	0	0	1	0	0	0	0	0	0
B33	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0
B34	0	0	0	0	0	1	0	0	0	1	0	0	1	0	0	0	0	0	0
B35	0	0	0	0	0	1	0	0	0	1	0	0	1	0	0	0	0	0	0

Source: Author (2017)

Notes: R1= Acts of God; R2= Cash flow difficulties; R3= change in design / variations by the client; R4= Change in scope of work; R5= change in the design by the Architect; R6= Changes in site conditions; R7= Consultant competence; R8= Contractor competence; R9= Nominated suppliers cash flow problems; R10= Consultants' design change; R11= Delay due to excessive approval procedures; R12= Equipment breakdown/ maintenance; R13= error/omission in design/estimate; R14= Inclement weather; R15= Inflation; R16= Labour shortage; R17= Poor contract management; R18= Production target slippage; R19= Social issues/area boys, original land owners.

Table 4.4b: Risks that impacted on costs of Projects 36 - 69

Proj Nr	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12	R13	R14	R15	R16	R17	R18	R19
B36	0	0	0	0	0	1	0	0	0	1	0	0	1	0	0	0	0	0	0
B37	0	0	1	1	0	1	0	0	0	1	0	0	1	0	0	0	0	0	0
B38	0	0	1	1	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0
B39	0	0	1	1	0	1	0	0	0	1	0	0	1	0	0	0	0	0	0
B40	0	0	1	1	0	1	0	0	0	1	0	0	1	0	0	0	0	0	0
B41	0	0	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
B42	0	0	0	1	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0
B43	0	0	0	1	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0
B44	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
B45	0	0	0	1	1	1	0	0	0	1	0	0	1	0	1	0	0	0	0
B46	0	0	0	1	1	0	0	0	0	1	0	0	1	0	0	0	0	0	0
B47	0	0	0	1	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0
B48	0	0	0	1	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0
C49	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
C50	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C51	0	0	0	1	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0
C52	0	0	0	1	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0
C53	0	0	0	1	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0
C54	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C55	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
C56	0	0	0	1	1	0	0	0	0	1	0	0	1	0	1	0	0	0	0
C57	0	0	0	1	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0
C58	0	0	0	1	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0
C59	0	0	0	1	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0
C60	0	0	1	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0
C61	0	0	1	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	1
C62	0	0	0	0	1	0	0	0	0	1	0	0	1	0	0	0	0	0	0
C63	0	0	0	1	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0
C64	0	0	0	0	1	0	0	0	0	1	0	0	1	0	0	0	0	0	0
C65	0	0	0	0	1	0	0	0	0	1	0	0	1	0	0	0	0	0	0
C66	0	0	1	0	1	0	0	0	0	1	0	0	1	0	0	0	0	0	0
C67	0	0	1	0	1	0	0	0	0	1	0	0	1	0	0	0	0	0	0
C68	0	0	1	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0
C69	0	0	1	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0

Source: Author (2017)

Notes: R1= Acts of God; R2= Cash flow difficulties; R3= change in design / variations by the client; R4= Change in scope of work; R5= change in the design by the Architect; R6= Changes in site conditions; R7= Consultant competence; R8= Contractor competence; R9= Nominated suppliers cash flow problems; R10= Consultants' design change; R11= Delay due to excessive approval procedures; R12= Equipment breakdown/ maintenance; R13= error/omission in design/estimate; R14= Inclement weather; R15= Inflation; R16= Labour shortage; R17= Poor contract management; R18= Production target slippage; R19= Social issues/area boys, original land owners.

Definitions for the 8 risks that impacted on project costs are presented in Table 4.5. Two of the risks have clients as their source (R3 and R4), while consultants serve as the source of three risks (R5, R10 and R13). The other three risks arose from unforeseeable causes (R6, R15 and R19).

Table 4.5: Definition of risks that impacted on project costs

Risk	Label	Category	Description	Source
R3	CLV	Client variation/design change	Instructions to vary initial tenders (and sometimes designs) that originate from clients; does not usually involve modification of the project brief.	Client
R4	CLS	Client scope change	Changes from or additions to initial designs (and at times tenders) requested by clients as modification of the project brief.	Client
R5	CND	Consultants' error/omission in design	Impacts caused by incomplete or inaccurate construction documents provided by designers.	Architect /Consultants
R6	UNS	Unforeseen site conditions	Impacts arising from unforeseeable conditions such as unknown ground conditions.	Unforeseeable
R10	CNV	Consultants' design change	Changes to initial designs that originate from designers (Architect and Engineers).	Architect /Consultants
R13	CNE	Consultants' error/omission in estimates	Impacts caused by incomplete or inaccurate price information provided by quantity surveyors.	Architect /Consultants
R15	UNE	Unforeseen economic conditions	Impacts arising from changes in the economic climate such as due to inflation.	Unforeseeable
R19	USD	Unforeseen social disturbance	Impacts arising from unforeseeable conditions such as social unrest.	Unforeseeable

Source: Author (2017).

The impact of the 8 risks in Table 4.5 was obtained for 5 classes of costs conventionally presented in final accounts. This was in order to provide further detail on what types of risks the different classes of project costs are susceptible to. For example costs associated with incomplete detailing of construction work are usually classed as 'Provisional Quantities', and may be more susceptible to certain types of risks than others. Information on the breakdown of risk effect on different cost classes was presented in detail in Appendix E and summarized in Table 4.6.

Table 4.6: Occurrence of risks in different classes of project cost presented in final accounts

Proj Nr	R3-CLV					R4-CLS					R5-CND					R6-UNS					R10-CNV					R13-CNE					R15-UNE					R19-USD				
	pq	**ps**	**va**	**vo**	**vs**	**pq**	**ps**	**va**	**vo**	**vs**	**pq**	**ps**	**va**	**vo**	**vs**	**pq**	**ps**	**va**	**vo**	**vs**	**pq**	**ps**	**va**	**vo**	**vs**	**pq**	**ps**	**va**	**vo**	**vs**	**pq**	**ps**	**va**	**vo**	**vs**	**pq**	**ps**	**va**	**vo**	**vs**
Sum of risk occurrence in all 69 projects	1	0	**12**	3	7	0	0	**31**	4	9	3	0	**14**	5	2	**18**	2	2	0	0	2	**44**	5	0	0	**36**	0	**13**	1	5	0	1	9	0	1	0	0	1	0	0

Source: Author (2017).

Notes: R3= change in design / variations by the client; R4= Change in scope of work; R5= change in the design by the Architect; R6= Changes in site conditions; R10= Consultants' design change; R13= error/omission in design/estimate; R15= Inflation; R19= Social issues/area boys, original land owners.pq=provisional quantities; ps=provisional sums; va=variations (addition); vo=variations (omissions); vs=variations (substitution)

The overall aim of this study is to predict the occurrence, type and degree of impact of risks on costs of building projects by developing an artificial neural network model. This was done using a sample of 69 projects. However, as has been shown in this section, in Table 4.4a, 4.4b and 4.5, risk occurrence varies from project to project. No single risk impacted on costs of all 69 projects. The modal value of 44 in Table 4.6 represents the largest subset of the sample of 69 projects that could be used to develop the ANN, since neural networks are a data-hungry procedure (Elhag and Boussabaine, 1998). The seven instances in which risks impacted on the costs of 10 or more projects were thus selected for use in developing the ANN.

The 7 selected instances referred to the impact of (i) R3 on variations; (ii) R4 on variations; (iii) R5 on variations; (iv) R6 on provisional quantities; (v) R10 on provisional sums; (vi) R13 on provisional quantities, and (vii) R13 on variations. Only 6 risks were thus employed to develop the ANN (R3, R4, R5, R6 and R13), but one out of these six risks impacted on more than one class of project cost (R13).

4.4 Results of Data Analysis for Objective 2: Construction Project Features Employed in Building Cost Prediction

The second objective of the study dealt with the identification of the features of construction projects that had been employed for the prediction of the costs of building projects. This process has been described in Chapter Three. The 8 CPFs which were adopted for use as predictors in ANN are identified by **bold face type** in Table 4.7.

The variables adopted as ANN predictors in this study were normalized by conversion to binary variables. Conversion of variables to a binary scale in effect transforms the parameter into one that has only two states. These states are usually different in terms of only size. This means that notwithstanding the parameter employed as a predictor in ANN, the ANN is really predicting based on differences in the sizes of the variables entered into it; such binary variables have only two sizes. This property of a binary scale makes it just as feasible to use a non-numerical variable as a numerical one.

Table 4.7: Construction project features adopted as ANN inputs in this study

S/N	CPFs	a	b	c	d	e	f	g	h	i	j	k	l	m	This study
1	Area of formworks													x	
2	**Cost of external work**														√
3	**Cost of finishing**														√
4	**Cost of services**														√
5	**Cost of structural element**														√
6	Duration	x							x						
7	Estimated Sum				x				x						
8	Estimating Method				x										
9	Floor Height											x			
10	Fluctuation measure						x								
11	**Gross floor area**	x			x	x				x					√
12	Ground conditions	x													
13	Initial contract sum							x			x				
14	Land Acquisition											x			
15	Location				x										
16	Lowest tender price	x													
17	Market conditions	x													
18	**Nature of project**														√
19	Number of basements											x		x	
20	Number of columns					x									
21	Number of stories	x			x					x					
22	Number of tenderers	x													
23	Payment method,						x								
24	Procurement Route				x		x								
25	Risk impact							x					x		
26	Risk probability							x					x		
27	Scope of project								x						
28	Site access	x													
29	Site slope	x													
30	Structural Material				x										
31	Type of client						x								
32	Type of contract	x													
33	**Type of project**	x			x		x								√
34	Typical floor area					x									
35	Volume of concrete													x	
36	Weight of steel													x	
37	Work space in site	x													
38	**Year**											x			√

Source: Researcher's summary

Note: a = Elhag and Boussabaine (1998); b = Palaneeswaran *et al*. (2008); c = Wang and Gibson (2010); d = Aibinu *et al*. (2011); e = Arafa and Alqedra (2011); f = Ahiaga-Dagbui and Smith (2012); g = Odeyinka *et al.* (2012); h = Ahiaga-Dagbui and Smith (2013); i = Gulcicek *et al*. (2013); j = Amusan *et al*. (2013); k = Kim *et al*. (2013); l = Odeyinka *et al*. (2013); m = Roxas and Ongpeng (2014).

The 8 CPFs employed in this study as identified in Table 4.7 are defined in Table 4.8. The units in which the CPFs were measured are also provided.

Table 4.8 Descriptions of CPFs employed in study

CPF Nr	CPF	Description of CPF
1	Gross floor area	Area covered by building, across all walls and partitions, measured to the external faces of extreme parts of the buildings. Expressed in square meters.
2	Project type	The intended use or purpose of the project. Examples include office, classroom, hotel and workshop.
3	Year	The year the project construction commenced.
4	Project nature	Whether the project is for a new construction or maintenance of an old building.
5	Costs of structural elements	Costs of substructure, load bearing walls and roof, all expressed as a proportion of the initial contract value of the project.
6	Costs of Services	Costs of mechanical and electrical engineering services, all expressed as a proportion of the initial contract value of the project.
7	Costs of Finishing	Costs of floor, wall and ceiling finishing and decoration, all expressed as a proportion of the initial contract value of the project.
8	Costs of External work	Costs of all works that are external to the building structure itself, such as fencing, external electrification and landscaping, expressed as a proportion of the initial contract value of the project.

Source: Author (2017)

4.5 Results of Data Analysis for Objective 3: Effect of Risk in Costs of Building Projects

The third objective of this study which was 'to determine the effects of risks on the final costs of building projects' was addressed in this section. Different levels of risk are associated with different projects and the number of risk events recorded on projects also differs; it is believed that the more complex and large a project is, the more risk it involves (Furlong *et al.*, 2017).

The effect of risks on the project costs was examined in three main areas; in terms of occurrence, in terms of the arithmetical sign of the risk which determines its effect on project costs, and in terms of the degree of impact of the risk. The third area was measured in relation to the initial cost of the projects. These three areas of assessing risk impact on the project costs were dealt with in Sections 4.5.1, 4.5.2 and 4.5.3 respectively.

4.5.1 Risk occurrence in building projects

The number of times that risks impacted on the costs of the 69 projects in the study was examined by constructing a frequency table of the projects and associated risks. Risks were identified at the heads of columns in Table 4.9a and 4.9b, while the rows referred to individual projects. The number of times a risk occurred on a project was recorded at the intersection of the row and the column that identified both the project and the risk. Both Table 4.9a and 4.9b contained similar information; Table 4.9a presented risk frequencies for Projects A01 to B35 while Table 4.9b presented the same information for Projects B36 to C69.

It was observed that not all of the risks occurred on every project; in fact the highest number of risks that occurred concurrently was observed on only two projects. These were Projects A03 and B45, on which 6 risks occurred. The mean, median and modal values for risk occurrence were found to be 3.02, 3 and 3 respectively. The risks that occurred most frequently were R10-CNV and R13-CNE, while the least frequent risk was R19-USD. The projects on which risks occurred most frequently were Project A02 (65 risk occurrences recorded); Project C61 (58 risk occurrences); and Project B45, on which 56 occurrences of risk was recorded.

Table 4.9a: Frequency of risks in building projects (Projects A01 to B35)

Proj Grp Nr	R3-CLV	R4-CLS	R5-CND	R6-UNS	R10-CNV	R13-CNE	R15-UNE	R19-USD
A01		3		1	21	9		
A02		46	17				2	
A03	1	13	15	1	2	1		
A04			6		7	12	1	
A05			6	1	7	6		
A06			4		7	12		
A07		3				3		
A08					6	6	10	
A09	2	1			4	1		
A10	4		5		10	26		
A11		5			3	11		
A12	1	4			18			
A13			8		34			
A14	6	4	1		5			
A15		3	1			1		
A16		7	8					
B17		1					2	
B18		2					1	
B19		2					1	
B20		2					1	
B21		2					1	
B22		1						
B23		1						
B24	8				4	12		
B25				1		4		
B26				1		3		
B27				1	3	4		
B28	1			1	3	4		
B29				1	3	4		
B30				1	2	4		
B31				1	3	4		
B32				1	3	4		
B33				1		4		
B34				1		5		
B35				3		6		

Source: Author (2017).

Notes: R3= change in design / variations by the client; R4= Change in scope of work; R5= change in the design by the Architect; R6= Changes in site conditions; R10= Consultants' design change; R13= error/omission in design/estimate; R15= Inflation; R19= Social issues/area boys, original land owners

Table 4.9b: Frequency of risks in building projects (Projects B36 to C69)

Proj Grp Nr	R3-CLV	R4-CLS	R5-CND	R6-UNS	R10-CNV	R13-CNE	R15-UNE	R19-USD
B36				1	3	4		
B37	1	1		1	4	1		
B38	1	1		1	4	1		
B39	1	1		1	4	1		
B40	2	1		1	4	1		
B41	1	4			1			
B42		1			2	2		
B43		1			1	2		
B44	1							
B45		9	6	2	6	30	3	
B46		1	13		2	4		
B47		5		1		1		
B48		10			1	2		
C49		1			1			
C50	6							
C51		1			1	3		
C52		9			2	2		
C53		10			2	2		
C54		10				2		
C55		1						
C56		17	1		5	18	1	
C57		10			4	32		
C58		11			3	12		
C59		7			4	9		
C60	8				6	14		
C61	3				5	48		2
C62			3		2	5		
C63		2			2	1		
C64			4		5	6		
C65			7		2	3		
C66	2		12		4	2		
C67	1		2		3	4		
C68	3			2		13		
C69	2				4	5		

Source: Author (2017).

Notes: R3= change in design / variations by the client; R4= Change in scope of work; R5= change in the design by the Architect; R6= Changes in site conditions; R10= Consultants' design change; R13= error/omission in design/estimate; R15= Inflation; R19= Social issues/area boys, original land owners

The frequency of occurrence of the 8 risks found to have impacted on project costs through the questionnaire survey was summarized by a piechart in Figure 4.1. Four risks are immediately recognizable as being the most frequent on the sampled projects. The four risks were R4-CLS, R5-CND, R10-CNV and R13-CNE. These four risks accounted for 90% of all occurrences of risk on the projects.

Different project stakeholders served as the source of the four most frequently occurring risks identified above. Three of the risks, R5-CND, R10-CNV and R13-CNE are associated with the design and construction consultants on the projects. This meant that risks arising from the actions or inactions of the project consultants made up 69% of all risks that occurred on the projects that were sampled. In terms of frequency of occurrence alone, the risk that occurred most frequently and was associated with clients was R4-CLS, which accounted for 21% of all recorded risks. This classification of risks according to source of the risk was based on evidence from literature, such as Perrenoud *et al.* (2016), Perrera *et al*. (2014) and Zou *et al.* (2006).

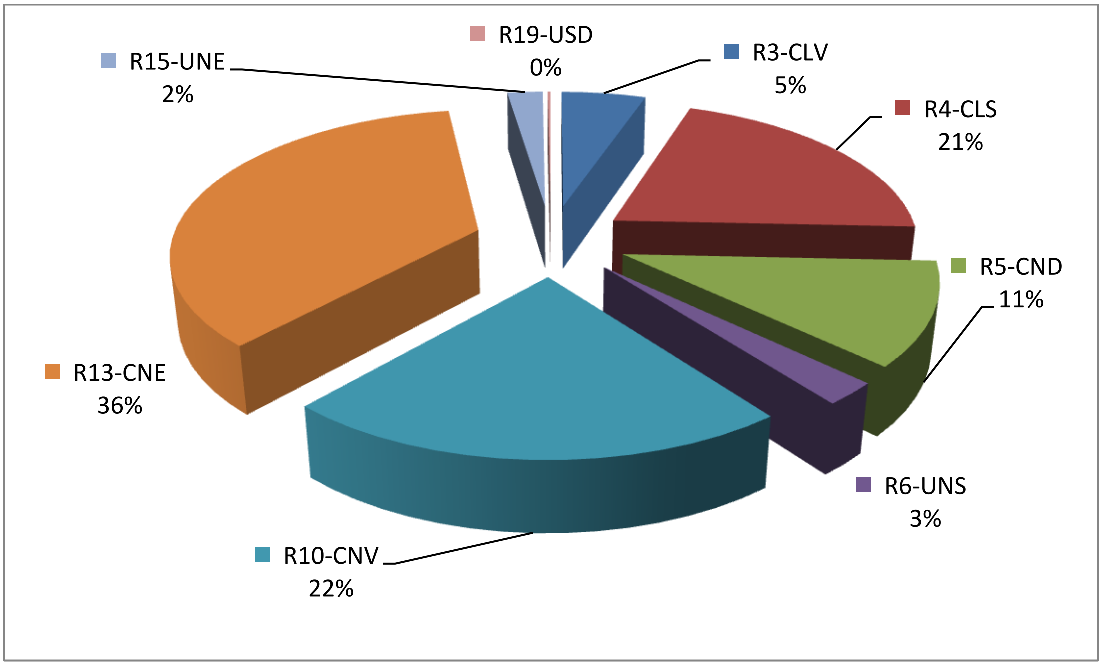


Figure 4.1: Summary of risk frequency

4.5.2 Type of risk effect on building project costs

The number of times that risks impacted either positively or negatively on the costs of the 69 projects in the study was examined by constructing a frequency table of the projects and associated risks. Within the context of this study, the phrase ‘positive and negative effects of risk’ refer to the arithmetical signs associated with numerical values of risks. Positive effects increase the costs of projects, while negative effects decrease the costs of projects.

Risks were identified at the heads of columns in Table 4.10a and 4.10b, while the rows referred to individual projects. Risks were further subdivided into positive and negative, based on the arithmetical signs associated with numerical values of the risks. The number of times a risk occurred on a project was recorded at the intersection of the row and the column that identified the project, the risk and the arithmetical sign of the risk. Both Table 4.10a and 4.10b contained similar information; Table 4.10a presented risk frequencies for Projects A01 to B35 while Table 4.10b presented the same information for Projects B36 to C69.

It was observed that both positive and negative risks occurred on most projects; in fact only on 11 projects were risks of only one type observed. On the other 58 projects both positive and negative risks were recorded. The mean, median and modal values for risk occurrence were found to be 1.58, 2 and 2 respectively for positive risks; the corresponding values were 2.35, 2 and 2 for negative risks. The positive risks that occurred most frequently were R10-CNV and R13-CNE, while the least frequent positive risk was R19-USD (it did not occur at all). The negative risks that occurred most frequently were R13-CNE and R4-CLS, while the least frequent negative risk was R19-USD.

Table 4.10a: Frequency of risks with positive effect on costs (Projects A01 to B35)

Proj Grp Nr	R3-CLV		R4-CLS		R5-CND		R6-UNS		R10-CNV		R13-CNE		R15-UNE		R19-USD	
	+ve	-ve	+ve	-ve	+ve	-ve	+ve	-ve	+ve	-ve	+ve	-ve	+ve	-ve	+ve	-ve
A01			3	0			0	1	4	17	5	4				
A02			0	46	0	17							0	2		
A03	0	1	13	0	4	11	1	0	2	0	0	1				
A04					0	6			3	2	9	3	0	1		
A05					0	6	0	1	6	1	2	4				
A06					0	4			3	2	8	4				
A07			0	3							2	1				
A08									2	0	3	3	6	4		
A09	0	2	0	1					2	1	1	0				
A10	0	4			0	5			6	4	14	12				
A11			2	3					2	1	3	8				
A12	0	1	0	4					8	10						
A13					0	8			16	18						
A14	0	6	4	0	0	1			4	1						
A15			1	2	1	0					0	1				
A16			1	6	1	7										
B17			0	1									0	2		
B18			0	2									0	1		
B19			0	2									0	1		
B20			0	2									0	1		
B21			0	2									0	1		
B22			0	1												
B23			0	1												
B24	0	8							0	4	2	10				
B25							1	0			0	4				
B26							1	0			0	3				
B27							1	0	1	2	0	4				
B28	1	0					1	0	1	2	0	4				
B29							1	0	1	2	0	4				
B30							1	0	1	1	0	4				
B31							1	0	1	2	0	4				
B32							1	0	1	2	0	4				
B33							1	0			0	4				
B34							1	0			1	4				
B35							0	3			1	5				

Source: Author (2017).

Notes: R3= change in design / variations by the client; R4= Change in scope of work; R5= change in the design by the Architect; R6= Changes in site conditions; R10= Consultants' design change; R13= error/omission in design/estimate; R15= Inflation; R19= Social issues/area boys, original land owners

Table 4.10b: Frequency of risks with positive effect on costs (Projects B36 to C69)

Proj Grp Nr	R3-CLV		R4-CLS		R5-CND		R6-UNS		R10-CNV		R13-CNE		R15-UNE		R19-USD	
	+ve	-ve	+ve	-ve	+ve	-ve	+ve	-ve	+ve	-ve	+ve	-ve	+ve	-ve	+ve	-ve
B36							1	0	1	2	0	4				
B37	0	1	0	1			1	0	0	4	0	1				
B38	0	1	0	1			1	0	0	4	0	1				
B39	0	1	0	1			1	0	0	4	0	1				
B40	1	1	0	1			1	0	0	4	0	1				
B41	0	1	1	3					0	1						
B42			0	1					2	0	2	0				
B43			0	1					1	0	0	2				
B44	1	0														
B45			0	9	2	4	2	0	5	1	16	14	0	3		
B46			1	0	5	8			1	1	4	0				
B47			0	5			1	0			1	0				
B48			0	10					1	0	0	2				
C49			0	1					1	0						
C50	0	6														
C51			0	1					1	0	0	3				
C52			0	9					0	2	2	0				
C53			0	10					0	2	2	0				
C54			0	10							1	1				
C55			0	1												
C56			0	17	1	0			4	1	12	6	0	1		
C57			0	10					3	1	13	19				
C58			0	11					3	0	6	6				
C59			0	7					4	0	6	3				
C60	0	8							5	1	6	8				
C61	0	3							3	2	28	19			0	2
C62					1	2			2	0	2	3				
C63			0	2					2	0	1	0				
C64					0	4			4	1	4	2				
C65					0	7			2	0	2	1				
C66	2	0			0	12			3	1	0	2				
C67	0	1			0	2			3	0	3	1				
C68	0	3					0	2			9	4				
C69	0	2							3	1	3	2				

Source: Author (2017).

Notes: R3= change in design / variations by the client; R4= Change in scope of work; R5= change in the design by the Architect; R6= Changes in site conditions; R10= Consultants' design change; R13= error/omission in design/estimate; R15= Inflation; R19= Social issues/area boys, original land owners

The frequency of occurrence of risks found to have positive impact on project costs was summarized by a piechart in Figure 4.2. Two risks are immediately recognizable as being the most frequent on the sampled projects. The two risks were R13-CNE and

R10-CNV which accounted for 49% and 33% of all occurrences of risk on the 69 projects that were sampled.

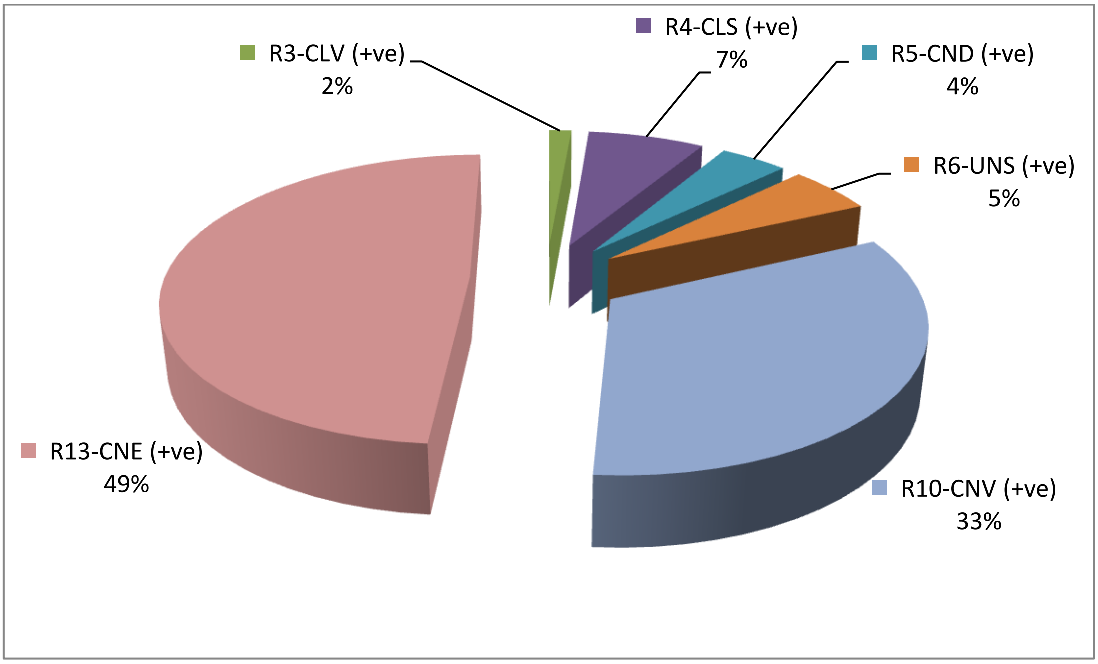


Figure 4.2: Frequency of risks with positive impact on project costs

Both of the two most frequently occurring positive risks R13-CNE and R10-CNV were associated with the project consultants. This meant that 82% of all risks that increased the costs of the projects that were sampled arose from the actions or inactions of the project consultants. With respect to clients as a source of positive risk, only 9% of all recorded risk occurrences was identified (R4-CLS, which accounted for 7% and R3-CLV, which accounted for 2%).

Although risks were classified into types was based on evidence from literature, such as Yildiz *et al.* (2014), Karim *et al.* (2012) and Chileshe and Yirenkyi-Fianko (2011), there is need for caution in comparing the results obtained in this study with those of earlier studies. This is based on the fact that risk categories are defined differently in different studies. This study has found that the project consultants accounted for the largest proportion of positive risks in contrast to the finding by Perrenoud *et al*. (2016) found that clients accounted for over half of all risk occurrences. However in the Perrenoud study there was only one category associated with consultants (unlike the 3 in this study) and and four categories that were associated with clients (unlike the 2 in this study).

The frequency of occurrence of risks found to have negative impact on project costs was summarized by a piechart in Figure 4.3. Two risks, R13-CNE and R4-CLS are recognizable as being the most frequently occurring negative risks on the sampled projects. The two risks accounted for 30% and 28% respectively of all occurrences of risk.

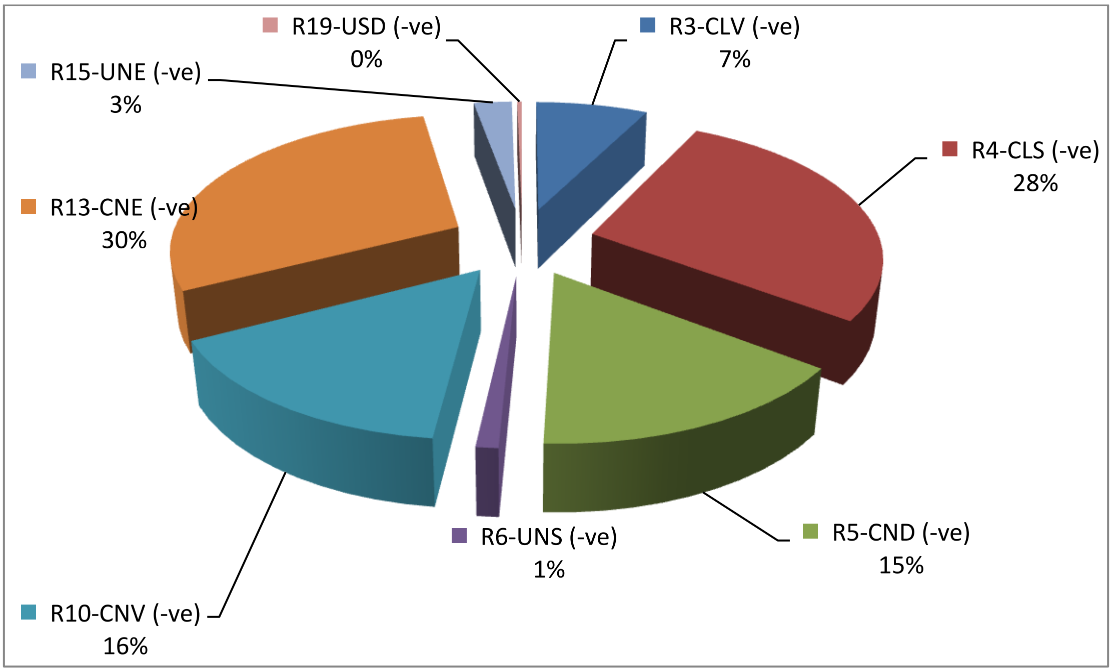


Figure 4.3: Frequency of risks with negative impact on project costs

Two other risks, R10-CNV and R5-CND were also found to be frequently occurring negative risks, accounting for 16% and 15% of risk occurrence respectively. Of these four frequently occurring negative risks, three (R13-CNE, R10-CNV and R5-CND) were associated with the project consultants. This meant that 61% of all risks that decreased the costs of the projects were associated the project consultants.

4.5.3 Impact of risks on project costs

The impact of risks on the costs of the 69 projects in the study was examined by estimating the numerical values of the risks. The impact of risks was estimated by considering the increase or decrease in the project costs arising as a consequence of the risk. This was then taken as a proportion of the initial contract value of the project. Risks were identified at the heads of columns in Table 4.11a and 4.11b, while the rows referred to individual projects. The percentage increase or decrease in the cost of the project associated with a risk that had occurred was recorded at the intersection of the row and the column that identified both the project and the risk. Both Table 4.11a and 4.11b contained similar information; Table 4.11a presented risk frequencies for Projects A01 to B35 while Table 4.11b presented the same information for Projects B36 to C69.

The mean and median values for risk occurrence were found to be 2.69% and 0.83% respectively. Modal values could not be computed, owing to non-repetition of the discrete values of risk impact. The risks that had the highest impact on project costs were R4-CLS and R5-CND, while the risk with the least impact was R19-USD. The projects on which risks had had the highest and least impacts on project costs were Project A03 (58.47%) and Project B43 (-10.53%).

Table 4.11a: Risk impact on costs (Projects A01 to B35)

Proj Grp Nr	R3-CLV	R4-CLS	R5-CND	R6-UNS	R10-CNV	R13-CNE	R15-UNE	R19-USD
A01		-1.49		0.08	9.31	5.75		
A02		10.39	5.25				20.88	
A03	50.09	-1.60	-0.59	-1.74	-1.30	13.61		
A04			4.61		0.21	-0.75	3.33	
A05			1.66	0.14	-1.57	6.04		
A06			8.08		-0.46	-2.40		
A07		0.77				-0.02		
A08					-0.63	-2.77	-4.54	
A09	2.44	0.07			11.07	-0.18		
A10	2.19		2.49		-1.35	2.25		
A11		-0.10			0.02	-2.04		
A12	0.31	0.97			2.22			
A13			3.22		-3.50			
A14	2.32	-4.91	2.12		-3.89			
A15		3.88	-0.11			0.85		
A16		1.17	2.78					
B17		3.37					10.06	
B18		8.66					6.85	
B19		8.88					6.71	
B20		8.01					3.93	
B21		24.69					2.35	
B22		10.65						
B23		29.36						
B24	9.24				7.27	21.39		
B25				-0.39		2.71		
B26				-0.58		2.73		
B27				-0.46	0.26	2.82		
B28	0.00			-0.55	1.18	2.91		
B29				-0.59	0.88	2.73		
B30				-1.17	0.00	2.39		
B31				-0.58	0.48	2.97		
B32				-0.58	0.45	2.82		
B33				-1.58		3.29		
B34				-0.48		1.38		
B35				2.21		3.47		

Source: Author (2017).

Notes: R3= change in design / variations by the client; R4= Change in scope of work; R5= change in the design by the Architect; R6= Changes in site conditions; R10= Consultants' design change; R13= error/omission in design/estimate; R15= Inflation; R19= Social issues/area boys, original land owners

Table 4.11a: Risk impact on costs (Projects B36 to C69)

Proj Grp Nr	R3-CLV	R4-CLS	R5-CND	R6-UNS	R10-CNV	R13-CNE	R15-UNE	R19-USD
B36				-0.78	0.65	3.42		
B37	0.21	1.25		-2.36	2.20	0.67		
B38	0.19	1.31		-2.44	2.16	0.82		
B39	2.30	1.20		-4.29	2.23	0.68		
B40	-0.49	1.31		-1.40	2.13	0.50		
B41	18.33	1.40			0.34			
B42		0.22			-3.63	-0.58		
B43		0.33			-16.75	5.89		
B44	-0.37							
B45		1.31	-1.89	-0.62	-9.98	0.55	1.26	
B46		-0.51	6.17		-1.13	-1.81		
B47		3.91		-2.11		-0.62		
B48		18.82			-12.42	1.74		
C49		0.66			-1.20			
C50	42.72							
C51		0.57			-3.05	1.60		
C52		4.45			9.36	-0.89		
C53		13.12			9.36	-0.89		
C54		24.41				-16.51		
C55		19.17						
C56		6.54	-1.88		0.01	0.83	6.90	
C57		4.32			7.34	6.15		
C58		5.80			-4.26	1.06		
C59		3.72			-8.78	0.55		
C60	6.98				-7.58	-0.99		
C61	4.25				-1.16	-5.29		6.63
C62			9.80		-4.55	4.10		
C63		20.02			-9.30	-0.17		
C64			16.89		6.54	-1.96		
C65			24.56		-10.71	0.04		
C66	-32.79		49.08		-3.48	0.77		
C67	3.44		15.06		-16.31	-4.55		
C68	6.41			0.11		-3.25		
C69	14.74				-2.49	-8.37		

Source: Author (2017).

Notes: R3= change in design / variations by the client; R4= Change in scope of work; R5= change in the design by the Architect; R6= Changes in site conditions; R10= Consultants' design change; R13= error/omission in design/estimate; R15= Inflation; R19= Social issues/area boys, original land owners

The impact of the 8 risks was summarized by a piechart in Figure 4.4. Three risks are recognizable as having the most impact on the sampled projects. The three risks are R4-CLS, R5-CND and R3-CLV; they accounted for 33%, 21% and 19% of all risk impact on the projects. Two of the risks, R4-CLS and R3-CLV are associated with the clients of the projects. This meant that risks arising from the actions of the project clients made up 52% of all recorded risk impacts. This value is less than the 73.7% obtained by Perrenoud *et al.* (2016).

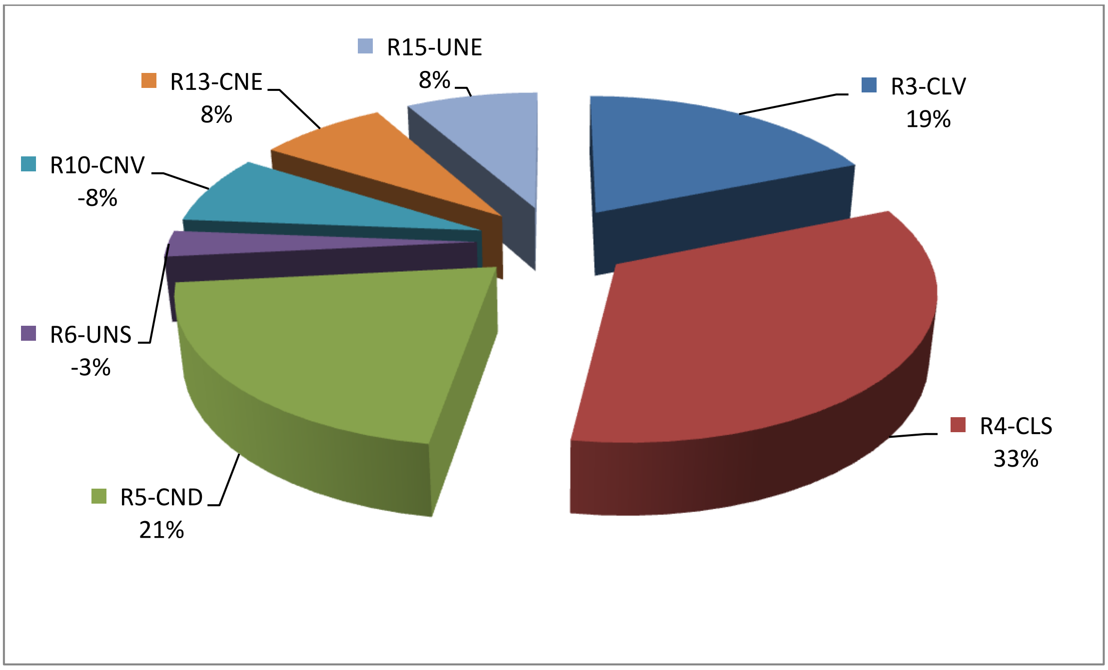


Figure 4.4: Impact of risks on project costs

The risks that had the most impact on costs in this study were found to be scope and design risks, which accounted for 33% and 21% of all cost impacts due to risks respectively. This finding was similar but lower than that of Perrenoud *et al.* (2016), where scope and design risks made up 63% and 10% of total cost impact due to risks. Economic risk such as inflation (coded as R15-UNE and accounting for 8% of cost impacts in this study) had been found by Chileshe and Yirenkyi-Fianko (2011) as 1 of the 5 risks with the most impact on project costs in their study.

4.6 Results of Data Analysis for Objective 4:

Development of Artificial Neural Network for Prediction of Cost Variance of Building Projects (ANN1)

This section deals with the first part of the fourth objective of the study, which was to develop an artificial neural network capable of predicting the effect of risk on the final cost of building projects. Apart from differences in the source and type of the input data, the procedure employed in developing the ANN closely followed the procedures described in the literature on risk modelling using ANN, for example in Odeyinka *et al.* (2013) and Odeyinka *et al.* (2012).

4.6.1 Optimal validation results for ANN1

In this subsection the comparison of validation results across the five training cycles was undertaken. The best validation results from each training cycle are presented in Table 4.12 and Figure 4.5. It was apparent from the results that min-max minimization technique produced the lowest error levels.

Table 4.12: Performance statistics for the best performing networks

S/No	Normalization type	Number of trial runs	Neurons in hidden layer	Network architecture	MSE	SSE	SAE	MAE
1	MIN2_1	27	21	2:21:1:1	0.0035	0.14	1.5541	0.038853
2	MIN2_2	27	13	2:13:1:1	0.0033	0.133	1.7387	0.043468
3	MIN2_3	27	7	2:7:1:1	0.0046	0.1859	1.9116	0.04779
4	**MIN2_4**	**27**	**31**	**2:31:1:1**	**0.0026**	**0.1048**	**1.4186**	**0.035465**
5	MIN2_5	27	25	2:25:1:1	0.0029	0.1169	1.6502	0.041255

Source: Author (2017)

Notes: SSE = sum of squared errors; MSE = mean squared error; SAE = sum of absolute errors; MAE = mean absolute error.

It was also observed that MIN2_4 gave the best performance outcomes of all the 4 minimization techniques during the five training cycles carried out, each comprising 27 trial runs.

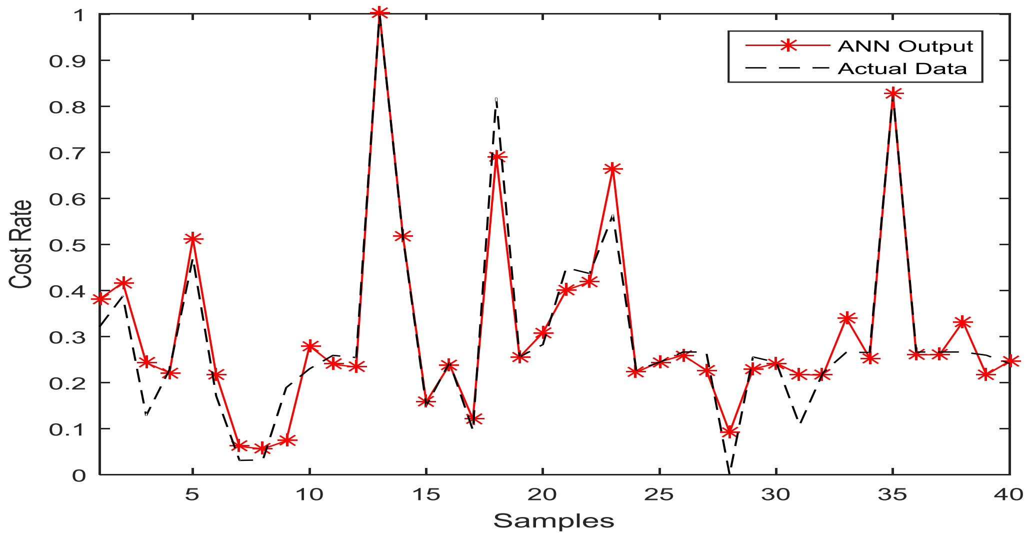


Figure 4.5: Simulated and target output of MIN2_4 network

The MSE and MAE of MIN2_4 network was the lowest of the 540 runs carried out; MIN2_4 also had the highest number of neurons in the first hidden layer. All of the performance indices values were given in normalized values. Performance outcomes for artificial neural networks vary widely; for example, Palaneeswaran *et al*. (2008) obtained a MAE value of 0.646 for the estimation of contractual claims. Jha and Chockalingam (2009) obtained MAPD of 8.044 percent and MSE of 0.958 for neural networks that modelled quality of construction works. Arafa and Alqedra (2011) reported a training MSE of 0.0014 for early stage cost estimates. These studies did not contain any indications as to whether the values of the performance indices provided were computed from normalized data.

The best performance network developed in this study was visually represented in Figure 4.6; for purposes of clarity and a lack of sufficient space, the entire 31 neurons of the first hidden layer were not represented. Only the first and last three neurons were provided, and this has support in the literature, for example Odeyinka *et al*. (2013).

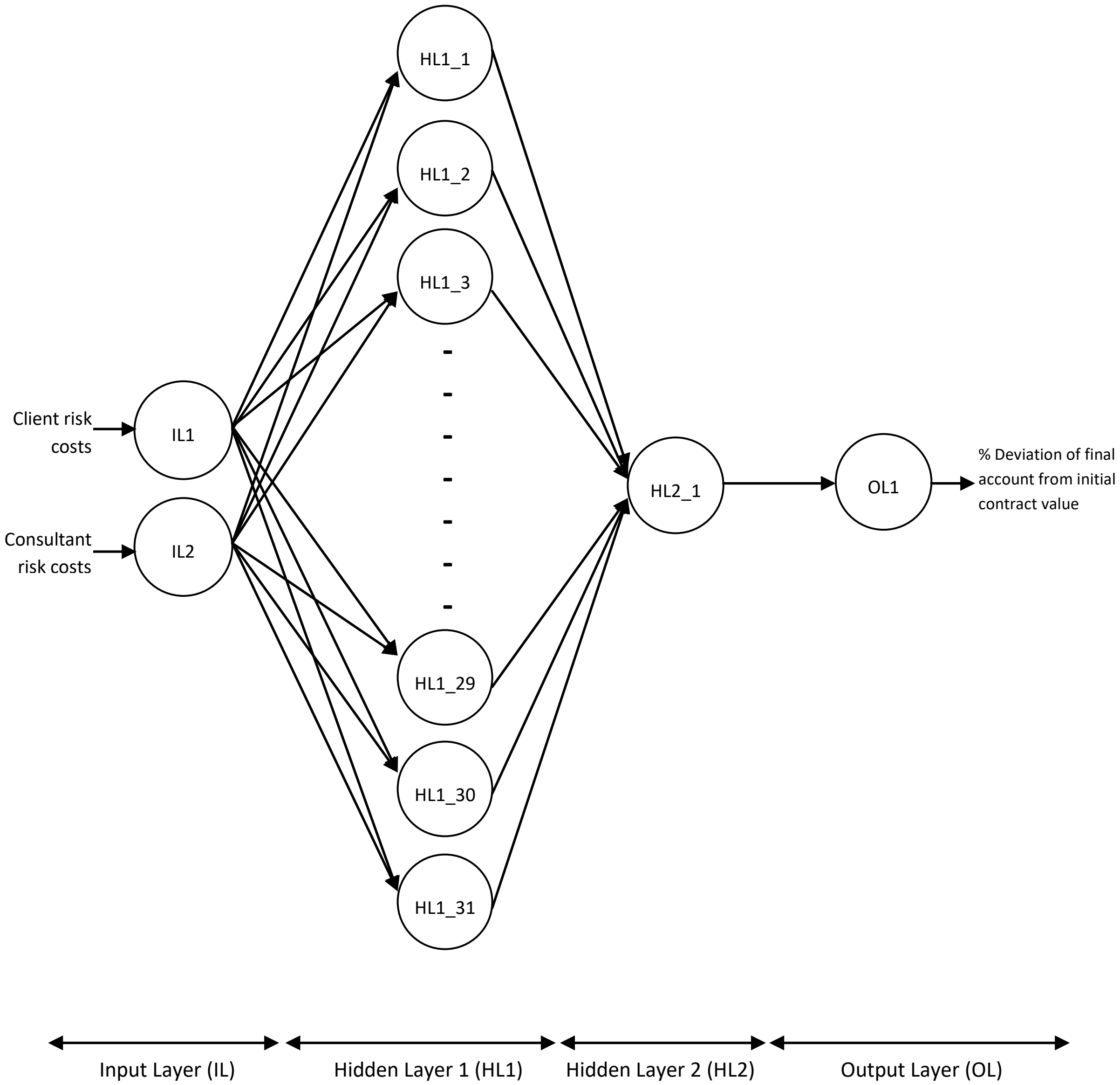


Figure 4.6: Visual representation of *2:31:1:1* developed network for (ANN1)

4.6.2 Multiple linear regression model

This study utilized the *Enter* procedure for variable selection in which all variables in a block are entered in a single step. This was advisable for two reasons; one, there were only two independent variables to be used in developing the regression model; two, the significance values in a linear regression output are based on fitting a single model. This means that significance values are generally invalid when a stepwise method is applied. Nevertheless, all of the variables to be included in the model had to pass the tolerance criterion to be entered in the equation, regardless of the entry method specified. The default tolerance level was 0.0001, and a variable is not entered if it would cause the tolerance of another variable already in the model to drop below the tolerance criterion. None of these situations were encountered during the regression model development carried out.

The change in the R^2 statistic that is produced by adding or deleting an independent variable was observed to be the same as the R^2 value itself. Generally, if the R^2 change associated with a variable (or group of variables) is large, that means that the variable is a good predictor of the dependent variable. Therefore, from the very large change associated with the removal of the independent variables, it was apparent that the two groups of risks were good predictors of the percentage deviation of the final contract value from the initial contract value.

The coefficients of the regression model were extracted from the statistical output and are presented in Table 4.13. The default linear regression model assumes that there is a linear, or "straight line," relationship between the dependent variable and each predictor, as shown in Equation 4.1.

Table 4.13: Multiple linear regression analysis results

x	*y*	*df*	*df*	*F*	$F_{0.05}$	*r*	*r2*	*P*	Remark
Consultant risks, Client risks	Final cost variance	2	31	43.761	3.32	0.859	0.738	0.000	Significant; good prediction ability

Source: Author (2017)

This relationship is described in the following formula.

yi = b0 + b1xi1 + ... + bpxip + ei ……..*Equation 4.1*

where

yi is the value of the i^{th} *case of the dependent scale variable*

p is the number of predictors

bj is the value of the j^{th} *coefficient, j=0,...,p*

xij is the value of the i^{th} *case of the* j^{th} *predictor*

ei is the error in the observed value for the i^{th} *case*

The derived regression model is provided as Equation 4.2; it showed that the percentage deviation of the final contract value from the initial contract value would always be negative (indicative of savings in projects costs) whenever the effects of the two groups of risks was zero, or less than zero.

Final cost variance = -4.834 + 1.056Consultant risks + 1.058Client risks

……..*Equation 4.2*

4.6.3 Predictive accuracy of the regression model

The error in the developed multiple linear regression model was represented by the difference between the actual value of the dependent variable (y) and the estimated value of y, which was obtained from solving for y in the regression model. The main measure of the error level employed was the mean absolute percentage deviation (MAPD), which was the same as the Mean Absolute Percent Error (MAPE) has the formulae as presented in Equation 4.3.

$MAPD = \sum^{n}_{i=1} |((Actual - Predicted)/Actual/n)*100|$ ……. *Equation 4.3*

In the Mean Absolute Percent Error (MAPE) that was used to evaluate the prediction performance *actual* referred to observed data values, *predicted* referred to predicted data values, and *n* was total number of testing cases. MAPE is the most suitable indicator to measure the relative error because of the input data used for the model estimation; preprocessed data and raw data have different scales (Azadeh *et al.*, 2011).

The six projects set aside for testing were used to test the model. The model's accuracy level was found to be 72%, based on a MAPE of 28.08%; this was close to the R^2 of 73.8%. The derived MAPE was also comparable with the average absolute error of 26.8% obtained by Tu and Huang (2013) in their study of Operation and Maintenance costs of condominiums in Taiwan. The results of the model testing were presented in Table 4.14.

Table 4.14: Test results of the regression model

S/No	Project Nr	Project type	CLT	CNT	FCV - ICV	Year	Const (b0)	b1	x1	b2	x2	Predicted y	Actual y	error	SSE	MSE	MAPE	SAE	MAE
1	A04	Multi-storey	4.06	3.33	6.83	2013	-4.834	1.056	4.06	1.058	3.33	2.98	6.83	3.85	14.82	14.82	56.38	3.85	3.85
2	A05	Multi-storey	6.14	0.14	5.40	2014	-4.834	1.056	6.14	1.058	0.14	1.80	5.40	3.60	12.95	12.95	66.68	3.60	3.60
3	A08	Multi-storey	-3.40	-4.54	-10.57	2012	-4.834	1.056	-3.40	1.058	-4.54	-13.24	-10.57	2.66	7.08	7.08	-25.17	2.66	2.66
4	B17	Single-storey	3.37	10.06	13.43	2010	-4.834	1.056	3.37	1.058	10.06	9.36	13.43	4.06	16.50	16.50	30.26	4.06	4.06
5	B21	Single-storey	24.69	2.35	27.04	2010	-4.834	1.056	24.69	1.058	2.35	23.73	27.04	3.32	10.99	10.99	12.26	3.32	3.32
6	B33	Single-storey	3.29	-1.58	0.00	2014	-4.834	1.056	3.29	1.058	-1.58	-3.04	0.00	3.04	9.23	9.23		3.04	3.04
															71.57	**10.22**	**28.08**	**20.52**	**2.93**

Source: Author (2017)

Notes: CLT = Client risks; CNT = Consultant risks; FCV-ICV = Final cost variance; b0 = constant; b1 = coefficient of x1; b2 = coefficient of x2; x1 = 1st independent variable (CLT); x2 = 2nd independent variable (CNT); y = dependent variable (FCV-ICV); SSE = sum of squared errors; MSE = mean squared error; MAPE = mean absolute percent error; SAE = sum of absolute errors; MAE = mean absolute error.

4.6.4 Comparison of predictive accuracy of artificial neural network and multiple linear regression

It is always difficult comparing different techniques in terms of their performance in a selected aspect. There is the danger that such comparison might turn out to be a case of comparing apples with oranges. However, an abundance of literature evidence was found that proved that comparisons of statistical regression and artificial neural network techniques have become almost standard procedures (Wang and Gibson, 2010; Gunduz *et al.*, 2011; Yeh and Deng, 2012; Gulcicek *et al.*, 2013; Tu and Huang, 2013). Where a suitable performance measure has been identified and computed, comparison can be successfully undertaken. Suitable performance measures found to have been used in literature include R^2, RMSE, MSE, MAE and percentage error (PE).

The results presented in Table 4.15 revealed that the ANN1 outperformed the regression model by an order of magnitude. For example, in terms of MAE, the ANN1 value was more than 100 times smaller than that of the regression model (0.0355 compared to 2.93). The MSE value for ANN1 was 0.0026, compared to the regression model, which had 10.22. These results prove conclusively that the ANN1 displayed superior performance when compared to the regression model. However, with an absolute error level of 28.08%, the regression model can be said to possess relatively adequate performance.

Table 4.15: Measures of Accuracy of MLR and ANN1 models

S/No	Model Type	SSE	MSE	MAPE	SAE	MAE	Model structure
1	Regression	71.57	10.22	28.08	20.52	2.93	*FCV-ICV = -4.834 + 1.056Consultant Risks + 1.058Client Risks*
2	ANN1	0.105	0.0026		1.419	0.0355	*2 : 31 : 1 : 1*

Source: Author (2017)

Notes: MLR = multiple linear regression; SSE = sum of squared errors; MSE = mean squared error; MAPE = mean absolute percent error; SAE = sum of absolute errors; MAE = mean absolute error; FCV-ICV = Cost deviation.

To provide some context from the literature to the results presented in this study, Wang and Gibson (2010) in their research into preproject planning reported R (coefficient of correlation) for ANN (0.75) as against that of the simple linear regression model (0.475). When identified outliers were excluded, the RMSE for the ANN model (0.081) was better than that of the simple linear regression model (0.086). Gulcicek *et al.,* (2013) obtained MSE values of 0.02210 for multiple regression and 0.00524 for ANN. Their research focused on cost assessment of construction projects using neural networks; they found that in terms of prediction power, ANNs yield a high performance and are frequently employed in engineering problems (Berlin *et al*., 2009; Gunduz *et al*., 2011; Yeh and Deng, 2012).

Tu and Huang (2013) revealed that ANN model outperformed regression model in predicting the operation and maintenance (O&M) costs of condominium properties. The O&M costs predicted by the ANN model had an average absolute error of 7.2%, compared to the regression model's 26.8%. They concluded that the ANN model was a more accurate and reliable cost prediction model as compared with the regression model. Le-Hoai *et al*. (2013) reported that their regression model had MAPE value of

2.30% and RMSE of 0.03. For the ANN model, the RMSE value was 0.024 while MAPE value was 8.96% for the testing sample. This study joined the aforementioned studies in finding that ANN models outperformed regression models when applied to the prediction of the values of variables.

4.7 Results of Data Analysis for Objective 4: Development of Artificial Neural Network for Prediction of Risk Effect in Cost of Building Projects (ANN2)

This section dealt with the second approach (ANN2) used to achieve the fourth objective of the study, which was to develop an artificial neural network for predicting the effect of risks on final project costs through the use of construction project features as network inputs.

4.7.1 Selection of threshold (cutoff point) and activation function for ANN2

The determination of the optimum threshold and activation function were carried out concurrently. Activation functions are the parts of a neural network that link the weighted sums of nodes in a layer to the values of nodes in the succeeding layer. The developed network was simulated with the test data, then a range of thresholds with an incremental step of 0.1 were applied to the simulation output. The output data was subjected to thresholds 0.1 up to 1.0. To aid comparison of performance amongst the thresholds, five (5) measures of performance were computed, using the 2 x 2 contingency table approach as presented in Table 3.15 of Chapter 3.

Line charts of 4 performance metrics (accuracy, precision, sensitivity and specificity) were plotted in Microsoft Excel. A receiver operating characteristics (ROC) chart was also plotted and used to decide on which threshold and activation function provided optimum performance in predicting the effect of risk on final costs of building project. From the literature on neural network development for use in the construction industry, different activation functions have been applied in different studies. In their study of construction costs of water treatment plants, Marzouk and Elkadi (2016) employed the hyperbolic tangent activation function for hidden layers and the identity function for the output layer. The hyperbolic tangent activation function that they employed takes real values and transforms them to the range (-1, 1), while the identity function acts as *purelin* in MATLAB by taking real values and returning them unchanged (IBM Corporation, 2011). In the case of the impact of risks on construction costs, Odeyinka *et al*. (2013) employed the sigmoid transfer function for the nodes in the hidden layer. This was also adopted by Jha and Chockalingham (2009) in their modeling of quality on construction projects.

From the results presented in Figure 4.7 to Figure 4.10, Tansig activation function was adjudged to be the best performing transfer function amongst the 3 that were tested. It had the highest accuracy level at 0.7 in Figure 4.7; the precision level of Tansig was also the highest in Figure 4.8, with a value of 0.857. All the three activation functions had the same level of sensitivity (0.75, in Figure 4.9), but Tansig was found to do better with respect to the specificity of the network, as presented in Figure 4.10 where Tansig had a value of 0.5. In terms of threshold, it was found that from threshold 0.2 to 0.9, the performance metrics obtained were similar. In particular there were no changes in the values of true positive rate and false positive rate when the following thresholds were applied – 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8 and 0.9. Faced with this situation, 0.3 was selected arbitrarily as the working threshold.

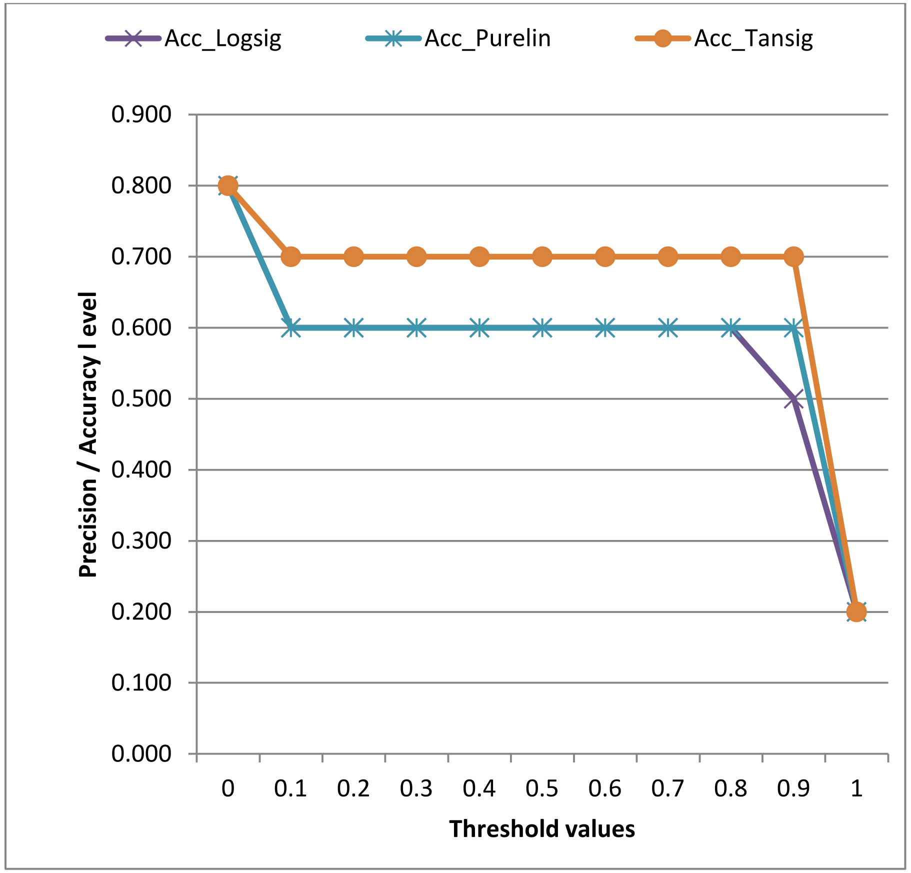


Fig. 4.7: Effect of threshold on accuracy of network

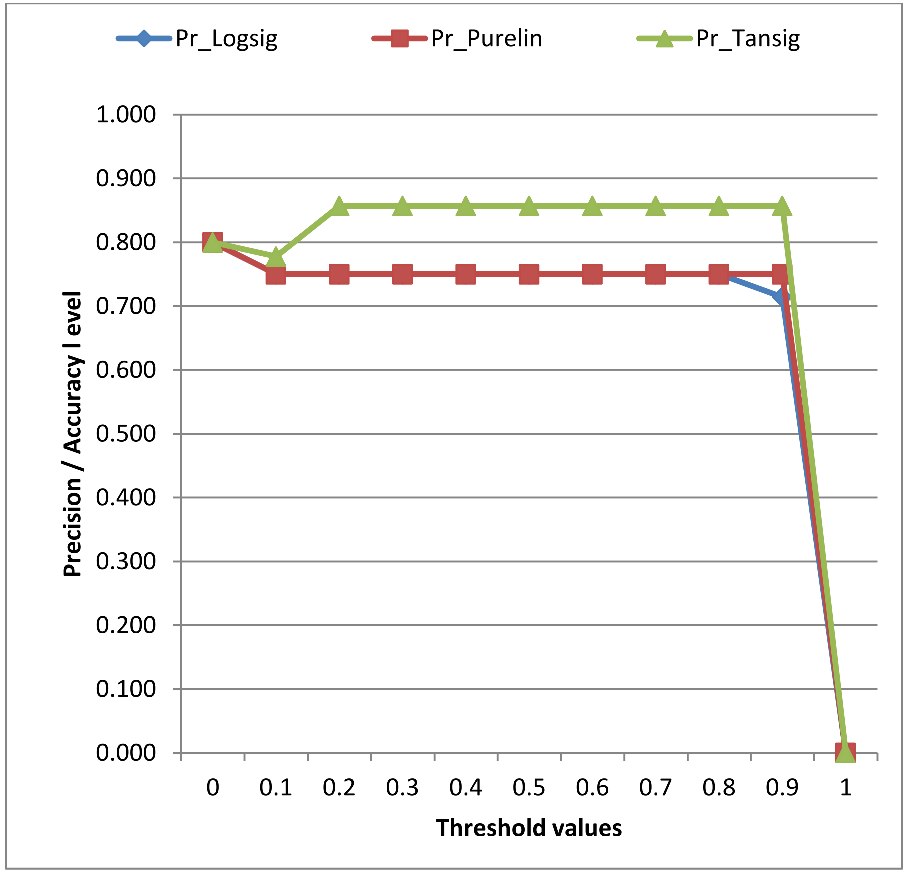


Fig. 4.8: Effect of threshold on precision of network

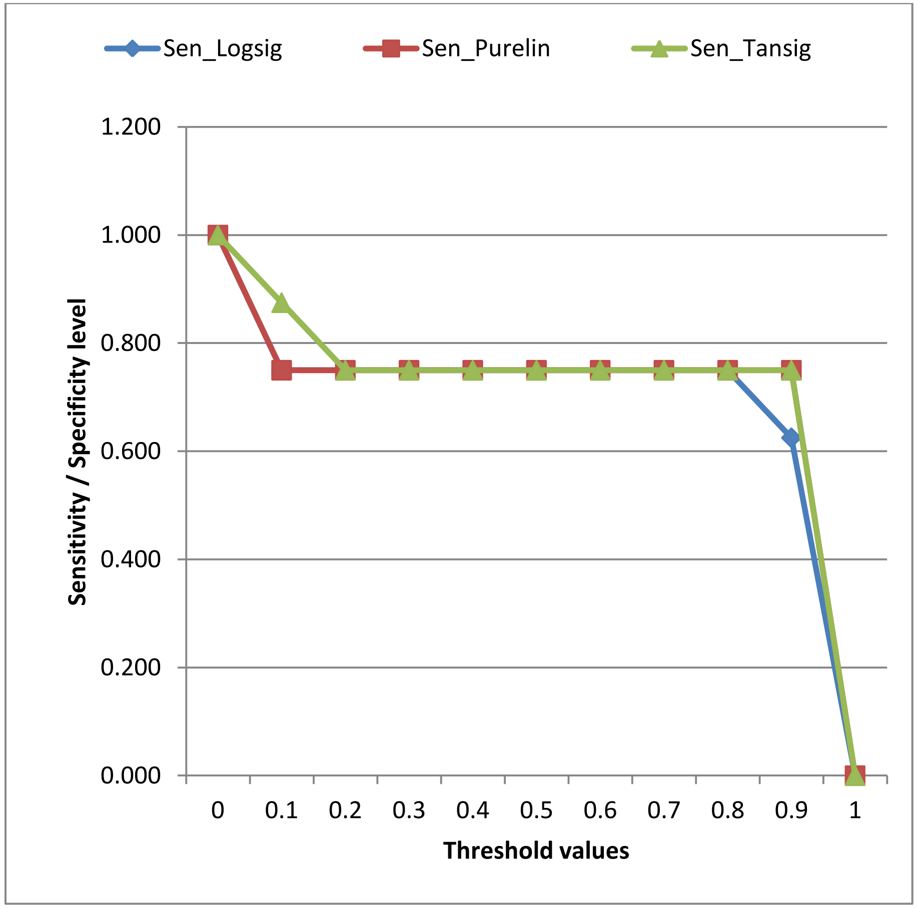


Fig. 4.9: Effect of threshold on sensitivity of network

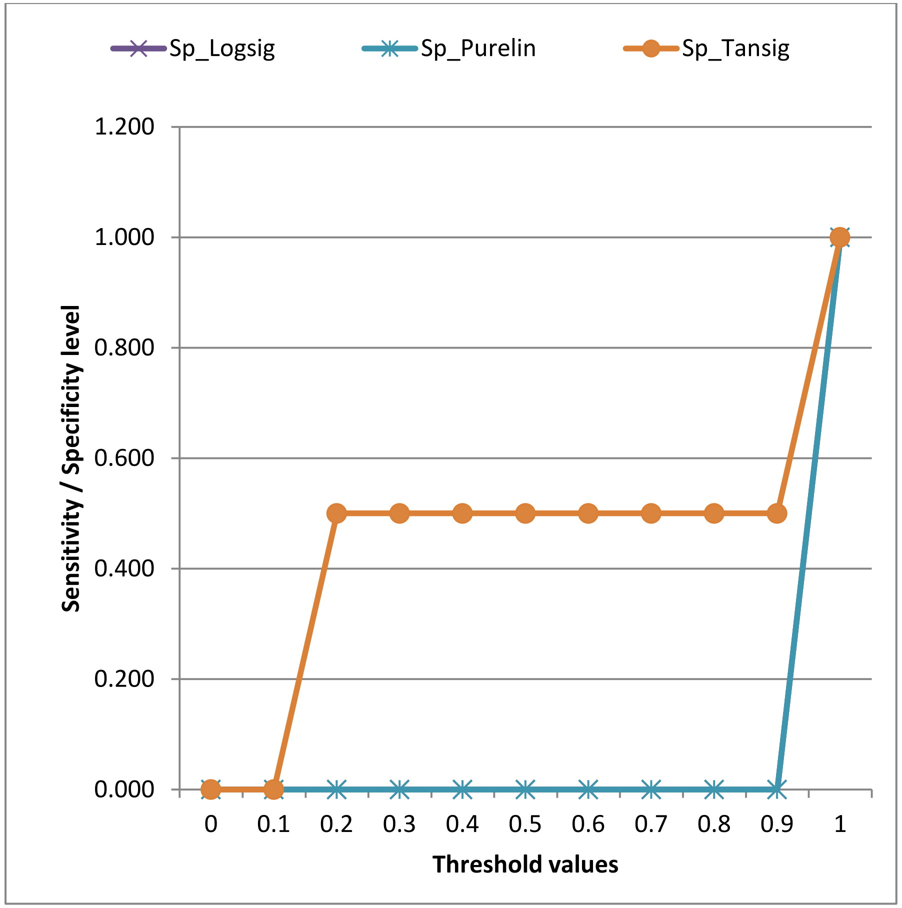


Fig. 4.10: Effect of threshold on specificity of network

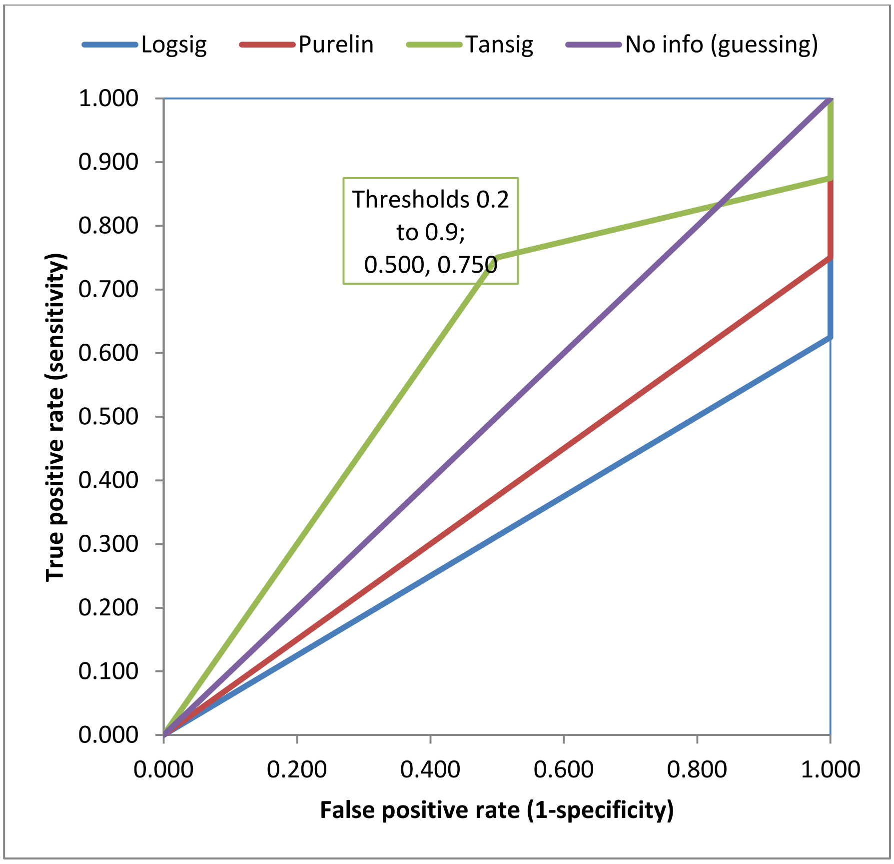


Fig. 4.11: ROC chart of prediction performance of different activation functions

4.7.2 Number of neurons for ANN2

Neurons are the processing elements of a neural network (the nodes in input, hidden and output layers). Experimentation was applied in the determination of the optimum number of neurons to be used in the network being developed for ANN2. Thirty-eight (38) networks were developed; the first network had 2 neurons, and number of neurons in each succeeding network was increased by one. Tansig activation function and a threshold of 0.3 were applied in the design and simulation of the networks. All of the networks were simulated with the test data, and then simulation output was used to compute the five (5) performance metrics presented in Table 3.15 of Chapter Three. A receiver operating characteristics (ROC) chart was also plotted and used to decide on which number of neurons provided optimum performance in predicting the effect of risk on final costs of building project. In order to conclusively show which threshold would aid optimum performance of the network, some further works were carried out as follows. The computation of performance metrics was repeated, using two more thresholds – 0.5 and 0.7. ROC charts were also plotted using the data thus generated.

From the results presented in Figure 4.12 to Figure 4.15, the neural network that had 19 neurons was adjudged to be the best performing network amongst the 38 that were tested. It was also found that thresholds 0.3 and 0.5 provided results that were similar, indeed almost identical (see Figure 4.13 and Figure 4.14). In particular there was no change in the values of true positive rate and false positive rate for the selected network with when 19 neurons when thresholds 0.3 and 0.5 were applied. It was decided to retain 0.3 as the final working threshold. The ROC chart confirmed that the choice of 19 neurons for the network was best; the developed network would correctly predict the occurrence of risk 7 times out of 10, without raising a false alarm at any time (0 times out of 10).

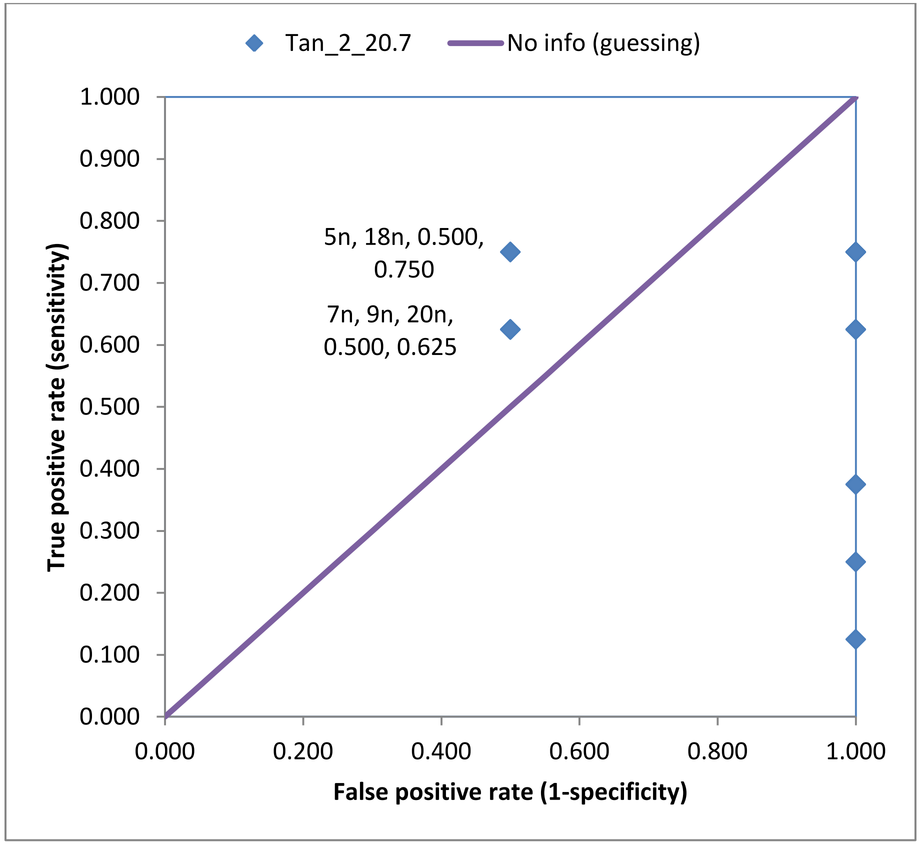


Fig. 4.12: ROC chart of performance of networks having between 2 and 20 neurons using 0.7 as threshold

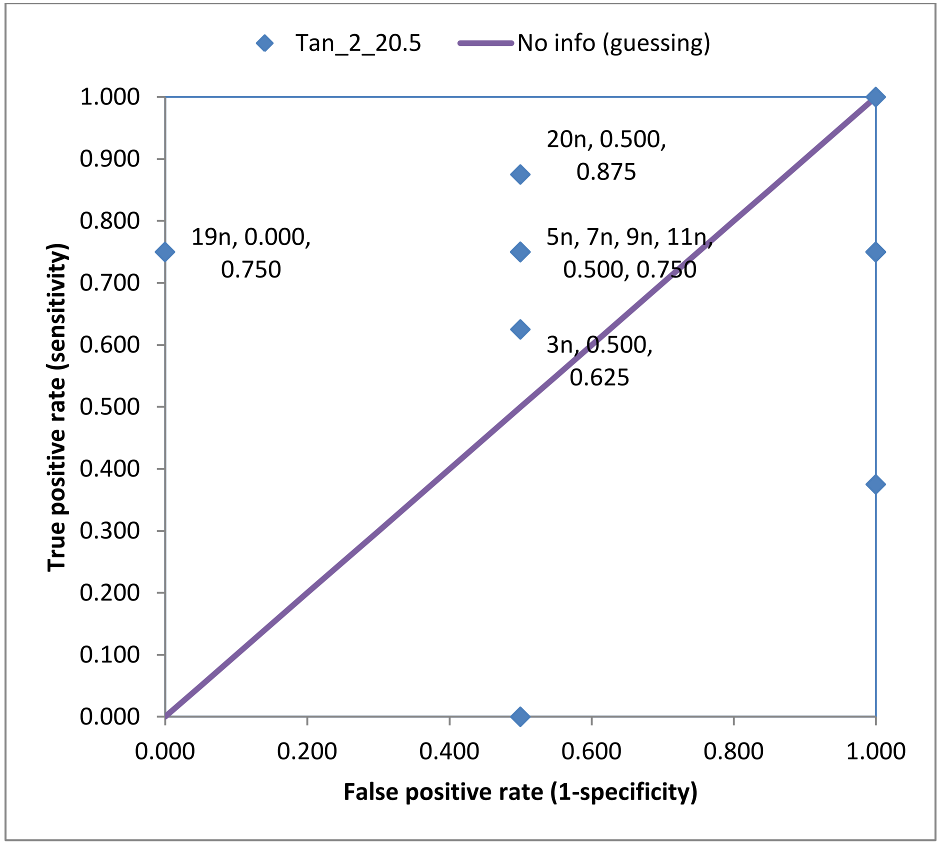
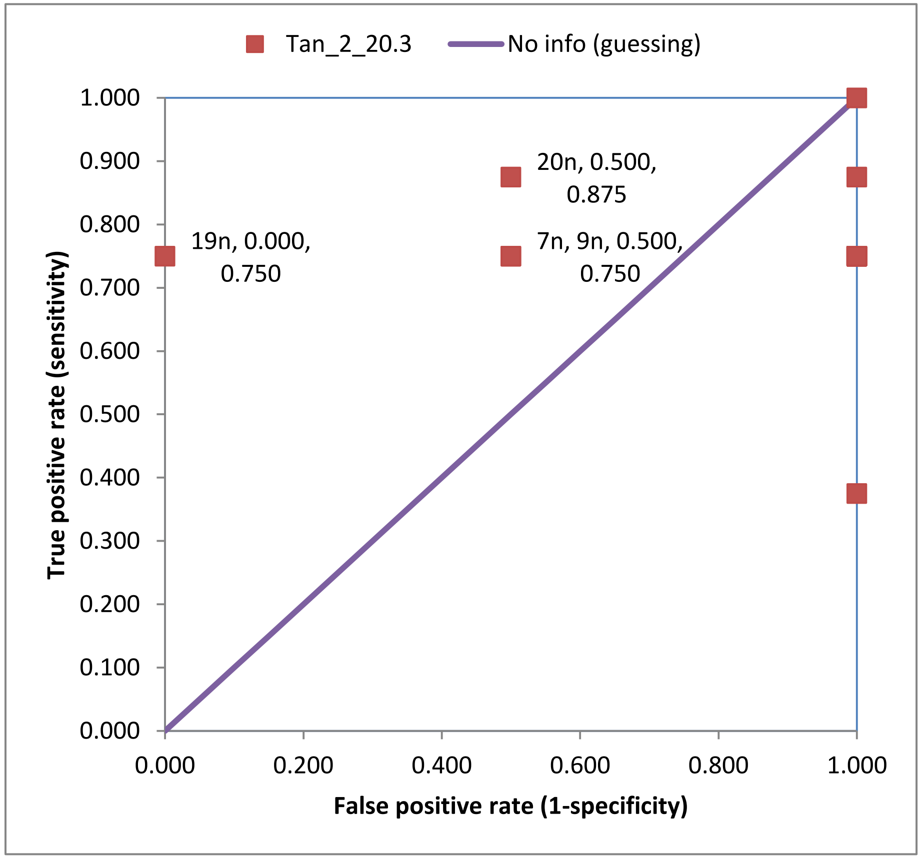


Fig. 4.13: ROC chart of performance of networks having between 2 and 20 neurons using 0.5 as threshold



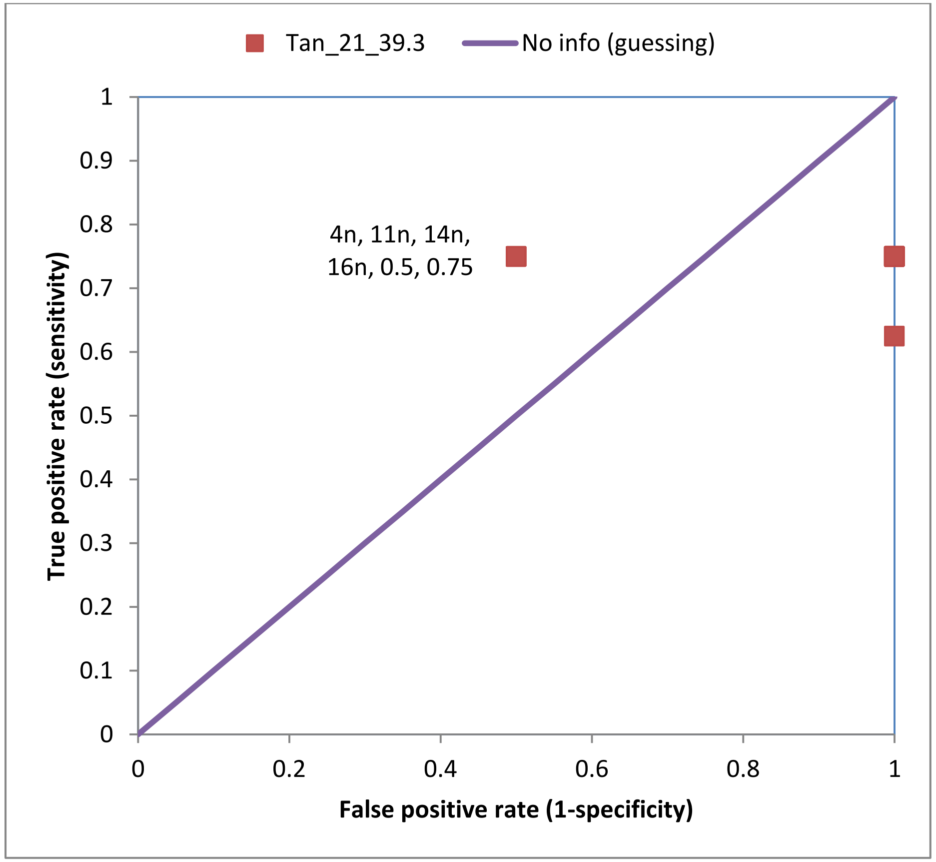


Fig. 4.14: ROC chart of performance of networks having between 2 and 20 neurons using 0.3 as threshold

Fig. 4.15: ROC chart of performance of networks having between 21 and 39 neurons using 0.3 as threshold

4.7.3 Number of network input features for ANN2

The determination of the optimum number of input features to be used in the network was carried out by trial and error experimentation. The networks in this study were initially created using 8 inputs. The process of experimentation involved creating 8 new networks; each network was however developed with only 7 inputs. A different input had been removed from each network. Tansig activation function and a threshold of 0.3 were applied in the design and simulation of the networks. All of the networks were simulated with the test data, and then simulation output was used to compute the five (5) performance metrics presented in Table 3.15 of Chapter Three. A receiver operating characteristics (ROC) chart was also plotted and used to decide on which network provided optimum performance in predicting the effect of risk on final costs of building project.

From the results presented in Figure 4.17 and Figure 4.18, the 2 neural networks from which inputs 3 and 5 had been removed were found to provide the most accurate prediction results. This observation was confirmed by perusal of the ROC chart, which revealed that networks developed separately without input 3 and input 5 would be able to correctly predict the occurrence of risk 9 times out of 10. However, these networks would also raise a false alarm 5 time out of 10 about the occurrence of risk, when in fact no risk event had happened. It was decided to retain the use of all 8 inputs, since better prediction performance had been obtained in that way.

The network developed in this study was visually represented in Figure 4.16. The entire 19 neurons of the hidden layer were presented.

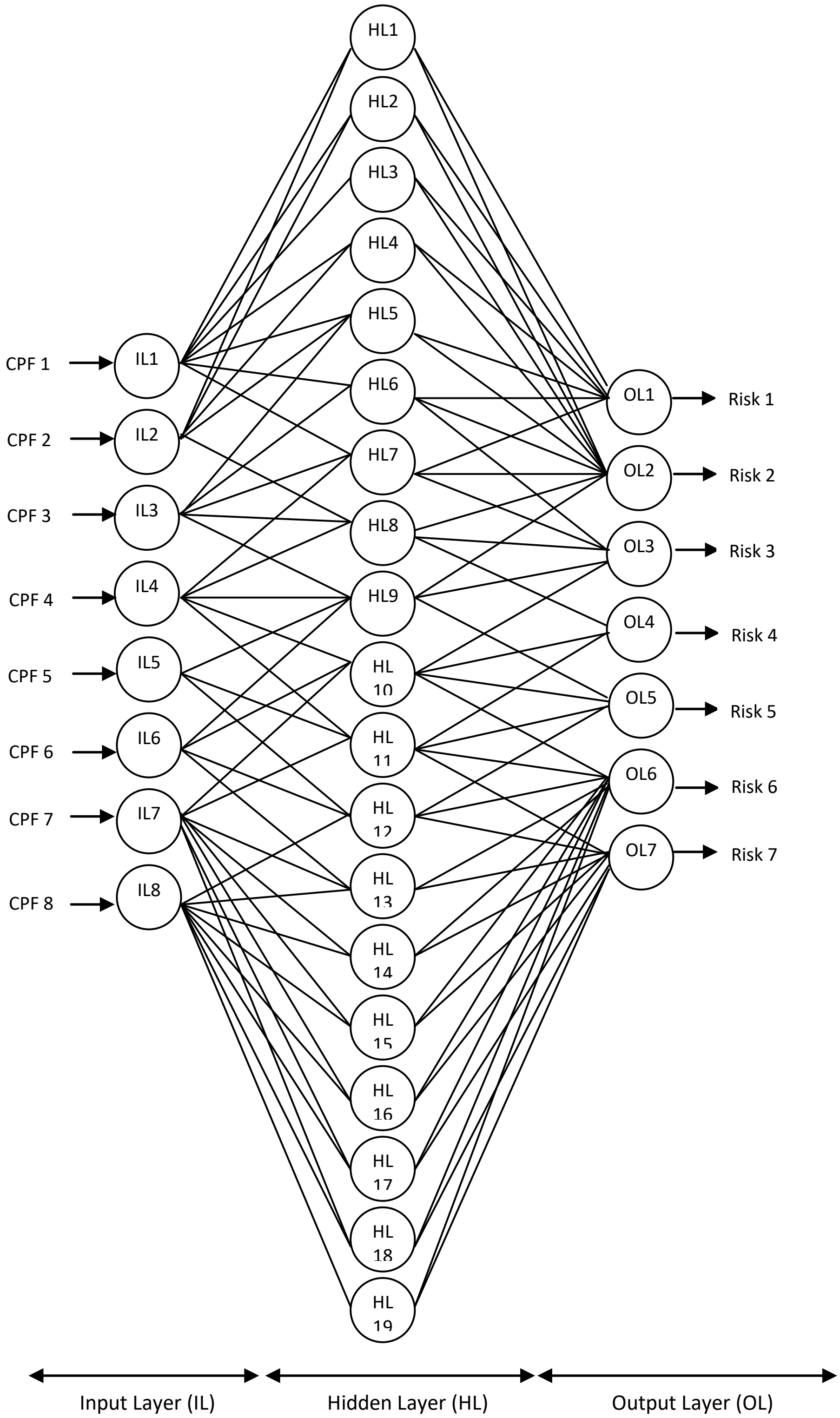


Figure 4.16: Visual representation of the developed *8:19:7* neural network

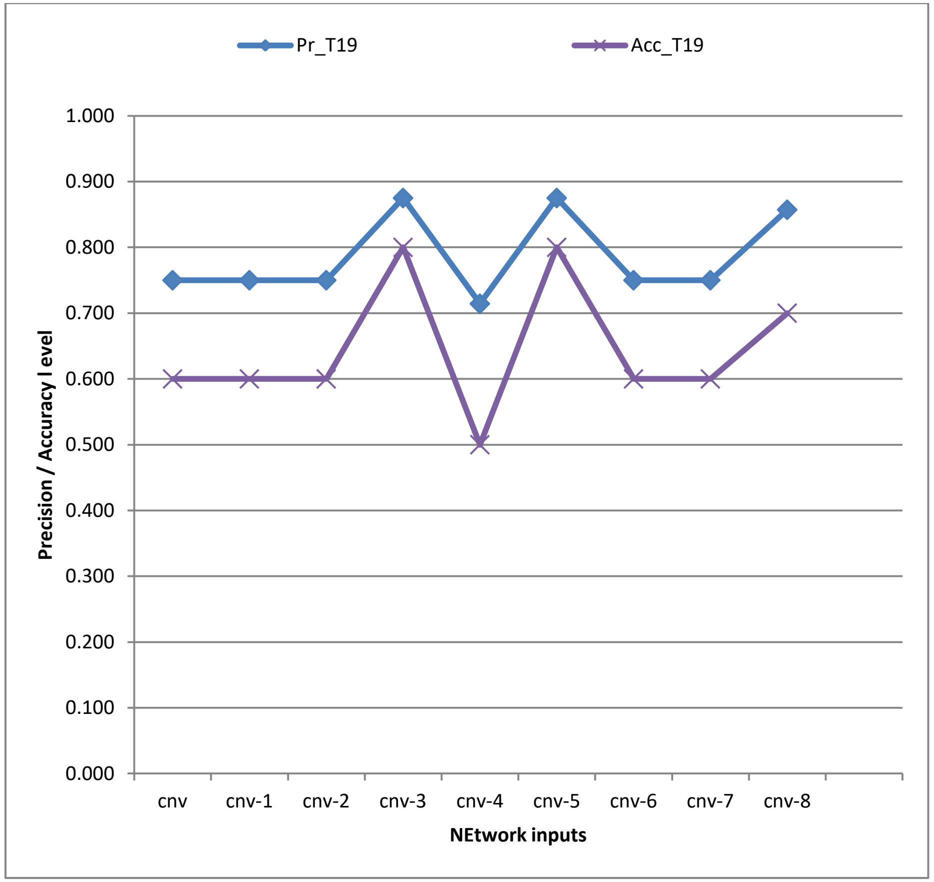


Fig. 4.17: Effect of input feature reduction on precision and accuracy

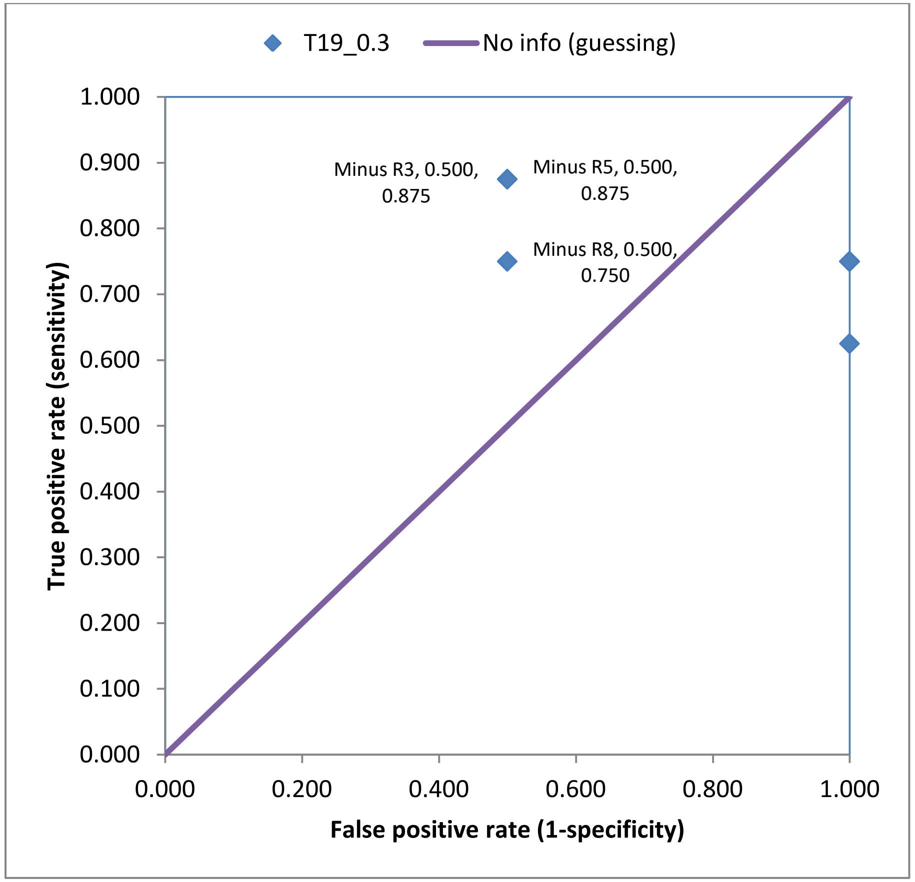


Fig. 4.18: ROC chart of performance of networks with 1 input feature removed

4.7.4 Post-processing of data for ANN2

At the beginning of the neural network development process, it was reported that the data was normalized through the process of reduction to its binary form. After the network had been developed and validated, it was necessary to post-process the data by reversing the normalization process. This would allow the data to be examined in real-life terms; appropriate statistics of real-life performance of the developed network could also be computed. This Section reported the results generated by the developed network for the prediction of risk occurrence, type and degree. The performance of the network was assessed in terms of its MAPE and MSE.

4.7.4.1 Results of ANN2 prediction of risk occurrence

The prediction results for risk occurrence were presented in Table 4.16 and Figure 4.19 to Figure 4.25. In Table 4.16 the first 10 rows represented the target of the network while the 11th to the 20th rows contained the data produced by the network during simulation. The two sets of data did not require any post processing, since they were already in binary form before normalization was done. Comparison of the simulated data with the target data was carried out, and the number of targets that were correctly predicted was entered beneath each column. The percentage of targets that were incorrectly predicted was also entered at the bottom of each column. The mean squared error of each of the 7 targets of the network (the risks which impacted the project costs) was provided. The last two rows of the table contained the average MAPE and MSE for all 7 targets together.

The results revealed that Risk R13-CNE(va) was predicted at higher level of accuracy compared to the other risks. The MSE of this risk was 0.1. In the case of even the worst predicted risks, the network still performed better than mere guesswork, since 6 out of 10 instances of risk occurrence were correctly predicted. For the best-predicted risk (R13-CNE(va)), this value was 9 out of 10.

Table 4.16: ANN prediction results for risk occurrence

S/Nr	Output type	R3-CLV	R4-CLS	R5-CND	R6-UNS	R10-CNV	R13-CNE(pq)	R13-CNE(va)
1	Target output of network	1	1	0	0	1	0	0
2		0	0	0	1	1	0	1
3		0	1	0	0	0	0	0
4		1	0	1	0	1	1	0
5		0	0	0	0	0	0	0
6		0	1	0	0	0	0	0
7		0	1	0	1	1	1	0
8		0	0	1	0	1	1	0
9		0	1	0	0	1	0	0
10		1	0	0	0	0	0	0
1	Simulated output of network	0	1	1	0	1	1	1
2		0	0	0	1	1	0	1
3		0	0	0	0	0	0	0
4		0	0	1	1	1	1	0
5		0	1	0	0	1	1	0
6		0	1	0	0	0	0	0
7		1	0	0	0	1	1	0
8		0	0	0	0	1	1	0
9		1	0	0	0	1	1	0
10		1	0	0	0	1	1	0
	Correct predictions *n*	6	6	8	8	8	6	9
	Incorrect predictions %	40	40	20	20	20	40	10
	MSE of risks	0.27	0.29	0.10	0.19	0.12	0.40	0.10
	Aggregate MAPE				27.14%			
	Aggregate MSE				0.2109			

Source: Author (2017)

Notes: MAPE = mean absolute percentage error; MSE = mean squared error

Although evidence from the literature suggested that the developed network performed relatively poorly compared to results from studies such as Chaphalkar *et al*. (2015) and Husin (2017). Chaphalkar *et al*. (2015) obtained an MSE of 0.01 in their study of construction dispute claims, while Husin (2017) had a validation MSE of 0.009 for estimating the standard building unit price. However, there are other studies such as Jha and Chockalingam (2009) attempt to model the quality of construction works that obtained a MAPE of 8.044 percent and an MSE of 0.958. Furthermore, two important considerations need to be borne in mind; (i) these studies did not contain any indications as to whether the performance metrics provided were computed from normalized or denormalized data, and (ii) no studies that followed the same approach as this study were found to which the results obtained could be compared.

The target and simulated values of the 7 risks that were predicted in this study were displayed in line charts for the purpose of visual comparison of the prediction performance of the developed network. Where targets have been correctly simulated, the two lines (red and blue) in the charts will have no spaces between them, forming almost a single line. Incorrect simulation will be identified as wide spaces between the two lines; the spaces represented the error between the target and simulated values.

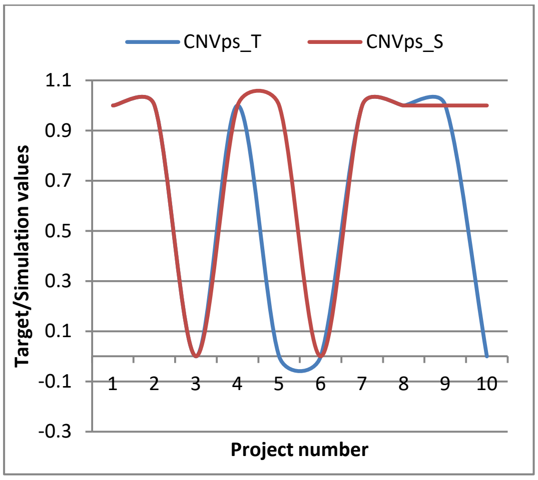


Figure 4.19: Simulation results for occurrence of R10-CNV

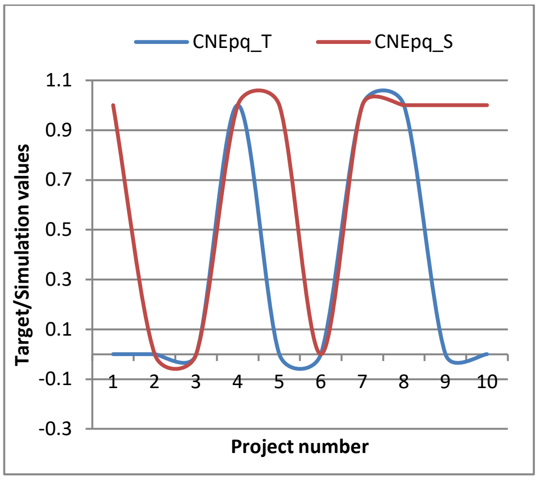


Figure 4.20: Simulation results for occurrence of R13-CNE(pq)

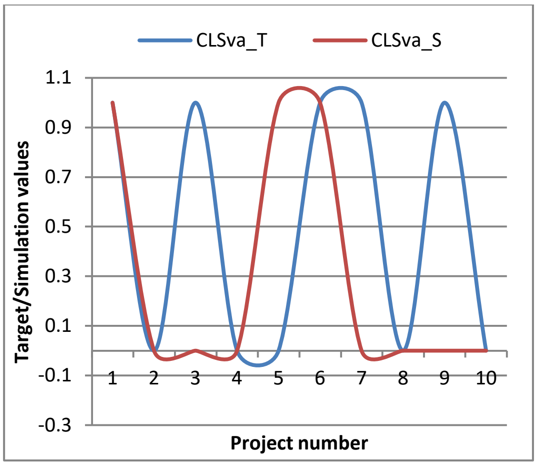


Figure 4.21: Simulation results for occurrence of R4-CLS

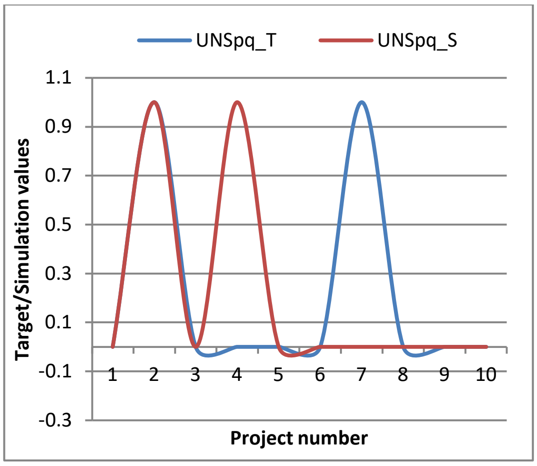


Figure 4.22: Simulation results for occurrence of R6-UNS

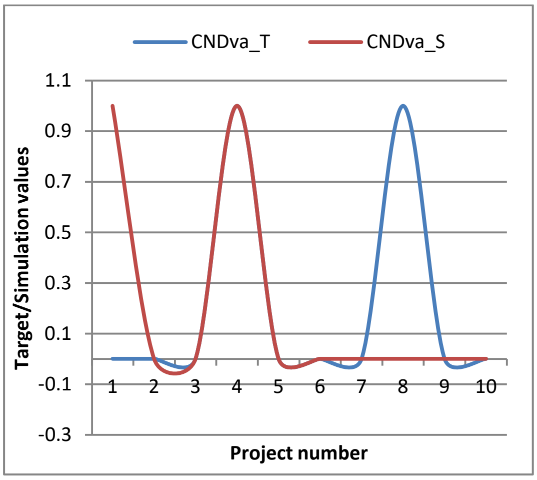


Figure 4.23: Simulation results for occurrence of R5-CND

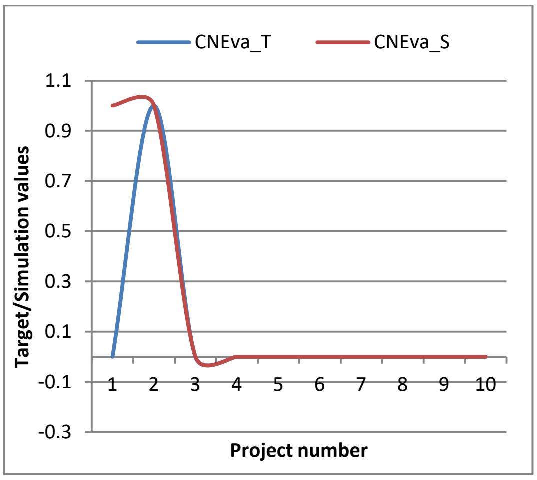


Figure 4.24: Simulation results for occurrence of R13-CNE(va)

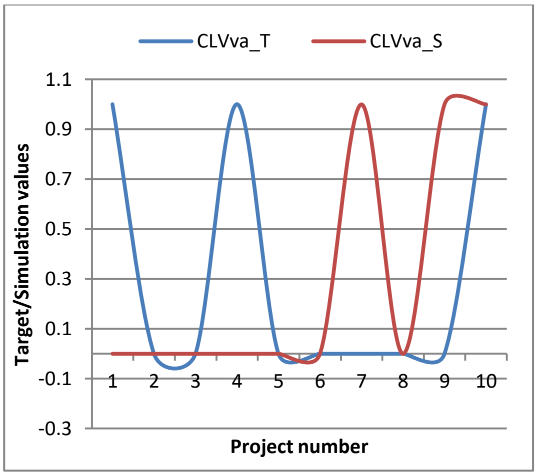


Figure 4.25: Simulation results for occurrence of R3-CLV

4.7.4.2 Results of ANN2 prediction of type of risk

The prediction results for type of risk were presented in Table 4.17 and Table 4.18 and Figure 4.26 to Figure 4.32. In Table 4.17 the data was provided in binary coding as employed in the development of the neural network, before it was converted back to real-life representation of the type of risk as presented in Table 4.18. In both tables the first 10 rows represented the target of the network while the 11^{th} to the 20^{th} rows contained the data produced by the network during simulation.

Table 4.17: ANN risk type prediction results for (before post-processing)

S/Nr	Output type	R3-CLV	R4-CLS	R5-CND	R6-UNS	R10-CNV	R13-CNE(pq)	R13-CNE(va)
1	Target output of network	0	0	11	1	1	10	10
2		1	0	0	0	11	10	0
3		0	0	11	1	0	0	10
4		0	11	0	10	1	11	0
5		0	0	0	0	0	0	0
6		0	0	11	1	0	0	10
7		1	11	11	11	1	11	10
8		0	1	0	10	1	10	0
9		0	0	11	1	1	10	10
10		0	0	0	0	0	0	0
1	Simulated output of network	1	1	11	11	0	0	10
2		1	0	0	0	11	10	0
3		1	0	0	0	0	0	0
4		10	11	0	10	11	11	1
5		0	11	11	11	1	11	10
6		0	0	11	1	0	0	10
7		0	11	1	10	11	11	10
8		0	11	0	10	11	11	0
9		0	11	1	10	11	11	10
10		0	11	1	10	11	11	10

Source: Author (2017)

Notes: 00 = zero impact = 0; 01 = negative impact = -1; 11 = positive impact = 1.

Comparison of the simulated data with the target data was carried out, and the number of targets that were correctly predicted was entered beneath each column in Table 4.18. The percentage of targets that were incorrectly predicted was also entered at the bottom of each column. The mean squared error of each of the 7 targets of the network (the risks which impacted the project costs) was provided. The last two rows of the table contained the average MAPE and MSE for all 7 targets together. The results revealed that Risks R5-CND and R13-CNE(va) were predicted at higher level of accuracy compared to the other risks. The MSE of these 2 risks were all not higher than 0.1. For these best-predicted risks (R5-CND and R13-CNE(va)), in 9 out of 10 instances the type of risk was correctly predicted.

Table 4.18: ANN prediction results for risk type (after post-processing)

S/Nr	Output type	R3-CLV	R4-CLS	R5-CND	R6-UNS	R10-CNV	R13-CNE(pq)	R13-CNE(va)
1	Target output of network	1	1	0	0	-1	0	0
2		0	0	0	-1	1	0	1
3		0	1	0	0	0	0	0
4		1	0	1	0	-1	1	0
5		0	0	0	0	0	0	0
6		0	1	0	0	0	0	0
7		0	1	0	-1	-1	1	0
8		0	0	1	0	-1	-1	0
9		0	1	0	0	-1	0	0
10		1	0	0	0	0	0	0
1	Simulated output of network	0	1	0	-1	0	-1	1
2		0	0	0	-1	1	0	1
3		0	0	0	-1	0	0	0
4		0	0	1	0	1	1	0
5		0	1	0	0	-1	1	0
6		0	1	0	0	0	0	0
7		1	-1	0	0	1	1	0
8		0	0	0	0	1	1	0
9		1	-1	0	0	1	1	0
10		1	-1	0	0	1	1	0
	Correct predictions *n*	6	5	9	7	3	5	9
	Incorrect predictions %	40	50	10	30	70	50	10
	MSE of risks	0.28	0.33	0.1	0.1	0.35	0.34	0.09
	Aggregate MAPE				37.14%			
	Aggregate MSE				0.2284			

Source: Author (2017)

Notes: 0 = zero impact; -1 = negative impact; 1 = positive impact; MAPE = mean absolute percentage error; MSE = mean squared error

Evidence from the literature suggested that the developed network performed relatively well compared to results from studies such as Odeyinka *et al*. (2012) and

Odeyinka *et al.* (2013) which obtained MAPE values of 3.7% and 9.8%. The two best predicted risks in this study (R5-CND and R13-CNE(va)) had MAPE values of 10%. It was also important to bear in mind; the fact that no studies that predicted risk type through the use of binarization of data were found to which the results obtained could be compared.

The target and simulated values of the 7 risks that were predicted in this study were displayed in line charts for the purpose of visual comparison. Correctly simulated targets were identified where the two lines (red and blue) in the charts had no spaces between them. Incorrectly simulated targets were identified as wide spaces between the two lines, representing the error between the target and simulated values.

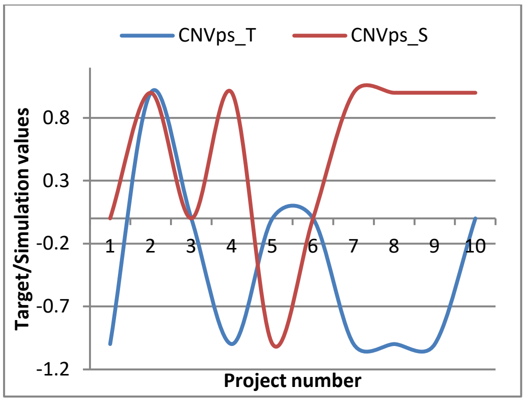


Figure 4.26: Simulation results for type of risk (R10-CNV)

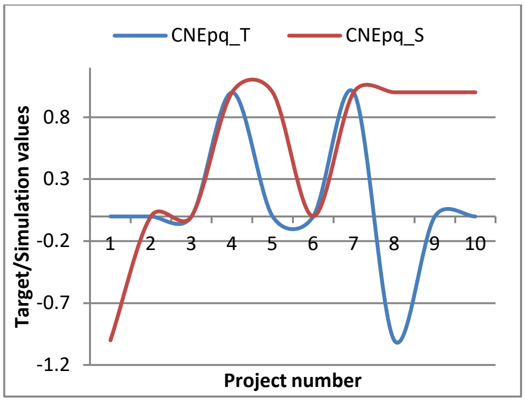


Figure 4.27: Simulation results for type of risk (R13-CNE(pq))

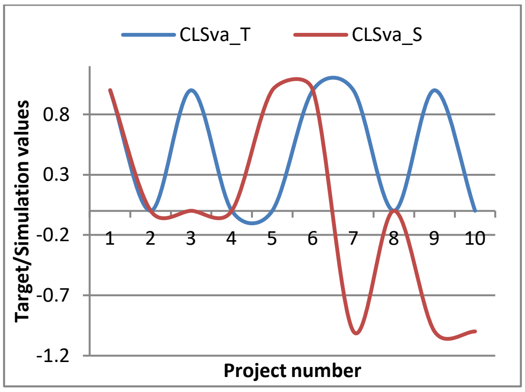


Figure 4.28: Simulation results for type of risk (R4-CLS)

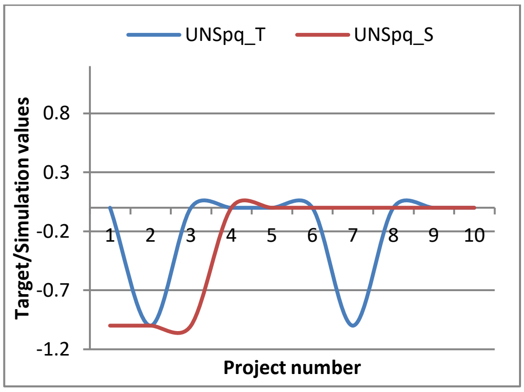


Figure 4.29: Simulation results for type of risk (R6-UNS)

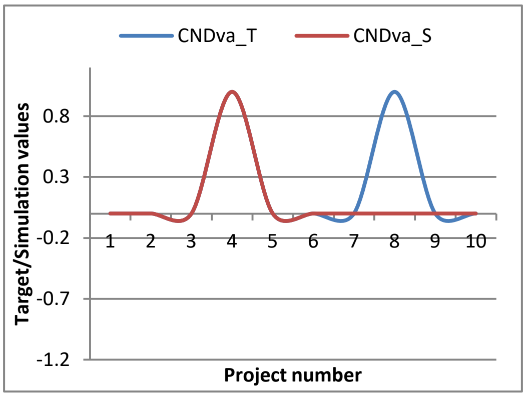


Figure 4.30: Simulation results for type of risk (R5-CND)

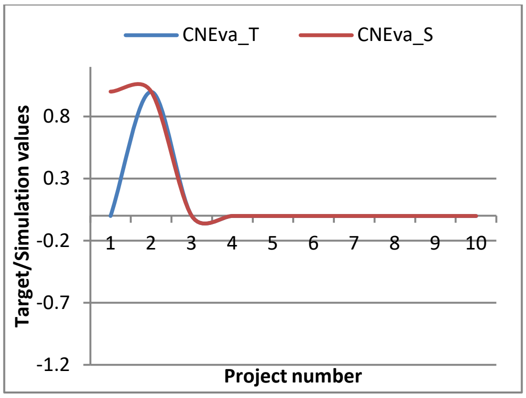


Figure 4.31: Simulation results for type of risk (R13-CNE(va))

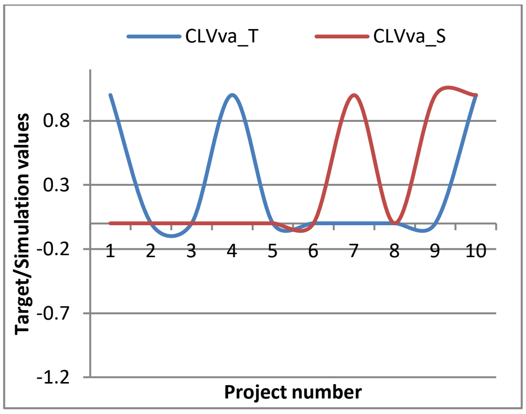


Figure 4.32: Simulation results for type of risk (R3-CLV)

4.7.4.3 Results of ANN2 prediction of degree of risk impact

The prediction results for degree of risk were presented in Table 4.19 and Table 4.20 and Figure 4.33 to Figure 4.39. In Table 4.19 the data was provided in binary coding as employed in the development of the neural network, before it was converted back to real-life representation of the degree of risk as presented in Table 4.20. In both tables the first 10 rows represented the target of the network while the 11^{th} to the 20^{th} rows contained the data produced by the network during simulation.

Table 4.19: ANN prediction results for risk degree (before post-processing)

S/Nr	Output type	R3-CLV	R4-CLS	R5-CND	R6-UNS	R10-CNV	R13-CNE(pq)	R13-CNE(va)
1	Target output of network	10	0	100	11	10	10	10
2		10	1	10	10	101	1	10
3		10	10	101	10	10	10	10
4		110	100	10	110	10	10	101
5		10	10	10	10	10	10	10
6		10	10	101	10	10	10	10
7		100	0	100	10	10	1	10
8		1	100	10	10	10	10	101
9		10	100	100	10	10	10	10
10		10	10	10	110	10	10	10
1	Simulated output of network	1	10	0	10	101	10	10
2		10	111	10	10	101	1	10
3		10	10	10	10	10	11	10
4		101	100	10	10	111	10	101
5		101	110	111	10	10	10	10
6		10	10	101	10	10	10	10
7		101	1	11	110	11	10	10
8		101	101	11	110	10	10	10
9		101	1	11	110	11	10	10
10		101	1	11	110	11	10	10

Source: Author (2017)

Notes: 000 = 1 = -22% to -11%; 001 = 2 = -11% to 0%; 010 = 3 =0% to 11%; 011 = 4 =11% to 22%; 100 = 5 =22% to 33%; 101 = 6 = 33% to 44%; 110 = 7 = 44% to 55%.

Comparison of the simulated data with the target data was carried out, and the number of targets that were correctly predicted was entered beneath each column in Table 4.20. The percentage of targets that were incorrectly predicted was also entered at the bottom of each column. The mean squared error of each of the 7 targets of the network (the risks which impacted the project costs) was provided. The last two rows of the table contained the average MAPE and MSE for all 7 targets together. The results revealed that Risks R13-CNE(pq) and R13-CNE(va) were predicted at higher level of accuracy compared to the other five risks. The MSE of these 2 risks were not higher than 0.1. For these two risks (R13-CNE(pq) and R13-CNE(va)), in at least 8 out of 10 instances of risk occurrence the degree of risk was correctly predicted.

Table 4.20: ANN prediction results for risk degree (after post-processing)

S/Nr	Output type	R3-CLV	R4-CLS	R5-CND	R6-UNS	R10-CNV	R13-CNE(pq)	R13-CNE(va)
1	Target output of network	3	1	5	4	3	3	3
2		3	2	3	3	6	2	3
3		3	3	6	3	3	3	3
4		7	5	3	7	3	3	6
5		3	3	3	3	3	3	3
6		3	3	6	3	3	3	3
7		5	1	5	3	3	2	3
8		2	5	3	3	3	3	6
9		3	5	5	3	3	3	3
10		3	3	3	7	3	3	3
1	Simulated output of network	2	3	1	3	6	3	3
2		3	7	3	3	6	2	3
3		3	3	3	3	3	4	3
4		6	5	3	3	7	3	6
5		6	7	7	3	3	3	3
6		3	3	6	3	3	3	3
7		6	2	4	7	4	3	3
8		6	6	4	7	3	3	3
9		6	2	4	7	4	3	3
10		6	2	4	7	4	3	3
	Correct predictions *n*	3	3	3	5	5	8	9
	Incorrect predictions *%*	70	70	70	50	50	20	10
	MSE of risks	0.38	0.25	0.44	0.11	0.19	0.09	0.1
	Aggregate MAPE	48.57%						
	Aggregate MSE	0.223						

Source: Author (2017)

Notes: 1 = -22% to -11%; 2 = -11% to 0%; 3 =0% to 11%; 4 =11% to 22%; =22% to 33%; 6 = 33% to 44%; 7 = 44% to 55%; MAPE = mean absolute percentage error; MSE = mean squared error.

Evidence from the literature suggested that the developed network performed relatively well compared to results from studies such as Odeyinka *et al.* (2013) which obtained MAPE values of 9.8%. The best predicted risk in this study (R13-CNE(va)) had a MAPE value of 10%. It has been pointed out earlier that no studies that predicted the degree of risk through the use of binarization of data were found to which the results obtained could be compared.

The target and simulated values of the 7 risks that were predicted in this study were displayed in line charts for the purpose of visual comparison of the prediction performance of the developed network with respect to the degree of risk. Correctly simulated targets were identified where the two lines (red and blue) in the charts had no spaces between them, forming a single line. Incorrectly simulated targets on the other hand had wide spaces between the two lines, which represented the error between the target and simulated values.

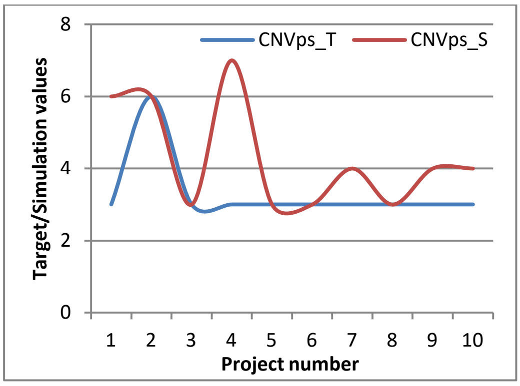


Figure 4.33: Simulation results for degree of risk (R10-CNV)

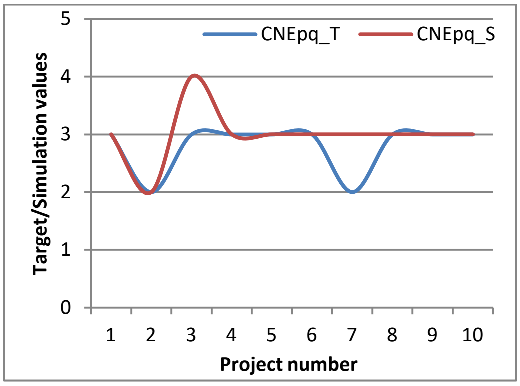


Figure 4.34: Simulation results for degree of risk (R13-CNE(pq))

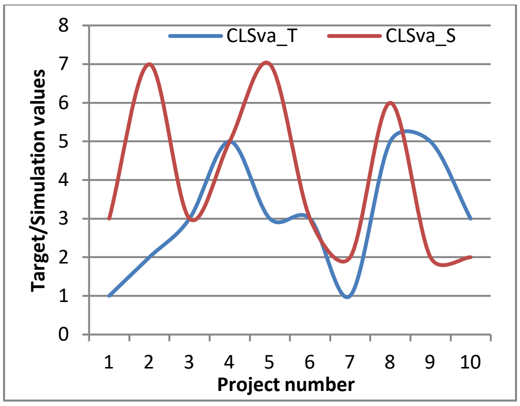


Figure 4.35: Simulation results for degree of risk (R4-CLS)

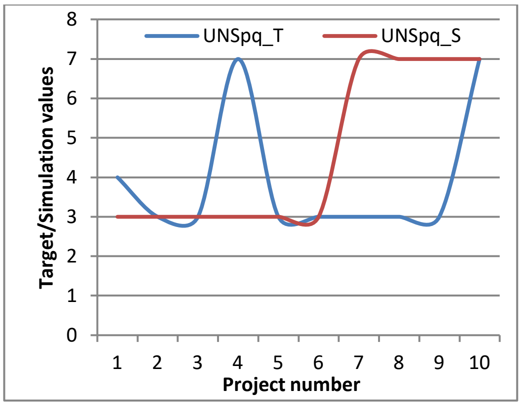


Figure 4.36: Simulation results for degree of risk (R6-UNS)

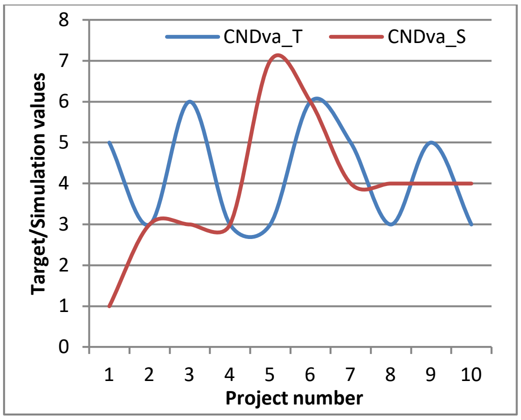


Figure 4.37: Simulation results for degree of risk (R5-CND)

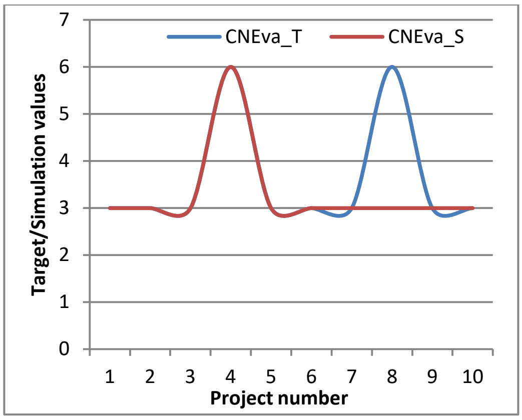


Figure 4.38: Simulation results for degree of risk (R13-CNE(va))

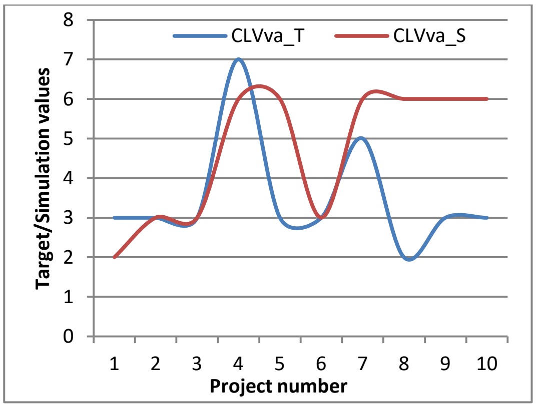


Figure 4.39: Simulation results for degree of risk (R3-CLV)

A review of relevant literature confirmed that performance outcomes of artificial neural networks developed for use in the construction industry vary widely. For example, Palaneeswaran *et al*. (2008) obtained a MAE value of 0.646 (equivalent to a MAPE of 64.6%) for their network, which estimated amount of contractual claims from 28 rework factors. Arafa and Alqedra (2011) reported a MSE of 0.0014 for the training subset of their data, which dealt with early stage cost estimates. Their study did not indicate whether this value was obtained from normalized or de-normalized data.

4.8 Results of Data Analysis for Objective 5: Performance Analysis of the Developed Artificial Neural Network (ANN2)

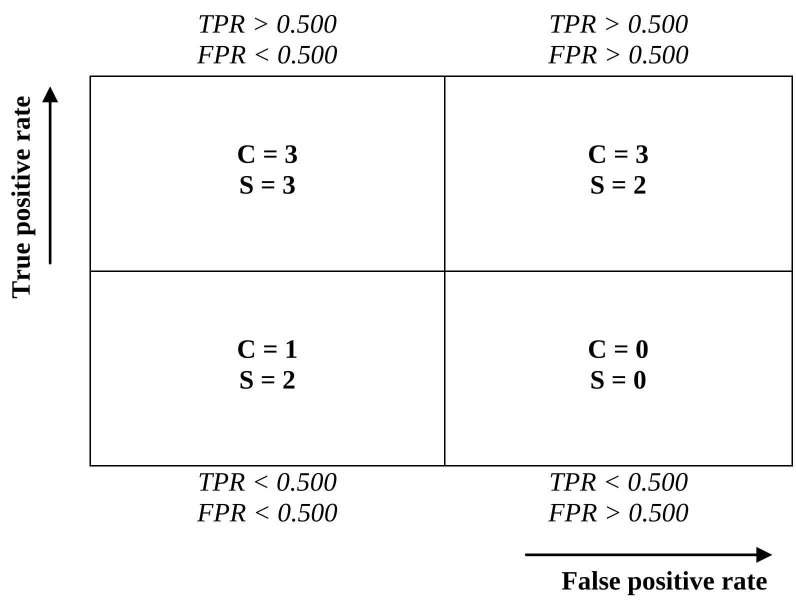
This section dealt with the fifth objective of the study, which was to undertake a performance analysis of the artificial neural network that had been developed for predicting the effect of risk on the final costs of building project based on knowledge of some selected construction project features. The main tool employed in analysis of the performance of the developed networks was the ROC chart. The performance of a measuring tool such as an artificial neural network is considered to be optimized when it meets the following two conditions. The tool is able to detect all or almost all occurrences of the parameter in which the researcher is interested; the tool does not trigger a false alarm where no occurrence was actually recorded. In this study the parameter in which the researcher is interested was the 'effect of risk on costs of building projects'.

The conditions for the optimization of a measuring tool could be expressed in another way. The ideal neural network should possess both high sensitivity and high specificity. However, in reality, these two values often have an inverse relationship (Hart, 2016), and researchers must sacrifice one measure in order to maximize the other. In the prediction of risk impact in building projects, it is better that the developed network correctly identifies when risk impact occurs (positive outcomes - sensitivity), even if it fails to identify correctly some instances where there is no risk impact (negative outcomes – specificity). This is because clients are more interested in the occurrence of risk (which might result in more money being needed to achieve their planned project). Rather than having a situation where a client is caught unawares when a risk materializes, without having made preparation for such a contingency, it is better that the developed tool puts the client on alert in time, even if it turns out to be a false alert.

4.8.1 Performance analysis of risk occurrence prediction using ANN2

The neural network that was developed was employed in two ways; it was used to predict the occurrence of all of the 7 risks, altogether in one operation (R3-CLV, R4-CLS, R5-CND, R6-UNS, R10-CNV, R13-CNE(pq), and R13-CNE(va)). This meant the network had 7 targets at one time, and the analysis of the performance of the targets thus generated together was presented in Figure 4.40. The network was also used to predict the occurrence of all of the 7 risks considered in this study, one at a time. This meant that the network had only one target at any one time and the analysis of the performance of the targets thus generated singly was presented in Figure 4.41.

Both methods of risk occurrence prediction (combined or separately) gave similar results in the case of R10-CNV, R13-CNE(pq) and R13-CNE(va). However there were significant differences in the case of R4-CLS, R6-UNS and R5-CND. When predicted in a combined manner, these three risks had high sensitivity and low specificity; for example, R6-UNS had a true positive rate of 1.0 and a false positive rate of 0.5. Separate prediction of these risks improved the results by raising the specificity of the risks, although there was a corresponding drop in their sensitivity. Using the example of R6-UNS once more, it now had a true positive rate of 0.5 and a false positive rate of 0.125. This result was considered better because while the sensitivity had been halved, the specificity had been reduced by a ratio of 4:1. The same trend was observed in the case of R3-CLV, which was to all appearances useless for prediction purposes under combined prediction of risk, since it had both true positive and false positive rates of 0.00. When R3-CLV was predicted separately however, it now had a true positive rate of 0.333 and a false positive rate of 0.286. The differences between the two approaches to prediction of risk occurrence (combination and separation) were summarized with the aid of a modified risk quadrant in Figure 4.40. The two main merits of the separation approach over the combination approach was observed to be (i) the reduction of the number of risks that had high true positive and false positive rates; (ii) the number of risks that had high true positive and low false positive rates was optimized (3 out of a total of 7 risks; these were R6-UNS, R5-CND, and R13-CNE(va)). According to Fawcett (2006), prediction results that fall wihin the upper left quadrant of the figure are preferred; any approach that maximizes the number of risks that have performance metrics located in this quadrant will thus be considered as better than other approaches.



Where:
C = combination approach; S = separation approach; TPR = true positive rate; FPR = false positive rate.

Figure 4.40: Combination and separation approaches to risk occurrence prediction

The performance of the the two approaches was also examined by direct review of the performance metrics that had been computed and used to create the ROC charts. These metrics had been presented graphically as line charts in Figure 4.43 to Figure 4.46. The first two charts, Figure 4.43 and Figure 4.44, dealt with the precision and accuracy of the networks developed through the different approaches of combination and separation. The last two charts presented the sensitivity and specificity of the networks under the two approaches of combination and separation.

It must be borne in mind that the two approaches also differed in the number of networks required for prediction. The combination approach made use of only one network; all seven risks were predicted at one and the same time by the eight input variables in an 8:19:7 network. The import of this was that the predictive power of the inputs was spread across the seven targets. This may explain why the network did not perform optimally. In thcase of the separation approach, seven different networks were employed; each had a single risk as target output and 8:19:1 as network structure. This meant that the power of eight input variables was focused on only one target, and could thus generate better predictions than the combination approach.

In Figure 4.43 the precision and accuracy of the network under combination approach was observed to exhibit an erratic pattern, with a range of 0.0 to 0.9. Comparatively, under the separation approach, the network's precision and accuracy had been forced into a narrower range of 0.3 to 0.9 in Figure 4.44. The same pattern was observed in the sensitivity and specificity of predictions; prediction fell within a wider range under the combination approach (Figure 4.45), and a narrower range under the separation approach (Figure 4.46). It was however observed that the performance metrics for Risk6 remained unchanged under both prediction approaches.

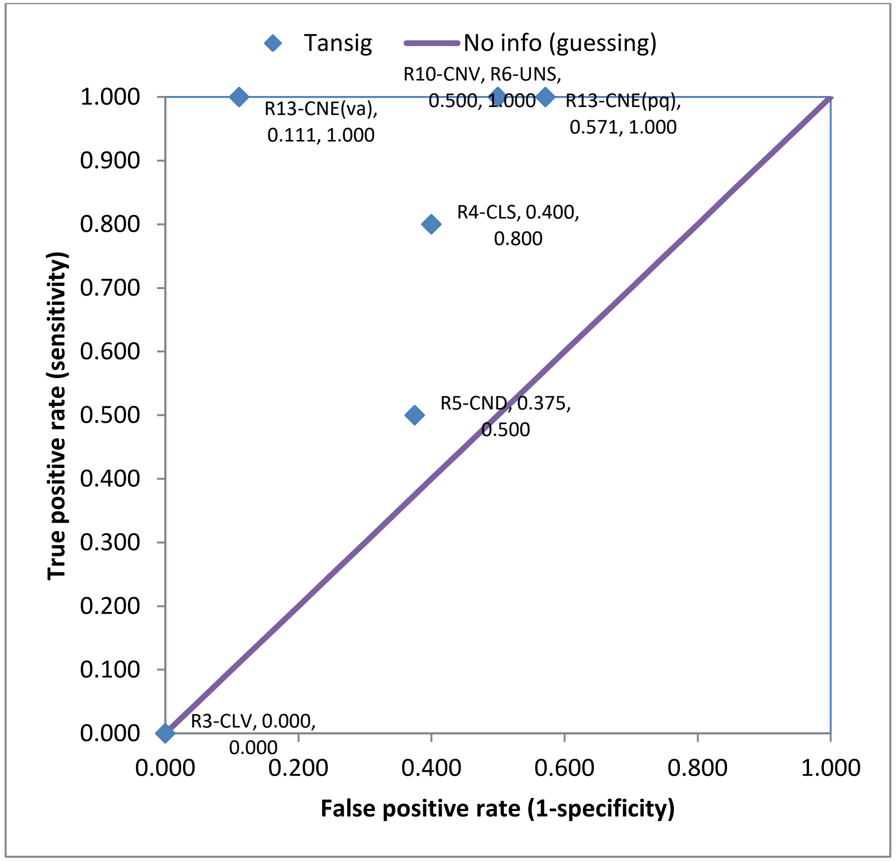


Fig. 4.41: ROC chart of network performance in risk occurrence prediction (all 7 risks predicted together, all at once)

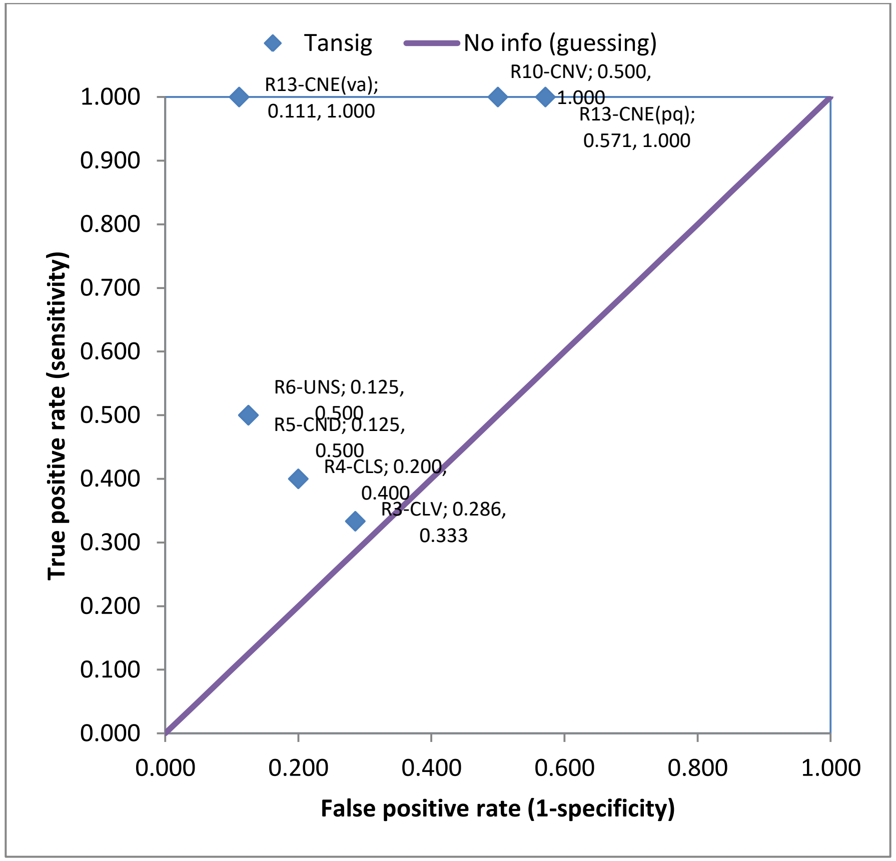


Fig. 4.42: ROC chart of network performance in risk occurrence prediction (all 7 risks were predicted separately, one risk at a time)

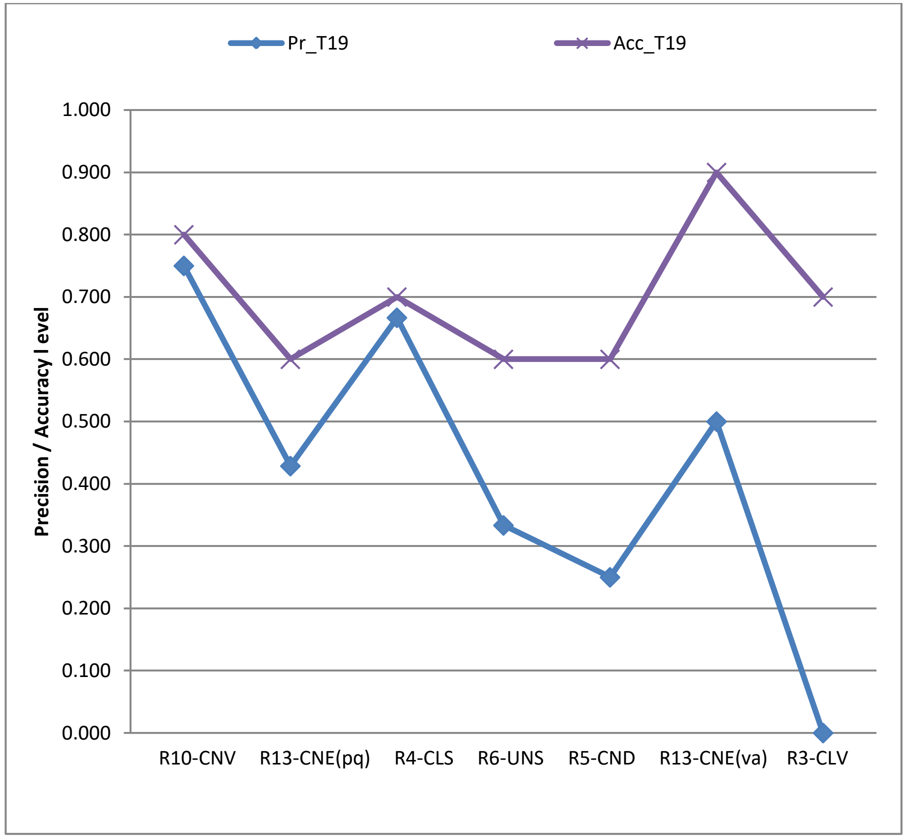


Fig. 4.43: Precision and accuracy of network in risk occurrence prediction (all 7 risks predicted together, all at once)

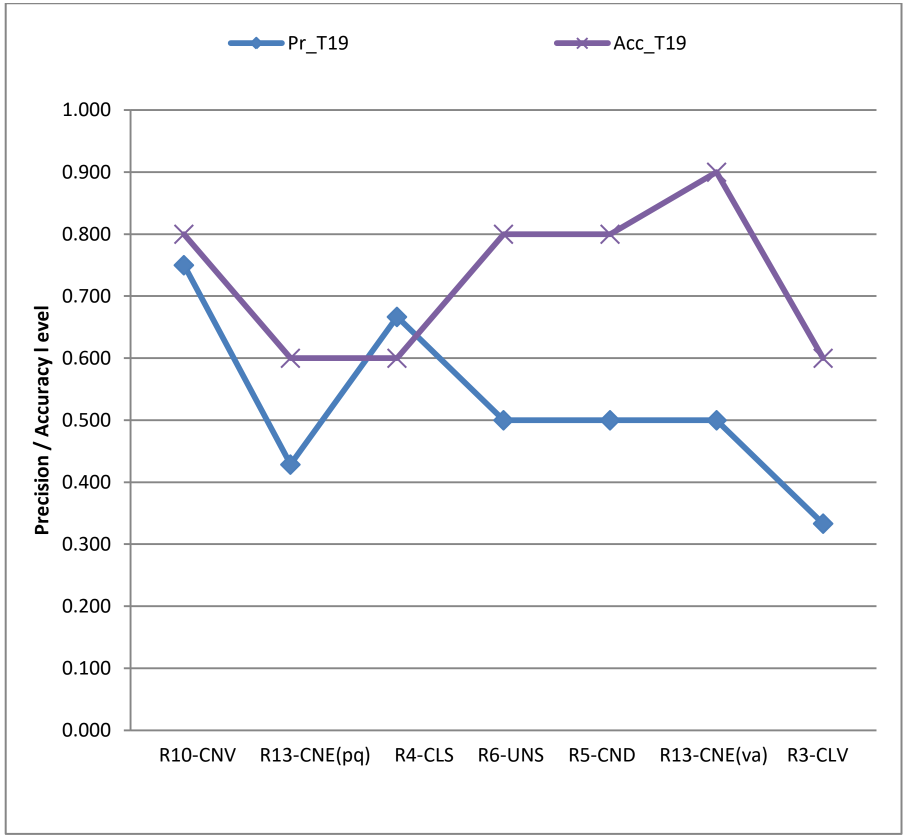


Fig. 4.44: Precision and accuracy of network in risk occurrence prediction (all 7 risks were predicted separately, one risk at a time)

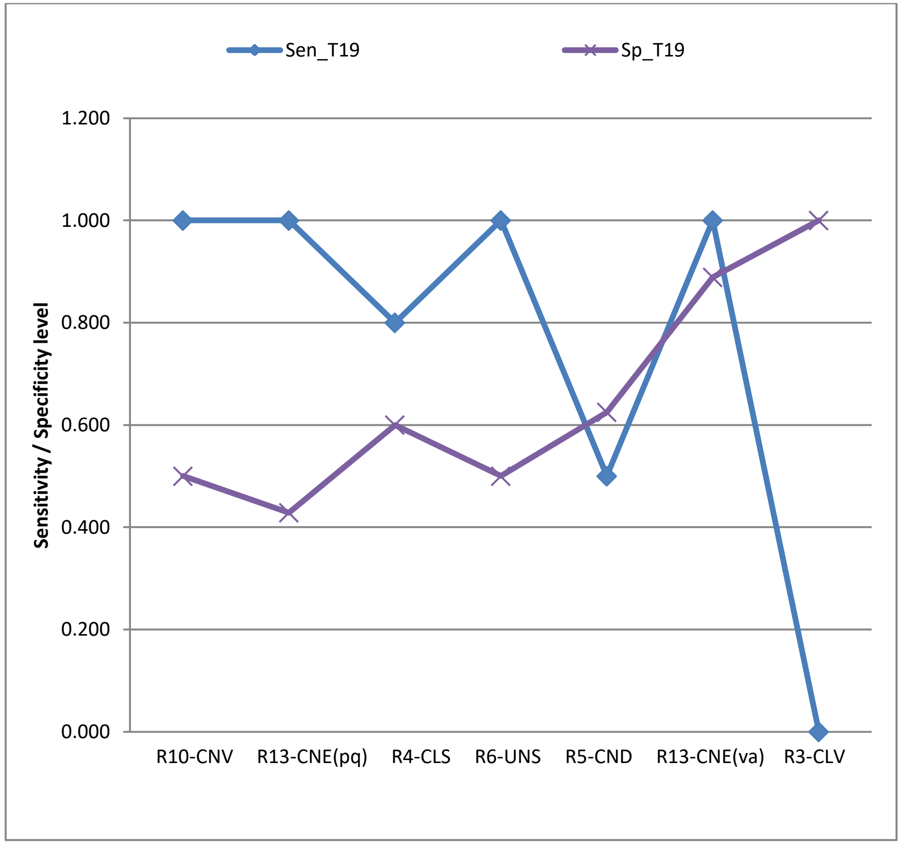


Fig. 4.45: Sensitivity and specificity of network in risk occurrence prediction (all 7 risks predicted together, all at once)

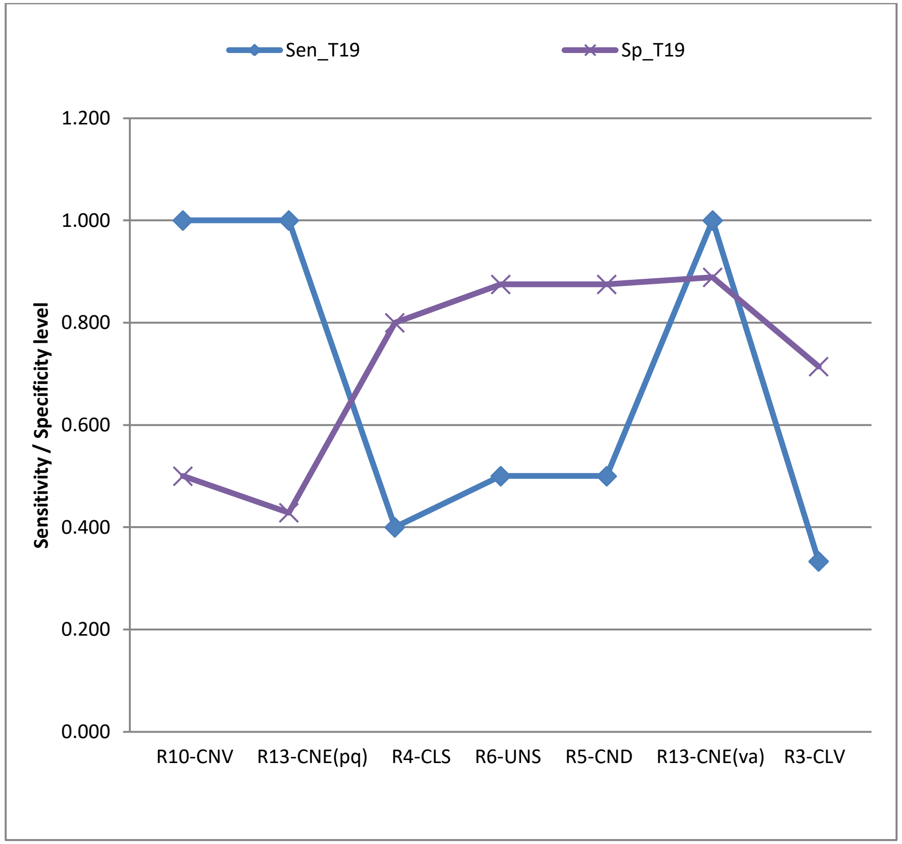
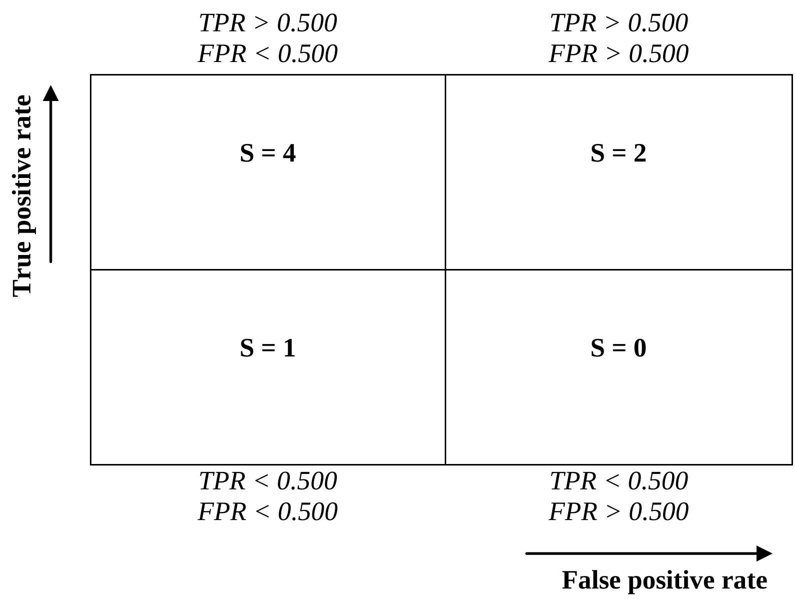


Fig. 4.46: Sensitivity and specificity of network in risk occurrence prediction (all 7 risks were predicted separately, one risk at a time)

4.8.2 Performance analysis of risk type prediction using ANN2

In the case of type of risk prediction, the developed neural network was used to predict the occurrence of the entire 7 risks (R3-CLV, R4-CLS, R5-CND, R6-UNS, R10-CNV, R13-CNE(pq), and R13-CNE(va)) one at a time. This was based on the findings from the prediction of risk occurrence, where separate prediction of targets had been proved to optimize prediction accuracy. This meant that the network had only one target at any one time; the performance analysis of the targets presented in Figure 4.48 was thus created with the output of seven networks, each of 8:19:1 structure. The performance of the network in the prediction of type of risk was summarized with the aid of a risk quadrant approach in Figure 4.47.



Where:
C = combination approach; S = separation approach; TPR = true positive rate; FPR = false positive rate.

Figure 4.47: Evaluation of risk type prediction using risk quadrant

It was observed that the network optimized the number of risks that had high true positive and low false positive rates (4 out of a total of 7 risks; these were R4-CLS, R6-UNS, R5-CND, and R13-CNE(va)). This according to Fawcett (2006) is the preferred outcome of a prediction exercise.

The performance of the network in the prediction of type of risk was also examined by direct review of performance metrics that were used to create the ROC charts. These metrics had been presented graphically as line charts in Figure 4.49 and Figure 4.50; the first chart dealt with the precision and accuracy of the networks while the second chart presented the sensitivity and specificity of the networks. In Figure 4.49 it was observed that R5-CND had the highest values for both precision and accuracy. R13-CNE(va) however exhibited the highest levels of both sensitivity and specificity. Another pertinent observation was that the performance metrics for R13-CNE(va) remained unchanged during prediction of both risk occurrence and type (see Figure 4.41, 4.42 and 4.48).

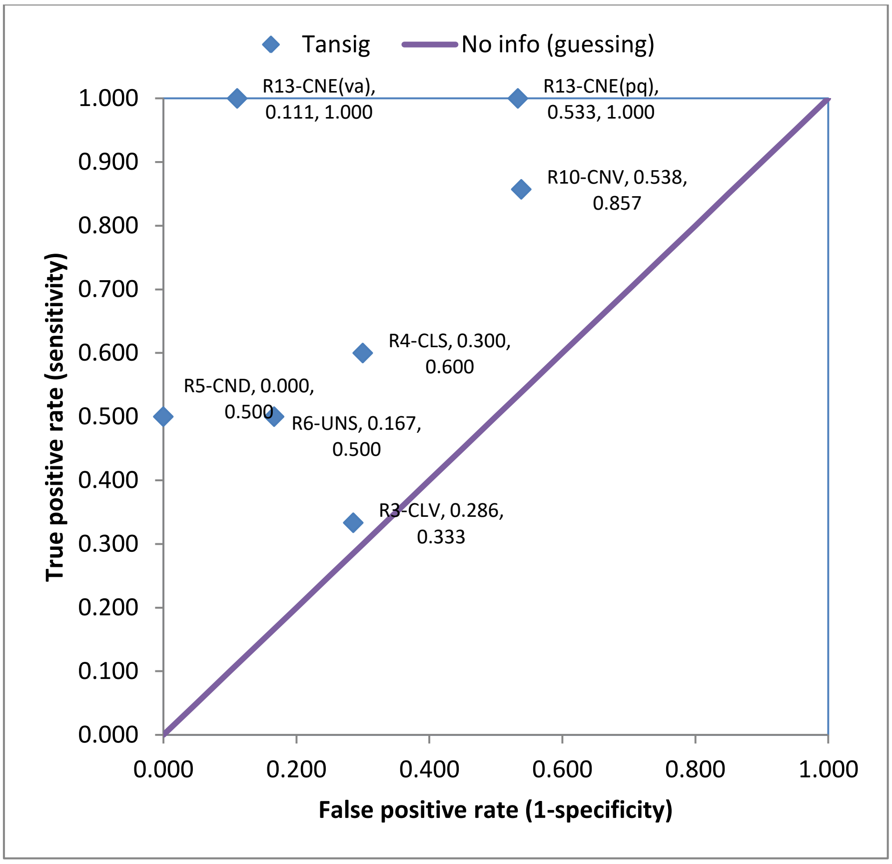


Fig. 4.48: ROC chart of network performance in risk type prediction (all 7 risks predicted separately, one risk at a time)

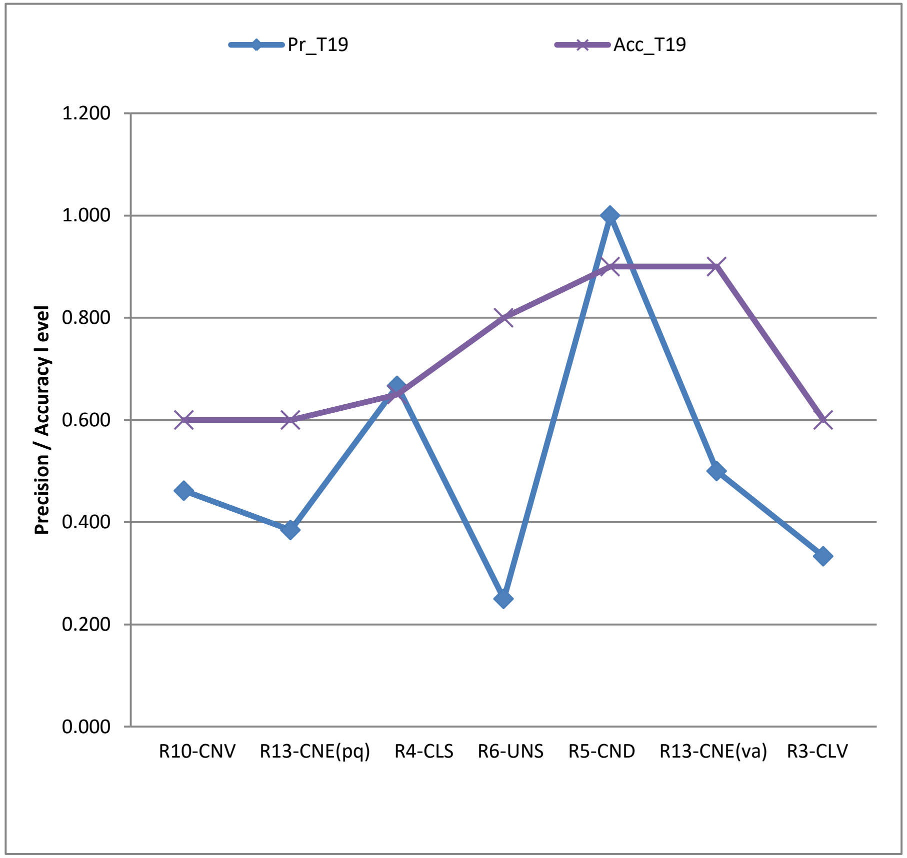


Fig. 4.49: Precision and accuracy of the network in predicting type of risk (all 7 risks predicted separately, one risk at a time)

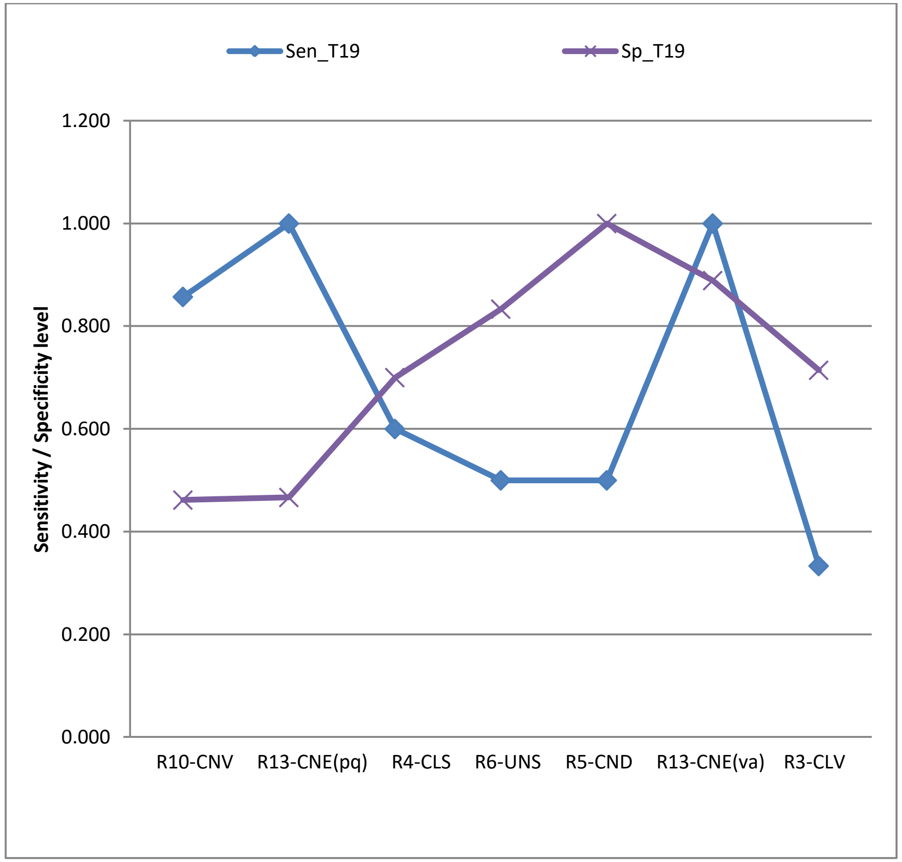
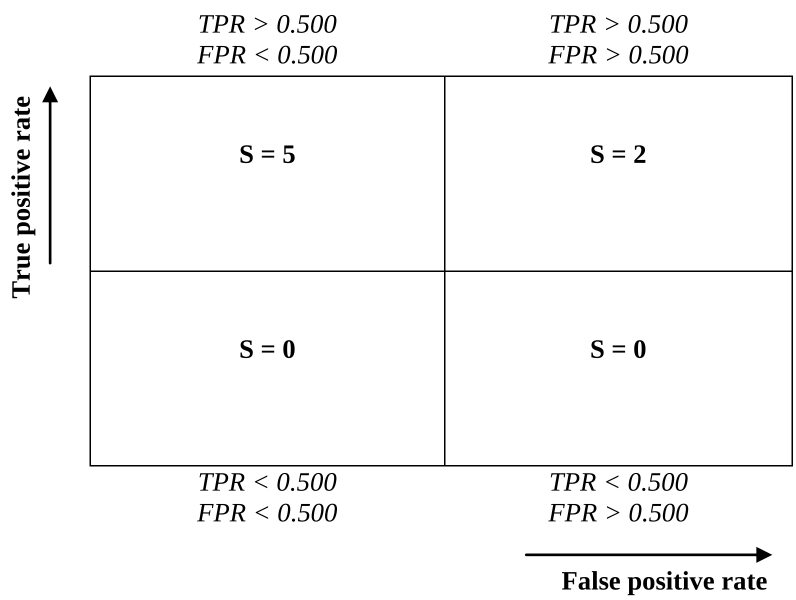


Fig. 4.50: Sensitivity and specificity of the network in predicting type of risk (all 7 risks predicted separately, one risk at a time)

4.8.3 Performance analysis of degree of risk prediction using ANN2

In the case of degree of risk prediction, the developed neural network was used to predict the occurrence of the entire 7 risks (R3-CLV, R4-CLS, R5-CND, R6-UNS, R10-CNV, R13-CNE(pq), and R13-CNE(va)) one at a time. This was based on the findings from the prediction of risk occurrence, where separate prediction of targets had been proved to optimize prediction accuracy. This meant that the network had only one target at any one time; the performance analysis of the targets presented in Figure 4.52 was thus created with the output of seven networks, each of 8:19:1 structure. The performance of the network in the prediction of degree of risk was summarized with the aid of a risk quadrant approach in Figure 4.51. It was observed that the network optimized the number of risks that had high true positive and low false positive rates (5 out of a total of 7 risks; these were Risk1, Risk2, Risk3, Risk4, and Risk6). Fawcett (2006) described this as the preferred situation in prediction, where the majority of the results fall wihin the upper left quadrant.



Where:
C = combination approach; S = separation approach; TPR = true positive rate; FPR = false positive rate.

Figure 4.57: Evaluation of risk degree prediction using risk quadrant

The performance of the networks in prediction of the degree of risk was also examined by direct review of the performance metrics that were used to create the ROC charts. These metrics had been presented graphically as line charts in Figure 4.53 (which dealt with the precision and accuracy) and Figure 4.54 (which presented the sensitivity and specificity). A systematic pattern was observed, where R10-CNV, R4-CLS, R5-CND, and R3-CLV had low precision and accuracy values (ranging from 0.3 to 0.7). Conversely, R13-CNE(pq), R6-UNSand R13-CNE(va) had relatively higher precision and accuracy values (ranging from 0.7 to 0.9). The same pattern was observed in the sensitivity and specificity of predictions; odd-positioned risks performed poorly compared to even-positioned numbered risks.

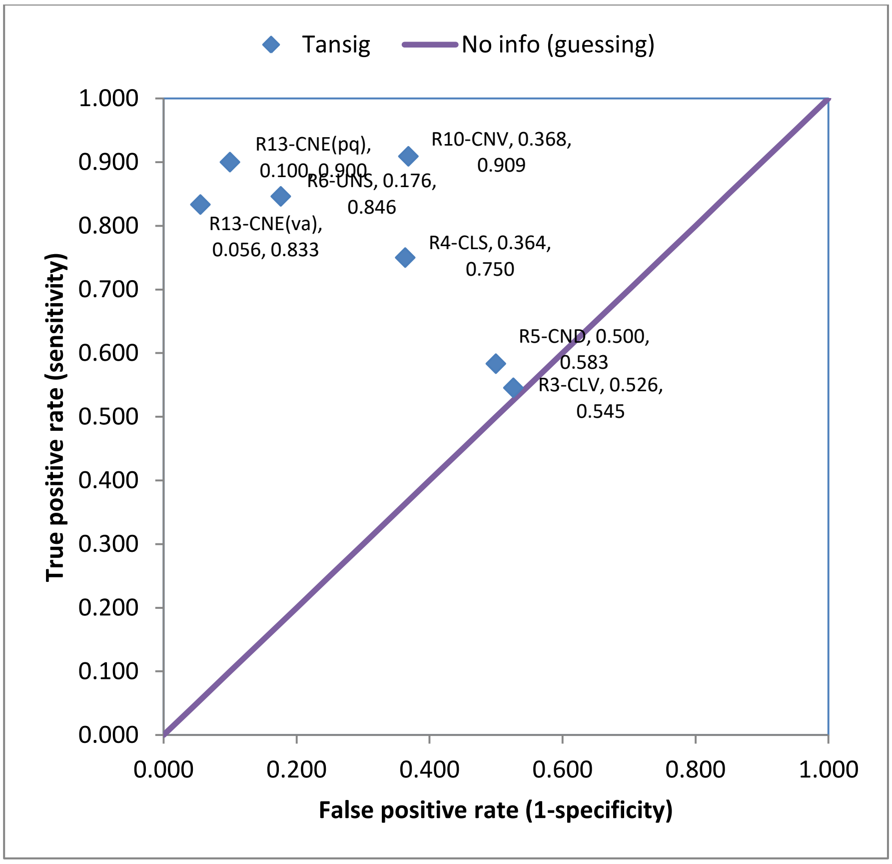


Fig. 4.52: ROC chart of network performance in risk degree prediction (all 7 risks predicted separately, one risk at a time)

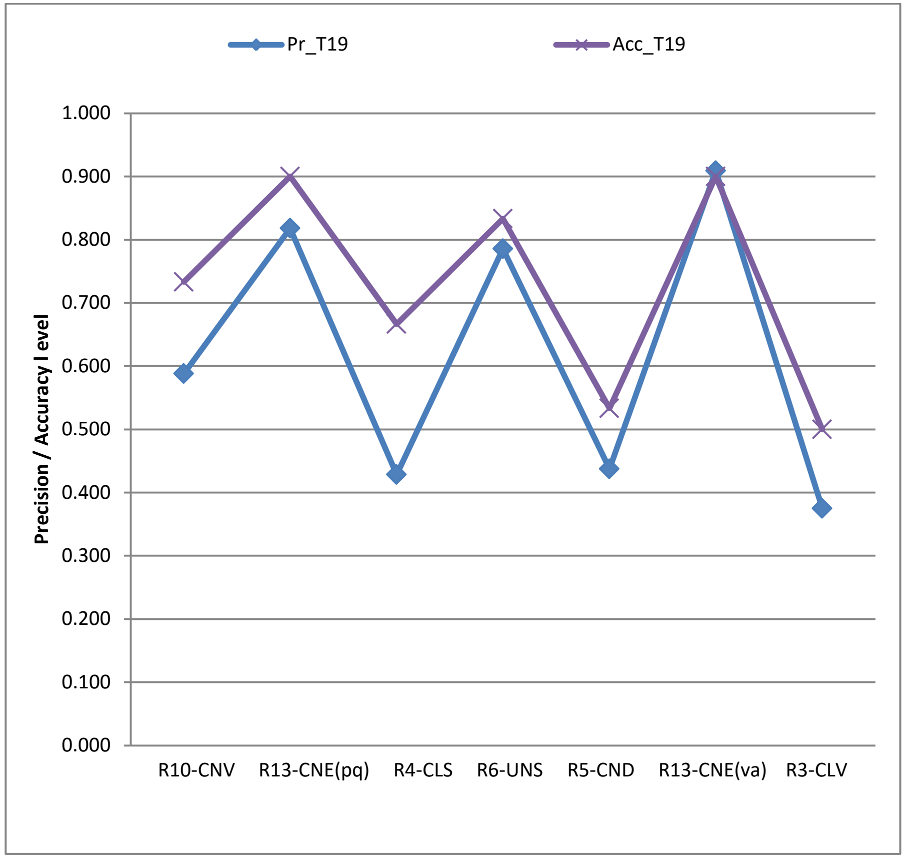


Fig. 4.53: Precision and accuracy of the network in predicting degree of risk (all 7 risks predicted separately, one risk at a time)

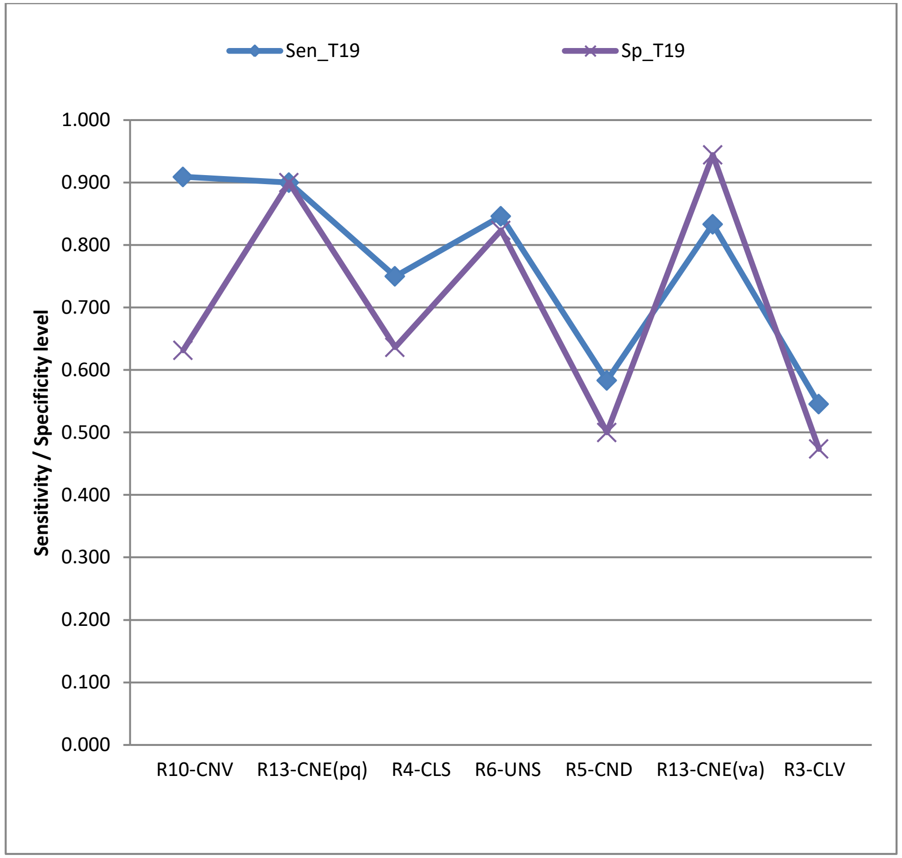


Fig. 4.54: Sensitivity and specificity of network in risk degree prediction (all 7 risks predicted separately, one risk at a time)

4.9 Summary of Findings

This section presented a summary of the results that have been obtained in this study with respect to the five objectives that were formulated in Chapter One.

1. Costs of building projects were impacted by 8 risks; these were (a) Client scope change; (b) Client variation/design change; (c) Consultants' error/omission in design; (d) Consultants' error/omission in estimates; (e) Consultants' design change; (f) Unforeseen economic conditions; (g) Unforeseen site conditions, and (h) Unforeseen social disturbance.
2. Project consultants were responsible for 69% of risks that occurred on building projects; however 52% of risk impacts resulted from the actions of project clients.
3. Variance between initial and final contract values of building projects was predicted with ANN1, a *2:31:1:1* MLP neural network, which on validation had an MSE of 0.0026. The regression model *Final cost variance = -4.834 + 1.056Consultant Risks + 1.058Client Risks* had an MSE of 10.22.
4. Effect of risk on building project costs was predicted with ANN2, an *8:19:7* MLP neural network which had a validation MSE of 0.2109. ‘Errors/omissions in design/estimates’ (R13-CNE(va)) was the most accurately predicted risk.

CHAPTER FIVE

5.0 CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

Costs of building projects are impacted by 8 risks, which include variation, scope and design changes; error/omission in design/estimates, and unforeseen economic, site and social conditions. Project consultants are responsible for 69% of risks occurrence; 52% of the cost impacts of risks however result from the actions of clients.

Eight risks were grouped into client and consultant risks and fed into ANN1, an MLP artificial neural network with 2:31:1:1 structure that predicted variance between initial and final contract values. A validation MSE of 0.0026 established ANN1's superiority over a conventional MLR statistical model *(Final cost variance = -4.834 + 1.056Consultant Risks + 1.058Client Risks)* which had an MSE of 10.22.

Eight features of construction projects including gross floor area and costs of building elements were inputted into ANN2, an 8:19:7 MLP network developed to predict risk effect in building costs. ANN2 used binarization to normalize data, with a resultant MSE of 0.2109. ANN2 obtained lower MSE of 0.09 and higher specificity when risks were predicted singly, one at a time.

5.2 Recommendations

This study has shown the possibility of carrying out risk assessment for building project by predicting risk effect on project costs using artificial neural network. The following recommendations were made as a means of fine-tuning and extending the approach taken in this study for predicting risk effect on project cost using artificial neural network.

1. Risks have differential impact on different classes of cost incurred during the construction of buildings. Project consultants need to pay close attention to the use of variation that add to ongoing works, because this was the only class of cost that was impacted by all of the risks considered in this study.
2. The results obtained have shown how construction project features can be used to estimate the effect of risk on building projects. This study recommended that researchers could reduce all input and output in an artificial neural network to a common 'risk-cost' basis as has been advocated by previous researchers. Initial contract values (ICV) of projects were recommended as a common base. This was because ICV are common to all building projects undertaken in the Nigerian construction industry.
3. With respect to the effect of risks on project costs, the effect of 'Errors/omissions in design/estimates' (which was coded as R13-CNE(va)) on variations was the risk that the artificial neural network developed in this study was able to predict with the highest level of accuracy. It is recommended that further research should focus on improving the prediction accuracy of other risks.
4. The following recommendations were put forward based on findings made with respect to the two approaches employed in the development of neural networks (ANN1 and ANN2). To improve clarity and specificity of the recommendations, they have been presented in the form of a table (Table 5.1).

Table 5.1: Recommendations for development of artificial neural networks for predicting risk effect on project costs

S/Nr	Specific aspect of network	Recommendations based on ANN1 (Prediction of Final cost variance from Risk effect)	Recommendations based on ANN2 (Prediction of Risk effect from Construction project features)
1	Normalization method	Min-max technique	Conversion to binary scale
2	Threshold	-	0.3 recommended, but all values between 0.3 and 0.5 share similar performance characteristics.
3	Activation function	*Tansig* recommended	*Tansig* recommended
4	Number of neurons	Thirteen (31) recommended	Nineteen (19) recommended
5	Number of inputs	Two (2) employed in ANN1.	Eight (8) employed in ANN2; not recommended to be reduced; false positive rates appear to be inversely related to number of inputs.
6	Number of outputs	Prediction of single output (final cost variance) recommended.	Prediction of single risk as output recommended; combining risks in one output increases false positive rates and decreases sensitivity of the network.
7	Number of hidden layers	Two (2) layers employed in ANN1; based on satisfactory performance, 2 hidden layers were recommended.	One (1) layer employed in ANN2; based on satisfactory performance, 1 hidden layer was recommended.
8	Training parameters	Train at (*epochs 1000; target MSE 0.0; minimum gradient* 10^{-7}*; mu 0.9; mu_dec 0.01; mu_inc 10*);	Train initially at *nntool* default settings (*epochs 1000; target MSE 0.0; minimum gradient* 10^{-7}*; mu 0.001; mu_dec 0.1; mu_inc 10*); if overfitting is suspected, modify setting to (*epochs 1000; target MSE 0.0; minimum gradient* 10^{-7}*; mu 1; mu_dec 0.7; mu_inc 1.3*).

Source: Author (2017)

5.3 Contribution of the Study to Knowledge

This study, like many other products of human endeavour, has its strengths and weaknesses. The step-by-step process of deductive reasoning applied in the design of the neural network and derivation of optimum network parameter settings lends itself to replicability easily. This was counted as one of the biggest contributions of the study to knowledge. Other contributions of the study include the discovery that risks are best predicted singly rather than in a combined manner. The use of binarization as a data normalization technique also allowed accurate prediction of risks within a heterogenous sample of building projects. The interdisciplinary nature of the study has allowed the study to contribute to knowledge through the transplanting of Artificial Intelligence (AI) concepts into Quantity Surveying (QS). This, it is hoped, will foster the development of greater expertise in the application of AI concepts by the QS community and serve to ensure that the QS profession is not left behind in the digitization of knowledge within the built environment field.

5.4 Area for Further Studies

The following represent new areas into which the research presented in this study could be expanded, in order to enhance understanding of the behaviour of project cost data when employed for the development of predictive artificial neural networks.

1) Comparison of the performance of radial basis function (RBF) and multi-layer perceptron (MLP) networks in the development of artificial neural network models for cost prediction.
2) The effect of project type on the accuracy of artificial neural network models of risk impact on building project costs.

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APPENDICES

Appendix A: Survey Questionnaire

FEDERAL UNIVERSITY OF TECHNOLOGY MINNA
DEPARTMENT OF QUANTITY SURVEYING
MAIN CAMPUS GIDAN-KWANO, MINNA, NIGER STATE.

Dear Sir/Ma,

RE: DEVELOPMENT OF AN ARTIFICIAL NEURAL NETWORK MODEL FOR PREDICTING THE IMPACT OF RISK ON COST OF BUILDING PROJECTS

Variability in construction costs between initial contract sums (ICS) and final accounts (FA) are important in the construction industry because they usually represent additional expenditures that deliver no additional benefits. Research efforts have been and are still focused on understanding the factors that contribute to construction costs variability. A major part of such research is on the contribution of risk events to changes in construction costs.

This survey is being conducted in order to develop models that will help to predict the variability between initial contract sums and final accounts of construction projects based on the impact of risk factors over the construction phase of building projects. The models will be developed using artificial neural network (ANN) techniques. This is a PhD work.

Your kind response to the questions and requests for information contained in the questionnaire and schedule attached herein will be highly appreciated and treated as strictly private and confidential. Please make contacts through the following addresses to clarify issues and make suggestions.

The entire questionnaire and schedule takes an estimated fifteen (15) minutes to complete.

1.	Mr. A. A. Oke Dept of Quantity Surveying, FUT Minna	08077934944	Researcher
2.	Professor Y. Ibrahim *MNIQS RQS* Dept of Quantity Surveying, ATBU Bauchi	08036134490	Main Supervisor
3.	Professor O. O. Morenikeji Dept of Urban and Reg. Planning, FUT Minna		Co-Supervisor
4.	Dr M. A. Aibinu Dept of Mechatronics, FUT Minna		Co-Supervisor

Thank you for your anticipated genuine contribution to knowledge.

(A. A. Oke)
abdganioke@futminna.edu.ng

SURVEY ON
"DEVELOPMENT OF AN ARTIFICIAL NEURAL NETWORK MODEL FOR PREDICTING THE IMPACT OF RISK ON COST OF BUILDING PROJECTS"

Questionnaire - Section A

General Information *(takes approximately 3 minutes to complete)*

1. **Designation of Respondent** ---

2. **Construction Experience**

   (a) Less than 10 years ☐
   (b) 11 – 20 years ☐
   (c) 21 – 30 years ☐
   (d) More than 30 years ☐

3. **Highest academic qualification obtained**

   (a) OND ☐
   (b) HND ☐
   (c) B.Sc ☐
   (d) PGD ☐
   (e) MSc ☐
   (f) PhD ☐
   (g) Others ☐

Questionnaire - Section B

Construction Project Features

4. **Year**
   Year construction of project was started: ……………………..

5. **Gross floor area: ………………………….**

6. **Project type**

   (i) Carpark ☐
   (ii) Hospital ☐
   (iii) Hostel ☐
   (iv) Hotel ☐
   (v) House ☐
   (vi) Library ☐
   (vii) Office ☐
   (viii) School ☐
   (ix) Warehouse ☐
   (x) Workshop ☐
   (xi) Others ☐

7. **Project nature**
   (i) New construction ☐
   (ii) Refurbishment ☐

8. **Value of structural element: N……………………….**

9. **Value of services element: N………………………….**

10. **Value of finishing element: N…………………………**

11. **Value of external work element: N …………………………..**

Appendix B: Questionnaire for Final Account Details for Project *(takes approximately 12 minutes to complete)*

Please indicate the **risk that you consider responsible** for each addition/omission item by inserting the appropriate risk reference under 'Risk Factors'.

S/No	Section of Final Account	Brief Description of costs items in Final Account	Value of costs items in Final Account		Risk
			Addition	Omission	
1					
2					
3					
4					
5					
6					
7					
8					
9					
10					
11					
12					

S/Nr	Risks	Risk Reference
1	Acts of God	R1
2	Cash flow difficulties	R2
3	change in design / variations by the client	R3
4	Change in scope of work	R4
5	change in the design by the Architect	R5
6	Changes in site conditions	R6
7	Consultant competence	R7
8	Contractor competence	R8
9	Nominated suppliers cash flow problems	R9
10	Incomplete drawings	R10
11	Delay due to excessive approval procedures	R11
12	Equipment breakdown/ maintenance	R12
13	error/omission in design/estimates	R13
14	Inclement weather	R14
15	Inflation	R15
16	Labour shortage	R16
17	Poor contract management	R17
18	Production target slippage	R18
19	Social issues/area boys, original land owners	R19

Appendix C: SPSS Analysis for reliability of the research instrument

Nonparametric Correlations

Correlations

			Test_sctnA	ReTest_sctnA
Kendall's tau_b	Test_sctnA	Correlation Coefficient	1.000	.844**
		Sig. (2-tailed)	.	.000
		N	24	24
	ReTest_sctnA	Correlation Coefficient	.844**	1.000
		Sig. (2-tailed)	.000	.
		N	24	24
Spearman's rho	Test_sctnA	Correlation Coefficient	1.000	.911**
		Sig. (2-tailed)	.	.000
		N	24	24
	ReTest_sctnA	Correlation Coefficient	.911**	1.000
		Sig. (2-tailed)	.000	.
		N	24	24

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

Descriptive Statistics

	Mean	Std. Deviation	N
Test_sctnA	1.4124E8	3.42834E8	24
ReTest_sctnA	2.0453E7	3.58360E7	24

Correlations

		Test_sctnA	ReTest_sctnA
Test_sctnA	Pearson Correlation	1	.823**
	Sig. (2-tailed)		.000
	N	24	24
ReTest_sctnA	Pearson Correlation	.823**	1
	Sig. (2-tailed)	.000	
	N	24	24

**. Correlation is significant at the 0.01 level (2-tailed).

Nonparametric Correlations

Correlations

			Test_qstnnr	ReTest_qstnnr
Kendall's tau_b	Test_qstnnr	Correlation Coefficient	1.000	.841**
		Sig. (2-tailed)	.	.000
		N	16	16
	ReTest_qstnnr	Correlation Coefficient	.841**	1.000
		Sig. (2-tailed)	.000	.
		N	16	16
Spearman's rho	Test_qstnnr	Correlation Coefficient	1.000	.887**
		Sig. (2-tailed)	.	.000
		N	16	16
	ReTest_qstnnr	Correlation Coefficient	.887**	1.000
		Sig. (2-tailed)	.000	.
		N	16	16

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

Descriptive Statistics

	Mean	Std. Deviation	N
Test_qstnnr	1.7500	.85635	16
ReTest_qstnnr	2.0625	1.12361	16

Correlations

		Test_qstnnr	ReTest_qstnnr
Test_qstnnr	Pearson Correlation	1	.849**
	Sig. (2-tailed)		.000
	N	16	16
ReTest_qstnnr	Pearson Correlation	.849**	1
	Sig. (2-tailed)	.000	
	N	16	16

**. Correlation is significant at the 0.01 level (2-tailed).

Nonparametric Correlations

Correlations

			Test	ReTest
Kendall's tau_b	Test	Correlation Coefficient	1.000	.852**
		Sig. (2-tailed)	.	.000
		N	40	40
	ReTest	Correlation Coefficient	.852**	1.000
		Sig. (2-tailed)	.000	.
		N	40	40
Spearman's rho	Test	Correlation Coefficient	1.000	.895**
		Sig. (2-tailed)	.	.000
		N	40	40
	ReTest	Correlation Coefficient	.895**	1.000
		Sig. (2-tailed)	.000	.
		N	40	40

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

Descriptive Statistics

	Mean	Std. Deviation	N
Test	8.4746E7	2.72445E8	40
ReTest	1.2272E7	2.93315E7	40

Correlations

		Test	ReTest
Test	Pearson Correlation	1	.835**
	Sig. (2-tailed)		.000
	N	40	40
ReTest	Pearson Correlation	.835**	1
	Sig. (2-tailed)	.000	
	N	40	40

**. Correlation is significant at the 0.01 level (2-tailed).

Appendix D: Complete list of the projects in the study sample

Proj Grp Nr	Year	Project Description	Location	GFA	Number of risk events	Initial Contract Value_ICV	Cost Deviation FCV - ICV
A01	2004	Hostel	Niger	913	34	18,631,148.45	1,657,281.55
A02	2011	Hotel	Abuja	4457	65	1,046,041,530.38	422,669,563.62
A03	2009	Hospital	Gombe	580	33	269,936,199.15	145,008,876.55
A04	2013	Office	Benue	642	26	72,525,775.35	4,951,432.50
A05	2014	Office	Abia	642	20	72,005,955.53	3,885,613.46
A06	2013	Office	Taraba	642	23	71,278,404.75	2,865,166.50
A07	2011	Warehouse	Kaduna	375	6	66,403,218.00	-525,210.00
A08	2012	School	Borno	1223	22	140,668,064.00	-14,875,431.00
A09	2012	School	Kaduna	2881	8	489,933,652.43	65,615,502.97
A10	2008	School	Gombe	1703	45	127,000,000.00	-3,399,206.48
A11	2015	Car park	Abuja	3081	19	523,881,350.58	-60,870,310.30
A12	2014	Office	Jigawa	655	23	75,346,244.40	-2,942.31
A13	2015	Hostel	Gombe	6646	42	600,600,000.00	-17,495,600.85
A14	2015	Library	Abuja	1840	16	207,388,304.81	-6,862,553.66
A15	2015	Workshop	Abuja	1422	5	198,899,132.52	-116,186.64
A16	2015	Hostel	Abuja	1845	15	227,092,280.15	-150,863.86
B17	2010	House	Abuja	1533	3	299,084,056.47	40,153,076.00
B18	2010	House	Abuja	1027	3	200,182,589.99	31,034,634.40
B19	2010	House	Abuja	1048	3	204,274,840.99	31,844,173.00
B20	2010	House	Abuja	1291	3	251,753,471.25	30,062,678.04
B21	2010	House	Abuja	616	3	120,108,325.35	32,477,705.00
B22	2010	House	Abuja	116	1	22,544,147.50	2,400,950.00
B23	2010	House	Abuja	61	1	11,839,600.00	3,475,900.00
B24	2015	House	Yobe	113	24	22,078,124.00	9,056,705.96
B25	2014	House	Abuja	683	5	30,744,958.83	0.00
B26	2014	House	Abuja	714	4	32,131,109.07	0.00
B27	2014	House	Abuja	711	8	31,977,000.00	0.00
B28	2014	House	Abuja	674	9	30,339,877.19	0.00
B29	2014	House	Abuja	693	8	31,188,504.90	0.00
B30	2014	House	Abuja	711	7	31,977,838.16	0.00
B31	2014	House	Abuja	728	8	32,801,010.00	0.00
B32	2014	House	Abuja	693	8	31,205,955.42	0.00
B33	2014	House	Abuja	717	5	32,272,686.60	0.00
B34	2014	House	Abuja	732	8	32,964,986.25	0.00
B35	2014	House	Abuja	716	7	32,226,417.56	0.00
B36	2014	House	Abuja	771	8	34,717,490.06	0.00

Proj Grp Nr	Year	Project Description	Location	GFA	Number of risk events	Initial Contract Value_ICV	Cost Deviation FCV - ICV
B37	2015	House	Abuja	829	8	37,332,533.43	-1,901.74
B38	2015	House	Abuja	1010	8	45,453,135.09	-1,448.91
B39	2015	House	Abuja	979	8	44,073,555.82	0.00
B40	2016	House	Abuja	855	9	38,513,661.72	-709,530.67
B41	2009	Hostel	Gombe	1000	6	114,977,068.50	21,080,016.75
B42	2010	Office	Kaduna	257	5	11,580,313.50	-989,478.00
B43	2010	Office	Lagos	43	4	1,928,797.50	-31,920.00
B44	2010	Warehouse	Lagos	390	1	48,691,944.00	-1,239,000.00
B45	2005	Office	Jigawa	364	56	45,441,808.13	-4,606,171.12
B46	2005	School	Gombe	817	20	102,187,284.45	-2,852,173.94
B47	2011	School	Abuja	198	7	24,700,871.00	292,332.54
B48	2015	Hospital	Kano	154	13	6,950,359.50	-35,805.00
C49	2008	Hospital	Gombe	665	2	83,152,391.70	-450,000.00
C50	2009	Hospital	Gombe	672	6	84,024,366.30	37,689,114.75
C51	2008	Hospital	Gombe	501	5	62,620,489.05	-549,533.84
C52	2012	House	Kaduna	217	13	9,756,140.63	1,217,616.75
C53	2012	House	Kaduna	217	14	9,754,350.90	2,126,706.75
C54	2010	Office	Kaduna	79	10	3,534,426.00	748,282.50
C55	2010	Office	Kaduna	33	3	1,472,635.50	-183,067.50
C56	2003	School	Kano	341	42	42,572,165.75	1,703,485.23
C57	2005	School	Gombe	718	46	89,688,700.00	13,415,813.02
C58	2005	School	Gombe	561	26	70,152,600.00	-4,907,007.52
C59	2005	School	Gombe	497	20	62,148,450.00	-10,716,583.50
C60	2005	School	Gombe	461	28	57,597,750.00	-9,887,221.16
C61	2005	School	Gombe	1092	58	136,446,896.25	-7,734,350.77
C62	2012	School	Gombe	848	10	105,945,000.00	-2,260,788.60
C63	2013	School	Gombe	210	5	26,250,000.00	-767,181.45
C64	2014	School	Gombe	912	15	114,030,000.00	-11,809,425.60
C65	2014	School	Gombe	389	12	48,615,000.00	-783,102.60
C66	2013	School	Gombe	391	20	48,930,000.00	-796,823.05
C67	2014	School	Gombe	473	10	59,101,000.00	-11,531,486.05
C68	2014	School	Kano	2547	18	496,684,314.00	-3,919,513.50
C69	2014	School	Nasarawa	661	11	82,635,000.00	-1,362,255.30

Appendix E: Cost changes and associated risk factors encountered in sampled projects

Proj Grp Nr	Risk label	Risk sort code	Cost category	Cost sort code	Risk type code	Risk costs (Net)	Initial Contract Sum_ICS	Risk degree
A01	R4-CLS	2	vs	5	1	-136,290.00	18631148.45	-0.7315169
A01	R4-CLS	2	vs	5	1	-132,800.00	18631148.45	-0.7127848
A01	R4-CLS	2	vs	5	1	-8,500.00	18631148.45	-0.0456225
A01	R6-UNS	4	va	3	2	15,800.00	18631148.45	0.0848042
A01	R10-CNV	5	ps	2	1	-56,738.91	18631148.45	-0.3045379
A01	R10-CNV	5	ps	2	1	-13,552.00	18631148.45	-0.0727384
A01	R10-CNV	5	ps	2	1	-5,918.00	18631148.45	-0.031764
A01	R10-CNV	5	ps	2	1	-2,530.00	18631148.45	-0.0135794
A01	R10-CNV	5	ps	2	2	43,720.00	18631148.45	0.2346608
A01	R10-CNV	5	ps	2	2	61,472.00	18631148.45	0.3299421
A01	R10-CNV	5	ps	2	2	188,358.00	18631148.45	1.0109844
A01	R10-CNV	5	ps	2	2	276,908.00	18631148.45	1.4862637
A01	R10-CNV	5	ps	2	2	527,490.00	18631148.45	2.8312264
A01	R10-CNV	5	va	3	2	726.00	18631148.45	0.0038967
A01	R10-CNV	5	va	3	2	2,640.00	18631148.45	0.0141698
A01	R10-CNV	5	va	3	2	2,775.00	18631148.45	0.0148944
A01	R10-CNV	5	va	3	2	9,120.00	18631148.45	0.0489503
A01	R10-CNV	5	va	3	2	27,390.00	18631148.45	0.1470119
A01	R10-CNV	5	va	3	2	58,500.00	18631148.45	0.3139903
A01	R10-CNV	5	va	3	2	61,425.00	18631148.45	0.3296898
A01	R10-CNV	5	va	3	2	90,720.00	18631148.45	0.4869265
A01	R10-CNV	5	va	3	2	92,882.00	18631148.45	0.4985307
A01	R10-CNV	5	va	3	2	93,120.00	18631148.45	0.4998082
A01	R10-CNV	5	va	3	2	108,000.00	18631148.45	0.5796744
A01	R10-CNV	5	va	3	2	168,000.00	18631148.45	0.9017158
A01	R13-CNE	6	pq	1	1	-307,115.00	18631148.45	-1.6483954
A01	R13-CNE	6	pq	1	1	-31,641.00	18631148.45	-0.1698285
A01	R13-CNE	6	pq	1	1	-12,300.00	18631148.45	-0.0660185
A01	R13-CNE	6	pq	1	2	236,210.00	18631148.45	1.2678231
A01	R13-CNE	6	pq	1	2	274,341.00	18631148.45	1.4724857
A01	R13-CNE	6	pq	1	2	470,990.00	18631148.45	2.5279708
A01	R13-CNE	6	pq	1	2	522,317.00	18631148.45	2.8034611
A01	R13-CNE	6	vo	4	1	-52,000.00	18631148.45	-0.2791025
A01	R13-CNE	6	vo	4	1	-29,040.00	18631148.45	-0.155868
A02	R4-CLS	2	va	3	2	21,000.00	1046041530	0.0020076
A02	R4-CLS	2	va	3	2	21,000.00	1046041530	0.0020076
A02	R4-CLS	2	va	3	2	29,340.00	1046041530	0.0028049
A02	R4-CLS	2	va	3	2	68,000.00	1046041530	0.0065007
A02	R4-CLS	2	va	3	2	75,000.00	1046041530	0.0071699
A02	R4-CLS	2	va	3	2	76,000.00	1046041530	0.0072655
A02	R4-CLS	2	va	3	2	92,750.00	1046041530	0.0088668
A02	R4-CLS	2	va	3	2	92,800.00	1046041530	0.0088715
A02	R4-CLS	2	va	3	2	95,000.00	1046041530	0.0090819
A02	R4-CLS	2	va	3	2	100,000.00	1046041530	0.0095598
A02	R4-CLS	2	va	3	2	120,000.00	1046041530	0.0114718
A02	R4-CLS	2	va	3	2	125,100.00	1046041530	0.0119594
A02	R4-CLS	2	va	3	2	132,600.00	1046041530	0.0126764
A02	R4-CLS	2	va	3	2	132,600.00	1046041530	0.0126764
A02	R4-CLS	2	va	3	2	150,000.00	1046041530	0.0143398
A02	R4-CLS	2	va	3	2	152,000.00	1046041530	0.014531
A02	R4-CLS	2	va	3	2	178,800.00	1046041530	0.017093
A02	R4-CLS	2	va	3	2	185,500.00	1046041530	0.0177335

Proj Grp Nr	Risk label	Risk sort code	Cost category	Cost sort code	Risk type code	Risk costs (Net)	Initial Contract Sum_ICS	Risk degree
A02	R4-CLS	2	va	3	2	209,300.00	1046041530	0.0200088
A02	R4-CLS	2	va	3	2	215,000.00	1046041530	0.0205537
A02	R4-CLS	2	va	3	2	216,000.00	1046041530	0.0206493
A02	R4-CLS	2	va	3	2	275,000.00	1046041530	0.0262896
A02	R4-CLS	2	va	3	2	289,800.00	1046041530	0.0277044
A02	R4-CLS	2	va	3	2	375,000.00	1046041530	0.0358494
A02	R4-CLS	2	va	3	2	394,000.00	1046041530	0.0376658
A02	R4-CLS	2	va	3	2	474,950.00	1046041530	0.0454045
A02	R4-CLS	2	va	3	2	494,190.00	1046041530	0.0472438
A02	R4-CLS	2	va	3	2	524,250.00	1046041530	0.0501175
A02	R4-CLS	2	va	3	2	540,000.00	1046041530	0.0516232
A02	R4-CLS	2	va	3	2	570,000.00	1046041530	0.0544911
A02	R4-CLS	2	va	3	2	600,000.00	1046041530	0.0573591
A02	R4-CLS	2	va	3	2	607,500.00	1046041530	0.0580761
A02	R4-CLS	2	va	3	2	650,000.00	1046041530	0.062139
A02	R4-CLS	2	va	3	2	750,000.00	1046041530	0.0716989
A02	R4-CLS	2	va	3	2	800,000.00	1046041530	0.0764788
A02	R4-CLS	2	va	3	2	912,000.00	1046041530	0.0871858
A02	R4-CLS	2	va	3	2	1,120,000.00	1046041530	0.1070703
A02	R4-CLS	2	va	3	2	1,600,000.00	1046041530	0.1529576
A02	R4-CLS	2	va	3	2	1,759,300.00	1046041530	0.1681864
A02	R4-CLS	2	va	3	2	2,281,910.00	1046041530	0.2181472
A02	R4-CLS	2	va	3	2	2,500,000.00	1046041530	0.2389962
A02	R4-CLS	2	va	3	2	5,700,000.00	1046041530	0.5449114
A02	R4-CLS	2	va	3	2	7,018,036.00	1046041530	0.6709137
A02	R4-CLS	2	va	3	2	10,658,000.00	1046041530	1.0188888
A02	R4-CLS	2	va	3	2	14,817,500.00	1046041530	1.4165308
A02	R4-CLS	2	va	3	2	50,515,500.00	1046041530	4.829206
A02	R5-CND	3	va	3	2	75,000.00	1046041530	0.0071699
A02	R5-CND	3	vs	5	2	316,800.00	1046041530	0.0302856
A02	R5-CND	3	vs	5	2	331,248.00	1046041530	0.0316668
A02	R5-CND	3	vs	5	2	1,158,000.00	1046041530	0.1107031
A02	R5-CND	3	vs	5	2	1,258,632.00	1046041530	0.1203233
A02	R5-CND	3	vs	5	2	1,285,800.00	1046041530	0.1229205
A02	R5-CND	3	vs	5	2	1,474,380.00	1046041530	0.1409485
A02	R5-CND	3	vs	5	2	2,153,388.00	1046041530	0.2058607
A02	R5-CND	3	vs	5	2	2,680,320.00	1046041530	0.2562346
A02	R5-CND	3	vs	5	2	2,734,638.00	1046041530	0.2614273
A02	R5-CND	3	vs	5	2	3,438,552.00	1046041530	0.3287204
A02	R5-CND	3	vs	5	2	3,477,006.00	1046041530	0.3323966
A02	R5-CND	3	vs	5	2	3,560,904.00	1046041530	0.3404171
A02	R5-CND	3	vs	5	2	4,623,000.00	1046041530	0.4419519
A02	R5-CND	3	vs	5	2	7,586,181.60	1046041530	0.7252276
A02	R5-CND	3	vs	5	2	9,271,200.00	1046041530	0.8863128
A02	R5-CND	3	vs	5	2	9,458,712.00	1046041530	0.9042387
A02	R15-UNE	7	va	3	2	104,191,280.00	1046041530	9.96053
A02	R15-UNE	7	va	3	2	114,253,346.02	1046041530	10.922448
A03	R3-CLV	1	va	3	2	135,223,230.62	269936199.2	50.094515
A03	R4-CLS	2	vo	4	1	-1,219,000.00	269936199.2	-0.4515882
A03	R4-CLS	2	vo	4	1	-400,453.88	269936199.2	-0.1483513
A03	R4-CLS	2	vo	4	1	-325,653.46	269936199.2	-0.1206409
A03	R4-CLS	2	vo	4	1	-325,653.46	269936199.2	-0.1206409
A03	R4-CLS	2	vo	4	1	-314,410.39	269936199.2	-0.1164758
A03	R4-CLS	2	vo	4	1	-303,910.42	269936199.2	-0.112586
A03	R4-CLS	2	vo	4	1	-275,961.65	269936199.2	-0.1022322
A03	R4-CLS	2	vo	4	1	-266,711.54	269936199.2	-0.0988054

Proj Grp Nr	Risk label	Risk sort code	Cost category	Cost sort code	Risk type code	Risk costs (Net)	Initial Contract Sum_ICS	Risk degree
A03	R4-CLS	2	vo	4	1	-248,970.00	269936199.2	-0.0922329
A03	R4-CLS	2	vo	4	1	-187,988.70	269936199.2	-0.0696419
A03	R4-CLS	2	vo	4	1	-187,988.70	269936199.2	-0.0696419
A03	R4-CLS	2	vo	4	1	-187,625.28	269936199.2	-0.0695073
A03	R4-CLS	2	vo	4	1	-75,000.00	269936199.2	-0.0277843
A03	R5-CND	3	va	3	2	175,000.00	269936199.2	0.0648301
A03	R5-CND	3	va	3	2	270,000.00	269936199.2	0.1000236
A03	R5-CND	3	va	3	2	375,050.00	269936199.2	0.1389402
A03	R5-CND	3	va	3	2	499,200.00	269936199.2	0.1849326
A03	R5-CND	3	va	3	2	529,660.00	269936199.2	0.1962167
A03	R5-CND	3	va	3	2	805,500.00	269936199.2	0.2984038
A03	R5-CND	3	va	3	2	835,543.00	269936199.2	0.3095335
A03	R5-CND	3	va	3	2	957,894.00	269936199.2	0.3548594
A03	R5-CND	3	va	3	2	1,867,500.00	269936199.2	0.6918301
A03	R5-CND	3	va	3	2	2,295,808.00	269936199.2	0.8505002
A03	R5-CND	3	va	3	2	8,200,000.00	269936199.2	3.0377549
A03	R5-CND	3	vo	4	1	-8,442,215.00	269936199.2	-3.1274853
A03	R5-CND	3	vo	4	1	-4,690,000.00	269936199.2	-1.7374476
A03	R5-CND	3	vo	4	1	-3,657,213.00	269936199.2	-1.3548435
A03	R5-CND	3	vo	4	1	-1,624,750.00	269936199.2	-0.6019015
A03	R6-UNS	4	ps	2	1	-4,700,000.00	269936199.2	-1.7411522
A03	R10-CNV	5	ps	2	1	-2,000,000.00	269936199.2	-0.7409158
A03	R10-CNV	5	ps	2	1	-1,500,000.00	269936199.2	-0.5556869
A03	R13-CNE	6	pq	1	2	36,725,049.64	269936199.2	13.605085
A04	R5-CND	3	va	3	2	140,400.00	72525775.35	0.1935863
A04	R5-CND	3	va	3	2	151,250.00	72525775.35	0.2085465
A04	R5-CND	3	va	3	2	214,800.00	72525775.35	0.2961706
A04	R5-CND	3	va	3	2	255,000.00	72525775.35	0.3515991
A04	R5-CND	3	va	3	2	439,200.00	72525775.35	0.6055778
A04	R5-CND	3	va	3	2	2,139,400.00	72525775.35	2.9498478
A04	R10-CNV	5	ps	2	1	-300,000.00	72525775.35	-0.413646
A04	R10-CNV	5	ps	2	1	-150,000.00	72525775.35	-0.206823
A04	R10-CNV	5	ps	2	1	-100,000.00	72525775.35	-0.137882
A04	R10-CNV	5	ps	2	2	0.00	72525775.35	0
A04	R10-CNV	5	ps	2	2	0.00	72525775.35	0
A04	R10-CNV	5	ps	2	2	210,000.00	72525775.35	0.2895522
A04	R10-CNV	5	ps	2	2	490,900.00	72525775.35	0.6768628
A04	R13-CNE	6	pq	1	1	-520,800.00	72525775.35	-0.7180895
A04	R13-CNE	6	pq	1	1	-195,000.00	72525775.35	-0.2688699
A04	R13-CNE	6	pq	1	1	-148,800.00	72525775.35	-0.2051684
A04	R13-CNE	6	pq	1	1	-60,000.00	72525775.35	-0.0827292
A04	R13-CNE	6	pq	1	1	-30,000.00	72525775.35	-0.0413646
A04	R13-CNE	6	pq	1	1	-30,000.00	72525775.35	-0.0413646
A04	R13-CNE	6	pq	1	1	-25,200.00	72525775.35	-0.0347463
A04	R13-CNE	6	pq	1	1	-14,000.00	72525775.35	-0.0193035
A04	R13-CNE	6	pq	1	1	-10,000.00	72525775.35	-0.0137882
A04	R13-CNE	6	pq	1	2	37,000.00	72525775.35	0.0510163
A04	R13-CNE	6	pq	1	2	120,000.00	72525775.35	0.1654584
A04	R13-CNE	6	pq	1	2	331,500.00	72525775.35	0.4570789
A04	R15-UNE	7	ps	2	2	2,415,000.00	72525775.35	3.3298506
A05	R5-CND	3	va	3	2	70,200.00	72005955.53	0.0974919
A05	R5-CND	3	va	3	2	110,000.00	72005955.53	0.1527651
A05	R5-CND	3	va	3	2	113,092.00	72005955.53	0.1570592
A05	R5-CND	3	va	3	2	237,050.00	72005955.53	0.3292089
A05	R5-CND	3	va	3	2	255,000.00	72005955.53	0.3541374
A05	R5-CND	3	va	3	2	410,400.00	72005955.53	0.5699529

Proj Grp Nr	Risk label	Risk sort code	Cost category	Cost sort code	Risk type code	Risk costs (Net)	Initial Contract Sum_ICS	Risk degree
A05	R6-UNS	4	va	3	2	103,600.00	72005955.53	0.143877
A05	R10-CNV	5	ps	2	1	-375,000.00	72005955.53	-0.5207903
A05	R10-CNV	5	ps	2	1	-300,000.00	72005955.53	-0.4166322
A05	R10-CNV	5	ps	2	1	-250,000.00	72005955.53	-0.3471935
A05	R10-CNV	5	ps	2	1	-178,850.00	72005955.53	-0.2483822
A05	R10-CNV	5	ps	2	1	-150,000.00	72005955.53	-0.2083161
A05	R10-CNV	5	ps	2	1	-100,000.00	72005955.53	-0.1388774
A05	R10-CNV	5	ps	2	2	224,910.00	72005955.53	0.3123492
A05	R13-CNE	6	pq	1	1	-195,000.00	72005955.53	-0.2708109
A05	R13-CNE	6	pq	1	1	-45,000.00	72005955.53	-0.0624948
A05	R13-CNE	6	pq	1	2	16,650.00	72005955.53	0.0231231
A05	R13-CNE	6	pq	1	2	219,375.00	72005955.53	0.3046623
A05	R13-CNE	6	pq	1	2	331,500.00	72005955.53	0.4603786
A05	R13-CNE	6	pq	1	2	4,024,100.00	72005955.53	5.5885655
A06	R5-CND	3	va	3	2	140,400.00	71278404.75	0.1969741
A06	R5-CND	3	va	3	2	255,000.00	71278404.75	0.3577521
A06	R5-CND	3	va	3	2	292,500.00	71278404.75	0.4103627
A06	R5-CND	3	va	3	2	5,073,105.00	71278404.75	7.11731
A06	R10-CNV	5	ps	2	1	-300,000.00	71278404.75	-0.4208848
A06	R10-CNV	5	ps	2	1	-150,000.00	71278404.75	-0.2104424
A06	R10-CNV	5	ps	2	1	-100,000.00	71278404.75	-0.1402949
A06	R10-CNV	5	ps	2	2	0.00	71278404.75	0
A06	R10-CNV	5	ps	2	2	0.00	71278404.75	0
A06	R10-CNV	5	ps	2	2	14,850.00	71278404.75	0.0208338
A06	R10-CNV	5	ps	2	2	210,000.00	71278404.75	0.2946194
A06	R13-CNE	6	pq	1	1	-615,000.00	71278404.75	-0.8628139
A06	R13-CNE	6	pq	1	1	-574,000.00	71278404.75	-0.805293
A06	R13-CNE	6	pq	1	1	-409,500.00	71278404.75	-0.5745078
A06	R13-CNE	6	pq	1	1	-297,600.00	71278404.75	-0.4175178
A06	R13-CNE	6	pq	1	1	-195,000.00	71278404.75	-0.2735751
A06	R13-CNE	6	pq	1	1	-114,800.00	71278404.75	-0.1610586
A06	R13-CNE	6	pq	1	1	-85,200.00	71278404.75	-0.1195313
A06	R13-CNE	6	pq	1	1	-74,400.00	71278404.75	-0.1043794
A06	R13-CNE	6	pq	1	2	40,000.00	71278404.75	0.056118
A06	R13-CNE	6	pq	1	2	67,500.00	71278404.75	0.0946991
A06	R13-CNE	6	pq	1	2	219,375.00	71278404.75	0.307772
A06	R13-CNE	6	pq	1	2	331,500.00	71278404.75	0.4650777
A07	R4-CLS	2	va	3	2	64,800.00	66403218	0.0975856
A07	R4-CLS	2	va	3	2	176,000.00	66403218	0.2650474
A07	R4-CLS	2	va	3	2	273,000.00	66403218	0.4111247
A07	R13-CNE	6	pq	1	1	-105,000.00	66403218	-0.1581249
A07	R13-CNE	6	pq	1	1	-35,000.00	66403218	-0.0527083
A07	R13-CNE	6	pq	1	2	126,000.00	66403218	0.1897498
A08	R10-CNV	5	ps	2	1	-839,500.00	140,668,064.00	-0.596795
A08	R10-CNV	5	ps	2	1	-50,000.00	140,668,064.00	-0.0355447
A08	R10-CNV	5	ps	2	2	0.00	140,668,064.00	0
A08	R10-CNV	5	ps	2	2	0.00	140,668,064.00	0
A08	R10-CNV	5	ps	2	2	0.00	140,668,064.00	0
A08	R10-CNV	5	ps	2	2	0.00	140,668,064.00	0
A08	R13-CNE	6	pq	1	1	-5,515,920.00	140,668,064.00	-3.9212312
A08	R13-CNE	6	pq	1	1	-1,862,400.00	140,668,064.00	-1.3239679
A08	R13-CNE	6	pq	1	1	-351,000.00	140,668,064.00	-0.2495236
A08	R13-CNE	6	pq	1	2	40,000.00	140,668,064.00	0.0284357
A08	R13-CNE	6	pq	1	2	324,150.00	140,668,064.00	0.2304361
A08	R13-CNE	6	pq	1	2	3,467,350.00	140,668,064.00	2.4649163
A08	R15-UNE	7	va	3	2	180,000.00	140,668,064.00	0.1279608

Proj Grp Nr	Risk label	Risk sort code	Cost category	Cost sort code	Risk type code	Risk costs (Net)	Initial Contract Sum_ICS	Risk degree
A08	R15-UNE	7	va	3	2	1,203,650.00	140,668,064.00	0.8556669
A08	R15-UNE	7	vo	4	1	-2,601,550.00	140,668,064.00	-1.8494248
A08	R15-UNE	7	vo	4	1	-778,500.00	140,668,064.00	-0.5534305
A08	R15-UNE	7	vs	5	1	-4,755,020.00	140,668,064.00	-3.3803124
A08	R15-UNE	7	vs	5	1	-351,000.00	140,668,064.00	-0.2495236
A08	R15-UNE	7	vs	5	1	-140,000.00	140,668,064.00	-0.0995251
A08	R15-UNE	7	vs	5	1	-18,000.00	140,668,064.00	-0.0127961
A08	R15-UNE	7	vs	5	2	432,500.00	140,668,064.00	0.3074614
A08	R15-UNE	7	vs	5	2	434,700.00	140,668,064.00	0.3090254
A09	R3-CLV	1	va	3	2	2,643,800.00	489,933,652.43	0.5396241
A09	R3-CLV	1	vs	5	2	9,294,700.00	489,933,652.43	1.8971344
A09	R4-CLS	2	va	3	2	331,425.00	489,933,652.43	0.0676469
A09	R10-CNV	5	ps	2	1	-5,500,133.70	489,933,652.43	-1.1226283
A09	R10-CNV	5	ps	2	1	-304,120.00	489,933,652.43	-0.0620737
A09	R10-CNV	5	ps	2	2	0.00	489,933,652.43	0
A09	R10-CNV	5	ps	2	2	60,042,965.00	489,933,652.43	12.255326
A09	R13-CNE	6	pq	1	1	-893,133.33	489,933,652.43	-0.1822968
A10	R3-CLV	1	va	3	2	117,330.00	127000000	0.0923858
A10	R3-CLV	1	va	3	2	249,980.26	127000000	0.1968349
A10	R3-CLV	1	va	3	2	1,108,000.00	127000000	0.8724409
A10	R3-CLV	1	va	3	2	1,300,000.00	127000000	1.023622
A10	R5-CND	3	va	3	2	38,316.00	127000000	0.0301701
A10	R5-CND	3	va	3	2	111,800.00	127000000	0.0880315
A10	R5-CND	3	va	3	2	280,768.00	127000000	0.2210772
A10	R5-CND	3	va	3	2	1,040,000.00	127000000	0.8188976
A10	R5-CND	3	va	3	2	1,693,490.00	127000000	1.3334567
A10	R10-CNV	5	ps	2	1	-1,823,290.00	127000000	-1.4356614
A10	R10-CNV	5	ps	2	1	-830,750.00	127000000	-0.6541339
A10	R10-CNV	5	ps	2	1	-642,945.00	127000000	-0.5062559
A10	R10-CNV	5	ps	2	1	-359,000.00	127000000	-0.2826772
A10	R10-CNV	5	ps	2	1	-34,400.00	127000000	-0.0270866
A10	R10-CNV	5	ps	2	1	-22,245.00	127000000	-0.0175157
A10	R10-CNV	5	ps	2	2	28,100.00	127000000	0.022126
A10	R10-CNV	5	ps	2	2	188,516.00	127000000	0.1484378
A10	R10-CNV	5	ps	2	2	258,614.00	127000000	0.2036331
A10	R10-CNV	5	ps	2	2	1,526,310.00	127000000	1.2018189
A10	R13-CNE	6	pq	1	1	-1,308,500.00	127000000	-1.030315
A10	R13-CNE	6	pq	1	1	-976,855.00	127000000	-0.7691772
A10	R13-CNE	6	pq	1	1	-900,130.00	127000000	-0.7087638
A10	R13-CNE	6	pq	1	1	-841,500.00	127000000	-0.6625984
A10	R13-CNE	6	pq	1	1	-730,080.00	127000000	-0.5748661
A10	R13-CNE	6	pq	1	1	-405,250.00	127000000	-0.3190945
A10	R13-CNE	6	pq	1	1	-404,255.00	127000000	-0.318311
A10	R13-CNE	6	pq	1	1	-231,580.00	127000000	-0.1823465
A10	R13-CNE	6	pq	1	1	-144,450.00	127000000	-0.1137402
A10	R13-CNE	6	pq	1	1	-108,150.00	127000000	-0.0851575
A10	R13-CNE	6	pq	1	1	-41,760.00	127000000	-0.0328819
A10	R13-CNE	6	pq	1	1	-40,000.00	127000000	-0.0314961
A10	R13-CNE	6	pq	1	1	-35,825.00	127000000	-0.0282087
A10	R13-CNE	6	pq	1	1	-7,234.00	127000000	-0.0056961
A10	R13-CNE	6	pq	1	2	18,550.00	127000000	0.0146063
A10	R13-CNE	6	pq	1	2	23,700.00	127000000	0.0186614
A10	R13-CNE	6	pq	1	2	30,740.00	127000000	0.0242047
A10	R13-CNE	6	pq	1	2	32,450.00	127000000	0.0255512
A10	R13-CNE	6	pq	1	2	43,225.00	127000000	0.0340354
A10	R13-CNE	6	pq	1	2	205,220.00	127000000	0.1615906

Proj Grp Nr	Risk label	Risk sort code	Cost category	Cost sort code	Risk type code	Risk costs (Net)	Initial Contract Sum_ICS	Risk degree
A10	R13-CNE	6	pq	1	2	214,500.00	127000000	0.1688976
A10	R13-CNE	6	pq	1	2	284,400.00	127000000	0.223937
A10	R13-CNE	6	pq	1	2	662,122.50	127000000	0.5213563
A10	R13-CNE	6	pq	1	2	1,421,585.00	127000000	1.1193583
A10	R13-CNE	6	pq	1	2	2,741,498.00	127000000	2.1586598
A10	R13-CNE	6	pq	1	2	3,357,886.00	127000000	2.6440047
A11	R4-CLS	2	va	3	2	300,000.00	523,881,350.58	0.0572649
A11	R4-CLS	2	va	3	2	1,273,700.00	523,881,350.58	0.2431276
A11	R4-CLS	2	va	3	2	3,528,600.00	523,881,350.58	0.6735495
A11	R4-CLS	2	vs	5	1	-4,883,400.00	523,881,350.58	-0.9321576
A11	R4-CLS	2	vs	5	1	-750,300.00	523,881,350.58	-0.1432195
A11	R10-CNV	5	ps	2	1	-200,000.00	523,881,350.58	-0.0381766
A11	R10-CNV	5	ps	2	1	-80,000.00	523,881,350.58	-0.0152706
A11	R10-CNV	5	ps	2	2	398,996.00	523,881,350.58	0.0761615
A11	R13-CNE	6	pq	1	1	-39,262,128.75	523,881,350.58	-7.4944696
A11	R13-CNE	6	pq	1	1	-262,800.00	523,881,350.58	-0.050164
A11	R13-CNE	6	pq	1	1	-54,953.00	523,881,350.58	-0.0104896
A11	R13-CNE	6	pq	1	2	187,761.00	523,881,350.58	0.0358404
A11	R13-CNE	6	pq	1	2	8,498,275.00	523,881,350.58	1.6221755
A11	R13-CNE	6	va	3	2	303,750.00	523,881,350.58	0.0579807
A11	R13-CNE	6	va	3	2	842,000.00	523,881,350.58	0.1607234
A11	R13-CNE	6	va	3	2	1,087,500.00	523,881,350.58	0.2075852
A11	R13-CNE	6	va	3	2	1,318,856.00	523,881,350.58	0.2517471
A11	R13-CNE	6	va	3	2	6,934,400.00	523,881,350.58	1.3236585
A11	R13-CNE	6	vs	5	2	9,708,900.00	523,881,350.58	1.8532631
A12	R3-CLV	1	va	3	2	230,000.00	75,346,244.40	0.3052574
A12	R4-CLS	2	va	3	2	14,080.00	75,346,244.40	0.0186871
A12	R4-CLS	2	va	3	2	150,000.00	75,346,244.40	0.1990809
A12	R4-CLS	2	va	3	2	170,000.00	75,346,244.40	0.225625
A12	R4-CLS	2	va	3	2	400,000.00	75,346,244.40	0.5308825
A12	R10-CNV	5	pq	1	1	-260,950.00	75,346,244.40	-0.3463344
A12	R10-CNV	5	pq	1	1	-183,936.00	75,346,244.40	-0.244121
A12	R10-CNV	5	pq	1	1	-110,400.00	75,346,244.40	-0.1465236
A12	R10-CNV	5	pq	1	1	-50,544.00	75,346,244.40	-0.0670823
A12	R10-CNV	5	pq	1	2	25,800.00	75,346,244.40	0.0342419
A12	R10-CNV	5	pq	1	2	333,200.00	75,346,244.40	0.4422251
A12	R10-CNV	5	pq	1	2	375,440.00	75,346,244.40	0.4982863
A12	R10-CNV	5	pq	1	2	435,160.00	75,346,244.40	0.577547
A12	R10-CNV	5	pq	1	2	652,400.00	75,346,244.40	0.8658693
A12	R10-CNV	5	pq	1	2	764,000.00	75,346,244.40	1.0139855
A12	R10-CNV	5	pq	1	2	772,280.00	75,346,244.40	1.0249748
A12	R10-CNV	5	pq	1	2	796,480.00	75,346,244.40	1.0570932
A12	R10-CNV	5	pq	1	2	813,195.00	75,346,244.40	1.0792774
A12	R10-CNV	5	pq	1	2	969,000.00	75,346,244.40	1.2860628
A12	R10-CNV	5	ps	2	1	-1,700,000.00	75,346,244.40	-2.2562505
A12	R10-CNV	5	ps	2	1	-1,500,000.00	75,346,244.40	-1.9908092
A12	R10-CNV	5	ps	2	1	-361,522.00	75,346,244.40	-0.4798142
A12	R10-CNV	5	ps	2	1	-97,148.00	75,346,244.40	-0.1289354
A13	R5-CND	3	va	3	2	56,000.00	600,600,000.00	0.009324
A13	R5-CND	3	va	3	2	80,000.00	600,600,000.00	0.01332
A13	R5-CND	3	va	3	2	650,000.00	600,600,000.00	0.1082251
A13	R5-CND	3	va	3	2	676,500.00	600,600,000.00	0.1126374
A13	R5-CND	3	va	3	2	2,205,400.00	600,600,000.00	0.3671995
A13	R5-CND	3	va	3	2	4,477,200.00	600,600,000.00	0.7454545
A13	R5-CND	3	va	3	2	4,840,000.00	600,600,000.00	0.8058608
A13	R5-CND	3	va	3	2	6,363,450.00	600,600,000.00	1.0595155

Proj Grp Nr	Risk label	Risk sort code	Cost category	Cost sort code	Risk type code	Risk costs (Net)	Initial Contract Sum_ICS	Risk degree
A13	R10-CNV	5	pq	1	1	-9,577,100.00	600,600,000.00	-1.5945887
A13	R10-CNV	5	pq	1	1	-8,342,500.00	600,600,000.00	-1.3890276
A13	R10-CNV	5	pq	1	1	-7,821,600.00	600,600,000.00	-1.3022977
A13	R10-CNV	5	pq	1	1	-6,170,000.00	600,600,000.00	-1.027306
A13	R10-CNV	5	pq	1	1	-3,778,200.00	600,600,000.00	-0.6290709
A13	R10-CNV	5	pq	1	1	-3,685,500.00	600,600,000.00	-0.6136364
A13	R10-CNV	5	pq	1	1	-3,669,450.00	600,600,000.00	-0.610964
A13	R10-CNV	5	pq	1	1	-3,245,500.00	600,600,000.00	-0.5403763
A13	R10-CNV	5	pq	1	1	-2,908,540.00	600,600,000.00	-0.4842724
A13	R10-CNV	5	pq	1	1	-1,228,500.00	600,600,000.00	-0.2045455
A13	R10-CNV	5	pq	1	1	-976,500.00	600,600,000.00	-0.1625874
A13	R10-CNV	5	pq	1	1	-761,800.00	600,600,000.00	-0.1268398
A13	R10-CNV	5	pq	1	1	-543,600.00	600,600,000.00	-0.0905095
A13	R10-CNV	5	pq	1	1	-434,000.00	600,600,000.00	-0.0722611
A13	R10-CNV	5	pq	1	1	-184,200.00	600,600,000.00	-0.0306693
A13	R10-CNV	5	pq	1	1	-12,400.00	600,600,000.00	-0.0020646
A13	R10-CNV	5	pq	1	2	171,000.00	600,600,000.00	0.0284715
A13	R10-CNV	5	pq	1	2	174,000.00	600,600,000.00	0.028971
A13	R10-CNV	5	pq	1	2	302,400.00	600,600,000.00	0.0503497
A13	R10-CNV	5	pq	1	2	488,400.00	600,600,000.00	0.0813187
A13	R10-CNV	5	pq	1	2	575,000.00	600,600,000.00	0.0957376
A13	R10-CNV	5	pq	1	2	581,275.00	600,600,000.00	0.0967824
A13	R10-CNV	5	pq	1	2	766,500.00	600,600,000.00	0.1276224
A13	R10-CNV	5	pq	1	2	793,500.00	600,600,000.00	0.1321179
A13	R10-CNV	5	pq	1	2	1,404,475.00	600,600,000.00	0.2338453
A13	R10-CNV	5	pq	1	2	1,829,100.00	600,600,000.00	0.3045455
A13	R10-CNV	5	pq	1	2	1,830,000.00	600,600,000.00	0.3046953
A13	R10-CNV	5	pq	1	2	2,051,502.00	600,600,000.00	0.3415754
A13	R10-CNV	5	pq	1	2	2,210,000.00	600,600,000.00	0.3679654
A13	R10-CNV	5	pq	1	2	2,505,000.00	600,600,000.00	0.4170829
A13	R10-CNV	5	pq	1	2	2,697,400.00	600,600,000.00	0.4491175
A13	R10-CNV	5	pq	1	2	4,076,145.00	600,600,000.00	0.6786788
A13	R10-CNV	5	pq	1	2	4,180,166.00	600,600,000.00	0.6959983
A13	R10-CNV	5	pq	1	2	5,692,500.00	600,600,000.00	0.9478022
A14	R3-CLV	1	va	3	2	49,680.00	207,388,304.81	0.0239551
A14	R3-CLV	1	va	3	2	80,550.00	207,388,304.81	0.0388402
A14	R3-CLV	1	va	3	2	369,335.00	207,388,304.81	0.1780886
A14	R3-CLV	1	va	3	2	386,900.00	207,388,304.81	0.1865583
A14	R3-CLV	1	va	3	2	600,800.00	207,388,304.81	0.2896981
A14	R3-CLV	1	va	3	2	3,327,205.27	207,388,304.81	1.604336
A14	R4-CLS	2	vo	4	1	-5,000,000.00	207,388,304.81	-2.4109363
A14	R4-CLS	2	vo	4	1	-4,040,000.00	207,388,304.81	-1.9480366
A14	R4-CLS	2	vo	4	1	-760,150.00	207,388,304.81	-0.3665347
A14	R4-CLS	2	vo	4	1	-380,000.00	207,388,304.81	-0.1832312
A14	R5-CND	3	pq	1	2	4,397,607.94	207,388,304.81	2.1204706
A14	R10-CNV	5	ps	2	1	-6,737,559.00	207,388,304.81	-3.2487652
A14	R10-CNV	5	ps	2	1	-2,744,500.00	207,388,304.81	-1.323363
A14	R10-CNV	5	ps	2	1	-217,620.00	207,388,304.81	-0.1049336
A14	R10-CNV	5	ps	2	1	-124,212.60	207,388,304.81	-0.0598937
A14	R10-CNV	5	ps	2	2	1,756,198.00	207,388,304.81	0.8468163
A15	R4-CLS	2	va	3	2	3,690,000.00	198,899,132.52	1.8552117
A15	R4-CLS	2	vo	4	1	-1,137,600.00	198,899,132.52	-0.5719482
A15	R4-CLS	2	vs	5	2	5,161,656.06	198,899,132.52	2.5951124
A15	R5-CND	3	pq	1	1	-218,510.00	198,899,132.52	-0.1098597
A15	R13-CNE	6	pq	1	2	1,693,800.00	198,899,132.52	0.8515874
A16	R4-CLS	2	va	3	2	60,000.00	227,092,280.15	0.026421

Proj Grp Nr	Risk label	Risk sort code	Cost category	Cost sort code	Risk type code	Risk costs (Net)	Initial Contract Sum_ICS	Risk degree
A16	R4-CLS	2	va	3	2	72,000.00	227,092,280.15	0.0317052
A16	R4-CLS	2	va	3	2	91,122.00	227,092,280.15	0.0401255
A16	R4-CLS	2	vs	5	1	-437,250.00	227,092,280.15	-0.1925429
A16	R4-CLS	2	vs	5	2	585,956.00	227,092,280.15	0.2580255
A16	R4-CLS	2	vs	5	2	736,000.23	227,092,280.15	0.3240974
A16	R4-CLS	2	vs	5	2	1,545,666.90	227,092,280.15	0.6806338
A16	R5-CND	3	pq	1	1	-1,200,000.00	227,092,280.15	-0.5284195
A16	R5-CND	3	va	3	2	6,000.00	227,092,280.15	0.0026421
A16	R5-CND	3	va	3	2	30,000.00	227,092,280.15	0.0132105
A16	R5-CND	3	va	3	2	232,625.00	227,092,280.15	0.1024363
A16	R5-CND	3	va	3	2	234,300.00	227,092,280.15	0.1031739
A16	R5-CND	3	va	3	2	460,000.00	227,092,280.15	0.2025608
A16	R5-CND	3	va	3	2	483,600.00	227,092,280.15	0.2129531
A16	R5-CND	3	va	3	2	6,072,300.00	227,092,280.15	2.673935
B17	R4-CLS	2	va	3	2	10,079,030.00	299,084,056.47	3.3699657
B17	R15-UNE	7	va	3	2	14,352,000.00	299,084,056.47	4.798651
B17	R15-UNE	7	va	3	2	15,722,046.00	299,084,056.47	5.2567316
B18	R4-CLS	2	va	3	2	2,318,100.00	200,182,589.99	1.1579928
B18	R4-CLS	2	va	3	2	15,013,694.40	200,182,589.99	7.5000001
B18	R15-UNE	7	va	3	2	13,702,840.00	200,182,589.99	6.8451707
B19	R4-CLS	2	va	3	2	2,820,620.00	204,274,840.99	1.3807966
B19	R4-CLS	2	va	3	2	15,320,613.00	204,274,840.99	7.5
B19	R15-UNE	7	va	3	2	13,702,940.00	204,274,840.99	6.7080899
B20	R4-CLS	2	va	3	2	2,547,095.00	251,753,471.25	1.0117418
B20	R4-CLS	2	va	3	2	17,622,743.04	251,753,471.25	7
B20	R15-UNE	7	va	3	2	9,892,840.00	251,753,471.25	3.9295744
B21	R4-CLS	2	va	3	2	10,809,749.16	120,108,325.35	8.9999999
B21	R4-CLS	2	va	3	2	18,842,601.00	120,108,325.35	15.688006
B21	R15-UNE	7	va	3	2	2,825,354.84	120,108,325.35	2.3523389
B22	R4-CLS	2	va	3	2	2,400,950.00	22,544,147.50	10.649992
B23	R4-CLS	2	va	3	2	3,475,900.00	11,839,600.00	29.358255
B24	R3-CLV	1	va	3	2	40,500.00	22,078,124.00	0.1834395
B24	R3-CLV	1	va	3	2	40,500.00	22,078,124.00	0.1834395
B24	R3-CLV	1	va	3	2	80,100.00	22,078,124.00	0.3628026
B24	R3-CLV	1	va	3	2	80,100.00	22,078,124.00	0.3628026
B24	R3-CLV	1	va	3	2	251,640.00	22,078,124.00	1.1397708
B24	R3-CLV	1	va	3	2	251,640.00	22,078,124.00	1.1397708
B24	R3-CLV	1	va	3	2	647,500.00	22,078,124.00	2.9327673
B24	R3-CLV	1	va	3	2	647,500.00	22,078,124.00	2.9327673
B24	R10-CNV	5	ps	2	2	376,000.00	22,078,124.00	1.7030432
B24	R10-CNV	5	ps	2	2	376,000.00	22,078,124.00	1.7030432
B24	R10-CNV	5	ps	2	2	426,510.00	22,078,124.00	1.9318217
B24	R10-CNV	5	ps	2	2	426,510.00	22,078,124.00	1.9318217
B24	R13-CNE	6	pq	1	1	-250,100.00	22,078,124.00	-1.1327955
B24	R13-CNE	6	pq	1	1	-250,100.00	22,078,124.00	-1.1327955
B24	R13-CNE	6	pq	1	2	10,600.00	22,078,124.00	0.0480113
B24	R13-CNE	6	pq	1	2	10,600.00	22,078,124.00	0.0480113
B24	R13-CNE	6	pq	1	2	54,500.00	22,078,124.00	0.2468507
B24	R13-CNE	6	pq	1	2	54,500.00	22,078,124.00	0.2468507
B24	R13-CNE	6	pq	1	2	575,020.00	22,078,124.00	2.6044785
B24	R13-CNE	6	pq	1	2	575,020.00	22,078,124.00	2.6044785
B24	R13-CNE	6	pq	1	2	734,210.00	22,078,124.00	3.325509
B24	R13-CNE	6	pq	1	2	734,210.00	22,078,124.00	3.325509
B24	R13-CNE	6	pq	1	2	1,236,545.00	22,078,124.00	5.6007702
B24	R13-CNE	6	pq	1	2	1,236,545.00	22,078,124.00	5.6007702
B25	R6-UNS	4	pq	1	1	-119,855.00	30,744,958.83	-0.3898363

Proj Grp Nr	Risk label	Risk sort code	Cost category	Cost sort code	Risk type code	Risk costs (Net)	Initial Contract Sum_ICS	Risk degree
B25	R13-CNE	6	va	3	2	33,630.00	30,744,958.83	0.1093838
B25	R13-CNE	6	va	3	2	130,625.00	30,744,958.83	0.4248664
B25	R13-CNE	6	va	3	2	172,980.00	30,744,958.83	0.5626288
B25	R13-CNE	6	va	3	2	496,120.00	30,744,958.83	1.6136629
B26	R6-UNS	4	pq	1	1	-185,182.90	32,131,109.07	-0.5763352
B26	R13-CNE	6	va	3	2	118,750.00	32,131,109.07	0.3695795
B26	R13-CNE	6	va	3	2	152,531.00	32,131,109.07	0.4747144
B26	R13-CNE	6	va	3	2	605,300.00	32,131,109.07	1.8838441
B27	R6-UNS	4	pq	1	1	-147,490.00	31,977,000.00	-0.4612378
B27	R10-CNV	5	ps	2	1	-222,100.00	31,977,000.00	-0.6945617
B27	R10-CNV	5	ps	2	2	80,460.00	31,977,000.00	0.2516184
B27	R10-CNV	5	ps	2	2	223,580.00	31,977,000.00	0.69919
B27	R13-CNE	6	va	3	2	35,725.00	31,977,000.00	0.1117209
B27	R13-CNE	6	va	3	2	142,500.00	31,977,000.00	0.4456328
B27	R13-CNE	6	va	3	2	160,950.00	31,977,000.00	0.5033305
B27	R13-CNE	6	va	3	2	563,008.00	31,977,000.00	1.7606655
B28	R3-CLV	1	vo	4	1	-1,500.00	30,339,877.19	-0.004944
B28	R6-UNS	4	pq	1	1	-165,630.00	30,339,877.19	-0.5459152
B28	R10-CNV	5	ps	2	1	-28,100.00	30,339,877.19	-0.0926174
B28	R10-CNV	5	ps	2	2	87,910.00	30,339,877.19	0.2897507
B28	R10-CNV	5	ps	2	2	298,060.00	30,339,877.19	0.9824034
B28	R13-CNE	6	va	3	2	53,600.00	30,339,877.19	0.1766652
B28	R13-CNE	6	va	3	2	118,750.00	30,339,877.19	0.3913991
B28	R13-CNE	6	va	3	2	151,200.00	30,339,877.19	0.498354
B28	R13-CNE	6	va	3	2	558,640.00	30,339,877.19	1.8412731
B29	R6-UNS	4	pq	1	1	-184,125.50	31,188,504.90	-0.5903633
B29	R10-CNV	5	ps	2	1	-185,100.00	31,188,504.90	-0.5934879
B29	R10-CNV	5	ps	2	2	201,470.00	31,188,504.90	0.6459752
B29	R10-CNV	5	ps	2	2	257,210.00	31,188,504.90	0.8246949
B29	R13-CNE	6	va	3	2	41,929.00	31,188,504.90	0.1344374
B29	R13-CNE	6	va	3	2	130,625.00	31,188,504.90	0.4188242
B29	R13-CNE	6	va	3	2	149,984.00	31,188,504.90	0.4808951
B29	R13-CNE	6	va	3	2	529,339.00	31,188,504.90	1.6972247
B30	R6-UNS	4	pq	1	1	-373,050.00	31,977,838.16	-1.1665892
B30	R10-CNV	5	ps	2	1	-0.04	31,977,838.16	-1.251E-07
B30	R10-CNV	5	ps	2	2	570.00	31,977,838.16	0.0017825
B30	R13-CNE	6	va	3	2	20,550.00	31,977,838.16	0.0642633
B30	R13-CNE	6	va	3	2	130,625.00	31,977,838.16	0.408486
B30	R13-CNE	6	va	3	2	134,850.00	31,977,838.16	0.4216983
B30	R13-CNE	6	va	3	2	478,881.44	31,977,838.16	1.4975416
B31	R6-UNS	4	pq	1	1	-191,560.00	32,801,010.00	-0.5840064
B31	R10-CNV	5	ps	2	1	-190,800.00	32,801,010.00	-0.5816894
B31	R10-CNV	5	ps	2	2	94,600.00	32,801,010.00	0.2884058
B31	R10-CNV	5	ps	2	2	254,080.00	32,801,010.00	0.7746103
B31	R13-CNE	6	va	3	2	52,990.00	32,801,010.00	0.1615499
B31	R13-CNE	6	va	3	2	142,500.00	32,801,010.00	0.4344378
B31	R13-CNE	6	va	3	2	176,400.00	32,801,010.00	0.5377883
B31	R13-CNE	6	va	3	2	603,660.00	32,801,010.00	1.8403702
B32	R6-UNS	4	pq	1	1	-181,440.00	31,205,955.42	-0.5814275
B32	R10-CNV	5	ps	2	1	-181,400.00	31,205,955.42	-0.5812993
B32	R10-CNV	5	ps	2	2	81,730.00	31,205,955.42	0.2619051
B32	R10-CNV	5	ps	2	2	238,880.00	31,205,955.42	0.7654949
B32	R13-CNE	6	va	3	2	44,100.00	31,205,955.42	0.1413192
B32	R13-CNE	6	va	3	2	142,500.00	31,205,955.42	0.4566436
B32	R13-CNE	6	va	3	2	173,720.00	31,205,955.42	0.5566886
B32	R13-CNE	6	va	3	2	518,500.00	31,205,955.42	1.6615418

Proj Grp Nr	Risk label	Risk sort code	Cost category	Cost sort code	Risk type code	Risk costs (Net)	Initial Contract Sum_ICS	Risk degree
B33	R6-UNS	4	pq	1	1	-510,510.00	32,272,686.60	-1.581864
B33	R13-CNE	6	va	3	2	49,546.26	32,272,686.60	0.1535238
B33	R13-CNE	6	va	3	2	142,500.00	32,272,686.60	0.4415499
B33	R13-CNE	6	va	3	2	214,120.00	32,272,686.60	0.6634713
B33	R13-CNE	6	va	3	2	654,229.00	32,272,686.60	2.027191
B34	R6-UNS	4	pq	1	1	-156,590.00	32,964,986.25	-0.4750192
B34	R10-CNV	5	ps	2	1	-211,150.00	32,964,986.25	-0.6405281
B34	R10-CNV	5	ps	2	2	171,030.00	32,964,986.25	0.5188232
B34	R10-CNV	5	ps	2	2	323,850.00	32,964,986.25	0.982406
B34	R13-CNE	6	va	3	2	53,600.00	32,964,986.25	0.1625968
B34	R13-CNE	6	va	3	2	118,750.00	32,964,986.25	0.3602307
B34	R13-CNE	6	va	3	2	151,200.00	32,964,986.25	0.4586685
B34	R13-CNE	6	va	3	2	558,640.00	32,964,986.25	1.6946465
B35	R6-UNS	4	pq	1	2	19,508.00	32,226,417.56	0.0605342
B35	R10-CNV	5	ps	2	1	-12,100.08	32,226,417.56	-0.0375471
B35	R10-CNV	5	ps	2	2	162,760.00	32,226,417.56	0.5050515
B35	R13-CNE	6	va	3	2	27,505.00	32,226,417.56	0.0853492
B35	R13-CNE	6	va	3	2	142,500.00	32,226,417.56	0.4421838
B35	R13-CNE	6	va	3	2	172,200.00	32,226,417.56	0.5343442
B35	R13-CNE	6	va	3	2	624,642.00	32,226,417.56	1.9382918
B36	R6-UNS	4	pq	1	1	-271,490.00	34,717,490.06	-0.7819978
B36	R10-CNV	5	ps	2	1	-187,100.00	34,717,490.06	-0.5389214
B36	R10-CNV	5	ps	2	2	112,320.00	34,717,490.06	0.3235257
B36	R10-CNV	5	ps	2	2	299,820.00	34,717,490.06	0.8635993
B36	R13-CNE	6	va	3	2	54,400.00	34,717,490.06	0.1566934
B36	R13-CNE	6	va	3	2	154,375.00	34,717,490.06	0.4446606
B36	R13-CNE	6	va	3	2	234,440.00	34,717,490.06	0.6752792
B36	R13-CNE	6	va	3	2	743,250.00	34,717,490.06	2.1408518
B37	R3-CLV	1	vs	5	2	80,226.50	37,332,533.43	0.214897
B37	R4-CLS	2	vs	5	2	465,500.00	37,332,533.43	1.2469017
B37	R6-UNS	4	pq	1	1	-881,680.00	37,332,533.43	-2.3616935
B37	R10-CNV	5	va	3	2	90,000.00	37,332,533.43	0.2410766
B37	R10-CNV	5	va	3	2	197,500.00	37,332,533.43	0.5290292
B37	R10-CNV	5	va	3	2	202,500.00	37,332,533.43	0.5424223
B37	R10-CNV	5	va	3	2	330,000.00	37,332,533.43	0.8839475
B37	R13-CNE	6	vs	5	2	248,640.00	37,332,533.43	0.6660143
B38	R3-CLV	1	vs	5	2	85,111.80	45,453,135.09	0.1872518
B38	R4-CLS	2	vs	5	2	594,720.00	45,453,135.09	1.3084246
B38	R6-UNS	4	pq	1	1	-1,108,932.00	45,453,135.09	-2.4397261
B38	R10-CNV	5	va	3	2	108,000.00	45,453,135.09	0.2376074
B38	R10-CNV	5	va	3	2	237,000.00	45,453,135.09	0.5214162
B38	R10-CNV	5	va	3	2	243,000.00	45,453,135.09	0.5346166
B38	R10-CNV	5	va	3	2	396,000.00	45,453,135.09	0.871227
B38	R13-CNE	6	vs	5	2	374,400.00	45,453,135.09	0.8237056
B39	R3-CLV	1	vs	5	2	1,013,791.80	44,073,555.82	2.3002269
B39	R4-CLS	2	vs	5	2	526,800.00	44,073,555.82	1.1952746
B39	R6-UNS	4	pq	1	1	-1,889,910.00	44,073,555.82	-4.2880815
B39	R10-CNV	5	va	3	2	108,000.00	44,073,555.82	0.2450449
B39	R10-CNV	5	va	3	2	237,000.00	44,073,555.82	0.5377374
B39	R10-CNV	5	va	3	2	243,000.00	44,073,555.82	0.551351
B39	R10-CNV	5	va	3	2	396,000.00	44,073,555.82	0.898498
B39	R13-CNE	6	vs	5	2	298,368.00	44,073,555.82	0.6769774
B40	R3-CLV	1	vo	4	1	-320,000.00	38,513,661.72	-0.830874
B40	R3-CLV	1	vs	5	2	130,826.50	38,513,661.72	0.3396886
B40	R4-CLS	2	vs	5	2	505,000.00	38,513,661.72	1.311223
B40	R6-UNS	4	pq	1	1	-538,735.00	38,513,661.72	-1.3988153

Proj Grp Nr	Risk label	Risk sort code	Cost category	Cost sort code	Risk type code	Risk costs (Net)	Initial Contract Sum_ICS	Risk degree
B40	R10-CNV	5	va	3	2	90,000.00	38,513,661.72	0.2336833
B40	R10-CNV	5	va	3	2	197,500.00	38,513,661.72	0.512805
B40	R10-CNV	5	va	3	2	202,500.00	38,513,661.72	0.5257875
B40	R10-CNV	5	va	3	2	330,000.00	38,513,661.72	0.8568388
B40	R13-CNE	6	vs	5	2	192,000.00	38,513,661.72	0.4985244
B41	R3-CLV	1	va	3	2	21,080,016.75	114,977,068.50	18.334105
B41	R4-CLS	2	va	3	2	380,000.00	114,977,068.50	0.3305007
B41	R4-CLS	2	va	3	2	1,032,890.00	114,977,068.50	0.8983444
B41	R4-CLS	2	va	3	2	1,250,000.00	114,977,068.50	1.0871733
B41	R4-CLS	2	vo	4	1	-1,057,890.00	114,977,068.50	-0.9200878
B41	R10-CNV	5	ps	2	2	395,000.00	114,977,068.50	0.3435468
B42	R4-CLS	2	va	3	2	25,872.00	11,580,313.50	0.2234136
B42	R10-CNV	5	ps	2	1	-400,000.00	11,580,313.50	-3.4541379
B42	R10-CNV	5	ps	2	1	-20,000.00	11,580,313.50	-0.1727069
B42	R13-CNE	6	pq	1	1	-46,000.00	11,580,313.50	-0.3972259
B42	R13-CNE	6	pq	1	1	-21,000.00	11,580,313.50	-0.1813422
B43	R4-CLS	2	va	3	2	6,300.00	1,928,797.50	0.3266284
B43	R10-CNV	5	ps	2	1	-323,000.00	1,928,797.50	-16.746185
B43	R13-CNE	6	pq	1	2	56,000.00	1,928,797.50	2.9033634
B43	R13-CNE	6	pq	1	2	57,600.00	1,928,797.50	2.9863166
B44	R3-CLV	1	pq	1	1	-180,000.00	48,691,944.00	-0.369671
B45	R4-CLS	2	va	3	2	1,580.00	45,441,808.13	0.003477
B45	R4-CLS	2	va	3	2	6,938.00	45,441,808.13	0.0152679
B45	R4-CLS	2	va	3	2	8,140.00	45,441,808.13	0.017913
B45	R4-CLS	2	va	3	2	8,700.00	45,441,808.13	0.0191454
B45	R4-CLS	2	va	3	2	15,000.00	45,441,808.13	0.0330092
B45	R4-CLS	2	va	3	2	98,520.00	45,441,808.13	0.2168048
B45	R4-CLS	2	va	3	2	99,000.00	45,441,808.13	0.217861
B45	R4-CLS	2	va	3	2	157,650.00	45,441,808.13	0.3469272
B45	R4-CLS	2	va	3	2	201,312.50	45,441,808.13	0.4430116
B45	R5-CND	3	vs	5	1	-2,317,860.00	45,441,808.13	-5.1007213
B45	R5-CND	3	vs	5	1	-1,600.00	45,441,808.13	-0.003521
B45	R5-CND	3	vs	5	2	42,540.00	45,441,808.13	0.0936142
B45	R5-CND	3	vs	5	2	250,100.00	45,441,808.13	0.5503742
B45	R5-CND	3	vs	5	2	352,176.00	45,441,808.13	0.7750044
B45	R5-CND	3	vs	5	2	817,759.00	45,441,808.13	1.7995741
B45	R6-UNS	4	pq	1	1	-202,601.00	45,441,808.13	-0.4458471
B45	R6-UNS	4	ps	2	1	-77,000.00	45,441,808.13	-0.1694475
B45	R10-CNV	5	ps	2	1	-3,186,000.00	45,441,808.13	-7.0111647
B45	R10-CNV	5	ps	2	1	-1,203,600.00	45,441,808.13	-2.6486622
B45	R10-CNV	5	ps	2	1	-137,025.00	45,441,808.13	-0.3015395
B45	R10-CNV	5	ps	2	1	-70,875.00	45,441,808.13	-0.1559687
B45	R10-CNV	5	ps	2	1	-55,000.00	45,441,808.13	-0.1210339
B45	R10-CNV	5	ps	2	2	117,525.00	45,441,808.13	0.2586275
B45	R13-CNE	6	pq	1	1	-1,037,108.00	45,441,808.13	-2.2822771
B45	R13-CNE	6	pq	1	1	-809,586.25	45,441,808.13	-1.781589
B45	R13-CNE	6	pq	1	1	-351,310.00	45,441,808.13	-0.7730986
B45	R13-CNE	6	pq	1	1	-295,740.00	45,441,808.13	-0.6508104
B45	R13-CNE	6	pq	1	1	-135,280.00	45,441,808.13	-0.2976994
B45	R13-CNE	6	pq	1	1	-100,310.00	45,441,808.13	-0.2207439
B45	R13-CNE	6	pq	1	1	-66,152.00	45,441,808.13	-0.1455752
B45	R13-CNE	6	pq	1	1	-65,320.00	45,441,808.13	-0.1437443
B45	R13-CNE	6	pq	1	1	-64,700.00	45,441,808.13	-0.1423799
B45	R13-CNE	6	pq	1	1	-39,600.00	45,441,808.13	-0.0871444
B45	R13-CNE	6	pq	1	1	-35,541.00	45,441,808.13	-0.0782121
B45	R13-CNE	6	pq	1	1	-19,500.00	45,441,808.13	-0.042912

Proj Grp Nr	Risk label	Risk sort code	Cost category	Cost sort code	Risk type code	Risk costs (Net)	Initial Contract Sum_ICS	Risk degree
B45	R13-CNE	6	pq	1	1	-15,600.00	45,441,808.13	-0.0343296
B45	R13-CNE	6	pq	1	1	-11,424.00	45,441,808.13	-0.0251398
B45	R13-CNE	6	pq	1	1	-9,480.00	45,441,808.13	-0.0208618
B45	R13-CNE	6	pq	1	1	-7,120.00	45,441,808.13	-0.0156684
B45	R13-CNE	6	pq	1	2	8,535.00	45,441,808.13	0.0187823
B45	R13-CNE	6	pq	1	2	9,250.00	45,441,808.13	0.0203557
B45	R13-CNE	6	pq	1	2	14,555.00	45,441,808.13	0.03203
B45	R13-CNE	6	pq	1	2	29,827.00	45,441,808.13	0.0656378
B45	R13-CNE	6	pq	1	2	31,080.00	45,441,808.13	0.0683952
B45	R13-CNE	6	pq	1	2	44,170.16	45,441,808.13	0.0972016
B45	R13-CNE	6	pq	1	2	49,974.40	45,441,808.13	0.1099745
B45	R13-CNE	6	pq	1	2	122,298.00	45,441,808.13	0.269131
B45	R13-CNE	6	pq	1	2	158,820.00	45,441,808.13	0.3495019
B45	R13-CNE	6	pq	1	2	279,510.00	45,441,808.13	0.6150944
B45	R13-CNE	6	pq	1	2	315,400.00	45,441,808.13	0.6940745
B45	R13-CNE	6	pq	1	2	479,570.00	45,441,808.13	1.0553497
B45	R13-CNE	6	pq	1	2	711,100.00	45,441,808.13	1.5648585
B45	R13-CNE	6	pq	1	2	1,061,572.00	45,441,808.13	2.336113
B45	R15-UNE	7	va	3	2	15,000.00	45,441,808.13	0.0330092
B45	R15-UNE	7	va	3	2	210,000.00	45,441,808.13	0.4621295
B45	R15-UNE	7	va	3	2	348,000.00	45,441,808.13	0.7658146
B46	R4-CLS	2	vs	5	1	-518,360.00	102,187,284.45	-0.5072647
B46	R5-CND	3	va	3	2	189,322.00	102,187,284.45	0.1852696
B46	R5-CND	3	va	3	2	327,722.00	102,187,284.45	0.3207072
B46	R5-CND	3	va	3	2	341,819.00	102,187,284.45	0.3345025
B46	R5-CND	3	va	3	2	416,827.00	102,187,284.45	0.407905
B46	R5-CND	3	va	3	2	418,937.00	102,187,284.45	0.4099698
B46	R5-CND	3	va	3	2	1,112,826.00	102,187,284.45	1.0890063
B46	R5-CND	3	va	3	2	1,614,050.00	102,187,284.45	1.5795018
B46	R5-CND	3	va	3	2	2,158,906.00	102,187,284.45	2.1126953
B46	R5-CND	3	vo	4	1	-122,600.00	102,187,284.45	-0.1199758
B46	R5-CND	3	vo	4	1	-83,600.00	102,187,284.45	-0.0818106
B46	R5-CND	3	vo	4	1	-37,700.00	102,187,284.45	-0.036893
B46	R5-CND	3	vo	4	1	-18,000.00	102,187,284.45	-0.0176147
B46	R5-CND	3	vo	4	1	-11,988.00	102,187,284.45	-0.0117314
B46	R10-CNV	5	ps	2	1	-1,516,060.00	102,187,284.45	-1.4836092
B46	R10-CNV	5	ps	2	2	359,165.00	102,187,284.45	0.3514772
B46	R13-CNE	6	pq	1	1	-843,375.00	102,187,284.45	-0.8253228
B46	R13-CNE	6	pq	1	1	-653,750.00	102,187,284.45	-0.6397567
B46	R13-CNE	6	pq	1	1	-198,740.00	102,187,284.45	-0.194486
B46	R13-CNE	6	pq	1	1	-153,760.00	102,187,284.45	-0.1504688
B47	R4-CLS	2	va	3	2	78,117.42	24,700,871.00	0.3162537
B47	R4-CLS	2	va	3	2	101,010.48	24,700,871.00	0.4089349
B47	R4-CLS	2	va	3	2	117,845.56	24,700,871.00	0.4770907
B47	R4-CLS	2	va	3	2	292,754.95	24,700,871.00	1.1852009
B47	R4-CLS	2	va	3	2	376,986.82	24,700,871.00	1.5262086
B47	R6-UNS	4	pq	1	1	-521,926.19	24,700,871.00	-2.112987
B47	R13-CNE	6	pq	1	1	-152,457.00	24,700,871.00	-0.6172131
B48	R4-CLS	2	va	3	2	12,500.00	6,950,359.50	0.1798468
B48	R4-CLS	2	va	3	2	15,000.00	6,950,359.50	0.2158162
B48	R4-CLS	2	va	3	2	29,750.00	6,950,359.50	0.4280354
B48	R4-CLS	2	va	3	2	62,400.00	6,950,359.50	0.8977953
B48	R4-CLS	2	va	3	2	74,000.00	6,950,359.50	1.0646931
B48	R4-CLS	2	va	3	2	88,000.00	6,950,359.50	1.2661216
B48	R4-CLS	2	va	3	2	90,000.00	6,950,359.50	1.294897
B48	R4-CLS	2	va	3	2	197,250.00	6,950,359.50	2.8379827

Proj Grp Nr	Risk label	Risk sort code	Cost category	Cost sort code	Risk type code	Risk costs (Net)	Initial Contract Sum_ICS	Risk degree
B48	R4-CLS	2	va	3	2	239,500.00	6,950,359.50	3.4458649
B48	R4-CLS	2	va	3	2	500,000.00	6,950,359.50	7.1938725
B48	R10-CNV	5	ps	2	1	-863,500.00	6,950,359.50	-12.423818
B48	R13-CNE	6	pq	1	2	40,000.00	6,950,359.50	0.5755098
B48	R13-CNE	6	pq	1	2	81,000.00	6,950,359.50	1.1654073
C49	R4-CLS	2	va	3	2	550,000.00	83,152,391.70	0.6614362
C49	R10-CNV	5	ps	2	1	-1,000,000.00	83,152,391.70	-1.2026112
C50	R3-CLV	1	va	3	2	1,174,200.00	84,024,366.30	1.3974518
C50	R3-CLV	1	va	3	2	1,662,485.00	84,024,366.30	1.9785749
C50	R3-CLV	1	va	3	2	2,855,015.00	84,024,366.30	3.3978418
C50	R3-CLV	1	va	3	2	4,300,425.00	84,024,366.30	5.1180689
C50	R3-CLV	1	va	3	2	12,951,135.00	84,024,366.30	15.413547
C50	R3-CLV	1	va	3	2	12,951,135.00	84,024,366.30	15.413547
C51	R4-CLS	2	va	3	2	360,000.00	62,620,489.05	0.5748917
C51	R10-CNV	5	ps	2	1	-1,910,000.00	62,620,489.05	-3.0501199
C51	R13-CNE	6	pq	1	2	200,000.00	62,620,489.05	0.3193843
C51	R13-CNE	6	pq	1	2	200,466.16	62,620,489.05	0.3201287
C51	R13-CNE	6	pq	1	2	600,000.00	62,620,489.05	0.9581528
C52	R4-CLS	2	va	3	2	6,000.00	9,756,140.63	0.0614997
C52	R4-CLS	2	va	3	2	13,500.00	9,756,140.63	0.1383744
C52	R4-CLS	2	va	3	2	21,900.00	9,756,140.63	0.224474
C52	R4-CLS	2	va	3	2	24,000.00	9,756,140.63	0.2459989
C52	R4-CLS	2	va	3	2	24,000.00	9,756,140.63	0.2459989
C52	R4-CLS	2	va	3	2	54,000.00	9,756,140.63	0.5534976
C52	R4-CLS	2	va	3	2	72,000.00	9,756,140.63	0.7379967
C52	R4-CLS	2	va	3	2	84,000.00	9,756,140.63	0.8609962
C52	R4-CLS	2	va	3	2	134,400.00	9,756,140.63	1.3775939
C52	R10-CNV	5	ps	2	2	383,800.00	9,756,140.63	3.9339326
C52	R10-CNV	5	ps	2	2	529,035.00	9,756,140.63	5.4225848
C52	R13-CNE	6	pq	1	1	-78,000.00	9,756,140.63	-0.7994965
C52	R13-CNE	6	pq	1	1	-9,000.00	9,756,140.63	-0.0922496
C53	R4-CLS	2	va	3	2	6,000.00	9,754,350.90	0.061511
C53	R4-CLS	2	va	3	2	13,500.00	9,754,350.90	0.1383998
C53	R4-CLS	2	va	3	2	21,900.00	9,754,350.90	0.2245152
C53	R4-CLS	2	va	3	2	24,000.00	9,754,350.90	0.246044
C53	R4-CLS	2	va	3	2	24,000.00	9,754,350.90	0.246044
C53	R4-CLS	2	va	3	2	54,000.00	9,754,350.90	0.5535991
C53	R4-CLS	2	va	3	2	72,000.00	9,754,350.90	0.7381321
C53	R4-CLS	2	va	3	2	84,000.00	9,754,350.90	0.8611542
C53	R4-CLS	2	va	3	2	134,400.00	9,754,350.90	1.3778467
C53	R4-CLS	2	va	3	2	845,800.00	9,754,350.90	8.6710024
C53	R10-CNV	5	ps	2	2	383,800.00	9,754,350.90	3.9346544
C53	R10-CNV	5	ps	2	2	529,035.00	9,754,350.90	5.4235797
C53	R13-CNE	6	pq	1	1	-78,000.00	9,754,350.90	-0.7996432
C53	R13-CNE	6	pq	1	1	-9,000.00	9,754,350.90	-0.0922665
C54	R4-CLS	2	va	3	2	3,600.00	3,534,426.00	0.1018553
C54	R4-CLS	2	va	3	2	15,000.00	3,534,426.00	0.4243971
C54	R4-CLS	2	va	3	2	20,000.00	3,534,426.00	0.5658627
C54	R4-CLS	2	va	3	2	20,800.00	3,534,426.00	0.5884973
C54	R4-CLS	2	va	3	2	23,650.00	3,534,426.00	0.6691327
C54	R4-CLS	2	va	3	2	70,000.00	3,534,426.00	1.9805196
C54	R4-CLS	2	va	3	2	80,000.00	3,534,426.00	2.263451
C54	R4-CLS	2	va	3	2	88,000.00	3,534,426.00	2.4897961
C54	R4-CLS	2	va	3	2	205,000.00	3,534,426.00	5.8000931
C54	R4-CLS	2	va	3	2	336,600.00	3,534,426.00	9.52347
C55	R4-CLS	2	va	3	2	282,240.00	1,472,635.50	19.165639

Proj Grp Nr	Risk label	Risk sort code	Cost category	Cost sort code	Risk type code	Risk costs (Net)	Initial Contract Sum_ICS	Risk degree
C55	R13-CNE	6	pq	1	1	-308,150.00	1,472,635.50	-20.925069
C55	R13-CNE	6	pq	1	2	65,000.00	1,472,635.50	4.4138553
C56	R4-CLS	2	va	3	2	3,500.00	42,572,165.75	0.0082213
C56	R4-CLS	2	va	3	2	7,712.75	42,572,165.75	0.0181169
C56	R4-CLS	2	va	3	2	8,720.75	42,572,165.75	0.0204846
C56	R4-CLS	2	va	3	2	8,720.75	42,572,165.75	0.0204846
C56	R4-CLS	2	va	3	2	24,000.00	42,572,165.75	0.0563749
C56	R4-CLS	2	va	3	2	37,600.00	42,572,165.75	0.0883206
C56	R4-CLS	2	va	3	2	40,000.00	42,572,165.75	0.0939581
C56	R4-CLS	2	va	3	2	49,800.00	42,572,165.75	0.1169778
C56	R4-CLS	2	va	3	2	86,400.00	42,572,165.75	0.2029495
C56	R4-CLS	2	va	3	2	100,800.00	42,572,165.75	0.2367744
C56	R4-CLS	2	va	3	2	187,200.00	42,572,165.75	0.4397239
C56	R4-CLS	2	va	3	2	227,880.00	42,572,165.75	0.5352793
C56	R4-CLS	2	va	3	2	294,685.00	42,572,165.75	0.6922011
C56	R4-CLS	2	va	3	2	298,530.00	42,572,165.75	0.7012328
C56	R4-CLS	2	va	3	2	375,183.00	42,572,165.75	0.8812871
C56	R4-CLS	2	va	3	2	453,960.00	42,572,165.75	1.0663305
C56	R4-CLS	2	va	3	2	579,750.00	42,572,165.75	1.3618053
C56	R5-CND	3	vo	4	1	-800,000.00	42,572,165.75	-1.8791621
C56	R10-CNV	5	ps	2	1	-90,755.80	42,572,165.75	-0.2131811
C56	R10-CNV	5	ps	2	1	-23,100.00	42,572,165.75	-0.0542608
C56	R10-CNV	5	ps	2	1	-20,000.00	42,572,165.75	-0.0469791
C56	R10-CNV	5	ps	2	1	-2,000.00	42,572,165.75	-0.0046979
C56	R10-CNV	5	ps	2	2	141,290.20	42,572,165.75	0.331884
C56	R13-CNE	6	pq	1	1	-1,329,380.00	42,572,165.75	-3.1226506
C56	R13-CNE	6	pq	1	1	-929,305.00	42,572,165.75	-2.1828934
C56	R13-CNE	6	pq	1	1	-618,700.00	42,572,165.75	-1.453297
C56	R13-CNE	6	pq	1	1	-295,865.00	42,572,165.75	-0.6949729
C56	R13-CNE	6	pq	1	1	-274,115.00	42,572,165.75	-0.6438831
C56	R13-CNE	6	pq	1	1	-139,185.00	42,572,165.75	-0.326939
C56	R13-CNE	6	pq	1	1	-30,300.00	42,572,165.75	-0.0711733
C56	R13-CNE	6	pq	1	1	-17,375.00	42,572,165.75	-0.0408131
C56	R13-CNE	6	pq	1	1	-12,500.00	42,572,165.75	-0.0293619
C56	R13-CNE	6	pq	1	1	-12,500.00	42,572,165.75	-0.0293619
C56	R13-CNE	6	pq	1	1	-3,300.00	42,572,165.75	-0.0077515
C56	R13-CNE	6	pq	1	1	-570.00	42,572,165.75	-0.0013389
C56	R13-CNE	6	pq	1	2	27,600.00	42,572,165.75	0.0648311
C56	R13-CNE	6	pq	1	2	36,260.00	42,572,165.75	0.085173
C56	R13-CNE	6	pq	1	2	45,825.00	42,572,165.75	0.1076408
C56	R13-CNE	6	pq	1	2	62,030.00	42,572,165.75	0.1457055
C56	R13-CNE	6	pq	1	2	1,472,900.00	42,572,165.75	3.4597723
C56	R13-CNE	6	pq	1	2	2,373,560.00	42,572,165.75	5.57538
C56	R15-UNE	7	va	3	2	2,939,315.00	42,572,165.75	6.9043117
C57	R4-CLS	2	va	3	2	17,365.00	89,688,700.00	0.0193614
C57	R4-CLS	2	va	3	2	51,893.60	89,688,700.00	0.0578597
C57	R4-CLS	2	va	3	2	83,880.00	89,688,700.00	0.0935235
C57	R4-CLS	2	va	3	2	134,000.00	89,688,700.00	0.1494057
C57	R4-CLS	2	va	3	2	180,250.00	89,688,700.00	0.2009729
C57	R4-CLS	2	va	3	2	247,500.00	89,688,700.00	0.2759545
C57	R4-CLS	2	va	3	2	502,000.00	89,688,700.00	0.5597138
C57	R4-CLS	2	va	3	2	565,010.00	89,688,700.00	0.6299679
C57	R4-CLS	2	va	3	2	679,215.00	89,688,700.00	0.7573028
C57	R4-CLS	2	va	3	2	1,417,509.00	89,688,700.00	1.5804767
C57	R10-CNV	5	ps	2	1	-2,220,000.00	89,688,700.00	-2.4752282
C57	R10-CNV	5	ps	2	1	-1,876,400.00	89,688,700.00	-2.0921253

Proj Grp Nr	Risk label	Risk sort code	Cost category	Cost sort code	Risk type code	Risk costs (Net)	Initial Contract Sum_ICS	Risk degree
C57	R10-CNV	5	ps	2	1	-22,600.00	89,688,700.00	-0.0251983
C57	R10-CNV	5	ps	2	2	10,700,890.00	89,688,700.00	11.931146
C57	R13-CNE	6	pq	1	1	-554,800.00	89,688,700.00	-0.6185841
C57	R13-CNE	6	pq	1	1	-251,650.00	89,688,700.00	-0.2805816
C57	R13-CNE	6	pq	1	1	-251,650.00	89,688,700.00	-0.2805816
C57	R13-CNE	6	pq	1	1	-99,630.00	89,688,700.00	-0.1110842
C57	R13-CNE	6	pq	1	1	-99,630.00	89,688,700.00	-0.1110842
C57	R13-CNE	6	pq	1	1	-89,130.00	89,688,700.00	-0.0993771
C57	R13-CNE	6	pq	1	1	-89,130.00	89,688,700.00	-0.0993771
C57	R13-CNE	6	pq	1	1	-65,490.00	89,688,700.00	-0.0730192
C57	R13-CNE	6	pq	1	1	-65,490.00	89,688,700.00	-0.0730192
C57	R13-CNE	6	pq	1	1	-64,000.00	89,688,700.00	-0.0713579
C57	R13-CNE	6	pq	1	1	-64,000.00	89,688,700.00	-0.0713579
C57	R13-CNE	6	pq	1	1	-52,630.00	89,688,700.00	-0.0586807
C57	R13-CNE	6	pq	1	1	-52,630.00	89,688,700.00	-0.0586807
C57	R13-CNE	6	pq	1	2	11,700.00	89,688,700.00	0.0130451
C57	R13-CNE	6	pq	1	2	11,700.00	89,688,700.00	0.0130451
C57	R13-CNE	6	pq	1	2	18,000.00	89,688,700.00	0.0200694
C57	R13-CNE	6	pq	1	2	18,000.00	89,688,700.00	0.0200694
C57	R13-CNE	6	pq	1	2	34,200.00	89,688,700.00	0.0381319
C57	R13-CNE	6	pq	1	2	34,200.00	89,688,700.00	0.0381319
C57	R13-CNE	6	pq	1	2	95,590.00	89,688,700.00	0.1065798
C57	R13-CNE	6	pq	1	2	95,590.00	89,688,700.00	0.1065798
C57	R13-CNE	6	pq	1	2	180,677.50	89,688,700.00	0.2014496
C57	R13-CNE	6	pq	1	2	180,677.50	89,688,700.00	0.2014496
C57	R13-CNE	6	pq	1	2	194,982.50	89,688,700.00	0.2173992
C57	R13-CNE	6	pq	1	2	194,982.50	89,688,700.00	0.2173992
C57	R13-CNE	6	pq	1	2	301,970.00	89,688,700.00	0.3366868
C57	R13-CNE	6	pq	1	2	665,500.00	89,688,700.00	0.742011
C57	R13-CNE	6	pq	1	2	665,500.00	89,688,700.00	0.742011
C57	R13-CNE	6	pq	1	2	1,152,955.00	89,688,700.00	1.2855075
C57	R13-CNE	6	pq	1	2	1,152,955.00	89,688,700.00	1.2855075
C57	R13-CNE	6	pq	1	2	1,152,955.00	89,688,700.00	1.2855075
C57	R13-CNE	6	pq	1	2	1,152,955.00	89,688,700.00	1.2855075
C58	R4-CLS	2	va	3	2	29,321.00	70,152,600.00	0.041796
C58	R4-CLS	2	va	3	2	56,196.00	70,152,600.00	0.0801054
C58	R4-CLS	2	va	3	2	59,940.00	70,152,600.00	0.0854423
C58	R4-CLS	2	va	3	2	93,660.00	70,152,600.00	0.133509
C58	R4-CLS	2	va	3	2	148,150.00	70,152,600.00	0.2111825
C58	R4-CLS	2	va	3	2	351,743.00	70,152,600.00	0.501397
C58	R4-CLS	2	va	3	2	424,080.00	70,152,600.00	0.6045107
C58	R4-CLS	2	va	3	2	679,215.00	70,152,600.00	0.9681965
C58	R4-CLS	2	va	3	2	680,114.50	70,152,600.00	0.9694787
C58	R4-CLS	2	va	3	2	732,186.00	70,152,600.00	1.0437047
C58	R4-CLS	2	va	3	2	815,500.00	70,152,600.00	1.1624658
C58	R10-CNV	5	ps	2	1	-2,200,000.00	70,152,600.00	-3.1360206
C58	R10-CNV	5	ps	2	1	-462,925.00	70,152,600.00	-0.6598829
C58	R10-CNV	5	ps	2	1	-325,200.00	70,152,600.00	-0.4635609
C58	R13-CNE	6	pq	1	1	-220,000.00	70,152,600.00	-0.3136021
C58	R13-CNE	6	pq	1	1	-190,000.00	70,152,600.00	-0.2708381
C58	R13-CNE	6	pq	1	1	-174,400.00	70,152,600.00	-0.2486009
C58	R13-CNE	6	pq	1	1	-77,700.00	70,152,600.00	-0.1107585
C58	R13-CNE	6	pq	1	1	-56,000.00	70,152,600.00	-0.079826
C58	R13-CNE	6	pq	1	1	-26,000.00	70,152,600.00	-0.0370621
C58	R13-CNE	6	pq	1	2	46,869.00	70,152,600.00	0.0668101
C58	R13-CNE	6	pq	1	2	62,280.00	70,152,600.00	0.0887779

Proj Grp Nr	Risk label	Risk sort code	Cost category	Cost sort code	Risk type code	Risk costs (Net)	Initial Contract Sum_ICS	Risk degree
C58	R13-CNE	6	pq	1	2	134,924.00	70,152,600.00	0.1923293
C58	R13-CNE	6	pq	1	2	136,421.50	70,152,600.00	0.1944639
C58	R13-CNE	6	pq	1	2	421,962.00	70,152,600.00	0.6014916
C58	R13-CNE	6	pq	1	2	686,322.50	70,152,600.00	0.978328
C59	R4-CLS	2	va	3	2	59,940.00	62,148,450.00	0.0964465
C59	R4-CLS	2	va	3	2	93,660.00	62,148,450.00	0.1507037
C59	R4-CLS	2	va	3	2	124,880.00	62,148,450.00	0.2009382
C59	R4-CLS	2	va	3	2	341,432.00	62,148,450.00	0.5493814
C59	R4-CLS	2	va	3	2	407,550.00	62,148,450.00	0.6557686
C59	R4-CLS	2	va	3	2	603,750.00	62,148,450.00	0.9714643
C59	R4-CLS	2	va	3	2	679,215.00	62,148,450.00	1.0928913
C59	R10-CNV	5	ps	2	1	-2,400,000.00	62,148,450.00	-3.8617214
C59	R10-CNV	5	ps	2	1	-2,200,000.00	62,148,450.00	-3.5399113
C59	R10-CNV	5	ps	2	1	-531,725.00	62,148,450.00	-0.8555724
C59	R10-CNV	5	ps	2	1	-325,200.00	62,148,450.00	-0.5232633
C59	R13-CNE	6	pq	1	1	-514,780.00	62,148,450.00	-0.8283071
C59	R13-CNE	6	pq	1	1	-172,800.00	62,148,450.00	-0.2780439
C59	R13-CNE	6	pq	1	1	-95,000.00	62,148,450.00	-0.1528598
C59	R13-CNE	6	pq	1	1	-48,000.00	62,148,450.00	-0.0772344
C59	R13-CNE	6	pq	1	1	-27,320.00	62,148,450.00	-0.0439593
C59	R13-CNE	6	pq	1	1	-13,000.00	62,148,450.00	-0.0209177
C59	R13-CNE	6	pq	1	2	123,000.00	62,148,450.00	0.1979132
C59	R13-CNE	6	pq	1	2	162,652.38	62,148,450.00	0.2617159
C59	R13-CNE	6	pq	1	2	927,618.00	62,148,450.00	1.4925843
C60	R3-CLV	1	va	3	2	158,950.00	57,597,750.00	0.2759656
C60	R3-CLV	1	va	3	2	191,250.00	57,597,750.00	0.3320442
C60	R3-CLV	1	va	3	2	313,860.00	57,597,750.00	0.5449171
C60	R3-CLV	1	va	3	2	363,390.00	57,597,750.00	0.6309101
C60	R3-CLV	1	va	3	2	407,750.00	57,597,750.00	0.707927
C60	R3-CLV	1	va	3	2	533,570.00	57,597,750.00	0.926373
C60	R3-CLV	1	va	3	2	845,000.00	57,597,750.00	1.4670712
C60	R3-CLV	1	va	3	2	1,208,550.00	57,597,750.00	2.098259
C60	R10-CNV	5	ps	2	1	-1,123,690.00	57,597,750.00	-1.9509269
C60	R10-CNV	5	ps	2	1	-1,047,282.00	57,597,750.00	-1.8182689
C60	R10-CNV	5	ps	2	1	-800,000.00	57,597,750.00	-1.3889431
C60	R10-CNV	5	ps	2	1	-800,000.00	57,597,750.00	-1.3889431
C60	R10-CNV	5	ps	2	1	-730,847.00	57,597,750.00	-1.2688812
C60	R10-CNV	5	ps	2	2	135,810.00	57,597,750.00	0.2357905
C60	R13-CNE	6	pq	1	1	-1,631,794.00	57,597,750.00	-2.8330864
C60	R13-CNE	6	pq	1	1	-1,251,905.00	57,597,750.00	-2.1735311
C60	R13-CNE	6	pq	1	1	-465,000.00	57,597,750.00	-0.8073232
C60	R13-CNE	6	pq	1	1	-172,900.00	57,597,750.00	-0.3001853
C60	R13-CNE	6	pq	1	1	-61,600.00	57,597,750.00	-0.1069486
C60	R13-CNE	6	pq	1	1	-59,250.00	57,597,750.00	-0.1028686
C60	R13-CNE	6	pq	1	2	96,000.00	57,597,750.00	0.1666732
C60	R13-CNE	6	pq	1	2	152,000.00	57,597,750.00	0.2638992
C60	R13-CNE	6	pq	1	2	170,400.00	57,597,750.00	0.2958449
C60	R13-CNE	6	pq	1	2	185,785.00	57,597,750.00	0.322556
C60	R13-CNE	6	pq	1	2	298,350.00	57,597,750.00	0.517989
C60	R13-CNE	6	pq	1	2	356,200.00	57,597,750.00	0.6184269
C60	R13-CNE	6	pq	1	2	660,000.00	57,597,750.00	1.1458781
C60	R13-CNE	6	pq	1	2	1,150,985.70	57,597,750.00	1.9983171
C61	R3-CLV	1	va	3	2	1,074,450.00	136,446,896.25	0.7874492
C61	R3-CLV	1	va	3	2	1,662,500.00	136,446,896.25	1.2184227
C61	R3-CLV	1	va	3	2	3,060,785.00	136,446,896.25	2.243206
C61	R10-CNV	5	ps	2	1	-2,250,000.00	136,446,896.25	-1.6489932

Proj Grp Nr	Risk label	Risk sort code	Cost category	Cost sort code	Risk type code	Risk costs (Net)	Initial Contract Sum_ICS	Risk degree
C61	R10-CNV	5	ps	2	1	-1,750,690.00	136,446,896.25	-1.2830559
C61	R10-CNV	5	ps	2	1	-300,000.00	136,446,896.25	-0.2198658
C61	R10-CNV	5	ps	2	2	711,301.70	136,446,896.25	0.521303
C61	R10-CNV	5	ps	2	2	2,001,718.95	136,446,896.25	1.4670315
C61	R13-CNE	6	pq	1	1	-6,700,550.00	136,446,896.25	-4.9107383
C61	R13-CNE	6	pq	1	1	-1,993,800.00	136,446,896.25	-1.4612278
C61	R13-CNE	6	pq	1	1	-675,750.00	136,446,896.25	-0.4952476
C61	R13-CNE	6	pq	1	1	-465,940.00	136,446,896.25	-0.3414808
C61	R13-CNE	6	pq	1	1	-424,700.00	136,446,896.25	-0.3112566
C61	R13-CNE	6	pq	1	1	-396,350.00	136,446,896.25	-0.2904793
C61	R13-CNE	6	pq	1	1	-367,320.00	136,446,896.25	-0.2692036
C61	R13-CNE	6	pq	1	1	-335,450.00	136,446,896.25	-0.2458466
C61	R13-CNE	6	pq	1	1	-296,500.00	136,446,896.25	-0.2173007
C61	R13-CNE	6	pq	1	1	-289,668.00	136,446,896.25	-0.2122936
C61	R13-CNE	6	pq	1	1	-286,420.00	136,446,896.25	-0.2099132
C61	R13-CNE	6	pq	1	1	-274,088.00	136,446,896.25	-0.2008752
C61	R13-CNE	6	pq	1	1	-218,640.00	136,446,896.25	-0.1602382
C61	R13-CNE	6	pq	1	1	-202,585.00	136,446,896.25	-0.1484717
C61	R13-CNE	6	pq	1	1	-170,250.00	136,446,896.25	-0.1247738
C61	R13-CNE	6	pq	1	1	-167,200.00	136,446,896.25	-0.1225385
C61	R13-CNE	6	pq	1	1	-136,168.00	136,446,896.25	-0.0997956
C61	R13-CNE	6	pq	1	1	-130,495.00	136,446,896.25	-0.0956379
C61	R13-CNE	6	pq	1	1	-129,035.00	136,446,896.25	-0.0945679
C61	R13-CNE	6	pq	1	1	-117,220.00	136,446,896.25	-0.0859089
C61	R13-CNE	6	pq	1	1	-103,975.00	136,446,896.25	-0.0762018
C61	R13-CNE	6	pq	1	1	-102,320.00	136,446,896.25	-0.0749889
C61	R13-CNE	6	pq	1	1	-63,465.00	136,446,896.25	-0.0465126
C61	R13-CNE	6	pq	1	1	-61,080.00	136,446,896.25	-0.0447647
C61	R13-CNE	6	pq	1	1	-45,200.00	136,446,896.25	-0.0331264
C61	R13-CNE	6	pq	1	1	-37,192.00	136,446,896.25	-0.0272575
C61	R13-CNE	6	pq	1	1	-32,900.00	136,446,896.25	-0.0241119
C61	R13-CNE	6	pq	1	1	-4,685.00	136,446,896.25	-0.0034336
C61	R13-CNE	6	pq	1	2	0.00	136,446,896.25	0
C61	R13-CNE	6	pq	1	2	10,695.00	136,446,896.25	0.0078382
C61	R13-CNE	6	pq	1	2	27,300.00	136,446,896.25	0.0200078
C61	R13-CNE	6	pq	1	2	53,302.50	136,446,896.25	0.0390646
C61	R13-CNE	6	pq	1	2	60,720.00	136,446,896.25	0.0445008
C61	R13-CNE	6	pq	1	2	76,877.50	136,446,896.25	0.0563424
C61	R13-CNE	6	pq	1	2	86,640.00	136,446,896.25	0.0634972
C61	R13-CNE	6	pq	1	2	96,700.00	136,446,896.25	0.0708701
C61	R13-CNE	6	pq	1	2	96,700.00	136,446,896.25	0.0708701
C61	R13-CNE	6	pq	1	2	128,200.00	136,446,896.25	0.093956
C61	R13-CNE	6	pq	1	2	133,860.00	136,446,896.25	0.0981041
C61	R13-CNE	6	pq	1	2	154,500.00	136,446,896.25	0.1132309
C61	R13-CNE	6	pq	1	2	222,270.00	136,446,896.25	0.1628985
C61	R13-CNE	6	pq	1	2	246,670.00	136,446,896.25	0.180781
C61	R13-CNE	6	pq	1	2	281,245.00	136,446,896.25	0.2061205
C61	R13-CNE	6	pq	1	2	285,090.00	136,446,896.25	0.2089384
C61	R13-CNE	6	pq	1	2	862,020.00	136,446,896.25	0.6317623
C61	R13-CNE	6	pq	1	2	969,135.00	136,446,896.25	0.7102653
C61	R13-CNE	6	pq	1	2	1,328,095.50	136,446,896.25	0.9733424
C61	R13-CNE	6	pq	1	2	1,890,880.00	136,446,896.25	1.3857992
C61	R19-USD	8	va	3	2	2,115,250.00	136,446,896.25	1.5502368
C61	R19-USD	8	va	3	2	6,930,676.50	136,446,896.25	5.0793948
C62	R5-CND	3	va	3	2	495,000.00	105,945,000.00	0.4672236
C62	R5-CND	3	va	3	2	20,887,390.00	105,945,000.00	19.715315

Proj Grp Nr	Risk label	Risk sort code	Cost category	Cost sort code	Risk type code	Risk costs (Net)	Initial Contract Sum_ICS	Risk degree
C62	R5-CND	3	vo	4	1	-11,000,000.00	105,945,000.00	-10.382746
C62	R10-CNV	5	ps	2	1	-4,721,249.00	105,945,000.00	-4.4563207
C62	R10-CNV	5	ps	2	1	-100,000.00	105,945,000.00	-0.0943886
C62	R13-CNE	6	pq	1	1	-902,000.00	105,945,000.00	-0.8513852
C62	R13-CNE	6	pq	1	1	-356,175.00	105,945,000.00	-0.3361886
C62	R13-CNE	6	pq	1	2	392,100.00	105,945,000.00	0.3700977
C62	R13-CNE	6	pq	1	2	1,362,060.00	105,945,000.00	1.2856293
C62	R13-CNE	6	pq	1	2	3,849,010.00	105,945,000.00	3.6330266
C63	R4-CLS	2	va	3	2	145,800.00	26,250,000.00	0.5554286
C63	R4-CLS	2	va	3	2	5,108,651.00	26,250,000.00	19.461528
C63	R10-CNV	5	ps	2	1	-2,100,000.00	26,250,000.00	-8
C63	R10-CNV	5	ps	2	1	-341,100.00	26,250,000.00	-1.2994286
C63	R13-CNE	6	pq	1	1	-44,000.00	26,250,000.00	-0.167619
C64	R5-CND	3	va	3	2	956,832.00	114,030,000.00	0.8391055
C64	R5-CND	3	va	3	2	7,297,655.00	114,030,000.00	6.3997676
C64	R5-CND	3	va	3	2	10,639,300.00	114,030,000.00	9.330264
C64	R5-CND	3	vo	4	2	360,700.00	114,030,000.00	0.3163203
C64	R10-CNV	5	ps	2	1	-7,500,000.00	114,030,000.00	-6.5772165
C64	R10-CNV	5	ps	2	1	-3,589,222.00	114,030,000.00	-3.147612
C64	R10-CNV	5	ps	2	1	-550,000.00	114,030,000.00	-0.4823292
C64	R10-CNV	5	ps	2	1	-130,000.00	114,030,000.00	-0.1140051
C64	R10-CNV	5	ps	2	2	19,221,115.00	114,030,000.00	16.856191
C64	R13-CNE	6	pq	1	1	-1,789,007.00	114,030,000.00	-1.5688915
C64	R13-CNE	6	pq	1	1	-926,600.00	114,030,000.00	-0.8125932
C64	R13-CNE	6	pq	1	1	-560,000.00	114,030,000.00	-0.4910988
C64	R13-CNE	6	pq	1	1	-453,850.00	114,030,000.00	-0.3980093
C64	R13-CNE	6	pq	1	2	282,200.00	114,030,000.00	0.2474787
C64	R13-CNE	6	pq	1	2	1,214,920.00	114,030,000.00	1.0654389
C65	R5-CND	3	va	3	2	368,500.00	48,615,000.00	0.7579965
C65	R5-CND	3	va	3	2	484,550.00	48,615,000.00	0.9967088
C65	R5-CND	3	va	3	2	780,000.00	48,615,000.00	1.6044431
C65	R5-CND	3	va	3	2	1,098,000.00	48,615,000.00	2.2585622
C65	R5-CND	3	va	3	2	1,250,000.00	48,615,000.00	2.5712229
C65	R5-CND	3	va	3	2	1,665,325.00	48,615,000.00	3.4255374
C65	R5-CND	3	va	3	2	6,294,240.00	48,615,000.00	12.947115
C65	R10-CNV	5	ps	2	1	-4,172,887.00	48,615,000.00	-8.583538
C65	R10-CNV	5	ps	2	1	-1,033,550.00	48,615,000.00	-2.1259899
C65	R13-CNE	6	pq	1	1	-282,000.00	48,615,000.00	-0.5800679
C65	R13-CNE	6	pq	1	1	-273,640.00	48,615,000.00	-0.5628715
C65	R13-CNE	6	pq	1	2	575,650.00	48,615,000.00	1.1840996
C66	R3-CLV	1	vo	4	1	-8,628,315.00	48,930,000.00	-17.633998
C66	R3-CLV	1	vo	4	1	-7,417,414.00	48,930,000.00	-15.159236
C66	R5-CND	3	va	3	2	66,750.00	48,930,000.00	0.1364194
C66	R5-CND	3	va	3	2	122,200.00	48,930,000.00	0.2497445
C66	R5-CND	3	va	3	2	181,500.00	48,930,000.00	0.3709381
C66	R5-CND	3	va	3	2	774,743.00	48,930,000.00	1.5833701
C66	R5-CND	3	va	3	2	782,032.00	48,930,000.00	1.5982669
C66	R5-CND	3	va	3	2	876,000.00	48,930,000.00	1.7903127
C66	R5-CND	3	va	3	2	1,892,900.00	48,930,000.00	3.8685878
C66	R5-CND	3	va	3	2	1,998,000.00	48,930,000.00	4.0833844
C66	R5-CND	3	va	3	2	2,469,935.00	48,930,000.00	5.047895
C66	R5-CND	3	va	3	2	2,639,040.00	48,930,000.00	5.3935009
C66	R5-CND	3	va	3	2	5,225,405.00	48,930,000.00	10.679348
C66	R5-CND	3	va	3	2	6,984,163.00	48,930,000.00	14.273785
C66	R10-CNV	5	ps	2	1	-870,000.00	48,930,000.00	-1.7780503
C66	R10-CNV	5	ps	2	1	-797,999.10	48,930,000.00	-1.6308994

Proj Grp Nr	Risk label	Risk sort code	Cost category	Cost sort code	Risk type code	Risk costs (Net)	Initial Contract Sum_ICS	Risk degree
C66	R10-CNV	5	ps	2	1	-100,000.00	48,930,000.00	-0.2043736
C66	R10-CNV	5	ps	2	2	66,500.00	48,930,000.00	0.1359084
C66	R13-CNE	6	pq	1	2	8,976.00	48,930,000.00	0.0183446
C66	R13-CNE	6	pq	1	2	367,500.00	48,930,000.00	0.751073
C67	R3-CLV	1	vs	5	2	2,033,404.00	59,101,000.00	3.4405577
C67	R5-CND	3	va	3	2	2,671,000.00	59,101,000.00	4.5193821
C67	R5-CND	3	va	3	2	6,230,300.00	59,101,000.00	10.541784
C67	R10-CNV	5	ps	2	1	-8,100,000.00	59,101,000.00	-13.705352
C67	R10-CNV	5	ps	2	1	-1,491,150.00	59,101,000.00	-2.5230538
C67	R10-CNV	5	ps	2	1	-50,000.00	59,101,000.00	-0.0846009
C67	R13-CNE	6	pq	1	1	-1,976,355.00	59,101,000.00	-3.3440297
C67	R13-CNE	6	pq	1	1	-560,000.00	59,101,000.00	-0.9475305
C67	R13-CNE	6	pq	1	1	-453,850.00	59,101,000.00	-0.7679227
C67	R13-CNE	6	pq	1	2	300,920.00	59,101,000.00	0.5091623
C68	R3-CLV	1	va	3	2	2,687,500.00	496,684,314.00	0.5410882
C68	R3-CLV	1	va	3	2	13,579,630.00	496,684,314.00	2.7340565
C68	R3-CLV	1	va	3	2	15,559,042.50	496,684,314.00	3.1325818
C68	R6-UNS	4	pq	1	2	224,495.00	496,684,314.00	0.0451987
C68	R6-UNS	4	pq	1	2	327,915.00	496,684,314.00	0.0660208
C68	R13-CNE	6	pq	1	1	-4,186,880.00	496,684,314.00	-0.842966
C68	R13-CNE	6	pq	1	1	-4,140,180.00	496,684,314.00	-0.8335637
C68	R13-CNE	6	pq	1	1	-3,932,140.50	496,684,314.00	-0.791678
C68	R13-CNE	6	pq	1	1	-2,393,320.00	496,684,314.00	-0.4818594
C68	R13-CNE	6	pq	1	1	-2,317,420.00	496,684,314.00	-0.4665781
C68	R13-CNE	6	pq	1	1	-2,117,575.00	496,684,314.00	-0.4263422
C68	R13-CNE	6	pq	1	1	-1,180,327.00	496,684,314.00	-0.2376413
C68	R13-CNE	6	pq	1	1	-928,625.00	496,684,314.00	-0.1869648
C68	R13-CNE	6	pq	1	1	-785,650.00	496,684,314.00	-0.1581789
C68	R13-CNE	6	pq	1	2	636,875.00	496,684,314.00	0.1282253
C68	R13-CNE	6	pq	1	2	940,920.00	496,684,314.00	0.1894402
C68	R13-CNE	6	pq	1	2	1,254,770.00	496,684,314.00	0.2526293
C68	R13-CNE	6	pq	1	2	3,016,100.00	496,684,314.00	0.6072469
C69	R3-CLV	1	va	3	2	6,886,935.00	82,635,000.00	8.3341623
C69	R3-CLV	1	vs	5	2	5,291,400.00	82,635,000.00	6.40334
C69	R10-CNV	5	ps	2	1	-1,500,000.00	82,635,000.00	-1.8152115
C69	R10-CNV	5	ps	2	1	-753,160.00	82,635,000.00	-0.9114298
C69	R10-CNV	5	ps	2	1	-100,000.00	82,635,000.00	-0.1210141
C69	R10-CNV	5	ps	2	2	297,440.00	82,635,000.00	0.3599443
C69	R13-CNE	6	pq	1	1	-3,819,195.00	82,635,000.00	-4.6217644
C69	R13-CNE	6	pq	1	1	-2,798,166.00	82,635,000.00	-3.3861753
C69	R13-CNE	6	pq	1	1	-1,120,000.00	82,635,000.00	-1.3553579
C69	R13-CNE	6	pq	1	2	349,200.00	82,635,000.00	0.4225812
C69	R13-CNE	6	pq	1	2	468,100.00	82,635,000.00	0.566467

Appendix F: List of the different classes of costs in final accounts impacted by risk

Proj Nr	CLS					CLV					CND					CNE					CNV					UNE					UNS					USD				
	pq	ps	va	vo	vs	pq	ps	va	vo	vs	pq	ps	va	vo	vs	pq	ps	va	vo	vs	pq	ps	va	vo	vs	pq	ps	va	vo	vs	pq	ps	va	vo	vs	pq	ps	va	vo	vs
A01	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	1	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
A02	0	0	1	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
A03	0	0	0	1	0	0	0	1	0	0	0	0	1	1	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
A04	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
A05	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
A06	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
A07	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
A08	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0
A09	0	0	1	0	0	0	0	1	0	1	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
A10	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
A11	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	1	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
A12	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
A13	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
A14	0	0	0	1	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
A15	0	0	1	1	1	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
A16	0	0	1	0	1	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
B17	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
B18	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
B19	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
B20	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
B21	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
B22	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
B23	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
B24	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
B25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
B26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
B27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
B28	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0

Proj Nr	CLS					CLV					CND					CNE					CNV					UNE					UNS					USD				
	pq	ps	va	vo	vs	pq	ps	va	vo	vs	pq	ps	va	vo	vs	pq	ps	va	vo	vs	pq	ps	va	vo	vs	pq	ps	va	vo	vs	pq	ps	va	vo	vs	pq	ps	va	vo	vs
B29	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
B30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
B31	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
B32	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
B33	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
B34	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
B35	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
B36	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
B37	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
B38	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
B39	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
B40	0	0	0	0	1	0	0	0	1	1	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
B41	0	0	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
B42	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
B43	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
B44	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
B45	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	1	0	0	0	0	0	1	0	0	1	1	0	0	0	0	0	0	0	0
B46	0	0	0	0	1	0	0	0	0	0	0	0	1	1	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
B47	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
B48	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C49	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C50	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C51	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C52	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C53	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C54	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C55	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C56	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
C57	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C58	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Proj Nr	CLS					CLV					CND					CNE					CNV					UNE					UNS					USD				
	pq	ps	va	vo	vs	pq	ps	va	vo	vs	pq	ps	va	vo	vs	pq	ps	va	vo	vs	pq	ps	va	vo	vs	pq	ps	va	vo	vs	pq	ps	va	vo	vs	pq	ps	va	vo	vs
C59	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C60	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C61	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
C62	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C63	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C64	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C65	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C66	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C67	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C68	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
C69	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Sum	0	0	31	4	9	1	0	12	3	7	3	0	14	5	2	36	0	13	1	5	2	44	5	0	0	0	1	9	0	1	18	2	2	0	0	0	0	1	0	0