ADDIS ABABA UNIVERSITY

SCHOOL OF GRADUATE STUDIES

Addis Ababa Institute of Technology (AAiT)

Department of Civil and Environmental Engineering

HYPOTHETICAL MODELING OF CONTRACTOR'S BID MARKUP ESTIMATION FOR ROAD CONSTRUCTION PROJECTS IN ETHIOPIA

BY: AMENESHEWA ALEMU

ADVISOR: ABRAHAM ASSEFA, PhD

A Thesis Submitted to School of Graduate Studies in Partial Fulfilment of the Requirements for the Degree of Master of Science in Civil Engineering (Construction Technology and Management)

MARCH, 2020
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ACKNOWLEDGEMENTS

I owe my gratefulness to the almighty GOD for empowering and giving me courage and strength to accomplish my educational career one step further.

I would also like to take this opportunity to express my sincere gratitude to my advisor Abraham Assefa (PhD), for his kind cooperation in providing the title of this research, guidance, valuable comments & suggestions at various stages of this research work.

I would like to extend my gratitude to all of the respondents of this research questionnaire, for providing the required data for this research. This work might have not been possible if it was not for their help.

Last, but not least I express my special gratitude to my family for their invaluable support.

ABSTRACT

Markup is a factor that estimators apply to certain work activities or to the total cost of a bid to cover general overhead and profit. Estimating markup is an important decision for contractors as its size has to be low enough to win a contract, but high enough to make a profit. Studies which are done on cost estimation practice in Ethiopian construction industry agree in the need for a change in the current practice of bid markup estimation. But these studies have a gap in introducing a systematic tool for solving the problem. This research focuses on identifying and analyzing factors affecting bid markup in road projects and developing a model which will support local contractors' decision in estimating bid markup size for road construction projects. The research uses integrated review of various literatures and questionnaire survey as data collection methods.

Twenty-one factors that are considered to affect bid markup have been identified from literature review. Based on the results of the analysis, it appears that 'complexity of project', 'number of competitors with strong desire to win a project', 'project location (region)', 'immediate need for work' and 'security need of project location', are the top five ranked factors in terms of influencing bid markup size.

Multiple linear regression (MLR) and artificial neural network (ANN) were selected for modeling bid markup estimation. The developed MLR equation contains eleven factors based on stepwise regression technique. The coefficient of correlation (R) was obtained as 0.882 with adjusted value of coefficient of determination (R^2) = 0.745. The overall regression model was statistically significant, $F(11, 73) = 23.297$, $p< 0.05$. For developing the ANN model, various network structures were generated and tested. The most satisfactory model was the ANN_8, which consists of 8 neurons in the hidden layer with R, R^2, MAPE and RMSE values of 92.06%, 84.75%, 6.43% and 2.47 respectively. Cross validation for both models was done and satisfactory result was obtained.

Statistical performance indicators shows that the ANN method of modeling predicts bid markup better than MLR method. But, the obtained values of the statistical performance indicators for the two models are closer to each other. Thus, both models can be considered as a satisfactory prediction tools for bid markup and can provide a starting point for estimators in a given road project bid markup estimation task.

Key words: Markup; Multiple linear regression; Artificial neural network

ABBREVIATIONS/ACRONYMS

AACE	Association for the Advancement of Cost Engineering
AHP	Analytical Hierarchy Process
AI	Artificial Intelligence
ANFIS	Adaptive Neuro Fuzzy Inference System
ANN	Artificial Neural Networks
ANOVA	Analysis of Variance
ASP	Active Server Pages
B	Unstandardized regression coefficient
CBR	Case Based Reasoning
CR	Competition Rating
df	Degree of freedom
DSS	Decision Support System
DV	Dependent Variable
ERA	Ethiopian Roads Authority
FNN	Fuzzy Neural Network
GA	Genetic Algorithm
GDP	Gross Domestic Product
GTP	Growth and Transformation Plan
IDVs	Independent Variables
MAPE	Mean Absolute Percentage Error
MATLAB	Matrix Laboratory

MLR	Multiple Linear Regression
MSE	Mean Squared Error
NN	Neural Network
OR	Opportunity Rating
PIBS	Partial Information of Bids with their Similarities
PNN	Probabilistic Neural NetworkSt
R	Coefficient of correlation
r	Pearson correlation coefficient
R^2	Coefficient of determination
RII	Relative Importance Index
RMSE	Root Mean Squared Error
RR	Risk Rating
Sig	Significance
SPSS	Statistical Package for Social Science
VIF	Variance Inflation Factor
α	Statistical significance level
β	Standardized regression coefficient

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CHAPTER 1: INTRODUCTION

1.1 GENERAL

With its contribution to the economic development and economic activities, construction sector has a significant affect in the development of any nation (Durdyev & Ismail, 2012). In developing countries, the construction industry is a vital sector providing mainly new infrastructure in the form of roads, railways, airports as well as new hospitals, schools, housing, and other buildings (Khan, 2008). According to a data obtained from World Bank, Africa development indicators (2013) cited in Lopes et al. (2017) the contribution of construction industry to the gross domestic product (GDP) of sub-Saharan countries ranges between 2.6-10.6%.

According to Planning and Development Commission (2016) report, during the first Growth and Transformation Plan (GTP-I) period (2010/11-2014/15 G.C.), the construction industry of Ethiopia on average grew at 28.7% per annum, pushing its share in gross domestic product (GDP) to rise from 4% in 2009/10 to 8.5% in 2014/15 G.C. In addition, the objective of the second Growth and Transformation Plan (GTP-II) period (2015/16-2019/20 G.C.) with regard to the construction industry was to enable the sector to play a vital role in speeding up the country's socio-economic development through strengthening linkages with other productive and service sectors as well as render the sector internationally competitive. According to Planning and Development Commission (2020) report, the construction industry has shown a growth of 15% in 2018/19 G.C and its share in GDP registered as 2.9%.

With regard to the road sector development, GTP-I & GTP-II emphasized the expansion of road infrastructures, upgrading and improving the standards of existing roads, to reduce transportation cost and support the acceleration of economic growth and development. During GTP-I period, the federal and regional road network has increased from 48,800 km in 2010 to 63,604 km in 2015 G.C. In addition, 46,810 km of all-weather woreda roads have been constructed. As a result, the total road network of the country has more than doubled during GTP-I period reaching 110,414 km. In GTP-II, the total road length was planned to increase from 110,414 km in 2014/15 to 220,000 km in 2019/20 (Planning and Development Commission, 2016). But this plan was found as an over ambitious plan and revised to be 142,000 km. Based on the data obtained from planning and development commission, a total road length of 126,773 km had been constructed till 2018/19 G.C.

Currently, Ethiopian Roads Authority (ERA) is responsible for planning and formulating long and short term plans and programs for road construction, design, maintenance of trunk and major link roads, as well as administration of contracts (ERA, 2015). According to the data obtained from ERA, the government has allocated 46.4 billion birr for the 2012 E.C. fiscal year. Figure 1.1 presents, ERA's yearly allocated capital budget from 2003 to 2012 E.C. fiscal year. The figure illustrates how there has been an enormous financial incremental investment from time to time in the Ethiopian road construction industry and this will, in turn, fascinate construction firms to actively participate in the sector.

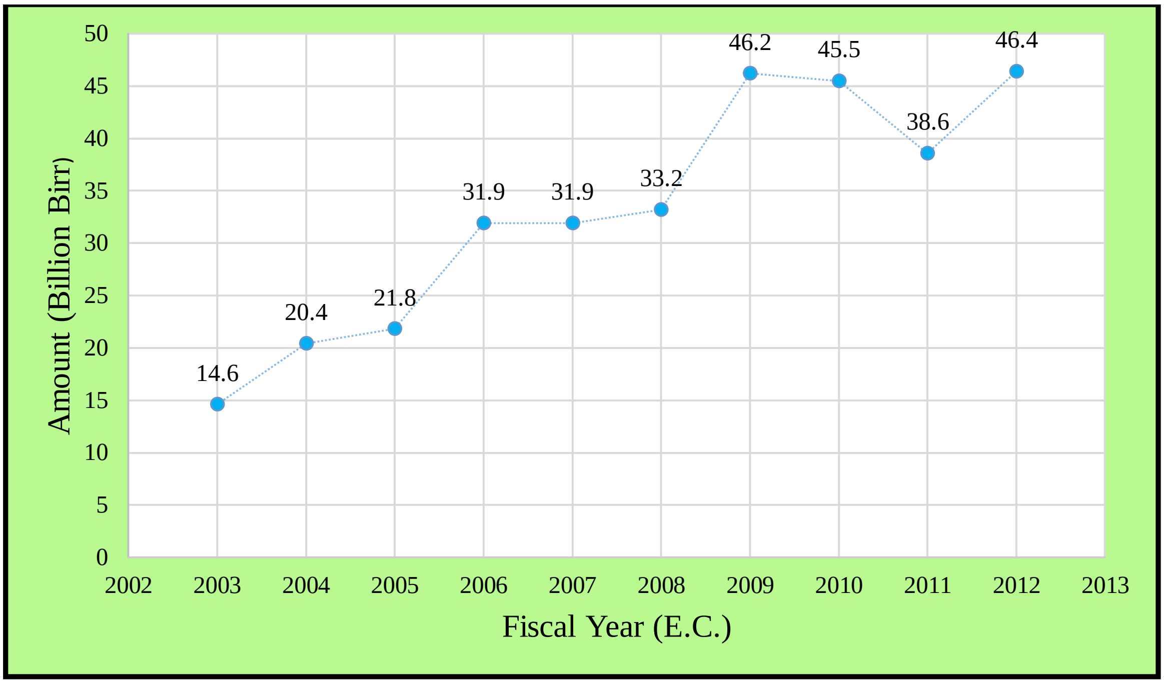

Figure 1.1: ERA's yearly allocated capital budget from 2003 to 2012 E.C. fiscal year

1.2 BACKGROUND TO THE RESEARCH

A significant amount of projects in the construction industry are assigned through what is known as "tender" or "bidding" processes (Christodoulou S. , 2010). A bidding process consists of a number of contractors competing to perform a particular job by submitting a sealed proposal until a certain date defined by the client (Cheung, P., A., & W., 2008).

It is useful to think of a bid as being made up of two basic elements; the estimate of direct job cost, which includes labor costs, material costs, equipment costs, and direct supervision costs, and the indirect cost named as markup or return, which must be sufficient to cover a portion of general overhead costs and allow a fair profit on the investment (Hendrickson, 2003). According to Association for the Advancement of Cost Engineering International, AACE International (2017) markup is a factor that estimators apply to certain items, systems, or to the total cost of a bid to cover general overhead, profit, and other indirect costs.

Many researchers have studied the development and use of bidding models for the optimization of contractors' bid prices in competitive bidding situations (Park & Chapin , 1992). Since the studies done by Friedman (1956) and Gates (1959) more than 1,000 papers have been published debating the principle of applying mathematical models (Cattell, Bowen, & Kaka, 2008). Most of the contributions to the optimal markup bid debate have been concerned with the selection of factors construction managers should take into account when deciding what price to bid (Christodoulou S. , 2010). Research by Drew and Skitmore (1992); Shash (1993); Drew et al. (2001) observed that different bidders apply different markup policies, which may be variable or fixed. A study by Li and Love (1999) combine rule-based expert systems with Artificial Neural Networks (ANN) for bid markup estimation. Ling and Liu (2005), Christodoulou S. (2010) and other studies also use ANN technique of modeling for bid markup estimation. Tan et al. (2009) use goal programming technique, where bid markup attributes provide the ground the model is built upon.

In the context of Ethiopia, even though there are a number of studies related to cost estimation of construction projects in general, the issue of bid markup decision making has received limited attention. Thus, this study will focus on assessing various factors influencing bid markup estimation and developing a model that facilitates local contractors' decisions on project bid markup size during competitive bidding in Ethiopian federal road projects.

1.3 STATEMENT OF THE PROBLEM

The construction industry is known for featuring strong levels of price competitiveness (Chao & Liu, 2007); and the competitive pressures are probably more intense than in any other industry (Skitmore M. , 2002). In this industry, competitive bidding has gained the burgeoning popularity of awarding construction contracts (Christodoulou S. , 2010). The main tenet of construction bid decision is to price contracts competitively to strike the trade-off between competitiveness (i.e., pricing as low as possible) and profitability (i.e., pricing as high as possible) (Chapman, Ward, & Bennell, 2000).

The usual format of a bidding process is based on the rule that -all other things being equal - the contract will be awarded to the competitor which submitted the lowest bid i.e., the lowest price (Cheung, P., A., & W., 2008). Bearing this in mind, it is easy to conclude that the client's decision is very straightforward but the contractor's decision on what price to bid is more difficult to reach, being probably one of the most difficult decisions construction managers have to face during the bid preparation process (Li & Love, 1999).

Accurate financial bid proposals maintain contractors' success and establish their potential profits, while inaccurate estimates could result in either significant monetary losses if the estimates are too low or no jobs at all if they are too high (Amr, 1997). Hendrickson (2003) stated that contractors' gross profit at the completion of projects is affected by the accuracy of the original estimate and the efficiency of the cost controlling system. Therefore, many bidding managers and researchers are interested in understanding what is involved in winning a contract.

Estimating the markup percentage is perhaps one of the most important and difficult decisions for a contractor when making a bid for a project as the markup estimate has to be low enough to win the contract but high enough to make a profit. The ability to understand the factors affecting bidding decisions in order to predict markup prices is important for organizations in order to win contracts in competitive bidding situations and increase their profitability (Nourah, 2013).

Akintoye (2000) argued that contractors set markup at a level perceived to be sufficient to win the tender at a margin that is in line with the strategic position of the firm within the market. Ling and Liu (2005) stated that deciding on a bid markup is a challenging job because many uncertain and complex factors need to be considered in the tendering stage. Moreover, the relationship between the factors is dynamic and complex. It is also required that the estimator be able to associate partial information of a new project, such as design information and market factors, with previous tendering situations and data without going through a deep reasoning and logical sequence (Ling & Liu, 2005).

In the context of Ethiopia, researches have been done related to construction cost estimation in general. The results, along with the observed research gaps, for some of the researches are presented below by particularly paying attention to bid markup estimation.

Tadesse (2006) prepares a construction cost estimation guideline for local contractors to establish the unit costs of construction activities and develop the overall project construction costs. This study agree that the contractors' cost estimate shall be competent to get the intended project and at the same time these estimates shall be accurate enough to keep the profitability of the construction company. This study suggest local contractors, to calculate their total annual head office overhead costs (all costs required to run the whole operation of the construction company) and express this amount as a percentage of the direct unit cost of an activity during bidding for projects so that it can be shared proportionally by all projects under the company. The study has also points out that a profit margin entirely depends on the market competitiveness and company strategies and its size should be decided accordingly. This study treats all project bids as the same and suggest a uniform bid markup size to be applied. But this does not reflect the fact that the size of bid markup to be used by contractors during bidding should incorporate the effect of various attributes affecting it.

Abeselom (2008) carryout a study to investigate the cost estimating practice of local contractors. In this study, the researcher points out that local contractors:

- ☞ need to have a competitive bidding strategy to identify their optimum bid markup.
- ☞ need to decide their bid markup size by considering factors such as project characteristics, financial goal, market conditions, number of bidders, size of the project, uncertainty in estimating direct costs, required working capital for the project, workload, availability of resources and so on.
- ☞ are deciding the size their overhead costs and profit based on intuition, experience and expected competition.

This study in general, indicated that, there is a need for change in overhead cost estimating practices due to the fact that, inaccurate estimation of these costs can challenge contractors with regard to winning tenders and/or obtaining anticipated profit from contracted projects. It also suggest that the decision on the size of bid markup or profit to be introduced should be based on the result of assessment and evaluation of several factors related to the inside and external environment of the firms. Although this study agree in the need for a change in the practice of bid markup estimation it does not introduce a systematic tool to estimate the size of bid markup.

Danait (2015) has done a research to evaluate the cost estimation practice of local building contractors. Similar to the past studies, this study has also reveal that the majority of the local contractors used a detailed analysis cost estimating method during bidding. And estimate their overhead costs as percentage of the total project cost. The majority of respondents indicate that good understanding of the magnitude and the scale of the project and assessment of risk and profit allowance are necessary tools in cost estimating process. Although this study points out that local contractors has to calculate their general overhead costs in detail manner it does not answer how this can be achieved. In addition, the study say nothing regarding on how to decide the size of profit margin.

In view of the previously mentioned research gap in Ethiopian context, this study will focus on identifying various factors affecting road project markup size and developing a model to systematically associate historical project data with new project data for estimating bid markup size which can produce a satisfactory balance between the probability of winning a contract and a profit generated as a result of winning a contract.

1.4 SIGNIFICANCE OF THE RESEARCH

It is both time consuming and complicated to identify all the related factors that form rational strengths of factors, and quantify their combined impact to come up with a bid markup size decision. This study is intended to help local contractors to understand the factors that influence their decisions when determining bid markup size and can act as a decision aid to overcome their shortcomings in judgment and limited short-term memory, which prevents them from processing large amounts of information. This will, in turn, enhance their profitability and ability to win contracts by competing against international construction firms.

1.5 RESEARCH OBJECTIVE & QUESTIONS

The following are the main objectives of this research:

1. Review and understand the factors that influence decisions on bid markup size during competitive bidding.
2. Identify and analyze the factors which are specifically considered by local contractors in bid markup estimation during competitive bidding for federal road projects in Ethiopia.

3. Develop a hypothetical bid markup estimation model that can support local contractors' decision making for bid markup size.

The research questions are as follows:

1. What are the factors which influence bid markup estimation in general and specifically in federal road construction projects in Ethiopia?
2. How can these factors be used to develop a model in order to help & improve the performance of local contractors' decision making of bid markup size during competitive bidding for federal road construction projects?

1.6 SCOPE AND LIMITATION OF THE RESEARCH

The scope of this study is restricted to the following points:

- ☞ There are various definitions given to markup by researchers. The definition used for markup for this study is adopted from AACE (2017)- a factor that estimators apply to certain items or to the total cost of a bid to cover head office overhead and profit.
- ☞ A contractor may be awarded a construction project either by direct negotiation with the owner or through competitive bidding. This study is concerned with local contractors seeking projects through competitive bidding.
- ☞ The study is based on the premise that, in competitive bidding environment, the "lowest responsible bidder" is awarded the contract.
- ☞ Since the study aims to enhance the performance of local contractors' ability to predict systematic markup size during bidding for federal road construction projects, the study population for the required data collection will only consist of grade one local contractors who are currently executing federal road projects.

The research work is limited by the following factors:

- ☞ A list of factors influencing bid markup size during competitive bidding were compiled from various pieces of literature forming the core of the study. Thus, the questionnaire that was prepared inherit the limitation related to the fact that it directs the participants to give opinions in regard to the certain given statements. There could be other factors that affect bid markup size, but not mentioned in the questionnaire.

- Due to difficulty in obtaining past projects bid data from contractors regarding bid markup size they had used, the developed models in this study were developed based on data obtained through hypothetical bid scenarios.
- In this study, respondents were requested to rate how important various factors contributed to their decision on markup and provide the amount of bid markup they use on hypothetical bid scenarios. Since this may affect their future competitiveness, there is a possibility that the respondents withheld commercially sensitive information.
- The research mainly focuses on studying the factors affecting bid markup estimation and develop a model based on data gathered from local contractors' who are currently executing federal road projects. Therefore, generalizability to other sectors of construction is reduced. To extend the generalizability of this study, future comparative research could perhaps focus on the other sectors of construction.

CHAPTER 2: LITERATURE REVIEW

2.1 INTRODUCTION

The previous chapter introduced the aims of this study and tries to provide sufficient background information to provide a framework for the research. In this chapter, background knowledge related to this research is presented so as to understand the general concepts. The literature review has been discussed and summarized from published paper by various researchers. The review of journal articles and thesis helped to refine the research objectives and gave an overview of the work which was achieved by previous researchers.

Most revenues generated by construction contractors come from open bidding projects (Wanous, Boussabaine, & Lewis, 2000). Harris and Mc Caffer (2000) cited in (Mohamed, Khalil, & Badawy, 2017) highlighted that a competitive bidding is the route for obtaining a sizeable proportion of construction business by contractors globally. They also stated that most contractors will only survive and make profit in the industry by winning tenders. There are many methods for evaluating and selecting bidders; the typical one is the low-bid method, in which the contractor submitting the lowest bid is awarded the project if the contractor possesses the required technical qualifications (Abotaleb & El-adaway, 2017). In order to win a project, the lowest responsible bidder's bid should be low enough to win the job, yet high enough to generate profit. And this event in turn, requires a need for intelligent decisions on the size of a firm's bid on a given project (Christodoulou S., 2000).

Construction companies are required to meet two business requirements so as to determine their bidding prices strategy so that they are a successful company. These two requirements are: (1) prices have to reflect a reasonable profit for the company, and (2) prices have to reflect customer requirements for them to make the purchasing transaction (Mochtar (2010) cited in Nourah (2013)).

According to CIOB (1997) cited in Ling and Liu (2005) estimating is the technical process of predicting costs of construction, and bidding is a separate and subsequent commercial function based upon the estimate. Typically, a bid amount includes direct costs, indirect costs and a bid markup (Dikmen, Birgonul, & Gur, 2007). After the definition given by AACE International (2017) direct costs are "costs of installed equipment, material, and labor directly involved in the physical construction of the permanent facility." AACE International (2017) also defines indirect costs as "all costs which do not become a final part of the installation, but which are required for its orderly completion. It includes (but is not limited to): field administration, direct supervision, capital tools, some start-up costs, contractor's fees, insurance, taxes, etc." The sum of direct and indirect costs is termed as base estimate. This base figure is increased by an estimated percentage called a bid markup (Dikmen, Birgonul, & Gur, 2007). AACE International (2017) defines bid markup as "a factor that estimators apply to certain items, systems, or to the total cost of a bid to cover overhead, profit, and other indirect costs". Similarly, bid markup can also be defined as "the sum of general overhead, profit and contingency in percentage (Dozzi, Abourizk, & Schroeder, 1996)." Head office overhead is the contractor's cost to operate his overall business, and profit is the contractor's motivation, namely, the amount of money a contractor wants to make from a project (Lee & Chang, 2004). Contingency is the funds set aside for unforeseen construction difficulties or risks that may produce cost overruns (Lee & Chang, 2004).

The bid markup is estimated as the percentage of the base estimate based on the estimators' intuitions and experiences. While the base estimate is found to be the same by competitor contractors, the offered bid prices greatly differ due to the variations in the bid markup size estimations (Polat, Baytekin, & Eray, 2015). This event is due to common factors, including: most of the bidders have an access to the same labor supply; use the same types of equipment; obtain supplies and materials from the same sources; and have somewhat comparable supervisory capabilities (Moselhi & Hegazy, 1993). Therefore, the amount of bid markup size is the key component in a bid price, which also determines winning or losing the contract in question. In other words, the right amount of bid markup size brings success in competitive bidding environment (Dikmen, Birgonul, & Gur, 2007). Since the amount of the bid markup size is critical in winning the contract, the size of it should be determined precisely (Polat et al. (2012) cited in Polat et al. (2016)).

According to Badu and Amoah (2004) a bid markup should ideally consider:

- ☞ A "risk-free" return on the contractor's investment in the project commensurate with the return available on other risk-free investment opportunities.

- A "premium" to compensate the contractor for the uncertainties in the project ("Contingency" is often considered to include this compensation).
- The risk-return preferences of the firm's equity holders, and not the management.
- The competitive environment in which the contract is awarded.
- A "reasonable" compensation for the human resources and skills to be utilized in the project, such as business, financial and managerial expertise, professional experience and technical know-how.
- Other difficult, if not impossible, to quantify factors such as a potential improved competitive position and opportunity to acquire new and valuable experience.
- An allowance for the recovery of an "appropriate share" of the head office overhead expenses if contractually excluded from being directly charged to the client.
- An adequate allowance for the marginal tax expenditures that the contractor may incur under the various sales and income tax laws applicable to the project or the firm.

Drew (2001) cited in Egemen and Mohamed (2005) pointed that contractor's bidding strategy should be concern with setting the markup level to a value that is likely to provide the best payoff. Without 'right' markups, selecting 'right' projects will be meaningless. 'Right markup' in this case will be the optimum balance between a bid price that is as 'practically low' as possible to win the tender and as 'practically high' as possible to maximize profit (Lee & Chang, 2004). A contractor's success depends on his or her ability to assign an appropriate markup size that brings enough jobs and profit to the company (Shash and Abdul-Hadi (1992) cited in Lee and Chang (2004)). Therefore, contractors should take a strategic approach to the bid markup size decision (Lee & Chang, 2004). Strategic markup bidding, assumes that the bidder applies a markup which happens to produce a satisfactory balance between the probability of winning the contract, and the profit generated after winning the contract (Skitmore & Pemberton, 1994). Thus, this research focuses on contractors' bidding strategies for determining the proper bid markup size in a competitive bidding situation.

2.2 REVIEW OF FACTORS AFFECTING BIDDERS' MARKUP DECISION

In most civil Engineering disciplines, including construction, decision makers frequently encounter complicated and unstructured problems where solutions have to be made quickly despite the limited information available (Hegazy & Moselhi, 1994). Preparing tenders is among the very complex and dynamic process involving difficult decisions, and a multidimensional analysis of interrelated and complementary factors that are constantly changing. The company's, decision-makers face a challenge to look at all factors related to their environment to enhance the likelihood of a successful implementation of a profitable project (Mohamed, Khalil, & Badawy, 2017).

Markup estimation is one of a decision problem that is so highly unstructured and difficult to analyze and formulate an adequate solution mechanism (Moselhi, Hegazy, & Fazio, 1993). Complexity of the bid markup estimation problem may be attributed to the interrelations between many influencing factors which are implicit and tangible, usually hard to quantify, subjectivity about the magnitude of these factors and difficulty of specifying generic rules valid under all scenarios. In order to develop a reliable decision support system, it is imperative to possess a sound knowledge of factors affecting bid markup decision of contractors (Dikmen, Birgonul, & Gur, 2007).

Selected previous studies dealing with bid markup influencing factors are summarized in Table 2.1.

Table 2.1: Summary of previous studies conducted to identify factors that influence bid markup size decision

Item No.	Researcher(s)	Study population	Number of factors	Identified key markup factors
1	Ahmad & Minkarah (1988) cited in Ye, Shen, Xia and Li (2014)	400 top general contractors in USA	31	Degree of hazard, degree of difficulty, type of job, uncertainty in estimate, historic profit, current work load, risk of investment, rate of return, etc.
2	Shash (1993) cited in Ye, Shen, Xia and Li (2014)	300 top general contractors in United Kingdom	55	The need for work, number of competitors, the amount of experience on such projects, the degree of difficulty, risk involving owing to the nature of work & current work load
3	Hatush & Skitmore (1997) citied in Ye, Shen, Xia and Li (2014)	Eight construction personnel in England	20	Past failures, financial status, financial stability, credit ratings, experience, ability, management personnel, management knowledge
4	Chua et al. (1999) cited in Ye, Shen, Xia and Li (2014)	153 top contractors in Singapore	28	Competition, risk, need for work, and company's position in bidding
5	Fayek, Ghoshal and Abourizk (1999)	Canadian Contractors	118	Type of project, potential profit from project, need for work, number of competitors for the project, likelihood of winning project, experience on similar projects, etc.
6	Dulami and Shan (2002)	General building contractors in Singapore	40	Project characteristics, project documentation, company characteristics, bidding situation and the economic environment
7	Badu and Amoah (2004)	Large building contractors in Ghana	36	Project cash flow, risk involved in investment, competition, availability of work & need for work
8	Liu and Ling (2005)	Contractors in Singapore	52	Type of client, project complexity, accuracy of estimate, subcontractor portion, etc.

Item No.	Researcher(s)	Study population	Number of factors	Identified key markup factors
9	(Egemen & Mohamed, 2005)	Contractors in Northern Cyprus and Turkish	44	Number of competitors, risk due to inflation, payment conditions of the project, desire of contractors to bid, etc.
10	Dikmen, Birgonul and Gur (2007)	Turkish Contractors	44	Foreign exchange, contract payment type, amount of cash required in advance, economical/financial risk, level of experience of contractor in similar type of projects, etc.
11	Nourah (2013)	Contractors in Saudi Arabia	60	Size of job, clarity of specifications, project cash flow, type of job, history of client payment in past projects, etc.
12	Ye, Shen, Xia and Li (2014)	Construction companies in China	53	Contract requirements, construction plan, procurement, contractor heterogeneity, potential competitors and tendering procedure
13	Polat, Baytekin and Eray (2015)	A construction company who execute railway projects in various countries	35	Type of railway, lack of necessary equipment that are needed for the project, Type of the project, inflation risk and low rate of investment
14	Mohamed, Khalil and Badawy (2017)	Construction companies in Egypt	32	Project cash flow, inflation in material prices, experience in similar old projects, availability of required cash, availability of qualified staff, degree of safety, etc.
15	Arabpour and Moselhi (2018)	Contractors in Canada and USA	23	Need for work, site conditions, technology needed, inflation rate, escalation rate, similar experience, etc.

2.3 REVIEW OF MARKUP ESTIMATION MODELS

2.3.1 General

Many construction markets exhibit severe price competition where contractors must cut their bids to compete, giving priority to winning enough contracts to sustain normal operations, and it is common to see a winning bid close to the expected project cost. While cutting bids not only gives up profits but also undoubtedly increases the risk of making a loss. Moreover, it poses a threat to the quality of the project. To avoid financial and quality disasters, a decision to cut the prices should not be made arbitrarily, but as a rational choice made with careful calculation (Chao C. L., 2007).

While bid markup decisions are an experience based and unstructured problem-solving activities, it is also observed that estimators idiosyncratically apply specific rules and constraints for estimating a project' s markup (Li & Love, 1999). The current practice of markup estimation is characterized by the strong nonlinearity between the factors influencing markup estimation and the markup size that should be applied accordingly. The uncertainty and complexity in the influencing factors vary considerably. These characteristics require modeling techniques for markup estimation to be capable of handling nonlinearity, uncertainty, and subjectivity (Liu & Ling, 2005). A model should be available at least for rationalizing the intuitions of the contractors, even the successful ones (Egemen & Mohamed, 2008). A structured and realistic model, which will gain acceptance in practice and deal systematically with different bidding situations and assist the contractors in reaching the correct decisions will be of great value (Egemen & Mohamed, 2005).

Bid markup estimation models has been treated by various researchers in different manners. According to Hegazy and Moselhi (1994) and Marzouk (2002), these models can be classified into three main categories:

1. Statistical models
2. Multi-criteria utility models and
3. Artificial intelligence based models

Based on the work of various researchers these categories are summarized and presented in the following sections.

2.3.2 Statistical Models

These models analyze the statistical bidding behavior of each competitor individually and determine the probability of winning this competitor at any bid markup level (King (1991) cited in Hosny and Elhakeem (2012)). Mathematical models are employed to solve the problem of determining markup size for contractors in order to help them to increase their probability of winning contracts by determining the optimal bid (Chapman et al. (2000) cited in Nourah T.B. (2013)).

These models treated bid markup estimation as a structured problem, leading to the development of probability-based models (Hegazy & Moselhi, 1994). It presents a bidding problem as a single-objective (profit) maximization and were mainly concerned with developing the formula for the probability of winning of a contractor against its opponents given a particular markup and under a low bid tendering scenario (Awwad & Ioannou, 2012).

The primary goal of such models is to provide users with the means to arrive at optimum bid markups based on expected value analysis (a tradeoff between the probability of winning at a given percent markup, and the corresponding profits/losses at such bid markup). The analysis is based on the premise that, in competitive bidding environments, the "lowest responsible bidder" is awarded the contract and that bidders strive for an optimum bid value, one that would result in a bid that is low enough for a bidder to win over competition, yet high enough to generate profit (Christodoulou S., 2004).

The use of these models, however, has been rare in the industry and frequently discredited due to their inability to incorporate many qualitative factors that characterize the decision making environment and render the problem multi-attributed in nature (Ahmad (1990) cited in Moselhi and Hegazy (1993). These factors include prevailing market conditions, anticipated job uncertainty, project complexity and contractor's keenness for the job (Moselhi & Hegazy, 1993). The accuracy of these models is compromised when the data set of competitors' historic bids is incomplete and/or where such competitors utilize a dynamic behavior (i.e., having bidding schemes that change significantly with time) (Abotaleb & El-adaway, 2017). Furthermore, such expected-profit-based models, although simple and straightforward, do not consider differences in attitude toward loss risk and degree of need for work, and the result may not be relevant to many situations (Chao C. L., 2007).

Studies that utilize statistical models for bid markup estimation are summarized below:

Friedman (1956) cited in Yuan (2011) study historical bid data and characterize a competitor's bidding pattern with a probability distribution function of the ratio of the competitor's bid to the bidder's cost estimates, or, simply, the bid ratio. With this information, an optimal markup size that maximizes the long-term expected profit by balancing a great profit and a high probability of winning can then be determined. Gates (1967) cited in Chao (2007) proposed a similar bidding model of the Friedman type. It was based on the probability of winning for a markup applied. The optimum markup is determined as the one that has the maximum expected profit, where the expected profit for a markup means the product of the probability of winning multiplied by the markup. According to Christodoulou (2010) the limitation with the aforementioned analytical models is their oversimplification of the bidding problem to one of consisting of only two parameters (cost estimate and bid markup). This simplification reduces the models' accuracy and usefulness, for they fail to capture all the other objective and subjective factors such as human intuition that govern bid decisions. Complex analytical models are also cumbersome and non-usable (Christodoulou S. , 2010).

(Chao & Kuo, 2016), developed a probabilistic approach to determine the minimum markup based on minimization of overall loss risk. Beside conventional approaches that are based on maximum expected profit, they considered the chance of winning versus the loss risk in evaluating various bid levels for solving the bid-cutting limit problem.

(Oo , Drew, & Lo, 2007), suggested a regression modelling to offer an appropriate tool for competitive bidding analysis for identifying contractor's markup behavior.

(Shafahi & Haghani, 2014), proposed a mathematical model that considered both monetary and non-monetary criteria while also selecting projects on which to bid and choosing the best markup percentage decision. It also allows for the importance of eminence and previous works as the most important non-monetary evaluation criterion used by owners for evaluating bids. These factors combined with the two decisions make the model complex and nonlinear. To solve this model, a customized, Genetic Algorithm (GA) was developed.

(Polat, Baytekin, & Eray, 2015), present analytical hierarchy process (AHP) method, to determine the weight of the factors that affect the bid markup size and the regression analysis method is employed to estimate the bid markup size considering the weights of the factors and the importance levels of these factors for the projects for which the contractors would offer their bids.

2.3.3 Multi-Criteria Utility Models

There are many factors that can affect the markup and final bid price estimation (Hosny & Elhakeem, 2012). Multivariate methods offer a means of better utilization of available data, depending on the adequacy of certain assumptions concerning the statistical properties of bids. The application of multivariate methods to seal bid markup strategies offers a potential improvement on previous bivariate methods in providing a means of better utilization of available data (Skitmore & Pemberton, 1994).

These models treated markup estimation as a semi-structured problem using decision analysis techniques such as the AHP (Hegazy & Moselhi, 1994). In order to consider the multi-attributed and subjective nature of bidding decisions, analytical decision analysis tools have been used (Moselhi & Hegazy, 1993).

Decision theory provides a contractor with an optimum markup value for a future bid based on statistical inferences from the analysis of historical bidding patterns of competitors (Abotaleb & El-adaway, 2017). Utility theory was also employed in quite a few studies in various forms, which might be due to its ability to reflect the preference of a decision-maker, and the behavior toward risk (Lee & Chang, 2004). The utility theory approach assumes that contractors consider numerous criteria in determining the bid markup, and hence the bid price. For a newly tendered project, an expected utility value is obtained using predetermined criteria and is compared to a markup utility function to obtain a bid markup (Dozzi, Abourizk, & Schroeder, 1996). Utility-theoretic models are beneficial in capturing the contractor's knowledge for simulating its behavior and for applying this knowledge to new projects recommending appropriate bid markups (Abotaleb & El-adaway, 2017).

Skitmore and Pemberton (1994) said the traditional decision theory based model's main problem is that, they require unrealistic amount of data for them to provide statistically acceptable results and typically, the data might be incomplete, deeming these models is unusable. On the other hand, Christodoulou (2004) said utility theory based models are not appropriate for calculations of the probability of winning because the probability of winning is primarily dependent on the level of competition. Accordingly, the value of markup resulting from such models cannot be considered the optimum value.

Noteworthy works utilizing utility theory in the domain of bid markup are summarized below:

Multi-attribute utility theory was utilized by Ahmad and Minkrah (1987) cited in Moselhi and Hegazy (1993) in developing a most preferred bid markup in competitive bidding. The developed model generates optimum bid markup which reflects the preference of a decision maker by maximizing an expected utility function using an optimization routine. The expected utility function is an additive form, combining three separate utility functions corresponding to general overhead, contingency, and profit. Three individual utility functions were then combined with a weighting factor into one additive function. This function was transformed into an expected utility curve considering the sources of uncertainty where the estimated utility value provides the bid-markup size for a certain project (Lee & Chang, 2004). According to Chao (2007) though such approaches assume the possibility to establish the utility function for representing the value scale of a bidder in a bidding situation, in practice it is difficult to elicit information required for developing the form and parameters of the utility function, and this difficulty may affect the correctness of the result. The model is also complicated and, similarly to probability-based models, requires analysis of a large amount of historical data (Moselhi & Hegazy, 1993).

Dozzi, Abourizk and Schroeder (1996) developed a multiple attribute linear utility model for bid markup determination using 21 criteria in the bidding decision. The study states that a bid markup function is derived from a straight-line relationship between three overall utilities and three bid markup sizes estimated for 3 scenarios: worst scenario, average scenario and best scenario that are commonly used in a company. Respectively, the three corresponding bid markup sizes can be labelled as maximum, average, and minimum mark-ups. The individual curves were combined into the final expected utility curves where the estimated utility value provides the bid markup size for a specific project.

The AHP was utilized by Seydel and Olson (1990) cited in Moselhi and Hegazy (1993) in developing their bid markup estimation model. They presented methodology where three attributes: profitability, risk, and work force continuity are considered in the determination of the optimum bid markup for the integration of stochastic bidding models with the AHP. They used AHP to determine the relative weight vector of the proposed criteria (profit, risk and continuity). They then used the simple additive weighting method to obtain the relative weight vector of the bid markup alternatives (Lai, Liu, & Wang, 2002). However, Moselhi and Hegazy (1993) argued that this study fall short in considering many of the qualitative factors, besides their dependency on a contractor's particular experience not the domain general knowledge, making them unable to provide experienced guidance that may help contractors modify their own practices.

Skitmore and Pemberton (1994) propose a multivariate approach for deriving optimal markup & other markup strategies against known competitors. They presented these approaches by assuming that the bidder can incorporate data for all auctions in which competitors and potential competitors have participated, regardless of the individual bidder's participation. This method had the merit of increasing the amount of data available for estimating the model's parameters. An optimal markup value is then reached against known competitors, and other types of strategic markup. However, according to Liu, Wang and Lai (2005) the incorrect mathematical deductions used for developing a formula for the expected profit when a bid markup decision variable is included, and the formula for estimating the contract datum parameter caused errors in this multivariate approach.

Lai, Liu and Wang (2002) proposed a model for determining the most preferred bid markup. In this regard, a previously proposed model by Seydel and Olson (1990) is extended by introducing two new bidding criteria, called the conditional positive profit and the expected positive profit ratios, respectively. Three models with two attributes and a single criterion model are proposed for analyzing the most preferred bid markup selection. The simple additive weighting method and the weighting product method are used to solve these models.

Awwad and Ioannou (2012) uses established principles of decision analysis and utility theory to develop a risk-sensitive bidding model that aims at determining the contractor's optimal bid markup for a project through maximizing its expected utility value of profit. This model weighs: the risk attitude of the contractor, the uncertainty about winning the project, and the uncertainty about the final cost of the project.

The developed model by Nourah (2013) for estimation of bid markup size, began with the development of a mathematical method to determine markup size recommended to contractors, based on the contractor's situation and input for this project. Then, a proper bidding strategy model is developed using a multi criteria decision making utilizing utility theory. Each input had a utility function which was then combined with a level of importance for each factor to form a single utility curve. The final model was designed, using a computer-scripting language called ASP (Active Server Pages) to facilitate the determination of bid markup size.

Through a multistage decision theory approach Abotaleb and El-adaway (2017) presents a more advanced model for the estimation of optimum markup that uses a Bayesian analytic framework. The optimum bid markup is the one corresponding to the highest expected profit, where the expected profit is the multiplication of the probability of winning and profit. The use of the Bayesian statistics in the model enables it to draw sound statistical inferences even in cases of data incompleteness and dynamic behaviors of competitors, thus tackling two important weak spots in the previous models.

2.3.4 Artificial Intelligence Based Models

Hawkins (2004) cited in Dikmen, Birgonul and Gur (2007) states that brain uses most memory to create a model of the world. Everything a person knows and has learned is stored in this model. The brain uses this memory-based model to make continuous predictions of future events. It is the brain's ability to make predictions about the future that is the puzzling problem of intelligence. The brain does not compute answers to problems. It retrieves the answers from the memory. Intelligence is rooted in the brain's ability to access memories rather than in its ability to process new data. The brain accesses previous experiences, compares them with existing circumstances, and predicts what is most likely to happen next (Hawkins (2004) cited in Dikmen, Birgonul and Gur (2007)).

Since the beginning of the 1990s, several models have been developed using artificial intelligence (AI) tools for the bidding problem (Hosny & Elhakeem, 2012). In contrast to traditional reasoning-intensive methods, AI tools employ a learning mechanism and simulate the human estimating ability to learn from examples and solve pattern recognition tasks similar in nature to the performed according to the current industry practice in estimating markups. AI has been concerned with encoding the domain experts' knowledge and the problem solving into more intelligent and automated computerized systems (Moselhi & Hegazy, 1993).

These models treated bid markup estimation as an unstructured reasoning-intensive problem using expert systems (Hegazy & Moselhi, 1994). The usual practice of bid markup estimation is to make bid decisions on the basis of intuition, derived from a mixture of gut feeling, experience, and guesses (Ahmad (1990) cited in Moselhi, Hegazy and Fazio (1993)). This event implies some form of pattern recognition is used, to derive a solution based on analogy with previous encounters, rather than computation or deep reasoning about the problem elements (Moselhi et al. (1991) cited in Moselhi, Hegazy and Fazio (1993)).

The models are mainly based on artificial neural networks, a form of regression technique where networks are trained through a set of input projects and associated output result (bid markup). Consequently, the trained network learns to generalize the input-output correlation, encodes the corresponding knowledge in its database and then uses it to build an analogy with similar past projects and accordingly estimate the optimum markup for new projects (Awwad & Ioannou, 2012).

Numerical models (such as expert systems and ANN) manage to capture several more of the factors influencing bid decisions (objective and subjective factors), yet unless complemented with competitive bidding history on competitors they fail to enumerate the resulting probability of success and therefore the optimum bid mark-up (Christodoulou S., 2004). Furthermore, the creation of knowledge base is a long and expensive process (Moselhi, Hegazy, & Fazio, 1993).

Notable works utilizing artificial intelligence based models are summarized below:

Moselhi and Hegazy (1993) introduced a decision-support system for markup estimation using artificial neural networks (ANN). The ANN used was modeled around the back propagation algorithm, having an input layer of 30 neurons, a hidden layer, and an output layer of seven neurons. In order to arrive at a suitable model performance, two alternative designs for the NN model are examined, and their results compared. The first model is based on a single NN architecture and the second is based on a five-network hierarchical system. However, Nourah (2013) said this method requires examples for training and historical data to be collected. Additionally, the value suggested by the ANN model for the bid markup cannot be considered as the optimum value thus, inadequate for estimating the probability of winning a given markup (Christodoulou S., 2000). Furthermore, such models just provide recommendations without any explanation or justification on why and how a particular mark-up percentage is recommended and therefore, they lack credibility in the user acceptance of the system and their results (Li, Love, & Shen, 1999).

A study by Moselhi, Hegazy and Fazio (1993) presents a decision support system (DSS) which uses neural networks for optimum markup estimation that derive solutions to new bid situations in analogy with past projects. Further effort to improve the generalization capabilities of the hand crafted net was also conducted using the genetic-algorithm (GA) technique as an automated network optimization procedure. Using the GA technique, the network was optimized, with an objective function to minimize the errors on the unseen examples, thus enhancing the generalization capabilities.

Li (1996) compared the accuracy of ANN-based bid markup systems with regression based systems for modelling historical cost data, identifying the effect of different layers and node numbers on the accuracy of an ANN-based bid mark-up estimating system. In the study, five attributes were used as input nodes for each bidder. The output node is markup percentage. Some input attributes have numerical values and other have nominal values, ranging in low, medium & high. The ANNs were then trained and tested against the bidding examples. For training neural networks, 155 examples were used, and five examples were used for testing. The regression method used in this study was a stepwise multiple linear regression program where bid markup size was the dependent variable, and the four input attributes used in neural network models were extracted as independent variables. The regressed equation is also formulated from the 155 examples, and then tested on the other five examples. The estimation results produced by regression are generally higher than actual values, with an average error rate greater than 10%. Results from neural networks, however, are more accurate. This event led the author to deduct that neural network-based cost estimation models are superior to regression-based models. The average estimation error rate of neural networks fluctuated around 10%. In general, the author recommended that, if sufficient historical cost data is available, neural networks can be trained to intelligently assist estimators.

Li, Love and Shen (1999) presented a computer based bid markup decision support system that integrated a rule-based expert system, and an ANN based system. They tried to apply the KT-1 method to extract rules from the trained ANN model. The rule base provided explanations to assist the user to understand why the markup output is recommended by the computer system. However, the authors underlined that there is a principal limitation of these automatically generated explanations. Human comprehension is based on experience and technical knowledge, which cannot be easily encoded into a computer. Thus, a neural network cannot create the insight required for the user to understand a specific aspect or decision. Instead, it can only communicate the necessary information for the user to generate real explanations.

According to Chao and Liu (2000) the accuracy of estimation results from ANNs is not high enough and the calculation system is in a 'black-box'. In response to this, they propose a fuzzy neural network (FNN) model to rectify these drawbacks of ANN for markup estimation. The FNN model embodies the fuzzy logic in a neural network as a way of retaining the strengths of both methods. (Chao & Liu, 2000), said that fuzzy logic and neural networks are complementary technologies. FNN is a computer system, which combines fuzzy logic inference mechanism with a neural network system. A system integrating that two will possess the advantages of both neural networks such as learning abilities, optimization abilities and connectionist structures, and fuzzy systems such as IF-THEN rules thinking and ease of incorporating expert knowledge. Because the results are produced within the scope of clearly stated rules and interpretable parameters, the inference process is now transparent. Moreover, the fuzzy neural network is able to model the complex relationships between the influence factors and the mark-up and achieve an acceptable estimation accuracy as all the outputs are in the scope of fuzzy logic inference rules. However, the authors pointed out that, as all the rules and membership functions are decided by users' experience, a long and expensive process is needed to create it and the system is inevitably subjective.

Fayek, Ghoshal and Abourizk (1999) developed a bidding strategy model that used the fuzzy set theory to determine bid markup size. The study identified three objectives for determining the bid markup size using the model: to win the project, to explore new geographical areas and to maximize the project's contribution. With these objectives, a factor's level can be identified. However, Nourah (2013) said this model is limited for considering only three objectives and recommend that the model could be enhanced based on the objectives of contractors, and the identification of contractors' needs.

The study by Christodoulou (2000) provides a tool for assessing both the objective and subjective factors affecting bid markup estimation in competitive bidding environments, and a method for calculation of optimum bid markup using probabilistic neural network (PNN) modeling. The model evaluates the subjective factors inherent in the bidder's decision-making process and proposes a bid markup in these factors. This event is done by means of ANN using back propagation algorithm, and their features of pattern recognition, generalization, and abstraction. The bid markup size is then evaluated against historical data on bid competitors to evaluate the probability of winning at the given markup, based on the evaluation of the project parameters and competition. Optimization is then performed by the method of Parzen Windows, which allows to approximate the underlying multi-dimensional probability distribution function.

The paper by Marzouk (2002) presents a bid markup estimating model utilizing Monte Carlo simulation and artificial neural networks (ANN). ANN are used for modeling and predicting bid markup percent in predefined parameters that influence that percent, whereas, Monte Carlo simulation is used to capture the uncertainty involved in these parameters. When some simulation runs are made, a range of bid markup is created to carry out range analysis which is more valuable for decision-making than crisp value.

Liu and Ling (2003) used a fuzzy neural network technique that uses fuzzy inference rules rather than a hidden layer, thus, they claim that results of their model are more traceable and much easier to understand. To remove the 'black-box' perception of the ANN based models, and improve their ability to explain what is inside them, they propose the use of FNN to predict markup. The FNN model, which contains a full explanation of its operations, could increase the user-acceptance of it. However, Dikmen, Birgonul and Gur (2007) said it is still hard to derive generic rules for complex situations.

Christodoulou (2004) in his study presents a method for arriving at optimum bid markup in static competitive bidding environments by the use of neuro-fuzzy systems and integrated multidimensional risk analysis algorithms. The proposed neuro-fuzzy system attempts to model the uncertainty in the factor assessments and account for their qualitative nature, by employing both classic stochastic simulations and fuzzy logic operations on the ANN inputs as a supplement to the ANN. The probability of winning at a given bid markup, and the optimum bid markup can be calculated by applying multi factored risk analysis methods composed of both quantitative and qualitative factors.

Chao (2007) proposed a fuzzy logic model for determining the minimum markup that incorporates the position of the bidder. The model considered the chance of winning versus the risk of making a loss in evaluating various bid levels.

Dikmen, Birgonul and Gur (2007) develops two models as part of decision support tool for bid markup estimation. These are, case based reasoning (CBR) models & linear bid markup estimation model. CBR models have been developed to estimate three ratings, called as Risk Rating (RR), Opportunity Rating (OR) and Competition Rating (CR). Linear estimation models using utility functions are developed to find the risk and profit mark-ups using the RR, OR and CR values for a project as the input parameters. The bid markup is defined as "the summation of risk and profit markup." In order to find the relation between the overall utility value and the risk, opportunity and competition ratings, linear regression technique has been used. The authors also suggest recommendations so as to overcome some of its limitation such as: incorporating a higher number of scenarios into the case base so that the case base covers the scenario space in a more comprehensive and homogeneous manner and to improve the accuracy of the model, different risk attitudes of the experts may be incorporated into the model and exponential relations may be considered instead of a linear relation between utility and bid markup values.

An iterative agent leaning model for bidders to make bid markup decisions is proposed by Hou, Shan and Ye (2011). The model is based upon iterative process that includes features as classifier, data storing, knowledge discovery and decision making. A classifier for public bidding information named PIBS is developed to make full use of history data for classifying new bidding information. The simulation and experimental study is performed to show the validity of the proposed classifier. Agent needs to collect history bidding information and then classify this information by its attributes, and store it into the database. Next agent finds the characteristic of bid price of each group through carefully analysis. When agent faces a new markup decision, she/he needs to search the right group whose attributes are most similar to the new bidding. Based on the characteristic of bid price of the compared group, the new bid markup decision can be improved.

The study by Arabpour and Moselhi (2018) aims to illustrate the accuracy of multiple linear regression (MLR), artificial neural network (ANN) and adaptive neuro-fuzzy inference system (ANFIS) techniques of modeling for estimating markup. For the developed MLR, to consider the dependency and interdependency between variables, the correlation between inputs and output was determined using the statistical package, SPSS 20. The ANN model was developed using "MATLAB 2017a". Since the object of the study was defined as a prediction (i.e. estimating) problem, the feed-forward type was selected for the architecture of the model. The numbers of neurons in the input and output layers are governed by the number of input and output parameters, respectively. A trial and error process was used to decide the number of hidden layers and nine different hidden layers are employed. The proposed ANFIS model was implemented using the fuzzy logic toolbox in "MATLAB

2017a" software. The generalized bell-shaped membership function was selected in view of its minimum error. There are two functions for the output layer: constant and linear membership function. Both functions were tried and the constant function was chosen as it yielded the least errors. The accuracy of each model is accounted for by using the following two statistical indicators: root mean squared error (RMSE) and coefficient of determination (R^2). The results of the analysis indicated that the developed ANN model outperformed the MLR model, and that the developed ANFIS model outperforms both other two models in estimating markup under different project conditions.

The major advantages and drawbacks of various modeling techniques which can be used for bid markup estimation are summarized in Table 2.2.

Table 2.2: Comparison for various modeling techniques which can be used for bid markup estimation

Modeling techniques	Advantages	Source/s	Draw backs	Source/s
Probabilistic approach	Provide users with the means to arrive at optimum bid markup based on expected value analysis (a tradeoff between the probability of winning at a given percent markup, and the corresponding profits/losses at such bid markup).	Christodoulou (2004)	Inability to incorporate many qualitative factors that characterize the decision making environment and render the problem multi-attributed in nature.	Ahmad (1990) cited in Moselhi and Hegazy (1993) and Christodoulou (2010)
			The accuracy is compromised when the data set of competitors' historic bids is incomplete and/or where such competitors utilize a dynamic behavior.	Abotaleb and El-adaway (2017)
	Simple and straightforward.	Chao (2007)	Do not consider differences in attitude toward loss risk and degree of need for work, and the result may not be relevant to many situations.	Chao (2007)
Multiple linear regression	Simple in both concept and application.	Goh (2008)	Require researchers to ascribe functional forms to fit the data patterns.	Goh (2008)
	The extent of the relationship between variables to be clearly defined.	Goh (2008)	It is almost impossible to simulate the estimation mechanism of experienced experts with pure mathematical models.	Chao and Liu (2000)
Multi-criteria utility	Consider the multi-attributed and subjective nature of bidding decisions.	Moselhi and Hegazy (Moselhi & Hegazy, 1993)	The value of the resulting bid markup cannot be considered as an optimum value.	Christodoulou (Christodoulou S., 2004)

Modeling techniques	Advantages	Source/s	Draw backs	Source/s
Multi-criteria utility	Beneficial in capturing the contractor's knowledge for simulating its behavior and for applying this knowledge to new projects recommending appropriate bid markup.	Abotaleb and El-adaway (2017) and Lee and Chang (2004)	The model is complicated and requires analysis of a large amount of historical data to provide statistically acceptable results.	Moselhi and Hegazy (1993) and Skitmore and Pemberton (1994)
Artificial neural network (ANN)	Able to provide a generic functional mapping from inputs (representing different problem encounters) to outputs (representing the conclusions or decisions).	Li (1996)	The creation of knowledge base is a long and expensive process.	Moselhi, Hegazy and Fazio (1993)
	Employ a learning mechanism and simulate the human estimating ability to learn from examples and solve pattern recognition tasks.	Moselhi and Hegazy (1993) and Awwad and Ioannou (2012)	The resulting bid markup cannot be considered as the optimum value thus, inadequate for estimating the probability of winning a given markup.	Christodoulou (2000) and (2004)
	Manage to capture several more of the factors influencing bid decisions (objective and subjective factors).	Christodoulou (2004)	Provide outputs without any explanation or justification on why and how a particular bid markup size is recommended.	Li, Love and Shen (1999)
Fuzzy neural network (FNN)	Uses fuzzy inference rules so that the results of the model are more transparent and traceable.	Chao and Liu (2000) and Liu and Ling (2003)	It is hard to derive generic rules for complex situations.	Dikmen, Birgonul and Gur (2007)

Modeling techniques	Advantages	Source/s	Draw backs	Source/s
Fuzzy neural network (FNN)	Able to model the complex relationships between the influence factors and the bid markup and achieve an acceptable estimation accuracy as all the outputs are in the scope of fuzzy logic inference rules.	Chao and Liu (2000)	As all the rules and membership functions are decided by users' experience, a long and expensive process is needed to create it and the system is inevitably subjective.	Chao and Liu (2000)

2.4 BID MARKUP ESTIMATION PRACTICE BY LOCAL CONTRACTORS

Tadesse (2006) prepares a construction cost estimation guideline for local contractors to establish the unit costs of construction activities and develop the overall project construction costs. This study has present the practice followed by local contractors during the time of research execution. According to this study, in most cases local contractors were using Ethiopian Transport Construction Authority's performance standards and material breakdowns as sole bases for estimating road project construction costs. Moreover, there were many instances whereby contractors use previously prepared unit prices by other contractors whom they believed are well organized contractors in estimating project construction costs without justification of the cost components included in these unit prices. In addition, most local contractors were using thirty percent (30%) of their direct costs to cover overhead costs and profit margin in their project cost estimates without justifications. This study suggest local contractors, to calculate their total annual head office overhead costs (all costs required to run the whole operation of the construction company) and express this amount as a percentage of the direct unit cost of an activity during bidding for projects so that it can be shared proportionally by all projects under the company. The study has also points out that a profit margin entirely depends on the market competitiveness and company strategies and its size should be decided accordingly.

Abeselom (2008) carryout a study to investigate the cost estimating practice of local contractors. According to the results of this study the following points can be noted:

- There is a wide application of the standard or the detailed estimating method, for preparing cost estimates for bid by local contractors. This is a method where, the costs of construction (material, labor, equipment and sub contract costs) are established and to which an allowance for overhead costs, other indirect costs, risks and profit is added.
- No local contractor uses probabilistic or statistical cost estimating method.
- 35% of the surveyed contractors identified overhead costs as the most difficult item to estimate, among the various project cost components. Overhead costs, though they are claimed to be difficult to estimate, the survey indicated that the effort by contractors to identify and incorporate them in a tender price is low.

- Regarding the overhead costs allocation method, the survey results revealed that 52% of the contractors introduce allowances for overhead costs by multiplying the total estimated direct cost or activity direct unit cost by an arbitrarily selected percent. The percent is decided based on intuition, experience and expected competition. The remaining 48% disclosed that, they will first identify relevant overhead cost items with the associated costs and then distribute the total sum to each project activity. The survey results indicated that the average percentage to cover head office overhead is 11.22%.
- The survey indicated that contractors allocate bid markup or profit amount based on the final estimated project cost which is comprised of the direct and estimated overhead costs. Based on the survey result, the ratio of the profit amount to total project costs for 55% of the contractors is between 11-15%. 10% of the contractors add more than 15% of the project estimated cost as a profit. The calculated average percentage for profit is 11.44%.

Danait (2015) has done a research to evaluate the cost estimation practice of local building contractors. The study believes that there local contractors lack efficient cost estimation system (contractors' policies, procedures, practices, methods, techniques, approaches and other analysis) to generate accurate and reliable cost estimates to win project bids. And having proper cost estimation system is vital to optimize cost, to attain the desired quality and minimizing delays. Based on the study's survey result, 46% of respondents believes that the performance of the local contractors in cost estimating practice is bad and the reasons for this includes: lack of competent professionals and published price information on material, labor and equipment (established standards). Similar to the past studies, this study has also reveal that the majority of the local contractors used a detailed analysis cost estimating method during bidding. And estimate their overhead costs as percentage of the total project cost. The majority of respondents indicate that good understanding of the magnitude and the scale of the project and assessment of risk and profit allowance are necessary tools in cost estimating process.

2.5 CHAPTER SUMMARY

This chapter helped to identify a direction for developing a plan for achieving the research objectives. It had presented the importance of determining the bid markup size and given details of previous research studies which had identified factors that affect bid markup size decision, as well as techniques of modeling for estimation of bid markup size.

The literature review has shown that, existing findings on the level of importance attached to factors that influence bid markup size vary from one study to another and from one country to another. This event gives an opportunity for this research to re-explore and re-examine these factors to establish an importance index for factors influencing the bidding markup size decision in the Ethiopian Road Construction Industry. Based on the identified factors, a model for bid markup estimation will be developed.

From the literature review presented, 21 factors have been identified as potentially influential to the bid markup size decision and these factors are categorized (grouped) into 4, including project characteristics, company characteristics, bidding situations and economic situations. These 21 factors are obtained by merging some factors which can be considered as an alternative expressions and combining some factors which can be grouped under one main factor.

Below is the list of the identified factors:

1. Project characteristics
    1.1 Strategic value of project
    1.2 Complexity of project (such as resources and technology required)
    1.3 Project location (region)
    1.4 Right of way status
    1.5 Expected size of contract
    1.6 Duration of project
    1.7 Security need of project location
    1.8 Clarity and completeness of tender documents (drawings, specifications, etc.)
    1.9 Pavement type
    1.10 Type of project delivery system
2. Company characteristics
    2.1 Current work load
    2.2 Immediate need for work
    2.3 Accuracy of the direct cost estimation
    2.4 Previous experience of the company on similar projects
    2.5 Availability of cash or overdraft facility to carry out project

2.6 Availability of credit facility from suppliers

2.7 Current required amount for head office overhead cost relative to the planned amount

3. Bidding situation

3.1 Number of competitors with strong desire to win a project

3.2 Previous experience of competitors on similar projects

4. Economic situation

4.1 Current state of the overall economy of the country

4.2 Amount of possible upcoming profitable projects out for tender in the remaining fiscal year

In terms of the technique used for modeling bid markup size, several approaches are available. After comparing and contrasting these several techniques, this research uses multiple linear regression (MLR) and artificial neural network (ANN) techniques for modeling markup estimation. MLR is selected in order to take its advantages of being simple to develop, the final model output is easy to be used by a new user and the nature and magnitude of the relationship between each of the bid markup factors and the bid markup can be observed easily. The ANN technique of modeling is selected because it can provide a generic functional mapping from the inputs (bid markup factors) to output (bid markup) whether it is a linear or non-linear functional relationship and its working mechanism is similar to the typical decision making characteristics (subjectivity, intuition and gut feeling) associated with the estimation of bid markup.

CHAPTER 3: RESEARCH METHODOLOGY

3.1 INTRODUCTION

The search for knowledge through an objective and systematic method of finding a solution to a problem is a research. Research can also be defined as a scientific and systematic search for pertinent information on a specific topic. On the other hand, research methodology is a research strategy that translates ontological and epistemological principles into guidelines that show how research is to be conducted and principles, procedures, and practices that govern research (Nayak & Singh, 2015).

This study is applied and exploratory type of research, because its purpose is initiated for solving a practical problem and aims to explore the percentage of bid markup that is to be used during the bidding of federal road construction projects respectively. It can also be said a descriptive type of research, because it aims to describe the key factors affecting bid markup size estimation in Ethiopian federal road construction projects.

This chapter will present the research strategy used and various sequential phases that the research will follow to achieve the ultimate goal of the research and draw findings to make conclusions and forward recommendations.

3.2 RESEARCH STRATEGY

Research strategy can be defined as the way in which the research objectives can be questioned. The research strategy can be classified into two types namely, quantitative approach and qualitative approach (Naoum, 2007). According to Lindlof & Taylor (2002) a quantitative approach can be defined as the generation of numerical data that describe a result which can be converted into numbers. For example, the importance of factors or the rank of factors. In this type of research, a statistical tool can be used in order to understand and make calculations of the obtained data. By contrast, according to Lindlof & Taylor (2002) a qualitative approach can be defined as a way of understanding and exploring people's beliefs, experiences, attitudes, behavior, and interactions. In other words, qualitative research is used to generate non-numerical data (Lindlof & Taylor, 2002). Deciding on which type of research to follow, depends on the purpose of the study and the type and availability of the information required (Naoum, 2007).

To identify the key factors influencing bid markup decision and develop a model for bid markup estimation of federal road projects in Ethiopia, this research deploys both qualitative and quantitative techniques. A qualitative method was used for identifying the factors affecting bid markup estimation in general and review the existing techniques which can be employed for the formulation of a suitable model for bid markup decision through an extensive literature review from previous studies. The collected factors were used for developing a model to estimate the percentage of bid markup that can be used in future bids for road projects (quantitative approach).

3.3 LITERATURE REVIEW PHASE

Previous related journals, thesis and other papers which were relevant to the selected study area were reviewed. This helps to achieve part of the research objective by observing and defining various factors that could influence bid markup size of a project. This phase was also helpful to review and understand existing modeling techniques for bid markup estimation.

3.4 DATA COLLECTION AND ANALYSIS PHASE

3.4.1 Study Population

A population is defined as the set of all individuals, items, or data of interest (Nayak & Singh, 2015). The study population for this research were local contractors who have grade-one license and are currently executing road construction projects at federal level in Ethiopia. Since ERA is responsible for administration of road contracts at the federal level, the lists of contractors were obtained from ERA.

3.4.2 Sample size

A sample is a "subgroup of a population". It can be a group of people, objects, or items that are taken from a larger population for measurement (Nayak & Singh, 2015). The sample should be representative in the sense that each sampled unit will represent the characteristics of a known number of units in the population and to ensure that it can generalize the findings from the research sample to the population as a whole (Nayak & Singh, 2015).

Based on the data obtained from ERA's Engineering Procurement directorate, during data collection phase of this study, there were 28 active grade-one local contractors who are executing federal road projects. Accordingly, the sample size of the population for the research was set as 28 and a questionnaire was distributed to all.

3.4.3 Data collection & measurement method

Based on the findings from the literature review, a structured questionnaire was prepared to investigate contractors' behavior when they perform their bid markup size decisions (bid markup factors that they consider) in bidding for federal road construction projects. The design of the questionnaire takes the objectives of the study into consideration to answer the research questions. Respondents were also asked to list any other factors that they deem important for bid markup estimation and rate its degree of importance.

An ordinal scale data measurement technique was used for the data which was collected through the questionnaire survey. As shown in table 3.1, a 5-point likert scale, that use integers in ascending order, was used for rating and ranking of the data. The numbers assigned (0, 1, 2, 3, 4) neither indicate that the intervals between scales are equal nor do they indicate absolute quantities. They are merely numerical labels (Iyer & Jha, 2005).

Table 3.1: Ordinal scale used for data measurement (Iyer & Jha, 2005)

Scale	Meaning
0	No impact
1	Affects with little degree
2	Affects with average degree
3	Affects with large degree
4	Affects with very large degree

3.4.4 Method of data analysis

Based on the response of the questionnaire, the data were analyzed in order to identify the weight and rank each factor in terms of its influence on bid markup size. Then, the ranked factors were used as an input during model development. A relative importance index (RII) method was used and each factor was ranked based on a calculated index. Evaluating the relative importance index is a useful approach to identify key factors from a number of alternatives.

The importance index was computed using the following equation (Tawil, 2008):

$$RII\ (\%) = \left[\frac{5(n_5)+4(n_4)+3(n_3)+2(n_2)+n_1}{5(n_1+n_2+n_3+n_4+n_5)}\right] \times 100 \qquad \textbf{(Eqn. 3.1)}$$

Where

- n_1 = number of respondents who answered "no impact"
- n_2 = number of respondents who answered "affects with little degree"
- n_3= number of respondents who answered "affects with average degree"
- n_4 = number of respondents who answered "affects with large degree"
- n_5 = number of respondents who answered "affects with very large degree"

Based on the results of the analysis, a discussion was carried on each key factors and a comparison with other related studies was done.

3.5 MODEL DEVELOPMENT PHASE

The second part of the questionnaire was carried out to gather actual past road projects bid data from the study population. Since it was difficult to obtain past project bid data from contractors related to the bid markup size, a hypothetical bid scenarios questionnaire was prepared & contractors were asked to respond. The percentage of bid markup to be used were requested, by presenting various hypothetical bidding scenarios based on the factors identified from the literature review.

In this hypothetical experiment, the respondents were informed that, if they provide too low markup percentage, it may lead to monetary losses and if they set it too high, the company cannot get the project. They were also informed that the project direct cost estimate had been prepared by estimators by considering any risk that the project may face, so that they assume to exclude any contingency in the markup percentage.

After collecting and organizing the data, estimation models were developed using multiple linear regression (MLR) and artificial neural network (ANN) techniques to generate bid markup size. The performance of the developed models were evaluated using several statistical indicators.

3.6 CONCLUSION AND RECOMMENDATION PHASE

Finally, a conclusion and possible recommendations were forwarded based on the initially set objectives and findings of the study.

CHAPTER 4: RESEARCH ANALYSIS & DISCUSSION

4.1 INTRODUCTION

4.1.1 Questionnaires Response Rate

The questionnaire has two main parts; the first part request respondents to define the degree of impact of various factors in affecting bid markup size decision during bidding and the second part request respondents to provide a specific percentage of markup by presenting various hypothetical bidding scenarios. A total of 28 questionnaires were distributed out of which 22 & 20 are collected yielding a response rate of 78.57% and 71.43% for the first and second parts of the questionnaire respectively (Table 4.1).

Table 4.1: Questionnaires response rate

Total number of questionnaires distributed	Number of questionnaires collected		Response rate (%)	
	First part	Second part	First part	Second part
28	22	20	78.57 %	71.43 %

4.1.2 Characteristics of Respondents

This section summarizes the characteristics of respondents including job position, educational qualification, general experience in construction and specific experience related to bidding as shown in Table 4.2. From Table 4.2, it can be observed that all respondents have a minimum of BSc degree in Civil engineering or construction technology and management. The general experience of respondents in the construction sector range from 4 to 37 years, with an average of 13 years. Their specific experience related to bidding for road construction project range from 2 to 30 years, with an average of 7 years.

Figure 4.1 below, illustrate the general and specific work experience of the respondents.

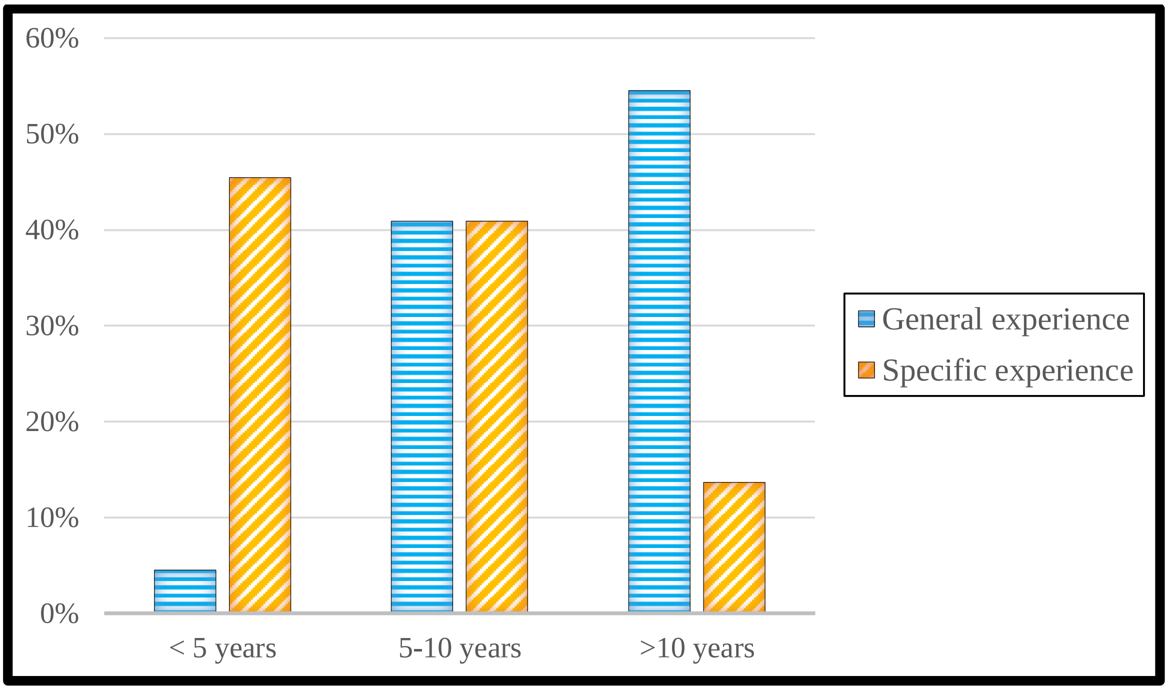

Figure 4.1: General and specific work experience of the respondents

4.2 FACTORS AFFECTING BID MARKUP ESTIMATION

4.2.1 Data Analysis and Ranking of Markup Factors

This section deals with the data analysis and ranking of bid markup factors. Based on the response of the questionnaire, the data is analyzed in order to identify the respective weight and rank of each factor. Table 4.2 presents the importance of factors, and their respective overall rank, in terms of their influence in deciding bid markup size.

Table 4.2: Additional factors identified by respondents

Item No.	Factors affecting bidders' bid markup estimation	RII (%)	Overall rank
1	Complexity of project (such as resources and technology required)	95.45	1
2	Number of competitors with strong desire to win a project	88.18	2
3	Project location (region)	87.27	3
4	Immediate need for work	87.27	3
5	Security need of project location	85.45	5
6	Previous experience of the company on similar projects	83.64	6
7	Strategic value of project	82.73	7
8	Previous experience of competitors on similar projects	82.73	7

Item No.	Factors affecting bidders' bid markup estimation	RII (%)	Overall rank
9	Accuracy of the direct cost estimation	80.91	9
10	Expected size of contract	79.09	10
11	Type of project delivery system	74.55	11
12	Current state of the overall economy of the country	74.55	11
13	Current work load	72.73	13
14	Duration of project	71.82	14
15	Clarity and completeness of tender documents (drawings, specifications, etc.)	70.91	15
16	Availability of cash or overdraft facility to carry out project	70.00	16
17	Current required amount for head office overhead cost relative to the planned amount	70.00	16
18	Amount of possible upcoming profitable projects out for tender in the remaining fiscal year	68.18	18
19	Right of way status	66.36	19
20	Pavement type	65.45	20
21	Availability of credit facility from suppliers	60.00	21

From the results, it appears that 'complexity of project (such as resources and technology required)', 'number of competitors with strong desire to win a project', 'project location (region)', 'immediate need for work' and 'security need of project location', are the top five ranked factors in terms of influencing bid markup size. The lowest-ranked factors are 'current required amount for head office overhead cost relative to the planned amount', 'amount of possible upcoming profitable projects out for tender in the remaining fiscal year', 'right of way status', 'pavement type' and 'availability of credit facility from suppliers'.

4.2.2 Additional Markup Factors Stated by Respondents

In addition to providing an importance rating for the markup factors that are compiled from the literature review, respondents were requested to list any other factors that they will consider in deciding bid markup size. The following are additional factors that the respondents stated:

- Payment record of the employer
- Project start time (season)
- Expectation of fraud and corruption
- Amount of performance bond
- Performance of the employees
- Price escalation conditions

There were also some additional factors identified by respondents. But these factors can be considered as either a sub-group or alternative expressions for the compiled factors from literatures. Table 4.3, presents these factors which are identified by the respondents.

Table 4.3: Additional factors identified by respondents

<table>
<tr><th>Item No.</th><th>Factors identified by respondents</th><th>Factors compiled from literature</th><th>Remark</th></tr>
<tr><td>1</td><td>Past profit recorded from past similar projects</td><td>Previous experience of the company on similar projects</td><td>Sub-group</td></tr>
<tr><td>2</td><td>Availability of resources</td><td rowspan="2">Current work load</td><td rowspan="2">Sub-group</td></tr>
<tr><td>3</td><td>Type of equipment required and its availability</td></tr>
<tr><td>4</td><td>Project work methodology</td><td rowspan="2">Complexity of project (such as resources and technology required)</td><td rowspan="2">Sub-group</td></tr>
<tr><td>5</td><td>The type of construction work</td></tr>
<tr><td>6</td><td>Number of prospective bidders</td><td>Number of competitors with strong desire to win a project</td><td>Alternative expression</td></tr>
<tr><td>7</td><td>Seeking relationship with employers</td><td rowspan="2">Strategic value of project</td><td rowspan="2">Alternative expression</td></tr>
<tr><td>8</td><td>Future business from the same client</td></tr>
</table>

Item No.	Factors identified by respondents	Factors compiled from literature	Remark
9	Current number of projects at hand over 70% progress	Current work load	Alternative expression
10	Design type and its completeness	Clarity and completeness of tender documents (drawings, specifications, etc.)	Alternative expression
11	Expectation of ambiguous contract provision		
12	Financial status of the company	Availability of cash or overdraft facility to carry out project	Alternative expression
13	Abundance of construction projects to bid	Amount of possible upcoming profitable projects out for tender in the remaining fiscal year	Alternative expression
14	Likelihood of winning future tender		
15	Number of planed projects to be floated for bid by the client		

4.2.3 Discussion on Factor Analysis Results

Based on the results of the analysis, a discussion regarding the top ten ranking factors affecting bid markup estimation are made in this section. Along with the discussion, a comparative analysis of the current study with other studies is also presented.

1) Complexity of Project (such as resources and technology required)

Among the 21 factors surveyed, 'Complexity of project (such as resources and technology required),' with RII of 95.45%, is perceived to be the most significant factor affecting bid markup size decision.

As pointed out by Flanagan and Norman (1982a) cited in Ye et al. (2014) the bid decision is in part determined by construction managerial complexity. The larger the project size, the higher the construction managerial complexity. This is probably the reason why contractors usually determine a marginal scale in line with project sizes (Fayek (1998) cited in Ye, Shen, Xia and Li (2014)). A project that has a high degree of technological complexity would be riskier (Chua & Li (2000) cited in Ling and Liu (2005)). Therefore, contractors want to be compensated through higher markup when there is a high degree of project complexity and vice versa.

2) Number of competitors with strong desire for project

'The number of competitors with strong desire to win a project,' is the 2nd ranked influencing factor on the bid markup size decision with RII value of 88.18%.

The number of competitors with a strong desire to win a project, is an important consideration in markup size decision. By knowing the number of competitors, contractors could surmise how competitive their bids would be and can provide contractors with a level of confidence about how much they can markup their bid and still have a good chance of winning the bid. A strong desire for the project by competitors would imply that they will reduce their bid markup size as much as possible in order to win the project.

3) Project location (region)

'Project location (region),' is among the strong influencing factors on the bid markup decision ranking 3rd with RII value of 87.27%.

The effect of this factor on bid markup size may vary from company to company based on its preference on project location (region) to carry out projects. The remoteness of the project site should also be analyzed prior to the decision for bid markup size.

4) Immediate need for work

'Immediate need for work,' also ranked 3rd in the analysis of the factors affecting bid markup size with RII value of 87.27%.

When the need for work is high, contractors would price a lower mark up so as to be more competitive (Hegazy & Moselhi (1995) cited in Ling and Liu (2005)). When contractors' workload is high (i.e. capital resources are nearly stretched to the maximum), they are likely to increase the bid markup (Smith & Bohn (1999) cited in Ling and Liu

(2005)). Thus, contractors should decide whether their company has an immediate need for new work or not before deciding their bid markup size to be applied to projects.

5) Security need of project location

The study identifies 'security need of project location,' as the 5th important factor with RII value of 85.45%.

There may be project sites which are risky in terms of security need for any contractor. In this case, all bidders tend to increase their bid markup size. But some project sites may be more risky in terms of security need for some contractors. And in this case, only those bidders will use a higher bid markup size. Thus, this factor also has a variable effect on bid markup size similar to 'project location'.

6) Previous experience of the company on similar projects

'Previous experience of the company on similar projects,' is the 6th highest-ranking factor having RII value of 83.64%.

According to Abdulaziz (2004) contractors who are specialized in certain types of projects possess the experience required to effectively and efficiently identify the following key projects' parameters: (1) most suitable working method and site logistics; (2) reasonable durations of activities, and hence, overall contract duration; (3) uncertainties, difficulties, and risks that may be encountered along the course of construction; (4) required quality level of technical staff and labor force; (6) approximate, yet reasonably accurate, unit rate cost and high level of certainty in cost estimates. Thus, acquiring experience on similar projects can help contractors in deciding a reasonable & competitive bid markup size during bidding for a new project.

7) Strategic value of the project

Based on the results of the analysis, 'strategic value of project,' ranked 7th with RII value of 82.73%.

There are some projects that contractors may assume as very useful for their company in a long term basis. For these types of projects, they may cut their bid markup size in order to win the bid and execute the project. This is due to a desire to establish a long term relationship with the client and ensuring that they are able to secure further work from such clients in a market dominated by competitive bidding. According Dulami and Shan (2002) having a good relationship with clients, would help contractors to generate future contracts crucial to their long term business operations.

8) Previous experience of competitors on similar projects

Another key factor affecting bid markup size, 'previous experience of competitors on similar projects,' also ranks 7th with RII value of 82.73%.

This attribute describes the competitiveness of potential competitors. According to a model by Porter (1980) cited in Ye et al. (2014) model, the competition for a construction work contract encompasses the existing competition among established firms and the potential competition imposed by new entrants. Potential competitors are more able to dominate the trend of project competition (Ye et al., (2008) cited in Ye et al. (2014)). A high level of profitability pulls potential entrants to pack into the project competition, giving rise to fiercer business competition and lower tender prices as a result (Park and Chapin (1992) cited in Ye et al. (2014)). Therefore, to achieve a competitive bid, contractors need to have adequate knowledge on the profile of potential competitors when competing for new construction project bids.

9) Accuracy of the direct cost estimation

The 9th most important factor influencing bid markup decision is 'accuracy of the direct cost estimation,' with RII value of 80.91%.

If the estimation of the direct cost is not reliable, the managerial team of the company may price a higher bid markup to cover for errors or omissions in the estimating. Thus, contractors should give greater emphasis for accurate estimation of direct cost to enhance their winning probability of bids.

10) Expected size of contract

"Expected size of contract," ranks 10th in the importance of bid markup size decision with RII value of 79.09%.

According to Abdulaziz (2004) the influence of the expected size of contract can be associated with two-sided implications. Although large projects are coupled with long durations and can provide organizational sustainability due to the positive cash flow contribution over their development course, the scale effort, especially in "horizontal" projects (i.e., large numbers of relatively small units that are spread over large plot areas), may have a negative bearing on bidding behavior. Dulami and Shan (2002) also stated increased value in a project would contribute positively to the annual business volume (will be useful for the upcoming years bid competition) i.e. to attain the minimum technical qualification criteria of the annual turnover, sustain overheads and give them the potential to earn a better profit.

Thus, contractors can decide their bid markup size by considering the two-sided implications. If they prefer to have organization sustainability and increase their annual business volume they may use lower size of bid markup for projects with the higher size of the contract value and vice versa.

4.2.4 Comparative Analysis of the Current Study with Previous Related Studies

This section presents a comparative analysis based on the results of the current study and other related studies done by various researchers. Table 4.4, compares the ranking of bid markup factors of the current study versus their respective ranking in previous related studies bid markup factors.

Table 4.4: Comparative analysis of the current study with other previous related studies

Markup factors	Factor's rank in the current study	Related studies			
		Researcher (s)	Study population	Number of identified factors	Factor's rank
Complexity of project (such as resources and technology required)	1	Dulami and Shan (2002)	Large size contractors in Singapore	40	1
		Tonnesen (2014)	Contractors working in University of Colorado at boulder campus	19	8
		Mohamed et al. (2017)	Construction companies in Egypt	32	19
Number of competitors with strong desire to win a project	2	Badu and Amoah (2004)	Large building contractors in Ghana	36	D3
		Dulaimi and Shan (2002)	Large size contractors in Singapore	40	7
		Tonnesen (2014)	Contractors working in University of Colorado at boulder campus	19	15
		Mohamed et al. (2017)	Construction companies in Egypt	32	16
		Nourah (2013)	Contractors in Saudi Arabia	60	36

Project location (region)	3	Tonnesen (2014)	Contractors working in University of Colorado at boulder campus	19	9
		Mohamed et al. (2017)	Construction companies in Egypt	32	11
		Badu and Amoah (2004)	Large building contractors in Ghana	36	21
		Nourah (2013)	Contractors in Saudi Arabia	60	31
		Dulaimi (2002)	Large size contractors in Singapore	40	37
Immediate need for work	3	Badu and Amoah (2004)	Large building contractors in Ghana	36	5
		Tonnesen (2014)	Contractors working in University of Colorado at boulder campus	19	5
		Mohamed et al. (2017)	Construction companies in Egypt	32	11
		Dulaimi (2002)	Large size contractors in Singapore	40	15
		Nourah (2013)	Contractors in Saudi Arabia	60	24
Security need of project location	5	Mohamed et al. (2017)	Construction companies in Egypt	32	6
		Dulaimi and Shan (2002)	Large size contractors in Singapore	40	9
		Nourah (2013)	Contractors in Saudi Arabia	60	44
Previous experience of the company on similar projects	6	Mohamed et al. (2017)	Construction companies in Egypt	32	3
		Badu and Amoah (2004)	Large building contractors in Ghana	36	11
		Tonnesen (2014)	Contractors working in University of Colorado at boulder campus	19	11
		Dulaimi and Shan (2002)	Large size contractors in Singapore	40	16
		Nourah (2013)	Contractors in Saudi Arabia	60	44
Strategic value of project	7	Tonnesen (2014)	Contractors working in University of Colorado at boulder campus	19	6
		Badu and Amoah (2004)	Large building contractors in Ghana	36	19
		Mohamed et al. (2017)	Construction companies in Egypt	32	21
		Nourah (2013)	Contractors in Saudi Arabia	60	22
		Dulaimi and Shan (2002)	Large size contractors in Singapore	40	23

Previous experience of competitors on similar projects	7	Dulaimi and Shan (2002)	Large size contractors in Singapore	40	3
		Nourah (2013)	Contractors in Saudi Arabia	60	32
Accuracy of the direct cost estimation	9	Nourah (2013)	Contractors in Saudi Arabia	60	7
		Dulaimi and Shan (2002)	Large size contractors in Singapore	40	13
		Badu and Amoah (2004)	Large building contractors in Ghana	36	14
		Mohamed et al. (2017)	Construction companies in Egypt	32	15
Expected size of contract	10	Nourah (2013)	Contractors in Saudi Arabia	60	1
		Dulaimi and Shan (2002)	Large size contractors in Singapore	40	5
		Badu and Amoah (2004)	Large building contractors in Ghana	36	6
		Mohamed et al. (2017)	Construction companies in Egypt	32	8
		Tonnesen (2014)	Contractors working in University of Colorado at boulder campus	19	14

The following points can be noted from the above table:

- **Complexity of project (such as resources and technology required)** – The significance of this factor has also been pinpointed by previous studies by Dulaimi and Shan (2002) and Tonnesen (2014). But contractors in Egypt, a study by Mohamed et al. (2017), give less attention to this factor when deciding bid markup.
- **Number of competitors with strong desire for project** – Even though large-size contractors in Singapore, a study by Dulaimi and Shan (2002) consider this factor as high influential factor, contractors in Saudi Arabia, a study by Nourah (Nourah, 2013) consider it as less influential in deciding bid markup size.
- **Project location (region)** – Except for the study by Tonnesen (2014) and Mohamed et al. (2017), most previous studies consider this factor as a less influential factor when deciding bid markup size.
- **Immediate need for work, previous experience of the company on similar projects and previous experience of competitors on similar projects** – Most of the previous studies consider these among the influential factors in deciding bid markup size. But Saudi Arabia contractors, a study by Nourah (2013) consider these factors as less influential.
- **Security need of project location** – Research conducted by Mohamed et al. (2017) and Dulaimi and Shan (2002) confirmed this factor is among the top ten influential factors of bid markup. On the contrary, a study result by Nourah (2013) show this factor is not an influential factor for bid markup.
- **Strategic value of project** – Only a study by Tonnesen (2014) consider this factor as an influential factor. This can be justified by the fact that the data for this study is collected from those contractors who are executing projects in a specific site. And most of the contractors may reduce their bid markup size seeking a relationship with the client to get future projects.
- **Accuracy of the direct cost estimation** – Previous studies consider this factor among the influential factors in deciding bid markup.
- **Expected size of the contract** – Contractors in Saudi Arabia, a study by Nourah (2013), identified this factor as the most prominent factor affecting bid markup size. A study by Dulaimi and Shan (2002), Badu and Amoah (2004) and Mohamed et al. (2017) also consider it among the top ten influential factors.

From the above noted points it can be said that, the influential factors which are considered in deciding bid markup size may vary from one country to another country, the type of project under bid and the size of the contractors.

4.3 DEVELOPMENT OF BID MARKUP ESTIMATION MODEL

4.3.1 Introduction

Developing a model that can support local contractors' decision making for estimating a bid markup size is the main objective of this research. In pursuance of this objective, two models are developed using multiple linear regression (MLR) and artificial neural network (ANN). The subsequent sections will present how these models are developed.

In order to develop a bid markup estimation model, it is essential to have real-life road projects bid data from contractors. However, it is difficult to obtain this kind of data from contractors due to the fact that, estimation of bid markup is done in a confidential manner and contractors are not willing to directly share their historical bid data. So, it is necessary to use other techniques in order to gather historical bid data required for the model development.

The selected technique was to prepare various hypothetical bid scenarios based upon the compiled bid markup factors from works of literatures and request respondents to provide an estimated percentage of bid markup for each scenario. The hypothetical project bidding scenarios are assumed to be a real-life road project bids.

The following steps are carried out to develop the hypothetical project bidding scenarios.

- ❖ **Step-1:** An ordinal measurement scale for each of the identified bid markup factors was defined.
- ❖ **Step-2:** By assuming each hypothetical project bidding scenario as a variable and each factor as an independent case, a random numbers ranging from 1 to 3 were generated using 'SPSS 24' for each scenario. In this manner, 90 hypothetical project bid scenarios were developed. Out of these projects, 5 projects were retained for cross-validation of the model.
- ❖ **Step-3:** Based on theoretical point of view, some of the randomly generated values for the following factors were edited manually:

- ‘Type of project delivery system’ - since the questionnaire is prepared for bidders who are participating to win projects the measurement scale called “own force” cannot be labeled as an option. So, this scale was replaced by the other delivery methods “DBB” and “DB” randomly.
- Since the value of ‘current workload’ dictates the value of ‘immediate need for work’ conditional relationship was given as follows:
    - If ‘current workload’ has a value of ‘High (3)’, then ‘immediate need for work’ should only have a value of either ‘Medium (2)’ or ‘Low (1)’.
    - If ‘current workload’ has a value of ‘Medium (2)’, then ‘immediate need for work’ should only have a value of either ‘Medium (2)’ or ‘Low (1)’.
    - If ‘current workload’ has a value of ‘Low (1)’, then ‘immediate need for work’ should only have a value of ‘High (3)’.
- Since the value of ‘immediate need for work’ dictates the value of ‘current required amount for head office overhead cost relative to the planned amount’ conditional relationship was given as follows:
    - If ‘immediate need for work’ has a value of ‘High (3)’, then ‘current required amount for head office overhead cost relative to the planned amount’ should only have a value of either ‘High (3)’ or ‘Medium (2)’.
    - If ‘immediate need for work’ has a value of ‘Medium (2)’, then ‘current required amount for head office overhead cost relative to the planned amount’ should only have a value of either ‘Medium (2)’ or ‘Low (1)’.
    - If ‘immediate need for work’ has a value of ‘Low (1)’, then ‘current required amount for head office overhead cost relative to the planned amount’ should only have a value of ‘Low (1)’.

- **Step-4:** Using SPSS, the correlation among each of the 90 hypothetical bid scenarios was analyzed. Since it is required to identify the strength of the relationship among each of project scenario, Pearson correlation coefficients was calculated.
- **Step-5:** The Pearson correlation coefficient values which were greater than positive 0.5 were identified by examining their correlation matrix. This is due to the fact that Pearson correlation coefficient values greater than positive 0.5 indicates a strong positive relationship between variables.
- **Step-6:** For those identified pairs of scenarios in the previous step, a comparison was done for each of pair by counting the number of differences. Here, it is obtained that the minimum number of differences counted for each pair of scenarios is 7 out of 21

cases. This implies that, each of the developed hypothetical project bid scenarios had at least 33.33% difference when compared to any other scenario.

Table 4.5 shows, the ordinal measurement scale of each factor along with their randomly assigned frequency of occurrence in the eighty-five hypothetical bid scenarios. The frequency of measuring scales assigned for each factor are obtained by manually counting the number of appearance of the scales in the eighty-five hypothetical bid scenarios.

Table 4.5: Ordinal measurement scale for bid markup factors

Item No.	Factors	Measurement		Frequency of the scales in hypothetical bid scenarios	
		Scale	Label	Number	Percent
1	Strategic value of project	Low	1	31	36.47 %
		Medium	2	28	32.94 %
		High	3	26	30.59 %
2	Complexity of project (such as resources and technology required)	Low	1	33	38.82 %
		Medium	2	23	27.06 %
		High	3	29	34.12 %
3	Clarity and completeness of tender documents (drawings, specifications, etc.)	Low	1	35	41.18 %
		Medium	2	28	32.94 %
		High	3	22	25.88 %
4	Right of way status	Unresolved	1	31	36.47 %
		Partially resolved	2	24	28.24 %
		Resolved	3	30	35.29 %
5	Expected size of contract	< 500 million birr	1	30	35.29 %
		From 500 million to 1 billion birr	2	27	31.76 %
		> 1 billion birr	3	28	32.94 %
6	Duration of the project	< 2 years	1	30	35.29 %
		From 2 to 3 years	2	22	25.88 %
		> 3 years	3	33	38.82 %

Item No.	Factors	Measurement		Frequency of the scale in hypothetical bid scenarios	
		Scale	Label	Number	Percent
7	Security need of project location	Low	1	33	38.82 %
		Medium	2	26	30.59 %
		High	3	26	30.59 %
8	Project location (region)	North	1	30	35.29 %
		East	2	32	37.65 %
		West and South	3	23	27.06 %
9	Pavement type	Gravel	1	33	38.82 %
		Double bitumen surface treatment (DBST)	2	25	29.41 %
		Asphalt concrete (AC)	3	27	31.76 %
10	Type of project delivery system	Design Bid Build (DBB)	1	39	45.88 %
		Design Build (DB)	2	46	54.12 %
		Own Force (OF)	3	-	-
11	Current work load	Low	1	30	35.29 %
		Medium	2	28	32.94 %
		High	3	27	31.76 %
12	Immediate need for work	Low	1	29	34.12 %
		Medium	2	26	30.59 %
		High	3	30	35.29 %
13	Accuracy of the direct cost estimation	Low	1	36	42.35 %
		Medium	2	21	24.71 %
		High	3	28	32.94 %
14	Previous experience of the company on similar projects	Poor	1	30	35.29 %
		Good	2	22	25.88 %
		Very good	3	33	38.82 %

Item No.	Factors	Measurement		Frequency of the scale in hypothetical bid scenarios	
		Scale	Label	Number	Percent
15	Availability of cash or overdraft facility to carry out project	Scarce	1	30	35.29 %
		Medium	2	27	31.76 %
		High	3	28	32.94 %
16	Availability of credit facility from suppliers	Low	1	21	24.71 %
		Medium	2	31	36.47 %
		High	3	33	38.82 %
17	Current required amount for head office overhead cost relative to the planned amount	Low	1	39	45.88 %
		Medium	2	29	34.12 %
		High	3	17	20.00 %
18	Number of competitors with strong desire for project	Low	1	33	38.82 %
		Medium	2	25	29.41 %
		High	3	27	31.76 %
19	Previous experience of competitors on similar projects	Poor	1	35	41.18 %
		Good	2	24	28.24 %
		Very good	3	26	30.59 %
20	Current state of the overall economy of the country	Bad	1	28	32.94 %
		Medium	2	29	34.12 %
		Good	3	28	32.94 %
21	Amount of possible upcoming profitable projects out for tender in the remaining fiscal year	Scarce	1	34	40.00 %
		Medium	2	28	32.94 %
		Abundant	3	23	27.06 %

Based on the responses of the questionnaire survey, graphical representations illustrating the frequency distribution of bid markup scores are shown in Figure 4.2 and 4.3.

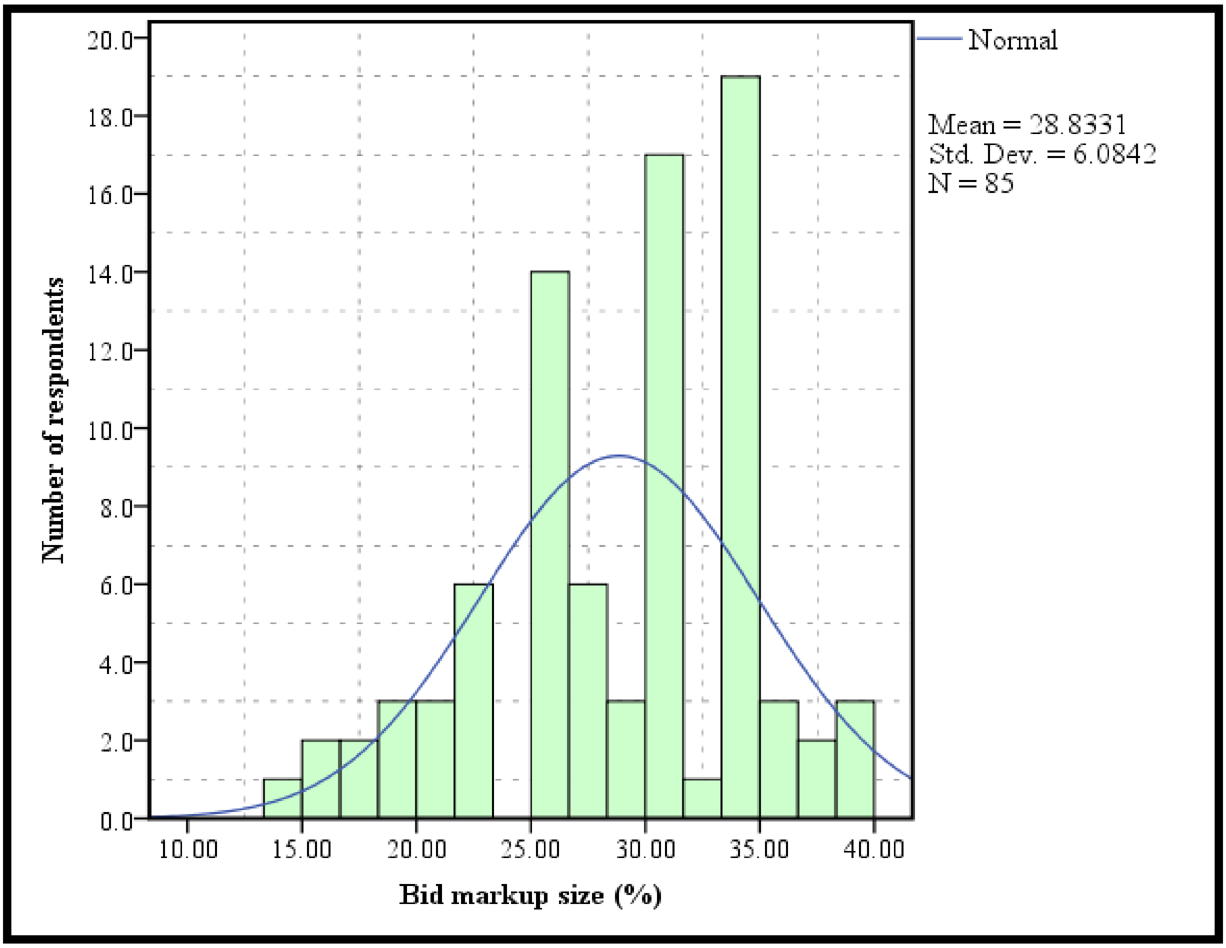

Figure 4.2: Histogram of bid markup size for the hypothetical project bids

The histogram shown in Figure 4.2, illustrates the distribution of the bid markup scores along with their corresponding number of respondents. The following points can be noted from the histogram:

- The histogram is negatively skewed (skewed left) as most of the bid markup scores provided are between 25 and 40%.
- The bid markup scores follow a roughly normal distribution as nearly half of the scores occur in the center.
- The mean score for the bid markup is 28.83% and with a standard deviation of 6.08.

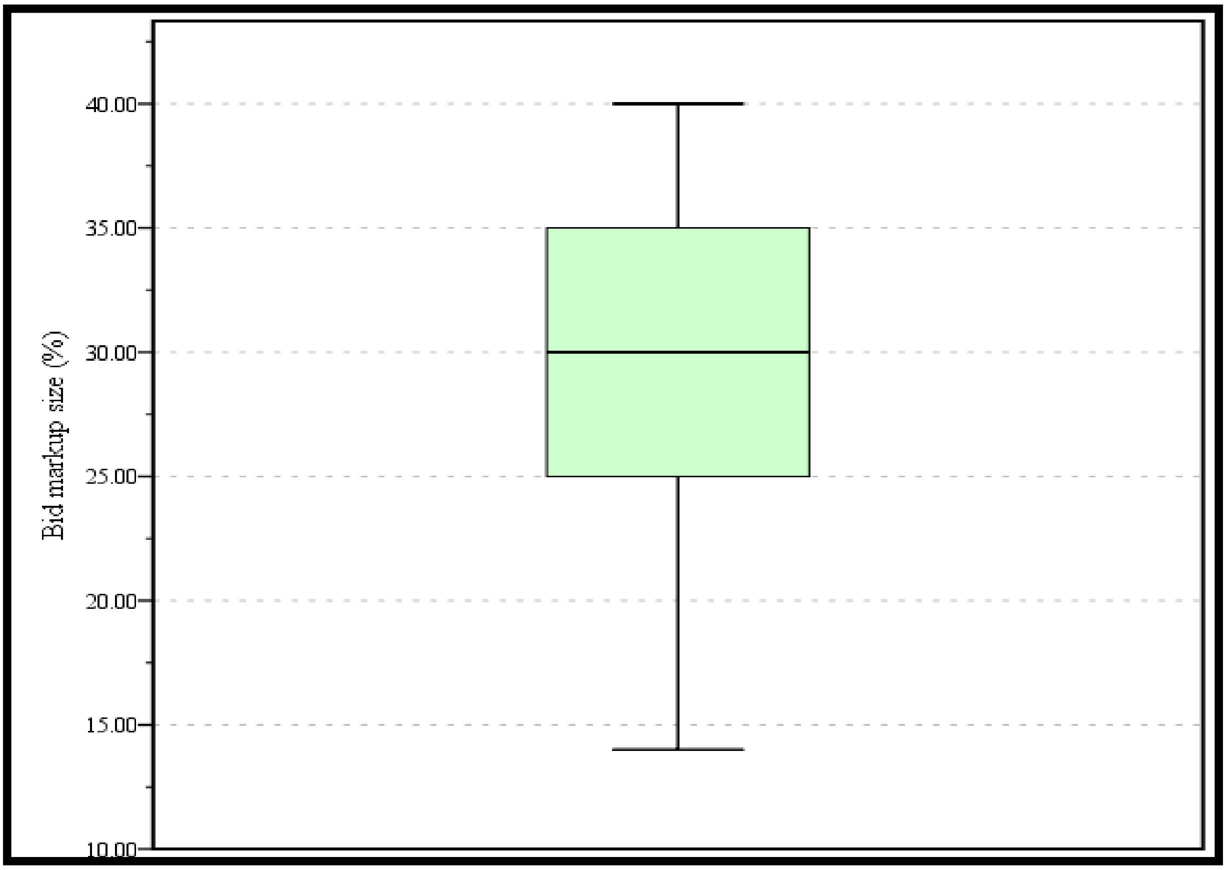

Figure 4.3: Box plot of bid markup size for the hypothetical project bids

The box plot in Figure 4.3, also shows the distribution of bid markup scores. Here, each distribution of scores is represented by a box and protruding lines (called 'whiskers'). The length of the box is the bid markup score interquartile range and contains 50 percent of the scores. This 50% of scores fall between 25^{th} and 75^{th} percentile marks. The 25^{th} percentile is at the bottom (lower quartile) and the 75^{th} percentile is at the top of the box (upper quartile). The line across the inside of the box represents the median value. The length of the whiskers shows the top or bottom 25% of the scores. The whiskers protruding from both ends of the box show the highest and lowest values which are not outliers. According to (Pallant, 2005), outliers are values that are substantially lower or higher than the other values in the data set and they can have a dramatic effect on the correlation coefficient. Scores that are outliers in the distribution are more than 1.5 box-lengths from the 25^{th} or 75^{th} percentile, and they are displayed by a circle; those that are more than 4 box-lengths (extreme outliers) away are shown by an asterisk (Alistair, Howard, & Stephen, 2002). Based on the above figure, the data set has no scores which are considered to be an outlier.

From the above box plot the following points can be noted:

- The length of the bottom whisker is longer than the upper one. This suggests that the bid markup scores are negatively skewed.
- The median score is in the middle of the box with a value of 30% which is near to the mean score (28.83%) as shown in the above histogram.
- The lowest and highest bid markup scores provided are 14% and 40%.

4.3.2 Development of Bid Markup Estimation Model Using Multiple Linear Regression

4.3.2.1 Introduction

Regression analyses are a set of statistical techniques that allow one to assess the relationship between one dependent variable (DV) and several independent variables (IDVs). The goal of regression is to arrive at the set of B values, called regression coefficients, for the IDVs that bring the DV values predicted from the equation as close as possible to the DV values obtained by measurement (Tabachnick & Fidell, 2013).

According to Keller (2012) cited in Gregory (2016) the application of multiple regression to a data set involves a general two-step process. Initially, it is important to determine how well the model fits the data. If the model fit is questionable or of low quality, another model needs to be employed to better fit the data. After a quality fit is achieved, the coefficients of regression can be examined and applied to predict the values of the dependent variable.

The general form of the multiple regression equation is provided below (Gregory P., 2016):

$$Y = b_0 + b_1X_1 + b_2X_2 + b_kX_k \qquad \textbf{Equation 4.1}$$

Where Y is the dependent variable; b_o is the regression constant; b is the regression coefficient for the independent variables; X is the independent or predictor variables and k is the quantity of independent variables.

For the current study, the MLR bid markup estimation model has previously identified twenty-one markup factors as an input and one output i.e., bid markup size. Hence, the inputs & output of the model will be considered as independent variable and dependent variable respectively. The magnitude of the 21 factors (MF_i) is used to model the function of the bid markup size (BM). The following equation can be used to express the relationship between BM and MF_i for each markup factors:

$$BM = f(MF_1, MF_2, MF_3, \ldots, MF_{21}) \quad \textbf{Equation 4.2}$$

Where BM represent the bid markup as a percentage of the total project value other than markup, and MF_i represent the magnitude of each identified bid markup size factors. The magnitude of each factor is obtained from their previously defined ordinal measurement scale.

4.3.2.2 Examining the correlation between the dependent variable and independent variables

A correlation is a statistical device that measures the nature and strength of a supposed linear association between two variables. The direction is indicated by the sign of the correlation coefficient whereas the strength of the linear relationship is determined by the distance of the correlation coefficient (r) from zero (Alistair, Howard, & Stephen, 2002). The correlation coefficient provides an indication of the linear relationship between variables. Pearson product-moment coefficient is designed for interval level (continuous) variables. It can also be used for one continuous variable and another dichotomous variable (Pallant, 2005).

For this study, the Pearson product-moment correlation was conducted to examine the nature and strength of the relationship between each IDV and DV using SPSS 24. Here, the null hypothesis is stated as 'there is no linear relationship between each IDVs and DV (correlation coefficient is zero)'. Table 4.6, presents the result of the correlation matrix between each IDV and DV.

Table 4.6: Pearson product-momentum correlational matrix between IDVs and DV

Item No.	Bid markup factors (IDVs)	Bid markup size (DV) (N=85)	
		Pearson correlation coefficient	Significance (2-tailed)
1	Previous experience of the company on similar projects	-0.493**	0.000
2	Previous experience of competitors on similar projects	-0.407**	0.000
3	Complexity of project (such as resources and technology required)	0.373**	0.000
4	Expected size of contract	-0.298**	0.006
5	Current work load	0.279**	0.010
6	Immediate need for work	-0.248*	0.022
7	Availability of credit facility from suppliers	-0.234*	0.031
8	Strategic value of project	0.233*	0.032
9	Number of competitors with strong desire for project	-0.232*	0.033
10	Current required amount for head office overhead cost relative to the planned amount	-0.212	0.051
11	Duration of project	-0.180	0.100
12	Security need of project location	-0.132	0.227
13	Availability of cash or overdraft facility to carry out project	-0.101	0.357
14	Pavement type	-0.093	0.399
15	Type of project delivery system	0.070	0.523
16	Clarity and completeness of tender documents (drawings, specifications, etc.)	-0.0697	0.526
17	Current state of the overall economy of the country	-0.063	0.569
18	Right of way status	0.059	0.589
19	Accuracy of the direct cost estimation	-0.031	0.781
20	Amount of possible upcoming profitable projects out for tender in the remaining fiscal year	0.027	0.816
21	Project location (region)	0.005	0.966

* Correlation is significant at the 0.05 level (2-tailed)

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

Interpretation of output from the correlation

❖ **Determining the direction of the relationship**

According to Pallant (2005), Pearson correlation coefficient (r) can take on only values from –1 to +1. The sign out at the front indicates whether there is a positive correlation (as one variable increases, so too do the other) or a negative correlation (as one variable increases, the other decreases). A discussion dealing with the direction of relationship for those factors having a significant relationship with bid markup size is presented below.

The factor 'previous experience of the company on similar projects' has a negative correlation with bid markup size implying that; when a company faces a new road project bid which is similar to a project which it has executed in the past, it will tend to decrease the bid markup size. Executing a similar project in the past will allow a contractor to acquire historical data on the required resources, suitable working methods, probable risks that it will face, productivity of various crews, amount of net profit obtained, etc. and this in turn give a chance for the contractor to provide a reasonable amount of bid markup.

'Previous experience of competitors on similar projects' has a negative correlation with bid markup size implying that; when a competitor of a company has got the experience in executing a similar project to the new project under bid, they will have the advantage which is mentioned above. And knowing this will pressure a company to decrease its bid markup size as much as possible.

'Complexity of project (such as resources and technology required)' has a positive correlation with bid markup size implying that; when a project demands a higher construction managerial complexity, technology, and resources, contractors want to be compensated through higher bid markup and prevent any risks which may come along with a higher complexity of the project.

'Expected size of contract' has a negative correlation with bid markup size. As the total contract price of a project increase, there are advantages that a contractor may obtain such as organizational sustainability and higher annual turnover. In seeking for those advantages contractors may decrease their bid markup size.

'Current workload' has a positive correlation with bid markup size. When a contractor has a number of projects in which it is capable of handling based on its current available amount of resources such as cash, manpower and machineries; and face a new project to bid, it will tend to use a higher bid markup. This is due to the fact that the company will have an interest in employing new (additional) resources only if it get a higher amount of profit from the new project under bid.

'Immediate need for work' has a negative correlation with bid markup size. Sometimes a company may run out of projects and face the issue of maintaining its survival. In this case, the company will use a much lower bid markup hoping to win the bid.

'Availability of credit facility from suppliers' has a negative correlation with bid markup size. It is known that road projects require an enormous amount of resources such as materials and machinery. If a contractor has a number of suppliers who are willing to provide materials and rent machineries with credit, it can save additional expenses such as interest paid to lenders, prevent productivity loss due to lack of resources, maintain a positive cash flow, etc. and this, in turn, gives a chance to decrease bid markup size.

'Strategic value of project' has a positive correlation with bid markup size implying that; a contractor will use a high markup for a project with a high strategic value. But this has a contradiction with the theoretical context because when a contractor assumes that winning the current bid will have a positive effect in securing a new project in the future it will decide to use a lower bid markup size.

'Number of competitors with strong desire for project' has a negative correlation with bid markup size implying that; when a contractor realize that there are a number of competitors having a strong desire to win the project under bid, it will tend to decrease its markup considerably in order to be a competent bidder with a lower amount of bid price.

- **Determining the strength of the relationship**

According to (Pallant, 2005), the size of the r-value (ignoring the sign) provides an indication of the strength of the relationship. A perfect correlation of 1 or –1 indicates that the value of one variable can be determined exactly by knowing the value of the other variable. On the other hand, a correlation of 0 indicates no relationship between the two variables. Knowing the value on one of the variables provides no assistance in predicting the value of the second variable.

Different authors suggest different interpretations for defining the strength of relationship based on the value of 'r' between -1 and 1; Cohen (1988) cited in Pallant (2005) suggests the following guideline:

- If r=0.10 to 0.29 or r=-0.10 to -0.29 then there is small strength of relationship
- If r=0.30 to 0.49 or r=-0.30 to -0.49 then there is medium strength of relationship
- If r=0.50 to 1.00 or r=-0.50 to -1.00 then there is large strength of relationship

Accordingly, the following points can be noted from table 4.7:

The factor 'previous experience of the company on similar projects' has large strength of relationship with bid markup size with the Pearson correlation coefficient of 0.493. The factors 'previous experience of competitors on similar projects', 'complexity of project (such as resources and technology required), 'expected size of contract', 'current work load', 'immediate need for work', 'availability of credit facility from suppliers', 'strategic value of project' and 'number of competitors with strong desire to win a project' have a medium strength of relationship with bid markup size. 'Current required amount for head office overhead cost relative to the planned amount', 'duration of project', 'security need of project location' and 'availability of cash or overdraft facility to carry out project' are among the factors which have a smaller strength of relationship with bid markup size based on the results of the study.

- **Assessing the significance level**

The selected level of significance is 0.05 implying that having a 5% probability of incorrectly rejecting the null hypothesis is acceptable. The "sig." values are shown in the above table are the probabilities associated with each IDVs and DV that the null hypothesis is correct. According to Pallant (2005) a two-tail test of significance means that a prior prediction concerning the direction of the relationship between the variables (either positive or negative) has yet been made.

Based on the results shown in Table 4.7, five factors have a statistical significant relationship at 0.01 level (their 'sig' value is less than 0.01) and four factors have a statistical significant relationship at 0.05 level (their 'sig' value is less than 0.05) with bid markup size. The remaining factors are considered to have no statistically significant relationship with the bid markup size based on the selected level of significance. According to Pallant (2005) statistical significance is strongly influenced by the size of the sample. In a small sample (e.g. N=30), it can be obtained a moderate correlations that do not reach statistical significance at the traditional $p<0.05$ level. In large samples (N=100+), however, very small correlations may be statistically significant. Many authors in the area of statistics suggest that statistical significance should be reported but ignored (Pallant, 2005).

4.3.2.3 Conducting multiple linear regression analysis

A regression analysis was conducted using SPSS 24 in order to find an analytical form of the relation between the DV and IDVs by composing an equation with parameters (i.e. coefficients and constant) which can help to estimate predicted outcomes in the future analysis. The multiple regression equation was obtained based on the data obtained from the 85 hypothetical project bids. For this study, the significance level is specified as 0.05 (α=0.).

The following are the major steps followed to conduct the MLR analysis:

Step-1: Selecting the regression technique

Regression techniques consist of standard multiple regression, sequential (hierarchical) regression, and stepwise (statistical) regression. Differences between these techniques involve the way variables enter the equation: what happens to variance shared by variables and who determines the order in which variables enter the equation? (Tabachnick & Fidell, 2013).

For this study, a stepwise regression technique is selected because this method help to obtain the 'best' equation to predict the dependent variable when there are a large number of predictor variables by including/excluding predictor variables (Tranmer & Elliot). If the only aim of the researcher is to develop a prediction equation then this method is helpful (Tabachnick & Fidell, 2013). Stepwise-type algorithms are very useful in predictive modeling as long as the selection criteria rely on predictive power rather than explanatory power (Shmueli, 2010) .

The stepwise regression technique is a step-by-step iterative construction of a regression model that involves automatic selection of independent variables; it interactively explores which predictors seem to provide a good fit. It improves a model's prediction performance by reducing the variance caused by estimating unnecessary terms (Ahmed, 2015). The regression equation starts out empty and IDVs are added one at a time, but they may also be deleted at any step where they no longer contribute significantly to regression. The order of entry of predictor variables is based solely on statistical criteria. Decisions about which variables are included and which omitted from the equation are based solely on statistics computed from the particular sample drawn; minor differences in these statistics can have a profound effect on the apparent importance of an IDV. Stepwise regression is, therefore, a model building rather than a model testing procedure (Tabachnick & Fidell, 2013).

Step-2: Checking the assumptions of MLR

A. Normality, linearity and homoscedasticity

Most of the underlying assumptions of MLR can be assessed by examining the residuals, having fitted a model (Tranmer & Elliot). Residuals are leftovers. They are the segments of scores not accounted for by the MLR analysis. They are also called "errors" between predicted and obtained scores where the analysis provides the predicted scores. Assumptions of regression analysis are that the residuals are normally distributed about the predicted DV scores, that residuals have a horizontal line relationship with predicted DV scores, and that the variance of the residuals about predicted DV scores is the same for all predicted scores (Tabachnick & Fidell, 2013).

One of the ways that these assumptions can be checked is by inspecting the histogram of regression standardized residuals (the standardized difference between an actual score and that predicted score from the model), the normal probability plot of the regression standardized residuals and the scatter plot of the standardized residuals.

Below are the outputs of residual plots from the MLR analysis of this study:

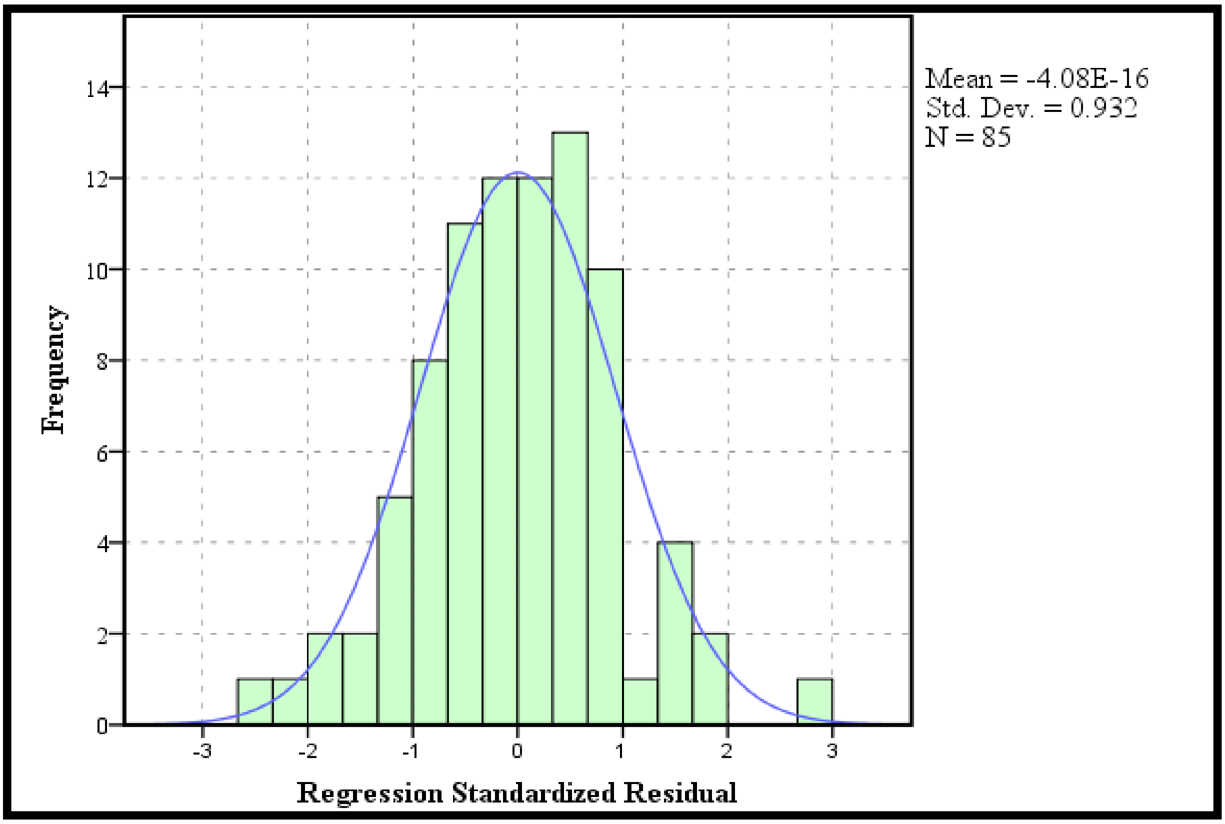

Figure 4.4: Histogram of regression standardized residuals

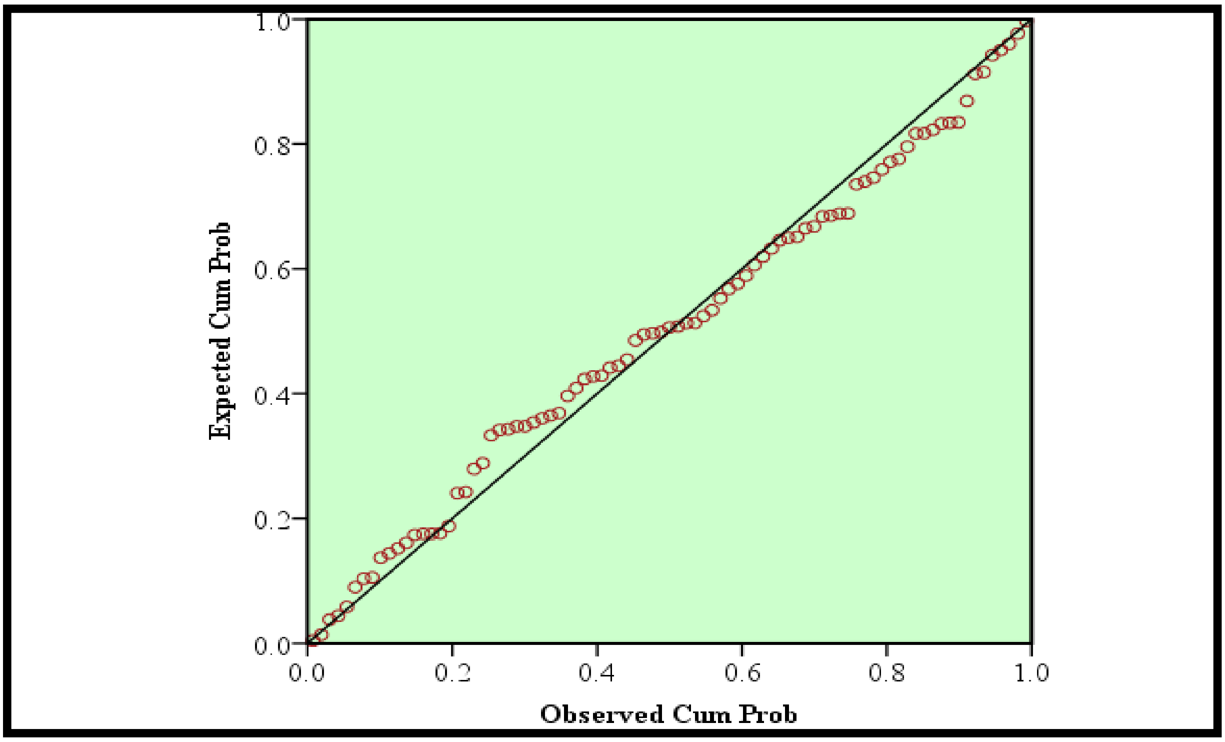

Figure 4.5: Normal P-P plot of regression standardized residuals

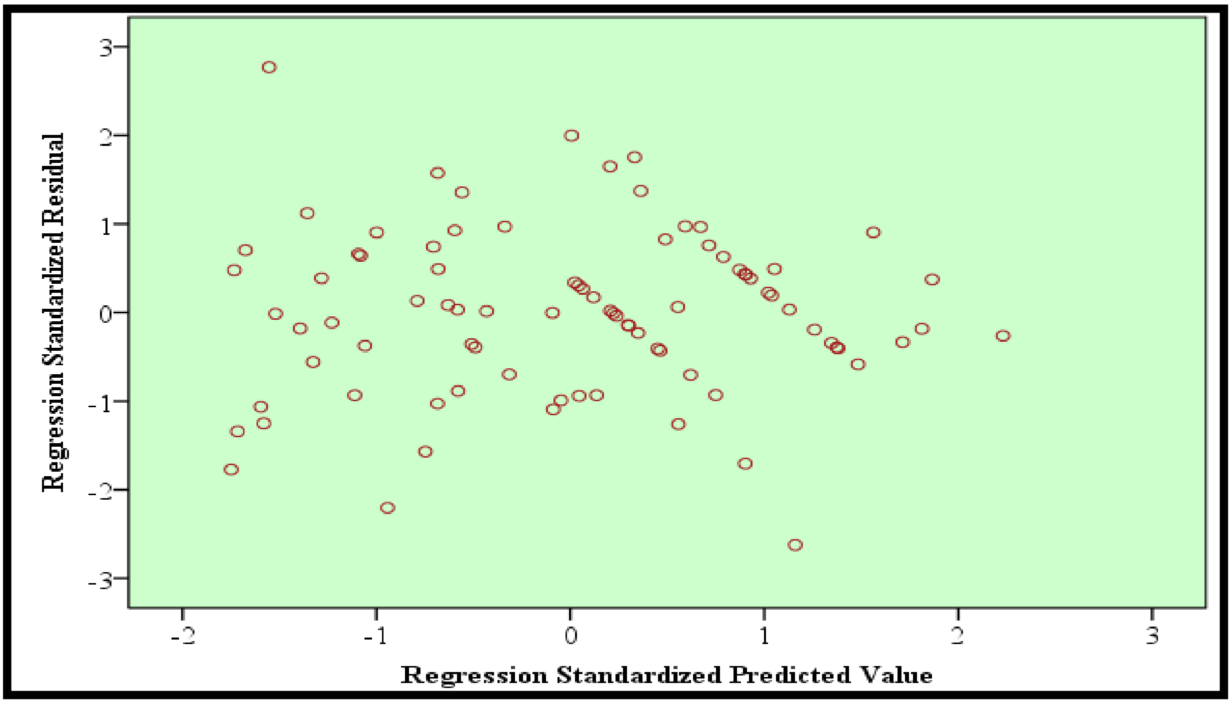

Figure 4.6: Scatter plot of regression standardized predicted values vs. residuals

Normality- The assumption of normality is that errors of prediction are normally distributed around each and every predicted DV score. The assumption that the residuals are normally distributed can be assessed by producing a normal probability plot. For this plot, the obtained values of the standardized residuals are plotted against the expected values from the standard normal distribution. If the residuals are normally distributed, they should lie, approximately, on the diagonal (Tranmer & Elliot). The residuals scatterplot should also reveal a pileup of residuals in the center of the plot at each value of predicted score and a normal distribution of residuals trailing off symmetrically from the center (Tabachnick & Fidell, 2013). The histogram shown in Figure 4.4 illustrates the marginal distribution of the residuals follows a normal distribution. And according to Figure 4.5 normal probability plot the points lie in an approximate diagonal line from bottom left to top right suggesting no major deviations from the assumption of normality.

Linearity- Linearity of the relationship between predicted DV scores and errors of prediction is also assumed. If nonlinearity is present, the overall shape of the scatterplot is curved instead of rectangular (Tabachnick & Fidell, 2013). In the scatter plot of the standardized residuals shown in Figure 4.6, the residuals are distributed in a rough rectangular shape with most of the scores concentrated in the center suggesting that there is a linear relationship between standardized predicted values and residuals.

Homoscedasticity- The assumption of homoscedasticity is the assumption that the standard deviations of errors of prediction are approximately equal for all predicted DV scores. Homoscedasticity means that the band enclosing the residuals is approximately equal in width at all values of the predicted DV. Homoscedasticity is related to the assumption of normality because when the assumption of normality is met, the relationships between variables are homoscedastic (Tabachnick & Fidell, 2013). According to the scatter plot shown in Figure 4.6, the data points are not placed closely in one specific place rather they are randomly distributed and also the assumption of normality is met with no major deviation it can be concluded that the assumption of homoscedasticity is met.

B. Multicollinearity and singularity

Multicollinearity and singularity are problems with a correlation matrix that occur when independent variables are too highly correlated. With multicollinearity, the variables are very highly correlated (say, 0.90 and above); with singularity, the variables are redundant; one of the variables is a combination of two or more of the other variables Multicollinear and singular variables are not needed because they inflate the size of error terms, they actually weaken an analysis (Tabachnick & Fidell, 2013). By carrying out a correlation analysis before we fit the regression equations, we can see which, if any, of the predictor variables are very highly correlated and avoid this problem (or at least this will indicate why estimates of regression coefficients may give values very different from those we might expect) (Tranmer & Elliot).

Recalling how the hypothetical bid projects are developed, there were a pair of IDVs in which their magnitude of measurement scale was decided based on their theoretical relationship. This includes 'current work load' and 'immediate need for work'; 'immediate need for work' and 'current required amount for head office overhead cost relative to the planned amount'. This has caused these pair of variables to have a high magnitude of Pearson correlation coefficient where 'current work load' and 'immediate need for work' has -0.759 and 'immediate need for work' and 'current required amount for head office overhead cost relative to the planned amount' has +0.849 correlation coefficient. Since this multicollinearity is caused by a theoretical relationship that exist between the variables, none of the variables are removed from the model. In addition, the main objective of this study is to develop a predictive model and according to a study by Makridakis et al. (1998) cited in Shmueli (2010) multicollinearity will not affect the ability of the model to predict.

Since none of the cases for a particular IDV are developed by combining other IDVs there is no problem of singularity.

Step-3: Presenting & interpreting the outputs of MLR analysis

In this step, the model outputs from the MLR analysis are presented and a discussion is made by interpreting the results of the model.

A. **IDVs entered/removed in the regression equation**

Table 4.7: IDVs entered/removed in the regression equation

Model number	Variables entered	Variables removed	Method
1	Previous experience of the company on similar projects	-	Stepwise (Criteria: Probability-of-F-to-enter <= 0.050, Probability-of-F-to-remove >= 0.100)
2	Complexity of project (such as resources and technology required)	-	
3	Previous experience of competitors on similar projects	-	
4	Availability of credit facility from suppliers	-	
5	Number of competitors with strong desire for project	-	
6	Expected size of contract	-	
7	Strategic value of project	-	
8	Current work load	-	
9	Project location (region)	-	
10	Clarity and completeness of tender documents (drawings, specifications, etc.)	-	
11	Current required amount for head office overhead cost relative to the planned amount	-	

It has taken eleven steps to iteratively construct the best regression model using the stepwise regression technique. As it can be seen from Table 4.7, eleven variables out of the total twenty one are entered to the model by attaining the statistical criteria (probability-of-F-to-enter <=0.05) required by stepwise regression technique. In the process of the analysis, no variable is removed once it has entered to the regression. Eight out of the eleven variables which enter to the model are those variables which have a significant correlation with the DV. Even though factors like 'clarity and completeness of tender documents (drawings, specifications, etc.)' and 'project location (region)' have a very low correlation with the DV they have met the statistical criteria and enter to the model. The reason for this case is given in the study by Wu, Haris and McAuley (2007) cited in Shmueli (2010) saying that- in contrast to explanatory power, statistical significance plays a minor role in assessing predictive performance. Tabachnick and Fidell (2013) also points that an IDV can have a high regression coefficient even though it has a low correlation with the DV because that particular IDV predicts the DV well only after another IDV suppresses irrelevant variance. Thompson (2006) cited in Stellefson et al. (2008) also gave an explanation on how to interpret the worth of an IDV by examining the regression coefficient and collinearity coefficient as follow: if collinearity coefficient is near to zero and if regression coefficient is greater than zero then the predictor variable does not directly explain any of the variation in the dependent variable, but its presence does increase the explanatory credit assigned to other predictor variables.

B. Model summary table

Table 4.8: Model summary table

Model number	R	R square (R^2)	Adjusted R square (Adj. R^2)	Standard Error of the estimate
1	0.493	0.243	0.234	5.324
2	0.619	0.383	0.368	4.837
3	0.692	0.479	0.459	4.474
4	0.752	0.566	0.544	4.108
5	0.780	0.609	0.584	3.925
6	0.802	0.644	0.616	3.769
7	0.826	0.682	0.653	3.583
8	0.853	0.728	0.700	3.334
9	0.865	0.748	0.718	3.234
10	0.873	0.763	0.731	3.157
11	0.882	0.778	0.745	3.073

The Model Summary table includes R, R^2, adjusted R^2 and Standard error of the estimate.

R- This is also called coefficient of correlation. It reflects the strength of the relationship between the DV and the combination of IDVs which have been weighted according to the regression equation. R-values have a potential range of zero to one. An R-value of 0 indicates no linear relationship between the set of predictors and the DV. The higher the R-value, the stronger the linear relationship between the set of predictors and the DV (Alistair, Howard, & Stephen, 2002).

Based on the result shown in Table 4.8, coefficient of correlation (R) was obtained as 0.882, which means that there is a strong linear relationship between the bid markup and the IDVs considering their combined effect.

R square- One way of rendering a correlation coefficient (R) more meaningful is to compute the coefficient of determination (R^2). This coefficient expresses the amount of the variance in the DV that is shared by the combination of the weighted IDVs. As with R, R^2 will have a value that falls between 0 and 1. Multiplying R^2 by 100 allows the amount of variance to be stated as a percentage. To obtain the proportion of the variance that is not shared, and hence not predicted by the IDVs, simply take the value of R^2 away from 1. Thus, R^2 can be considered a measure of the goodness of fit of the model produced by the regression equation (Alistair, Howard, & Stephen, 2002).

Table 4.8 shows that, R^2 was 0.243 when only one predictor was included in the first model. On the second step, another predictor is added to the model and the value of R^2 has increased to 0.383. By introducing other predictor variables, which met the statistical criteria, in the model in stepwise manner, the value of R^2 has reached a value of 0.778 in the eleventh step. A value of 0.778 means that 77.80 % of the variance in the bid markup size can be explained by the changes in IDVs value. The remaining 22.20% of the variation in the bid markup is presumed to be due to random variability.

Adjusted R square- When a small sample is involved, the R square value in the sample tends to be a rather optimistic overestimation of the true value in the population. The Adjusted R square statistic 'corrects' this value to provide a better estimate of the true population value (Pallant, 2005). The adjusted R Square value is also adjusted for the number of variables included in the regression equation. It is used to estimate the expected shrinkage in R Square that would not generalize to the population because the solution is over-fitted to the data set by including too many independent variables. If the adjusted R Square value is much lower than the R Square value, it is an indication that the regression equation may be over-fitted to the sample, and of limited generalize ability (Ahmed, 2015).

The calculated value of the adjusted R^2 for the final model is 0.745 suggesting that it is not far away from the R^2 value. Thus, the regression equation is a good fit for the developed model.

Standard error of the estimate- The regression equation allows to compute predicted values for DV and then compare these with the actual score. Unless the model is perfect (i.e. R^2 has a value of 1), then there will be a difference between the predicted and observed scores. These differences reflect errors in the model and are known as error scores or residual scores. A description of the dispersion of error scores may be obtained by computing their standard deviation. This standard deviation of the error scores is known as the standard error and it provides a general indication of the average error in the prediction. Therefore, a model that has a high goodness of fit would produce a low standard error. There will be a relatively good match between the predicted and observed values of the DV (Alistair, Howard, & Stephen, 2002).

Based on the results shown in Table 4.8, the standard error of the final MLR model in predicting the bid markup size is found to be 3.073. Comparing this value to the range of the value of the bid markup size in the data set, it can be said that the MLR model is a good fit.

C. ANOVA table

Table 4.9: ANOVA table

Model		Sum of squares	Degree of freedom (df)	Mean square	F	Significance
11	Regression	2420.087	11	220.008	23.297	0.000
	Residual	689.385	73	9.444		
	Total	3109.472	84			

After developing a model, its quality and representativeness in describing the dependence between the considered phenomena must be assessed. In order to justify the use of the regression equation for prediction, it should be determined whether the predictor variables are important for the behavior of the dependent variable. The Analysis of Variance (ANOVA) is used for this purpose (Matejevic & Zlatanovic, 2017). The ANOVA table reports a significant F statistic, indicating that using the model is better than guessing the mean (Ahmed, 2015). It tests the null hypothesis that there is no linear relationship between the predictors and the DV and all regression coefficients are zero. F is the ratio of the mean square for regression to the mean square for the residual (Alistair, Howard, & Stephen, 2002).

As shown in Table 4.9, there are 84 (number of cases - 1) total degrees of freedom (df), the df for the regression effect has 11 degrees of freedom and df for error variance (residual) is 73 (Number of cases - number of IDVs in the model). The table also shows the significance level associated with the observed value of F is 0.000. Since this sig. value is less than 0.05 we can reject the null hypothesis at 95% significance level and conclude that there is a significant linear relationship between the set of IDVs and the DV.

Thus, the result of the ANOVA table indicates that the model, as a whole, is a significant fit to the data indicating that prediction of the bid markup size is accomplished better using the model.

D. Coefficients table

Since the best model is required to form the regression equation, only the output of the 11th model is presented here.

Table 4.10: Coefficients table

Model		Unstandardized coefficients		Standardized coefficients	T	Significance	95.0 % confidence interval for B		Correlations			Collinearity statistics	
		B	Standard Error	Beta (β)			Lower bound	Upper bound	Zero-order	Partial	Part	Tolerance	VIF
11	(Constant)	37.542	3.256		11.530	0.000	31.052	44.031					
	Previous experience of the company on similar projects	-2.343	0.446	-0.333	-5.249	0.000	-3.233	-1.454	-0.493	-0.523	-0.289	0.753	1.328
	Complexity of project (such as resources and technology required)	2.317	0.413	0.327	5.610	0.000	1.494	3.140	0.373	0.549	0.309	0.896	1.116
	Previous experience of competitors on similar projects	-3.016	0.430	-0.419	-7.020	0.000	-3.873	-2.160	-0.407	-0.635	-0.387	0.852	1.174
	Availability of credit	-1.673	0.447	-0.217	-3.746	0.000	-2.563	-0.783	-0.234	-0.402	-0.206	0.905	1.105

	facility from suppliers											
	Number of competitors with strong desire to win a project	-1.803	0.414	-0.250	-4.352	0.000	-2.629	-0.978	-0.232	-0.454	-0.240	0.923	1.083
	Expected size of contract	-1.784	0.435	-0.244	-4.102	0.000	-2.651	-0.917	-0.298	-0.433	-0.226	0.861	1.161
	Strategic value of project	2.360	0.455	0.319	5.191	0.000	1.454	3.265	0.233	0.519	0.286	0.806	1.240
	Current work load	2.525	0.613	0.342	4.116	0.000	1.302	3.747	0.279	0.434	0.227	0.441	2.267
	Project location (region)	-1.155	0.479	-0.150	-2.413	0.018	-2.110	-0.201	0.005	-0.272	-0.133	0.786	1.273
	Clarity and completeness of tender documents (drawings, specifications, etc.)	-1.078	0.445	-0.143	-2.422	0.018	-1.964	-0.191	-0.070	-0.273	-0.134	0.868	1.153
	Current required amount for head office overhead cost relative to the planned amount	1.437	0.637	0.183	2.256	0.027	0.168	2.706	-0.212	0.255	0.124	0.463	2.161

The coefficient table shows the regression coefficients and their significance tests, including B weights, the standard error of B (Std. Error), b weights (Beta), constant, T-tests for the coefficients, and their significance levels (Sig.) for the test of the null hypothesis that the value of a coefficient is zero in the population (Tabachnick & Fidell, 2013).

Constant (y-intercept) - The constant value in the regression equation is the point where the regression line (i.e. line of best fit) crosses the y-axis when x=0. This point is also called y-intercept. It is an additive constant applied to every individual IDV (Stellefson, Hanik, Chaney, & Don, 2008). The figure should be Significance at 0.05 or below to have a confidence degree 95 %, this means that finding has 95% chance of being true (Ahmed, 2015).

Based on the results of Table 4.10, the value of the constant obtained for the regression equation is 37.542 with standard error of 3.256.

B (unstandardized coefficient) - B is the partial regression coefficient. It defines the direction and magnitude of the slope of the regression line. The use of the term partial means that this effect is predicted after the influence of all the other IDVs has been statistically controlled (Alistair, Howard, & Stephen, 2002). The "B" values are the coefficients for each variable, that is, they are the value which the variable's data should be multiplied by in the final linear equation (Ahmed, 2015). The value of B signifies how many predicted units change (either up or down) in the dependent variable there will be for any one unit increase in the independent variable. In the best case scenario, where the independent variable (s) perfectly predicts the outcome variable, the B weight perfectly matches the dispersions of the individual's actual score and individual's predicted score. When the predictor variable (s) is useless (i.e. does not predict or explain any of the variations in the outcome variable), the b weight will equal 0 to "kill" the useless independent variable and remove its influence from the regression equation (Thompson (2006) cited in Stellefson et al. (2008)). The regression coefficients that are computed accomplish two intuitively appealing and highly desirable goals: they minimize (the sum of the squared) deviations between predicted and actual values and they optimize the correlation between the predicted and actual values for the data set (Tabachnick & Fidell, 2013).

As it can be seen from Table 4.10, all of the IDVs have a statistically significant impact in predicting the DV value since there significance level associated with the observed value for 't' is less than 0.05.

According to the results obtained from Table 4.10, the variables with positive regression coefficients which have an impact of increasing bid markup size include: 'complexity of project (such as resources and technology required)', 'strategic value of project', 'current work load' and 'current required amount for head office overhead cost relative to the planned amount'. Out of these variables 'strategic value of project' has an unexpected result which is contradictory to its theoretical context. Theoretically, when a contractor assumes that the new project under bid has a strategic value for the company, it will tend to decrease its bid markup size to increase the probability of winning the bid. This contradiction is may be caused by the negligence of the respondents when deciding the bid markup size for the hypothetical bid projects.

The remaining variables has a negative regression coefficients having an impact of reducing bid markup size. These variables include: 'previous experience of the company on similar projects', 'previous experience of competitors on similar projects', 'availability of credit facility from suppliers', 'number of competitors with strong desire to win a project', 'expected size of contract', 'project location (region)' and 'clarity and completeness of tender documents (drawings, specifications, etc.)'. The sign for all of the variables with negative regression coefficients matched with their theoretical context.

In order to interpret the meaning of the regression coefficients let consider the variable for 'complexity of project (such as resources and technology required)'. This variable has a regression coefficient of + 2.317 with standard error of 0.413. And this can be interpreted as- for every increase of one unit of this variable the regression equation predicts an increase of 2.317 (with a standard error of 0.413) units of the bid markup size keeping the other IDVs constant. It can also be noted from the table that, there is a 95% chance that the actual value of the regression coefficient for this variable is between +1.494 and +3.140.

β (Standardized coefficient) - The slope, indicated by the value of B, is influenced by the scale upon which the IDV was measured. As different IDVs may be measured on scales of very different units, it is very difficult to compare their relative influence. The use of standardized scores may overcome this difficulty. Standardized scores are calculated by finding the difference between a score and the mean in units of standard deviation. That is, subtract the mean from each score and divide by the standard deviation (Alistair, Howard, & Stephen, 2002). Standardised beta values indicate the number of standard deviations that scores in the dependent variable would change if there was a one standard deviation unit change in the predictor (Pallant, 2005). A positive β means that the slope of the regression line is positive, tilting from lower left to upper right, whereas a negative β indicates that the slope of the regression in negative, tilting from upper left to lower right. Thus, the sign of b or β indicates the kind of correlation between the variables (Huck (2004) cited in Stellefson et al. (2008)).

According to the results obtained from Table 4.10, the variable 'previous experience of competitors on similar projects' makes the strongest statistically significant unique contribution in explaining the bid markup size with a value of $\beta=0.419$, when the variance explained by all other IDVs in the model is controlled. And the variable 'clarity and completeness of tender documents (drawings, specifications, etc.)' makes the least unique contribution from the listed variables even though its contribution is statistically significant (sig. <0.05).

To interpret the meaning of the standardized coefficients, let consider the variable for 'complexity of project (such as resources and technology required)'. This variable has a standardized coefficient of +0.327. And this can be interpreted as- one standard deviation increase in this variable predicts 0.327 of a standard deviation increase in the bid markup size keeping the other IDVs constant.

Part correlation coefficient - The other potentially useful piece of information in the coefficients table is the Part correlation coefficients. If this value is squared, it gives an indication of the contribution of that variable to the total R squared. In other words, it tells how much of the total variance in the dependent variable is uniquely explained by that variable and how much R squared would drop if it wasn't included in the model (Pallant, 2005).

According to the results obtained from Table 4.10, out of the eleven IDVs the variable 'previous experience of competitors on similar projects' has the highest part correlation coefficient of 0.387. If this value is squared it gives 0.149, indicating that this variable uniquely explains 14.9 percent of the variance in the total bid markup.

If the part correlation of each IDV's which are included in the model are squared and added up it gives a value of 66.4%. Recalling the total R^2 value of the model from Table 4.9, its value was 77.8% which is not equal to the all squared part correlation values added up. This is because the part correlation values represent only the unique contribution of each variable, with any overlap or shared variance removed. The total R^2 value, however, includes the unique variance explained by each variable and also that shared.

Tolerance and VIF - Another method to detect multicollinearity is to examine the values of tolerance and VIF shown in the coefficients table. Tolerance is an indicator of how much of the variability of the specified IDV is not explained by the other IDVs in the model and is calculated using the formula $1–R^2$ for each variable. If this value is very small (less than .10), it indicates that the multiple correlation with other variables is high, suggesting the possibility of multicollinearity. The other value given is the VIF (Variance inflation factor), which is just the inverse of the Tolerance value (1 divided by Tolerance). VIF values above 10 would be a concern here, indicating multicollinearity. These values, however, still allow for quite high correlations between independent variables (above 0.9), so they should be taken as a warning sign, and correlation matrix should be checked also (Pallant, 2005).

Since the value of tolerance for each of the IDV in the regression model is > 0.4, no high multicollinearity is detected in the developed model using this method.

Step-4: Conclusion

A stepwise MLR was performed between the bid markup size as the DV and its influencing factors as IDVs. The analysis was performed using SPSS 24 software. The underlying assumptions of MLR including normality, linearity, and homoscedasticity was assessed by examining the residual plots. Based on the results of the plots, those assumptions were met. Multicollinearity and singlularity assumptions were also checked and found no major problem. From the result of MLR analysis, the best regression model contains eleven IDVs which attain the statistical criteria set out by the stepwise technique. Since the number of samples are relatively small and number of IDVs is high, it is decided to use the value of the adjusted $R^2= 0.745$ as the model's amount of variance in the DV that is shared by the combined effect of the eleven IDVs and this is statistically significant at $\alpha=0.05$. From the ANOVA table (Table 4.10) result, the overall regression model was statistically significant, $F(11,73)= 23.297$, $p< 0.05$. The unstandardized coefficients of parameters of the regression equation and their significance level are calculated and it was observed that all the IDVs included in the model were significant at the confidence level of 95%. 'Previous experience of competitors on similar projects' uniquely explains 14.9 % of the variance in the total bid markup size, which is the highest rank from all IDVs in the model.

The following equation was developed to compute the bid markup size using the constant and the unstandardized coefficients:

$$\text{Bid markup size} = 37.542 - 2.343 * (X_1) + 2.317 * (X_2) - 3.016 * (X_3) - 1.673 * (X_4) - 1.803 * (X_5) - 1.784 * (X_6) + 2.360 * (X_7) + 2.525 * (X_8) - 1.155 * (X_9) - 1.078 * (X_{10}) + 1.437 * (X_{11})$$

Equation 4.3

Where X_1 - X_{11} are the IDVs which are described in Table 4.11.

Table 4.11: Independent variables for the regression equation

Label	Independent variable (IDV)
X_1	Previous experience of the company on similar projects
X_2	Complexity of project (such as resources and technology required)
X_3	Previous experience of competitors on similar projects
X_4	Availability of credit facility from suppliers
X_5	Number of competitors with strong desire to win a project
X_6	Expected size of contract
X_7	Strategic value of project
X_8	Current work load
X_9	Project location (region)
X_{10}	Clarity and completeness of tender documents (drawings, specifications, etc.)
X_{11}	Current required amount for head office overhead cost relative to the planned amount

For this study, it can be recalled that "immediate need for work' was among those IDVs which has a significant correlation with the DV. But during the regression analysis, this variable is not included in the model. The reason for this can be given to its high multicollinearity with the two IDVs- 'current work load' and 'current required amount for head office overhead cost relative to the planned amount'. According to a study by Stellefson et al. (2008) if two or more independent variables are entered in a multiple regression and those variables are correlated with each other to a high degree and correlated with the dependent variable, then the B weights for the independent variables are arbitrarily allocated predictive/explanatory credit among the correlated independent variables. This allocation of predictive/explanatory credit given to each independent variable can happen only one time, since more than one independent variable cannot be given predictive/ explanatory credit for the commonly explained area of the dependent variable. For this reason, certain IDVs with a sufficiently large correlation coefficient with the DV may be denied credit for predicting or explaining the DV. Thompson (2006) cited in Stellefson et al. ((2008) also give an explanation saying that- if collinearity coefficient is greater than zero and if regression coefficient is zero then the predictor variable explains some of the variations in the dependent variable, but other predictor variables are getting explanatory credit for what is being explained by the predictor variable.

Cross-validation with a second sample is highly recommended for statistical regression. After the statistical regression on the larger subsample is run, predicted scores are created for the smaller cross-validation sample using the regression coefficients produced by the analysis (Tabachnick & Fidell, 2013).

For this purpose, this study has retained 5 hypothetical project bid scenarios and made a cross-validation with the developed regression equation. Table 4.12, shows obtained results of the error of the estimate between the actual and predicted bid markup size. Compared to the values of error of estimates for the large sample, it can be said that there is a good match between the predicted and actual values of the bid markup. This demonstrates that the viability of the MLR model as a tool for modeling bid markup size.

Table 4.12: Cross validation for the regression equation

Hypothetical bid projects	Actual bid markup size	Predicted bid markup size	Error of the estimate
1	30	34.44	-4.44
2	32	31.22	0.78
3	25	31.61	-6.61
4	35	31.82	3.18
5	20	25.71	-5.71

4.3.3 Development of Bid Markup Estimation Model Using Artificial Neural Network

4.3.3.1 Introduction

Artificial neural network (ANN) is a kind of computational method, which is basically inspired by the human brain (Polat, Bingol, Gurgun, & Yel, 2016). It attempts to mimic the generalization capabilities of the human brain with artificial neurons and network to solve the complex problem (Arabpour & Moselhi, 2018). Neural networks have been widely used as a tool to approximate the 'true' relationships between dependent and independent variables without imposing any restriction on the parameter space of the model. This is due to the fact that the neural network 'learns' the underlying functional relationship from data itself. A major justification for the use of a neural network as an estimation device is its approximation abilities, i.e., its ability to provide a generic functional mapping from inputs (representing different problem encounters) to outputs (representing the conclusions or decisions) (Li H., 1996). The typical decision-making characteristics (subjectivity, intuition and gut feeling) associated with the estimation of markup suggest that ANN technique can be a suitable tool that could be developed and used as decision aids (Li & Love, 1999).

Neural network structure consists of an input and output layer, as well as one or more hidden layers as shown in the Figure 4.7 (Arabpour & Moselhi, 2018).

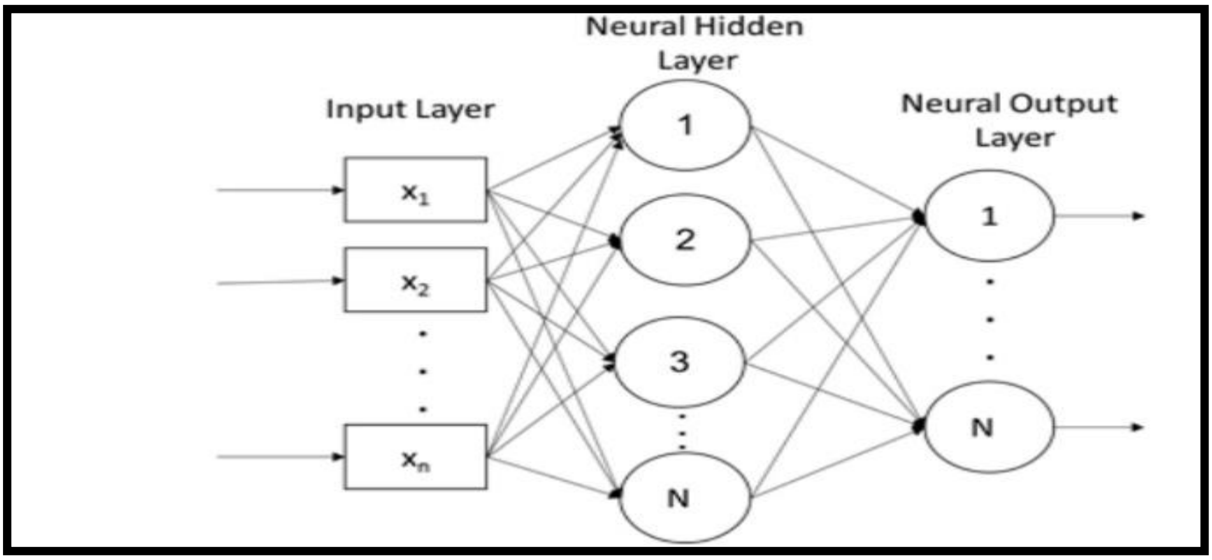

Figure 4.7: Sample architecture of ANN (Hegazy (1993) cited in Arabpour and Moselhi (2018))

Each layer consists of one or more artificial neurons, known as a processing element, and referred to as a node (Arabpour & Moselhi, 2018). The nodes are the highly interconnected computational units of the system, and their role is to receive input information and transform into output by processing them (Gershenson (2003) cited in Polat et al. (2016)).

4.3.3.2 ANN model development

The procedures carried out for developing the present neural network (NN) model for the bid markup estimation problem are described in this section. Figure 4.8 illustrates the steps followed in developing the NN model.

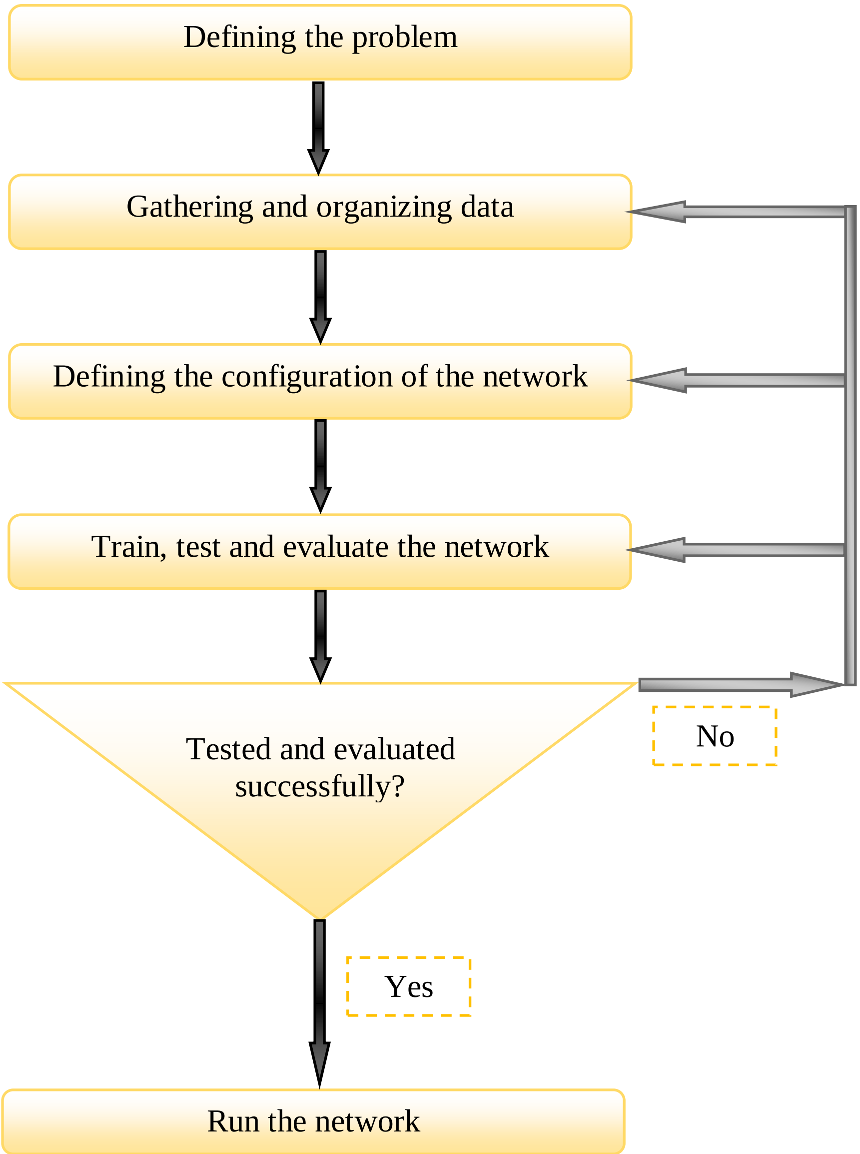

Figure 4.8: Neural network design procedures (adapted from Ismaail et al. (2011))

Step-1: Defining the problem

It is an attempt to develop NN model that can estimate the size of bid markup. The characteristic factors that need to be considered in formulating the NN model have been identified from a literature review and verified through a questionnaire survey. Through this process, a list of 21 factors affecting bid markup size was compiled and considered as an input parameter in the present model. It is a fitting problem where input parameters (factors) are matched up to associated target output parameter (bid markup size) to create a neural network which not only estimates the known targets given known inputs but can generalize to estimate outputs for inputs that were not used to design the solution.

Step-2: Gathering and organizing data

Once input and output parameters are identified their corresponding data for training, testing and evaluating of the NN based model were gathered by preparing 90 various hypothetical project bidding scenarios (based upon the compiled bid markup factors) which request respondents to provide an estimated percentage of bid markup for each scenario. The number of data for training and testing of the NN based model is 85 project bid cases and the remaining 5 projects will be reserved for evaluation of the best model.

This step also involves organizing the data into two matrices, the input matrix X and target matrix T. Each i^{th} column of the input matrix will have 21 markup attribute factors representing a value that is already known. The input is a 21*85 matrix, representing 85 samples of 21 markup attribute factors. Each corresponding column of the target matrix T, will have one element representing the bid markup size which is provided by the respondents. The target (output) is a 1*85 matrix, representing 85 samples of a specific bid markup size.

Step-3: Defining the configuration of the network

In this step the following necessary parameters which dictate the configuration of the network were defined:

A. Data division for training, testing and validation of the model

Data obtained from the 85 hypothetical project bidding scenarios were classified randomly into three categories including:

- Training 70% (59 samples) - these are presented to the network during training, and the network is adjusted according to its error.
- Validation 15% (13 samples) - these are used to measure network generalization, and to halt training when generalization stops improving.
- Testing 15% (13 samples) **-** these do no effect the training and so provide an independent measure of network performance during and after training.

B. Type of architecture of ANN

The feed-forward and feed-back are two major types of architecture exist in ANN based on the connection patterns. The feed-forward ANN approach (i.e., have no loops) is used to solve classification problem utilizing extension of conventional fitting and principal component analysis techniques. On the other hand, the feed-back approach (i.e., have loops) is used to handle combinatorial optimization problems (Reeves (1993) cited in Polat et al. (2016)).

Feed forward neural networks' type is used in this study for their recognized prediction and classification capabilities (Moselhi et al., (1991) and Reeves (1993) cited in Arabpour and Moselhi (2018)).

C. Type of training algorithm

A neuron has a bias, which is summed with the weighted inputs to form the net input. The central idea of neural networks is that the bias and weight of a neuron can be adjusted so that the network exhibits some desired or interesting behavior. Thus, a network can be trained by adjusting these parameters to achieve some desired end (Howard & Mark, 2004). Training algorithms are procedures which employs the learning rules to modify weights and biases of a network during the training process to accurately map and correlate the input pattern to its associated output (Kisi (2007) cited in Arabpour and Moselhi (2018)). ANNs use a learning algorithm to automatically generate functional relationships between inputs and outputs that are presented in a set of historical data, even though the data may be noisy and incomplete (Kohonen (1988) cited in Li and Love (Li & Love, 1999)).

The back propagation training algorithm is by far the most widely utilized ANN paradigm for its simplicity and good generalization capabilities (a sample network is shown in Figure 4.9). Back propagation incorporates a learning algorithm called "generalized delta rule", which is responsible for training the network. The algorithm uses a gradient descent method to determine a unique set of network weights that enables the network to produce outputs that are very close to the desired outputs associated with several training examples. During training, the NN is presented with the data of thousands of times (called cycles). After each cycle, the error between the NN outputs and the actual outputs are propagated backward to adjust the weights in a manner that is mathematically guaranteed to converge (Rumelhart et al. (1986) cited in Hegazy and Moselhi (1994)). The NN would be saved whenever a new minimum average error is reached. When this is achieved, the network is said to be knowledgeable about all the examples, with the unique weight matrix encoding the examples' knowledge (Hegazy & Moselhi, 1994).

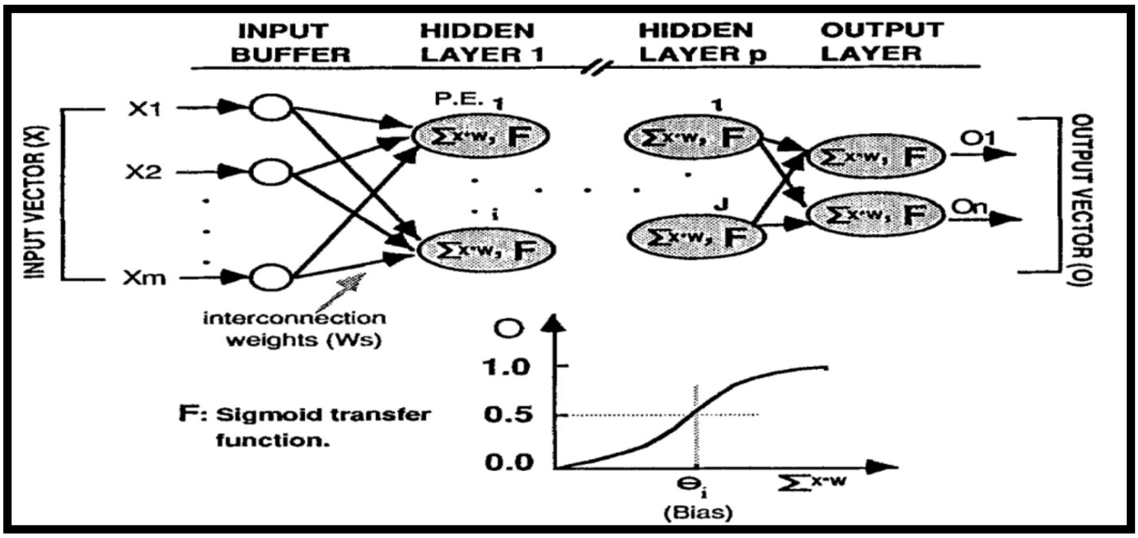

Figure 4.9: Sample network for a Multilayer, feed forward back propagation network (Hegazy & Moselhi, 1994)

The past researches proved that the feed forward back-propagation rule is the most commonly used technique for solving estimation and prediction problems (Hegazy & Moselhi, 1994), (Liu & Ling, 2005), (Ismaail, Hossam, & Abdel Razek, 2011), (Polat, Bingol, Gurgun, & Yel, 2016) and (Arabpour & Moselhi, 2018). Levenberg-Marquardt training algorithm appears to be the fastest method for training moderate-sized feed forward neural networks (up to several hundred weights). It also has a very efficient MATLAB implementation, since the solution of the matrix equation is a built-in function. In many cases, it can obtain lower mean square errors than any of the other algorithms tested (Howard & Mark, 2004).

Thus, in constructing the ANN model for this study, three-layered feed forward back propagation ANN models were first established. The network will be trained with Levenberg-

Marquardt back propagation algorithm and gradient-descent-with-momentum adaptation is used as the learning function of the network. The neural net fitting application of the "MATLAB 2016a", which is based on the feed forward back-propagation learning algorithm technique, was utilized to generate the ANN model which is used for bid markup size estimation.

D. Number of neurons in input, hidden and output layers

The numbers of neurons in the first and last layers are governed by the number of input and output parameters, respectively. This study has compiled 21 factors which have an impact on the bid markup size decision (input parameters) and it target to develop a model which can estimate bid markup size (output parameter) based on these factors. Thus, the input and output layers will have 21 and 1 neuron respectively.

The number of neurons for the hidden layer would be determined by trial and error to obtain the best model structure. Using MATLAB, different number of neurons in the hidden layer would be experimented to investigate the estimating accuracy of the ANN models (Liu & Ling, 2005). During this procedure if the network doesn't give satisfactory accuracy, adding or removing of hidden neurons would be performed until reaching the best acceptable model structure that can predict/assess the bid markup size.

E. Number of hidden layers

Hidden layer is a layer of neurons in ANN that does not connect to the outside world but connects to other layers of neurons. Having too few facts or too many hidden layers/neurons can cause the network to "Memorize". When this happens, it performs well during training but tests poorly (Ismaail, Hossam, & Abdel Razek, 2011). A trial and error process would be used in attempt to obtain the number of hidden layers for the network which can give the best model.

F. Type of activation function

In ANN, the neurons are used to learn patterns or relationships between inputs and output of the problem by setting weights to each neuron's connections. These weights are adjusted in each training process to obtain the correct patterns from defined data set and use this knowledge in forecasting or predicting new events (Tam et al. (2007) cited in Polat et al. (2016)). Basically, inputs of the system are multiplied by assigned weights and then a mathematical function is used to compute activation of the neuron, then the output of the system is determined by another function. Threshold, piecewise linear, sigmoid or Gaussian are different types of the activation functions used in ANN. Among these alternatives, sigmoid function is the most commonly preferred one in ANN (Jain et al. (1996) cited in Polat et al. (2016)).

For this study, a sigmoid & linear transfer functions are used in the hidden & output layer of the network respectively. The sigmoid transfer function takes the input, which may have any value between plus and minus infinity, and squashes the output into the range 0 to 1. The linear transfer function calculates the neuron's output by simply returning the value passed to it. If linear output neurons are used the network outputs can take on any value. A network of two layers, where the first layer is sigmoid and the second layer is linear, can be trained to approximate any function (with a finite number of discontinuities) arbitrarily well (Howard & Mark, 2004).

G. Number of training iterations

The number of training iterations which will provide a better validation check will be designed by the MATLAB system.

Step-4: Training and testing of the network

Once the network weights and biases have been initialized, the network is ready for training. A pair of input and associated output patterns is called a training example. In training over several examples, the network generalizes the process by which the outputs correlate to the inputs (Hegazy & Moselhi, 1994). Neural networks learn from actual case projects (actual bid situations); by feeding the network the input values of the parameters in the actual project case and concurrently feeding it the actual value of its output. By repeating these training cases, the network will gain the knowledge and experience as with normal human beings and will be able to predict the output (i.e. estimated bid markup) given a new set of input data. In other words the network learns by associating input values to the output value (Arabpour & Moselhi, 2018).

Associated with each connection of neurons is a numerical value which is the strength of the weight of that connection. At the beginning of a training process, the connection weights are assigned with random values. As examples are presented during the training, the feed-forward mechanism modifies the connection weights in an iterative process. The modification of weights is accomplished through the gradient descent on the total error in a given training case (Li H., 1996). As the training proceeds, the network weights are continuously adjusted until the error in the calculated outputs converges to an acceptable level (Ismaail, Hossam, & Abdel Razek, 2011). When the iterative process is converged, the collection of connection strengths captures and stores the information in the examples used in training. Such a trained neural network is ready to be used. When presented with an incomplete pattern of information, the neural competition will result in a complete pattern of information according to the information learned and stored in its connection strengths (Li H., 1996).

The training data set, is used for computing the gradient and updating the network weights and biases. The error on the validation data set is monitored during the training process. The validation error will normally decrease during the initial phase of training, as does the training set error. However, when the network begins to over fit the data, the error on the validation set will typically begin to rise. When the validation error increases for a specified number of iterations, the training is stopped, and the weights and biases at the minimum of the validation error are returned. The test data set error will not be used during the training, but it is used to compare different models (Howard & Mark, 2004). Testing the network is essentially the same as training it, except that the network is shown facts it has never seen before, and no corrections are made when the network is wrong (Ismaail, Hossam, & Abdel Razek, 2011). The default performance function for feed forward networks in MATLAB is mean square error (MSE) which is the average squared error between the network outputs and the target outputs.

In this study, actual data of 85 hypothetical bid projects were used for training, validating and testing various network structures. Starting from one hidden node network structure, various ANN models were generated. Table 4.13 presents the performances of the generated models. The ideal model is identified with minimum MAPE (Mean absolute percentage error) and RMSE (Root mean square error), and maximum R (coefficient of correlation) and R^2 (coefficient of determination), which means that MAPE and RMSE values should be close to zero, on the other side, R and R^2 values should be close to one (Polat, Bingol, Gurgun, & Yel, 2016). The MAPE and RMSE are good measures of the magnitude of the errors incurred by the predictions (Liu & Ling, 2005).

Based on the results presented in Table 4.13, the ANN model with eight hidden nodes (ANN_8) identified to have the best estimation performance (i.e. smallest MAPE and RMSE, and largest R and R^2) and subsequently selected as the best ANN model for this study. According to Table 4.13 the best model (ANN_8) has R value of 92.06%, which means there was a linear relationship between the actual bid markup size and its input factors. The R^2 value was calculated as 84.75%, which means that the overall markup factors highly explain the differences between actual and predicted bid markup size. MAPE measures the accuracy of the model (Polat, Baytekin, & Eray, 2015). Since the best model has MAPE value of 6.43%, which is less than 10%, the proposed model can be accepted as successful. In this model, RMSE was calculated as 2.47, thus it can be stated that the error rate of the model is satisfactory compared to other similar studies.

Table 4.13: Performance indicators of ANN bid markup size estimation models

Performance indicator	**Developed models**									
	ANN_1	**ANN_2**	**ANN_3**	**ANN_4**	**ANN_5**	**ANN_6**	**ANN_7**	**ANN_8**	**ANN_9**	**ANN_{10}**
Number of neurons	1	2	3	4	5	6	7	8	9	10
R (%)	87.21	84.26	83.85	86.02	82.13	88.95	85.12	92.06	86.07	89.37
R^2 (%)	76.06	71.00	70.31	73.99	67.45	79.12	72.45	84.75	74.08	79.87
MAPE (%)	8.51	10.28	8.72	8.95	10.11	7.12	8.91	6.43	8.99	7.37
RMSE	2.97	3.41	3.42	3.17	3.53	2.92	3.20	2.47	3.28	2.73

The characteristics and architecture of the selected ANN model that was obtained through the trial and error process are presented in Table 4.14 and Figure 4.10 respectively.

Table 4.14: Characteristics of the best ANN model

Model	**No. of input nodes**	**No. of hidden layers**	**No. of hidden nodes**	**Training function**	**Transfer function**	**No. of output nodes**
ANN-8	21	1	8	Levenberg-Marquardt	Sigmoid	1

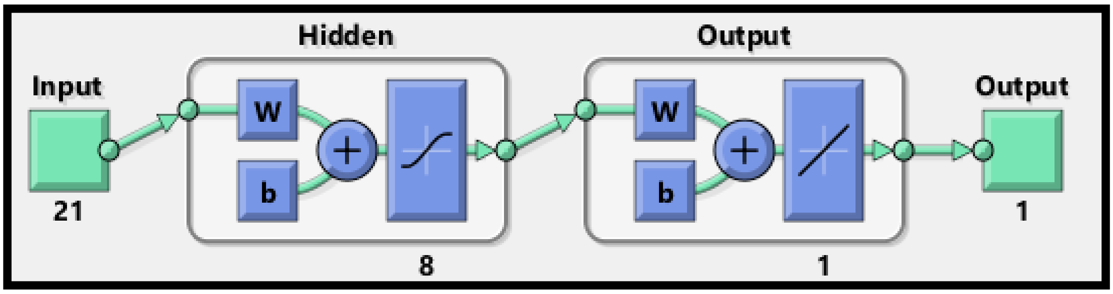

Figure 4.10: The architecture of the best ANN model

It is also useful to plot the regression and error histogram plots to understand the performance of the selected model.

The regression plots in Figure 4.11, illustrate the network outputs concerning to targets for training, validation and testing data sets of the best ANN model. The result here is reasonable, since the test set error and the validation set error have similar characteristics.

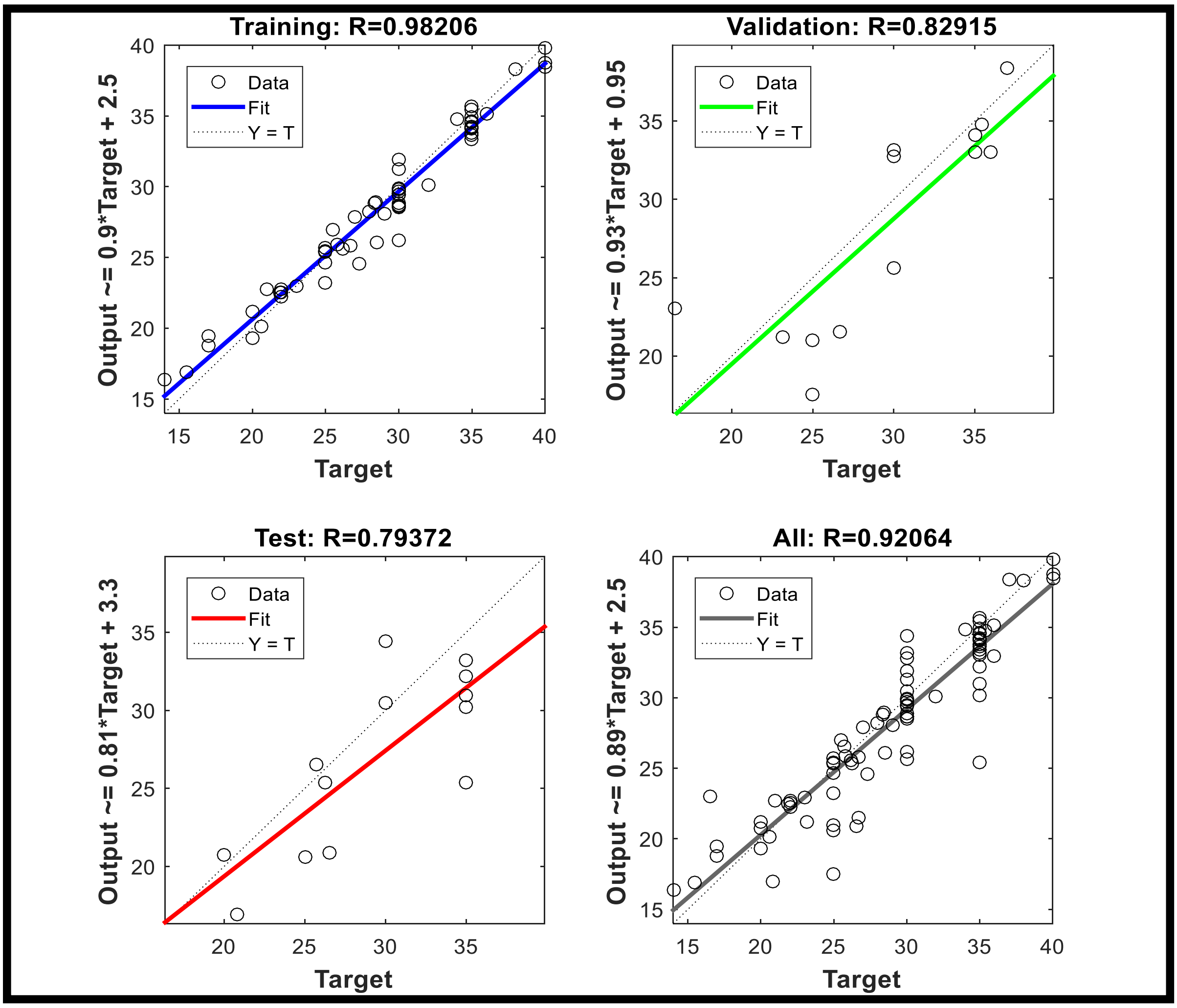

Figure 4.11: The regression plot of the best ANN model

The error histogram in Figure 4.12 below, shows how much error was there in the target value compared to the output of the model.

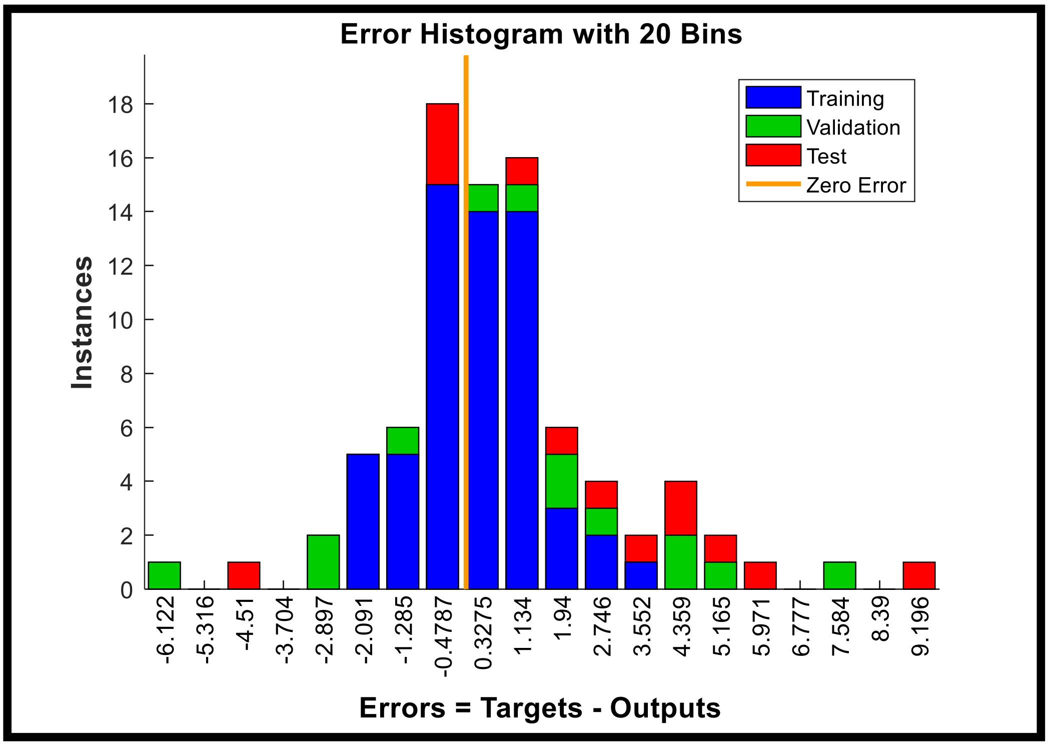

Figure 4.12: The error histogram of the best ANN model

Step-5: Evaluating the developed model

It is important to evaluate the performance of the network after the training process. If the results are good, the network will be ready for use. If not, this means that it needs more or even better data or even redesign the network (Ismaail, Hossam, & Abdel Razek, 2011).

To evaluate the predictive performance of the network, five projects that were previously reserved (those projects which the networks have never been exposed) are introduced to the selected designed model without providing their corresponding targeted bid markup size. Cross validation was done by comparing what the model predict, based on the provided inputs, with the actual markup size used.

Table 4.15, presents the actual and predicted bid markup percentages for the test sample. Compared to the values of error of estimates for the large sample, it can be said that there is a good match between the predicted and actual values of the bid markup. This demonstrates that the viability of the ANN model as a tool for modeling bid markup size.

Table 4.15: Actual and predicted bid markup size for the test sample

Hypothetical bid projects	Actual bid markup size	Predicted bid markup size	Error of the estimate
1	30	35.09	-5.09
2	32	26.61	5.39
3	25	28.29	-3.29
4	35	32.64	2.36
5	20	23.32	-3.32

Step-6: Conclusion

To develop ANN model that can estimate bid markup size (output parameter), a list of 21 factors (input parameters) affecting it were compiled. Estimated percentage of bid markup for training, validating, testing and evaluating of the NN based model were obtained from 90 hypothetical project bidding scenarios. The neural net fitting application of the "MATLAB 2016a" was utilized to generate the ANN model.

The setting parameters of the ANN were as follows: the feed-forward back propagation network was utilized as the type of architecture; the training function was selected as Levenberg-Marquardt method; gradient-descent-with-momentum adaptation was used as the learning function of the network; the model performance evaluation was determined with mean squared error (MSE) function, and sigmoid transfer function was selected as the activation function of the bid markup size estimation model. Actual data of 85 hypothetical bid projects were divided into three parts; 70% (59 projects), 15% (13 projects) and 15% (13 projects) of them were used in training, validation process and testing process of the network respectively. Additional 5 hypothetical bid projects data were used for evaluation of the designed ANN model. The number of training iterations are set by the MATLAB system. In order to find the best ANN model, a trial and error method based on the variation of the number of neurons in the hidden layer was performed. For that purpose, the performance of the generated models were evaluated with using several statistical indicators, which include R, R^2, MAPE and RMSE. Based on the findings presented in Table 4.13, the most satisfactory model was the ANN_8, which consists of 8 neurons in the hidden layer with R, R^2, MAPE and RMSE values of 92.06%, 84.75%, 6.43% and 2.47 respectively. Therefore, ANN_8 is selected for representing ANN model of this study. In order to solve new problems which are related to the current problem using the proposed ANN model, a simple script is generated from MATLAB software (presented in appendix C).

4.3.4 Comparison of Models Developed Using Multiple Linear Regression and Artificial Neural Network

In this section, performances of the two proposed models which are developed using MLR and ANN techniques will be compared using statistical performance indicators including: R, R^2, MAPE and RMSE. It also presents a comparative analysis based on the performance results of the developed models for the current study and other related studies.

Table 4.16 presents the results of statistical performance indicators for the models. Based on the results, the ANN model has slightly outperform the MLR model when compared using the statistical performance indicators. These finding reveal that, ANN modeling technique can predict the size of bid markup in a better way than MLR method. But, the obtained values of the statistical performance indicators for the two models are closer to each other. Thus, it can be said that both models provide a starting point to estimators for a given project bid markup estimating task. Appendix B presents the actual input data and the associated bid markup size given by respondents for each of the 90 hypothetical bid scenarios and the bid markup size predicted by the developed models using MLR and ANN technique.

Table 4.16: Statistical performance indicators of MLR and ANN bid markup estimation models

Performance indicator	Developed models	
	MLR	**ANN_8**
R (%)	86.31	92.06
R^2 (%)	74.50	84.75
MAPE (%)	8.37	6.43
RMSE	2.85	2.47

Figure 4.13 & 4.14 illustrate a scatter plot of actual vs. predicted value of bid markup size, based on the 85 hypothetical project bid scenarios, using both methods of modeling for a

visual comparison. As it is observable, the ANN model's predictions slightly have better performance compared with the MLR model.

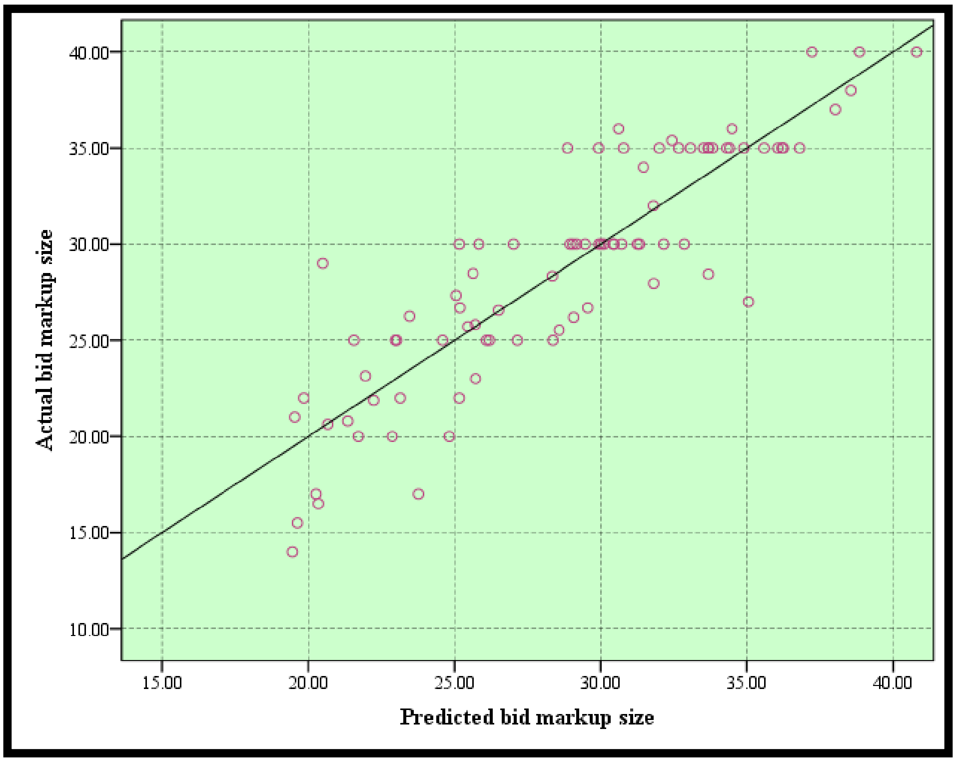

Figure 4.13: Scatter plot of actual vs. predicted value of bid markup size using MLR

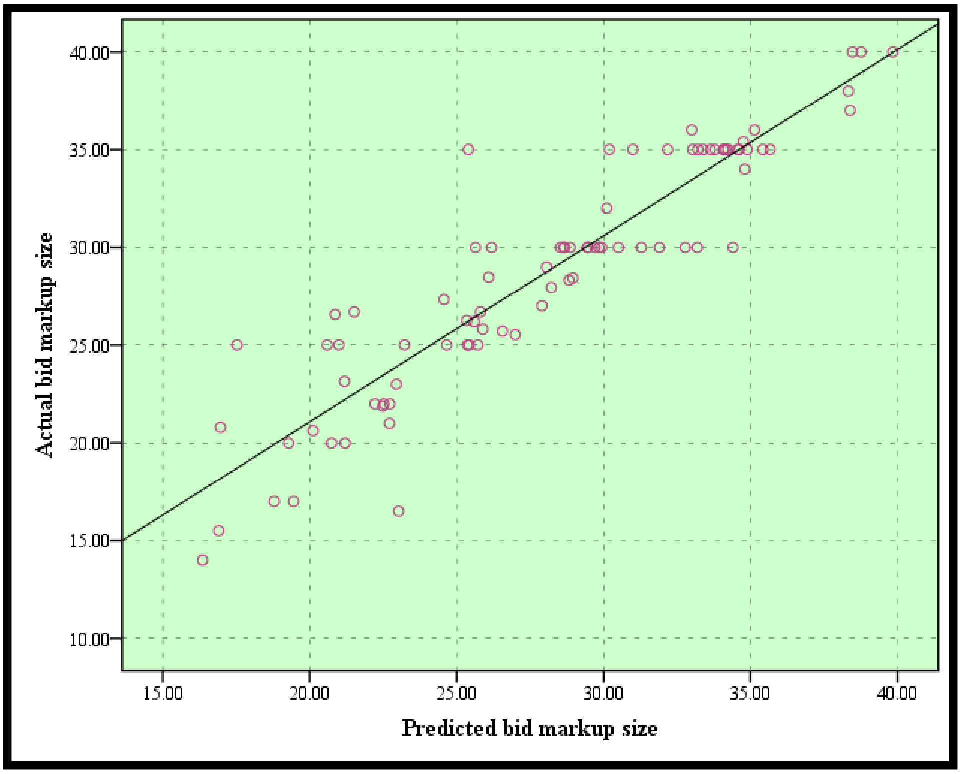

Figure 4.14: Scatter plot of actual vs. predicted value of bid markup size using ANN

To check the viability of the models developed in this study, it is useful to compare the performance results of each model with other related studies. Table 4.17 presents the model performance results obtained in the current study and other related studies. From the observed results, it can be concluded that the performances of the developed models in the current study are satisfactory when compared to other related studies.

Table 4.17: Model performance results of the current study and other related studies

Related studies	Modeling Method	Performance indicator			
		R (%)	R^2 (%)	MAPE (%)	RMSE
Current study	MLR	86.31	74.50	8.37	2.85
	ANN	92.06	84.75	6.43	2.47
Arabpour and Moselhi (2018)	MLR	27.28	7.44	-	11.98
	ANN	66.72	44.51	-	7.48
Polat et al. (2016)	MLR	99.30	98.70	2.73	0.41
	ANN	99.29	98.60	2.82	0.43
Polat et al. (2015)	MLR	95.40	91.10	1.68	0.0366
Liu and Ling (2005)	MLR	-	-	14.80	-

CHAPTER 5: CONCLUSION AND RECOMMENDATIONS

This chapter presents the conclusion and recommendations, which mainly based on the results of the data analysis and discussions made in the previous chapter, which conforms to the research objectives stated in the introduction part. To address the major problems identified through the research process future study areas will also be highlighted.

5.1 CONCLUSION

This study aimed to lay down the methodology for developing a bid markup estimation model. In this section, the major findings of the research which have been discussed in previous chapters will be briefly summarized in accordance with the main and specific objectives of the research.

The first specific objective of this study was to review and understand the factors that influence decisions on bidding markup size during competitive bidding. To achieve this objective, various pieces of literature related to the present study were explored. This literature review has given details of previous researches that have studied factors that affect bid markup size decisions, as well as techniques of modeling bid markup size estimation which aid to identify a direction for the study. The following points were revealed from the literature review:

- The existing findings regarding the level of importance attached to factors that influence bid markup size differ from one study to another and from one country to another.
- Twenty-one factors have been identified as potentially influential to the bid markup size decision and these factors are categorized (grouped) into four including project characteristics, company characteristics, bidding situations and economic situations.
- In terms of the techniques used for modeling bid markup size estimation, several approaches were explored for solving bidding markup size problems; and for this study, multiple linear regression analysis (MLR) and artificial neural network (ANN) were selected for modeling bid markup estimation.

In order to achieve the other specific objective of this study, a list of 21 markup factors which was compiled from previous researches were re-examined to establish an importance index for factors influencing the bidding markup size decision in road construction projects at federal level in Ethiopia. A questionnaire was presented to the study population requesting them to define the degree of impact of each factor in affecting bid markup estimation during bidding. This question aimed to understand which factors influence an organization's decision when bidding markup decisions, and which one of these factors is ranked as most important by the organization. Based on the results from the analysis, the following conclusions can be drawn:

- It appears that 'complexity of project (such as resources and technology required)', 'number of competitors with strong desire to win a project', 'project location (region)', 'immediate need for work' and 'security need of project location', are the top five ranked factors in terms of influencing bid markup size.
- The lowest-ranked factors are 'current required amount for head office overhead cost relative to the planned amount', 'amount of possible upcoming profitable projects out for tender in the remaining fiscal year', 'right of way status', 'pavement type' and 'availability of credit facility from suppliers'.
- The highest-ranked markup factor has RII of 95.45% and the lowest-ranked factor has RII of 60%. This indicates that all 21 factors are considered relevant, because both the highest and lowest ranked factors are nearly from the mid importance point to the highest importance point.
- The following are additional factors that the respondents stated: payment record of the employer, project start time (season), the expectation of fraud and corruption, amount of performance bond, the performance of the employees and price escalation conditions.

Developing a model that can support local contractors' decision making for estimating a bid markup size was the main objective of this research. In pursuance of this objective, two models were developed using multiple linear regression (MLR) and artificial neural network (ANN). Various hypothetical project bidding scenarios, based upon the compiled bid markup factors from literatures, were prepared and respondents were requested to provide an estimated percentage of bid markup for each scenario. These bidding scenarios were assumed to be a real-life road project bids and used for developing the markup estimation models in this study. The following major conclusions have been derived and summarized in accordance with the main objective of the study:

- Based on the response of the hypothetical project bidding scenarios a Pearson product-moment correlation was conducted to examine the nature and strength of the linear relationship between each IDV and DV. Based on the results, the factor 'previous experience of the company on similar projects' has the highest strength of linear relationship with bid markup size. The factors 'previous experience of competitors on similar projects', 'complexity of the project (such as resources and technology required), 'expected size of the contract', 'current work load', 'immediate need for work', 'availability of credit facility from suppliers', 'strategic value of the project' and 'number of competitors with strong desire for the project' have a medium strength of linear relationship with bid markup size.
- A stepwise MLR was performed between the bid markup size as the DV and its influencing factors as IDVs. After checking the underlying assumptions for MLR are met, the analysis was carried out to obtain the regression equation shown in equation 4.3. This equation contains eleven IDVs which attain the statistical criteria set out by the stepwise technique. The coefficient of correlation (R) was obtained as 0.882, which means that there is a strong linear relationship between the bid markup and the IDVs considering their combined effect. An adjusted value of the coefficient of determination (R^2) = 0.745 was obtained which implies that 74.50 % of the variance in the bid markup size can be explained by the combined effect of changes in the eleven IDVs value. The remaining 22.20% of the variation in the bid markup is presumed to be due to random variability. From the ANOVA table (table 4.10) result, the overall regression model was statistically significant, $F(11, 73) = 23.297$, $p< 0.05$.
- The unstandardized coefficients of parameters of the regression equation and their significance level are calculated and it was observed that all the IDVs included in the model were significant at the confidence level of 95%. 'Previous experience of competitors on similar projects' uniquely explains 14.9 % of the variance in the total bid markup size, which is the highest rank from all IDVs in the model.
- For developing the ANN model for bid markup estimation various network structures were generated and tested. Based on the findings presented in table 4.13, the most satisfactory model was the ANN_8, which consists of 8 neurons in the hidden layer with R, R^2, MAPE and RMSE values of 92.06%, 84.75%, 6.43% and 2.47 respectively. Therefore, ANN_8 is selected for representing the ANN model of this study.

- To evaluate the predictive performance of the developed models using both MLR and ANN technique, five projects that were previously reserved were introduced to the regression equation and the selected best neural network without providing their corresponding targeted bid markup size. Cross-validation was done by comparing what the model predicts, based on the provided inputs, with the actual markup size used, and satisfactory result was obtained.
- The performances of the two proposed models were compared using statistical performance indicators including: R, R^2, MAPE, and RMSE. The results in table 4.16 indicate that the ANN model has slightly outperformed the MLR model when compared using all of the performance indicators. These findings reveal that the ANN method of modeling can predict the size of bid markup in a better way than the MLR method. But since the performance differences are not that much large both models can be considered as satisfactory prediction tools for bid markup size. Therefore, both models provide a starting point to estimators for a given project bid markup estimating task.

5.2 RECOMMENDATIONS

In light of the research findings and conclusion, the following recommendations are made to improve the practice of estimating bid markup size for road construction projects.

- Contractors are recommended to consider all the factors identified in this study (based on their respective relative importance index) when deciding the size of markup for competitive bidding of federal road projects.
- The methodology laid down in modeling markup estimation can be followed by contractors. It can be used as a decision aid for contractors to overcome their limited cognitive capacity by providing structured frameworks.
- The bid markup size for the hypothetical project bid scenarios was not decided by the management team of the company rather it was done by one professional and this may decrease the generalizability of the research to the studied contractors (populations). To get valuable and practical findings from the researches done in higher institutions, contractors are recommended to give a response that can entirely represent them as a company, specifically to those researches related to project cost estimation.
- The development of the bid markup estimation model requires the presence of a structured database for projects executed in the past in the construction companies.

Thus, contractors are recommended to develop a standard database system for storing information regarding projects executed in the past. This will help to provide the required information for researchers and enhance the construction industry and higher institutions linkage.

- Various pieces of literature revealed that Artificial Intelligence (AI) tools employ a learning mechanism and simulate the human estimating ability to learn from examples and solve pattern recognition tasks similar in nature to the one performed in this study and other related problems. To enhance the application of AI tools in researches, courses related to AI should be incorporated in the curriculum for postgraduate program in construction technology and management stream.

To address the major problems identified through the research process the following areas are suggested for future studies:

- Future studies should focus on extending the proposed models by using actual bid data of past road projects to develop a more generalized and accurate bid markup size estimation model.
- The bid markup estimation model should also be extended to other sectors of construction projects to enhance the systematical way of decision making for managerial problems in the construction industry.
- It has been widely acknowledged by various researchers that the major drawback of using ANNs is that the knowledge learned by a neural network may be difficult to interpret. Because of the lack of interpretability, a neural network-based markup model cannot explain why and how estimates are produced. Literatures proposes a fuzzy neural network (FNN) technique of modeling to rectify these drawbacks. Thus, future studies are recommended to study the FNN technique of modeling.
- According to previous researches, the value suggested by the MLR & ANN model for the bid markup cannot be considered as an optimum value. This value is only the result of the obtained analytical form of relation between the DV and IDVs by composing an equation with parameters and it is the result of pattern recognition performed by the ANN of the knowledge base it was trained on with, and it can therefore only be considered as the best prediction of an appropriate bid markup for a project of given attributes. Thus, future studies should look for alternative modeling techniques such as neuro-fuzzy systems to obtain optimum bid markup.

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APPENDICES

A. QUESTIONNAIRE

Dear Madam/ Sir

I am currently under taking a Degree of Master of Science in Civil Engineering (Construction Technology and Management) at Addis Ababa University, Addis Ababa Institute of Technology. In fullfilment of this program, I am required to research a topic area and produce a thesis. The topic I have chosen is "Hypothetical modeling of Contractor's Bid Markup Estimation for Road Construction Projects in Ethiopia".

The construction industry is known for featuring strong levels of price competition as significant amount of projects are assigned through what is known as "least price tender" or "least price bidding" processes (Chao & Liu, 2007). The main intent of construction bid decision is to price contracts competitively and strike the trade-off between competitiveness (i.e., pricing as low as possible) and profitability (i.e., pricing as high as possible) (Chapman, Ward, & Bennell, 2000).

During competitive bidding of a road project, most of the bidders have an access to the same labor supply; use the same types of equipment; obtain supplies and materials from the same sources; and have somewhat comparable site supervisory capabilities and expenses. Therefore, it is postulated that the amount of bid markup size is the key component in bid price, which also determines winning or losing the contract in question (Moselhi & Hegazy, 1993). In other words, the right amount of bid markup size brings success in competitive bidding environment (Dikmen, Birgonul, & Gur, 2007).

For the purpose of this questionnaire and research, the definition used for bid markup is- "a factor that estimators apply to certain work activities or to the total cost of a bid to cover head office overhead and profit". It is assumed that cost estimate has already been prepared by estimators with considering any risk that the project may face. So any contingency will be excluded from the markup percentage.

PROJECT BID MARK-UP (%) = ∑ (HEAD OFFICE OVERHEAD (%) +

The main objective of this research is to develop a model which will support local contractors in deciding the bid markup size, -which produces a satisfactory balance between the probability of winning the contract and the profit generated as a result of winning the contract during competitive bidding for road construction projects in Ethiopia.

The aim of this questionnaire is to identify the key factors affecting bid mark-up estimation and to obtain project bid markup size by presenting hypothetical project bidding scenarios to the respondents. The questionnaire includes two sections: Section I – Organization and respondent profile data and Section II – Factors affecting bid mark-up size decision and project bid markup size estimation for hypothetical project bidding scenarios.

Your contribution to this study is highly appreciated and it would contribute to the knowledge on the subject of mark-up estimation in Ethiopian road projects. Your response will be kept strictly confidential, and it will be exclusively used for the research.

You may kindly be aware of time constraints in such academic researches; hence, I sincerely request you to complete and return the questionnaire in two weeks' time.

Thank you for your invaluable time and cooperation.

Kind Regards,

Ameneshewa Alemu

E-mail: ameneshewaa@yahoo.com

SECTION – 1

1. Organization and Respondent Profile

1.1. Name of Organization:..

1.2. Grade or Class of the Organization: ....

1.3. How long has your Organization been involved in the road construction sector?

....

1.4. Your name, title and contact address:

Name (Optional): ....

Job title: ....

Contact address (optional):

E-mail: ....

Tel: ....

1.5. Your educational qualification: ....

1.6. Your general work experience in construction projects: .... Years

1.7. Your specific work experience related to bidding for road construction projects:

..... Years

SECTION – 2

2. Factors Affecting Bid Markup Size Decision and project bid markup estimation

2.1 In the table below; there are various factors affecting bid markup size decision that are identified from various literatures. Based on your experience in the sector, please define the degree of impact of these factors in affecting bid markup size decision during bidding of a road construction project by marking (√) taking into consideration the definition of the levels shown in the table below.

Symbol	Meaning
0	No impact
1	Affects with little degree
2	Affects with average degree
3	Affects with large degree
4	Affects with very large degree

No.	Group	Factors affecting bid markup size decision	Degree of impact				
			0	**1**	**2**	**3**	**4**
1	**Project characteristics**	Strategic value of project					
		Complexity of project (such as resources and technology required)					
		Project location (region)					
		Right of way status					
		Expected size of contract					
		Duration of project					
		Security need of project location					
		Clarity and completeness of tender documents (drawings, specifications, etc.)					
		Pavement type					
		Type of project delivery system					
2	**Company characteristics**	Current work load					
		Immediate need for work					
		Accuracy of the direct cost estimation					

2	**Company characteristics**	Previous experience of the company on similar projects					
		Availability of cash or overdraft facility to carry out the work					
		Availability of credit facility from suppliers					
		Current required amount for head office overhead cost relative to the planned amount					
3	**Bidding situation**	Number of competitors with strong desire to win a project					
		Previous experience of competitors on similar projects					
4	**Economic situation**	Current state of the overall economy of the country					
		Amount of possible upcoming profitable projects out for tender in the remaining fiscal year					

2.2 List any other factors that you deem important for bid markup estimation by rating the degree of impact of the factors.

No.	**Factors affecting bid markup size decision during bidding of a road construction project**	**Degree of impact**				
		0	**1**	**2**	**3**	**4**

B. HYPOTHETICAL BID SCENARIOS

B-1. Ordinal measurement scale for bid markup factors

Item No.	Factors	Measurement Scale	Label
1	Strategic value of project	Low	1
		Medium	2
		High	3
2	Complexity of the project (such as resources and technology required)	Low	1
		Medium	2
		High	3
3	Clarity and completeness of tender documents (drawings, specifications, etc.)	Low	1
		Medium	2
		High	3
4	Right of way status	Unresolved	1
		Partially resolved	2
		Resolved	3
5	Expected size of contract	< 500 million birr	1
		From 500 million to 1 billion birr	2
		> 1 billion birr	3
6	Duration of project	< 2 years	1
		From 2 to 3 years	2
		> 3 years	3
7	Security need of project location	Low	1
		Medium	2
		High	3
8	Project location (region)	North	1
		East	2
		West and South	3
9	Pavement type	Gravel	1
		Double bitumen surface treatment (DBST)	2
		Asphalt concrete (AC)	3
10	Type of project delivery system	Design Bid Build (DBB)	1
		Design Build (DB)	2
		Own Force (OF)	3

Item No.	Factors	Measurement	
		Scale	**Label**
11	Current work load	Low	1
		Medium	2
		High	3
12	Immediate need for work	Low	1
		Medium	2
		High	3
13	Accuracy of the direct cost estimation	Low	1
		Medium	2
		High	3
14	Previous experience of the company on similar projects	Poor	1
		Good	2
		Very good	3
15	Availability of cash or overdraft facility to carry out project	Scarce	1
		Medium	2
		High	3
16	Availability of credit facility from suppliers	Low	1
		Medium	2
		High	3
17	Current required amount for head office overhead cost relative to the planned amount	Low	1
		Medium	2
		High	3
18	Number of competitors with strong desire to win a project	Low	1
		Medium	2
		High	3
19	Previous experience of competitors on similar projects	Poor	1
		Good	2
		Very good	3
20	Current state of the overall economy of the country	Bad	1
		Medium	2
		Good	3
21	Amount of possible upcoming profitable projects out for tender in the remaining fiscal year	Scarce	1
		Medium	2
		Abundant	3

B-2. Legend for the hypothetical bid project scenarios

Item No.	Label	Markup factors
1	RW	Right of way status
2	PT	Pavement type
3	PL	Project location (region)
4	SV	Strategic value of project
5	AD	Accuracy of the direct cost estimation
6	D	Duration of project
7	SP	Security need of project location
8	CC	Clarity and completeness of tender documents (drawings, specifications, etc.)
9	PEcompe	Previous experience of competitors on similar projects
10	PD	Type of project delivery system
11	CW	Current work load
12	IW	Immediate need for work
13	ES	Expected size of contract
14	PEcompa	Previous experience of the company on similar projects
15	ACa	Availability of cash or overdraft facility to carry out project
16	ACr	Availability of credit facility from suppliers
17	HO	Current required amount for head office overhead cost relative to the planned amount
18	NC	Number of competitors with strong desire to win a project
19	CP	Complexity of project (such as resources and technology required)
20	EC	Current state of the overall economy of the country
21	PP	Amount of possible upcoming profitable projects out for tender in the remaining fiscal year

B-3. Responses and results obtained from respondents and the developed models respectively for the 90 hypothetical bid scenarios

Item No.	Label for markup factors	Project Case-1	Project Case-2	Project Case-3	Project Case-4	Project Case-5	Project Case-6	Project Case-7	Project Case-8	Project Case-9
1	RW	2	2	2	3	3	1	1	3	2
2	PT	3	1	1	1	2	1	3	2	2
3	PL	2	2	2	2	1	3	1	2	2
4	SV	2	1	3	3	1	1	2	3	2
5	AD	1	2	3	1	1	3	3	2	2
6	D	1	1	2	1	1	2	3	3	3
7	SP	1	2	2	2	1	3	2	1	1
8	CC	2	3	3	3	1	1	3	3	3
9	PEcompe	2	1	2	1	1	1	2	1	1
10	PD	2	2	2	1	2	2	2	1	2
11	CW	1	2	3	2	3	3	3	1	3
12	IW	3	2	2	2	2	1	1	3	1
13	ES	3	2	1	3	3	2	2	1	1
14	PEcompa	1	3	1	2	1	2	1	2	1
15	ACa	2	3	1	3	3	3	2	2	1
16	ACr	3	2	2	2	1	2	3	2	1
17	HO	3	2	2	1	2	1	1	2	1
18	NC	2	1	1	1	1	1	3	2	3
19	CP	1	1	2	3	2	3	3	2	1
20	EC	3	1	1	2	3	3	3	3	1
21	PP	1	3	2	1	1	1	2	2	3
Bid markup size provided by respondents (%)		**25.00**	**30.00**	**40.00**	**35.00**	**38.00**	**35.00**	**34.00**	**35.00**	**35.00**
Bid markup size provided by MLR model (%)		**24.59**	**25.83**	**38.85**	**34.31**	**38.56**	**34.90**	**31.46**	**32.67**	**33.82**
Bid markup size provided by ANN model (%)		**25.37**	**29.47**	**39.84**	**32.17**	**38.33**	**34.89**	**34.81**	**34.17**	**30.99**

Item No.	Label for markup factors	Project Case-10	Project Case-11	Project Case-12	Project Case-13	Project Case-14	Project Case-15	Project Case-16	Project Case-17	Project Case-18
1	RW	1	3	1	1	1	1	2	1	1
2	PT	3	1	2	1	3	3	1	1	2
3	PL	1	2	3	1	2	3	1	3	1
4	SV	1	2	2	3	2	1	1	3	2
5	AD	3	2	3	3	2	1	1	1	1
6	D	2	3	3	3	2	3	2	3	2
7	SP	1	3	1	1	2	1	3	2	2
8	CC	3	1	3	2	2	1	2	1	2
9	PEcompe	2	1	1	3	3	1	1	3	1
10	PD	2	2	2	2	2	2	1	1	1
11	CW	3	3	1	1	3	2	1	1	1
12	IW	2	2	3	3	1	1	3	3	3
13	ES	3	3	1	3	1	1	2	1	3
14	PEcompa	1	1	1	3	1	3	3	2	3
15	ACa	3	1	2	2	1	1	2	2	2
16	ACr	2	2	2	1	2	3	1	3	3
17	HO	2	2	2	3	1	1	3	2	2
18	NC	3	3	3	3	3	2	3	1	1
19	CP	3	2	3	1	3	3	1	1	3
20	EC	1	2	2	1	1	2	1	2	2
21	PP	2	2	1	2	1	1	3	1	3
Bid markup size provided by respondents (%)		**30.00**	**36.00**	**35.00**	**23.14**	**27.95**	**28.33**	**27.33**	**25.71**	**26.19**
Bid markup size provided by MLR model (%)		**30.43**	**34.49**	**32.01**	**21.95**	**31.82**	**28.34**	**25.05**	**25.45**	**29.08**
Bid markup size provided by ANN model (%)		**33.18**	**32.99**	**33.20**	**21.19**	**28.22**	**28.82**	**24.57**	**26.56**	**25.60**

Item No.	Label for markup factors	Project Case-19	Project Case-20	Project Case-21	Project Case-22	Project Case-23	Project Case-24	Project Case-25	Project Case-26	Project Case-27
1	RW	1	3	1	2	3	2	1	2	3
2	PT	1	2	3	3	3	3	3	3	1
3	PL	3	1	2	3	2	2	3	1	2
4	SV	1	2	2	3	1	2	1	1	3
5	AD	2	1	1	3	1	1	3	1	1
6	D	2	3	2	2	3	3	3	1	1
7	SP	2	3	3	1	1	2	3	3	3
8	CC	1	3	2	2	3	1	3	2	3
9	PEcompe	1	1	3	3	1	3	3	3	1
10	PD	1	2	1	2	1	2	1	1	1
11	CW	1	1	3	2	1	1	3	2	1
12	IW	3	3	2	2	3	3	2	1	3
13	ES	2	3	2	1	2	2	3	1	2
14	PEcompa	3	2	3	1	3	3	3	2	1
15	ACa	2	2	1	1	2	1	2	1	3
16	ACr	2	3	1	1	3	3	1	3	1
17	HO	3	2	2	2	2	3	1	1	2
18	NC	2	1	2	1	3	3	1	3	3
19	CP	3	1	1	3	2	2	1	1	1
20	EC	2	3	2	3	1	1	3	2	3
21	PP	3	1	2	2	1	2	1	2	2
Bid markup size provided by respondents (%)		**25.53**	**25.81**	**28.48**	**40.00**	**16.50**	**17.00**	**15.50**	**14.00**	**35.00**
Bid markup size provided by MLR model (%)		**28.58**	**25.71**	**25.63**	**37.22**	**20.35**	**20.27**	**19.62**	**19.45**	**30.78**
Bid markup size provided by ANN model (%)		**26.99**	**25.89**	**26.09**	**38.76**	**23.03**	**18.80**	**16.90**	**16.35**	**25.40**

Item No.	Label for markup factors	Project Case-28	Project Case-29	Project Case-30	Project Case-31	Project Case-32	Project Case-33	Project Case-34	Project Case-35	Project Case-36
1	RW	3	3	3	1	2	3	2	2	1
2	PT	2	3	2	3	2	1	3	1	1
3	PL	3	2	1	2	3	1	3	1	2
4	SV	3	2	3	3	3	1	1	2	3
5	AD	1	3	2	1	1	2	1	3	3
6	D	1	2	1	1	1	2	3	2	3
7	SP	2	2	1	2	3	3	1	3	3
8	CC	3	1	2	1	1	1	2	2	1
9	PEcompe	1	1	1	3	2	2	1	1	1
10	PD	2	1	1	2	2	1	2	2	1
11	CW	2	1	3	3	1	3	2	2	1
12	IW	2	3	1	1	3	2	2	1	3
13	ES	1	3	2	3	2	1	1	2	3
14	PEcompa	2	1	2	3	2	1	2	1	3
15	ACa	2	1	3	1	3	3	2	3	2
16	ACr	1	2	3	2	1	1	2	2	3
17	HO	2	3	1	1	2	2	1	1	2
18	NC	2	1	2	1	2	1	3	1	2
19	CP	3	1	2	3	3	1	3	1	3
20	EC	2	3	2	1	2	2	1	2	3
21	PP	2	3	3	3	2	2	1	1	2
Bid markup size provided by respondents (%)		**37.00**	**30.00**	**27.00**	**36.00**	**30.00**	**35.00**	**30.00**	**28.44**	**26.69**
Bid markup size provided by MLR model (%)		**38.03**	**32.16**	**35.06**	**30.61**	**32.86**	**36.80**	**29.47**	**33.68**	**29.56**
Bid markup size provided by ANN model (%)		**38.39**	**32.77**	**27.90**	**35.14**	**28.53**	**35.67**	**29.84**	**28.95**	**21.52**

Item No.	Label for markup factors	Project Case-37	Project Case-38	Project Case-39	Project Case-40	Project Case-41	Project Case-42	Project Case-43	Project Case-44	Project Case-45
1	RW	2	1	2	1	2	3	1	3	2
2	PT	2	1	1	2	1	2	2	3	1
3	PL	3	1	2	3	1	2	3	1	2
4	SV	3	1	1	1	2	2	2	2	2
5	AD	3	2	2	3	3	1	3	3	2
6	D	3	3	3	2	3	2	1	1	3
7	SP	1	1	3	2	3	3	2	3	1
8	CC	2	1	3	2	1	2	3	2	1
9	PEcompe	3	3	2	2	3	3	1	2	2
10	PD	2	1	1	1	1	1	2	1	1
11	CW	2	2	1	3	2	3	1	2	1
12	IW	1	1	3	2	1	1	3	2	3
13	ES	2	1	3	3	2	1	2	2	3
14	PEcompa	3	3	1	2	3	3	3	2	3
15	ACa	3	3	3	2	3	2	2	2	2
16	ACr	3	3	3	3	2	2	3	2	3
17	HO	1	1	3	2	1	1	3	1	2
18	NC	2	3	2	3	2	3	3	2	1
19	CP	1	2	2	3	1	2	1	1	1
20	EC	2	1	2	1	3	2	3	3	3
21	PP	1	3	3	2	1	1	2	3	1
Bid markup size provided by respondents (%)		**21.00**	**29.00**	**26.25**	**26.69**	**21.88**	**20.00**	**20.63**	**26.56**	**20.80**
Bid markup size provided by MLR model (%)		**19.53**	**20.50**	**23.47**	**25.18**	**22.23**	**24.82**	**20.67**	**26.51**	**21.35**
Bid markup size provided by ANN model (%)		**22.72**	**28.06**	**25.34**	**25.81**	**22.49**	**19.29**	**20.12**	**20.87**	**16.96**

Item No.	Label for markup factors	Project Case-46	Project Case-47	Project Case-48	Project Case-49	Project Case-50	Project Case-51	Project Case-52	Project Case-53	Project Case-54
1	RW	3	1	3	3	1	3	3	1	2
2	PT	1	1	3	3	1	1	3	2	3
3	PL	2	1	2	1	1	3	2	3	1
4	SV	1	1	2	3	1	3	1	3	2
5	AD	3	2	3	1	1	3	3	2	1
6	D	3	1	2	1	3	2	1	2	1
7	SP	1	3	2	1	2	3	3	1	1
8	CC	1	1	2	1	1	2	1	1	1
9	PEcompe	1	2	3	3	2	3	1	2	2
10	PD	2	2	2	2	1	2	1	1	1
11	CW	2	2	2	1	3	1	3	3	3
12	IW	2	2	1	3	1	3	1	1	2
13	ES	1	1	3	3	3	3	2	3	2
14	PEcompa	2	3	1	3	1	3	3	3	1
15	ACa	3	3	2	2	1	3	1	1	3
16	ACr	3	1	2	1	3	2	1	2	2
17	HO	1	1	1	3	1	3	1	1	2
18	NC	1	3	1	2	2	1	1	3	3
19	CP	2	3	2	2	2	3	2	3	2
20	EC	1	1	3	2	2	3	2	3	1
21	PP	2	3	3	3	1	2	2	3	1
Bid markup size provided by respondents (%)		**30.00**	**30.00**	**30.00**	**25.00**	**30.00**	**25.00**	**35.00**	**35.00**	**35.00**
Bid markup size provided by MLR model (%)		**31.32**	**29.18**	**27.02**	**27.15**	**28.96**	**26.20**	**33.07**	**28.87**	**34.41**
Bid markup size provided by ANN model (%)		**34.41**	**26.19**	**25.64**	**20.60**	**29.70**	**25.72**	**33.63**	**33.38**	**33.02**

Item No.	Label for markup factors	Project Case-55	Project Case-56	Project Case-57	Project Case-58	Project Case-59	Project Case-60	Project Case-61	Project Case-62	Project Case-63
1	RW	2	1	2	3	1	1	3	2	1
2	PT	1	1	1	3	2	2	2	3	1
3	PL	3	1	2	3	1	1	2	1	1
4	SV	2	2	3	3	2	1	3	2	1
5	AD	2	1	1	2	2	2	3	3	1
6	D	1	3	1	2	3	1	3	3	1
7	SP	1	3	1	2	2	2	1	3	2
8	CC	1	3	1	1	1	2	1	1	2
9	PEcompe	1	2	1	2	1	1	1	3	1
10	PD	2	1	1	1	1	1	2	2	1
11	CW	3	1	2	2	1	2	2	2	3
12	IW	1	3	1	1	3	1	1	2	2
13	ES	1	2	1	1	1	1	2	1	1
14	PEcompa	1	1	2	3	1	1	2	2	1
15	ACa	1	1	1	3	1	1	1	1	2
16	ACr	3	2	3	2	3	3	2	2	1
17	HO	1	3	1	1	3	1	1	2	1
18	NC	2	1	3	1	3	1	2	2	3
19	CP	2	1	2	3	3	3	1	2	1
20	EC	3	1	1	3	2	1	1	3	1
21	PP	3	2	2	1	1	1	1	3	1
Bid markup size provided by respondents (%)		**35.00**	**35.00**	**35.40**	**35.00**	**35.00**	**35.00**	**32.00**	**30.00**	**35.00**
Bid markup size provided by MLR model (%)		**35.59**	**29.93**	**32.44**	**33.52**	**36.24**	**36.06**	**31.81**	**30.11**	**33.69**
Bid markup size provided by ANN model (%)		**34.11**	**30.19**	**34.76**	**35.42**	**33.79**	**34.62**	**30.10**	**28.86**	**34.24**

Item No.	Label for markup factors	Project Case-64	Project Case-65	Project Case-66	Project Case-67	Project Case-68	Project Case-69	Project Case-70	Project Case-71	Project Case-72
1	RW	3	3	3	3	1	2	2	1	1
2	PT	1	3	3	2	2	1	1	2	1
3	PL	2	3	1	2	1	3	3	1	2
4	SV	1	3	2	2	3	3	3	1	3
5	AD	1	1	1	2	1	2	1	3	1
6	D	1	3	1	1	1	1	3	1	1
7	SP	2	1	2	2	3	1	1	1	3
8	CC	1	2	3	1	3	3	2	1	2
9	PEcompe	1	1	3	3	3	2	2	1	3
10	PD	2	1	2	1	2	2	2	2	2
11	CW	2	3	1	1	1	1	2	2	2
12	IW	1	1	3	3	3	3	2	1	2
13	ES	3	1	1	2	3	2	2	3	3
14	PEcompa	3	2	1	3	1	3	1	2	1
15	ACa	3	1	1	3	3	3	1	1	3
16	ACr	2	2	1	3	3	1	2	1	3
17	HO	1	1	2	3	3	2	1	1	1
18	NC	2	2	1	1	1	2	1	1	1
19	CP	1	2	2	1	3	3	1	1	3
20	EC	2	1	1	3	1	3	1	3	2
21	PP	2	1	3	1	1	3	2	1	3
Bid markup size provided by respondents (%)		**25.00**	**35.00**	**30.00**	**25.00**	**30.00**	**25.00**	**30.00**	**30.00**	**30.00**
Bid markup size provided by MLR model (%)		**22.97**	**36.20**	**31.25**	**21.56**	**30.45**	**28.36**	**30.71**	**29.94**	**30.02**
Bid markup size provided by ANN model (%)		**17.52**	**34.08**	**31.89**	**21.00**	**28.67**	**24.66**	**30.50**	**29.44**	**28.64**

Item No.	Label for markup factors	Project Case-73	Project Case-74	Project Case-75	Project Case-76	Project Case-77	Project Case-78	Project Case-79	Project Case-80	Project Case-81
1	RW	2	2	1	1	1	3	2	3	3
2	PT	2	3	2	1	3	2	1	3	2
3	PL	3	1	2	2	1	2	2	3	1
4	SV	1	2	3	1	1	1	3	1	1
5	AD	3	1	2	2	1	1	3	1	3
6	D	2	3	2	3	3	2	1	3	1
7	SP	1	1	3	1	2	1	1	2	3
8	CC	1	1	2	3	2	1	2	2	3
9	PEcompe	2	3	2	3	3	1	2	1	3
10	PD	2	1	2	2	2	2	2	1	2
11	CW	3	3	1	3	3	2	3	2	2
12	IW	1	2	3	2	2	1	1	1	2
13	ES	2	3	2	2	3	1	1	1	1
14	PEcompa	2	3	3	2	2	1	1	3	2
15	ACa	1	3	2	1	1	2	2	1	2
16	ACr	3	1	2	2	3	3	2	3	1
17	HO	1	1	3	2	2	1	1	1	2
18	NC	2	3	2	2	3	1	1	1	3
19	CP	1	2	1	1	1	2	3	3	1
20	EC	2	2	2	1	3	3	2	1	1
21	PP	1	3	2	1	2	1	1	2	3
Bid markup size provided by respondents (%)		**17.00**	**22.00**	**23.00**	**20.00**	**22.00**	**35.00**	**40.00**	**30.00**	**22.00**
Bid markup size provided by MLR model (%)		**23.77**	**25.16**	**25.72**	**22.87**	**19.84**	**33.67**	**40.81**	**29.06**	**23.15**
Bid markup size provided by ANN model (%)		**19.46**	**22.53**	**22.95**	**21.21**	**22.73**	**34.57**	**38.47**	**29.93**	**22.22**

Item No.	Label for markup factors	Project Case-82	Project Case-83	Project Case-84	Project Case-85	Project Case-86	Project Case-87	Project Case-88	Project Case-89	Project Case-90
1	RW	3	3	3	1	2	3	3	2	2
2	PT	2	1	3	1	2	3	3	3	1
3	PL	3	2	1	2	2	2	2	1	1
4	SV	2	2	1	1	3	1	2	2	1
5	AD	3	3	1	1	1	2	3	2	2
6	D	3	2	3	1	1	3	2	1	3
7	SP	1	3	1	2	3	1	2	3	1
8	CC	1	3	2	2	2	2	3	2	1
9	PEcompe	2	2	2	3	1	2	1	1	3
10	PD	1	1	1	2	1	2	1	1	1
11	CW	1	1	2	1	3	2	1	2	2
12	IW	3	3	2	3	1	2	3	1	1
13	ES	3	3	1	2	3	1	2	1	3
14	PEcompa	3	1	3	3	2	1	3	3	3
15	ACa	1	3	3	3	2	2	1	2	3
16	ACr	3	3	3	1	3	3	1	2	1
17	HO	2	3	2	3	1	1	3	1	1
18	NC	2	3	1	1	2	3	2	2	1
19	CP	3	1	1	3	3	2	3	1	3
20	EC	2	3	3	2	2	3	3	2	3
21	PP	1	1	2	3	1	1	2	3	1
Bid markup size provided by respondents (%)		**25.00**	**20.00**	**30.00**	**25.00**	**30.00**	**32.00**	**25.00**	**35.00**	**20.00**
Bid markup size provided by MLR model (%)		**23.03**	**21.71**	**25.16**	**26.10**	**34.44**	**31.22**	**31.61**	**31.82**	**25.71**
Bid markup size provided by ANN model (%)		**23.23**	**20.75**	**31.28**	**25.43**	**35.09**	**26.61**	**28.29**	**32.64**	**23.32**

C. MATLAB SCRIPT FOR THE DEVELOPED ANN MODEL

```
% Solve an Input-Output Fitting problem with a Neural Network
% Script generated by Neural Fitting app
% Created 28-Nov-2019 13:27:06
%
% This script assumes these variables are defined:
%
%   input_matrix - input data.
%   output_matrix - target data.

x = input_matrix;
t = output_matrix;

% Choose a Training Function
% For a list of all training functions type: help nntrain
% 'trainlm' is usually fastest.
% 'trainbr' takes longer but may be better for challenging problems.
% 'trainscg' uses less memory. Suitable in low memory situations.
trainFcn = 'trainlm';  % Levenberg-Marquardt backpropagation.

% Create a Fitting Network
hiddenLayerSize = 8;
net = fitnet(hiddenLayerSize,trainFcn);

% Setup Division of Data for Training, Validation, Testing
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 15/100;
net.divideParam.testRatio = 15/100;

% Train the Network
[net,tr] = train(net,x,t);

% Test the Network
```

```
y = net(x);
e = gsubtract(t,y);
performance = perform(net,t,y)

% View the Network
view(net)

% Plots
% Uncomment these lines to enable various plots.
%figure, plotperform(tr)
%figure, plottrainstate(tr)
%figure, ploterrhist(e)
%figure, plotregression(t,y)
%figure, plotfit(net,x,t)
```

DECLARATION

I, the undersigned, declare that this thesis is my original work and has not been presented for a degree in any other university. All sources of materials used for the thesis have been duly acknowledged.

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