NEURAL NETWORK-BASED COST PREDICTIVE MODEL FOR BUILDING WORKS.

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Abstract

Neural Network Based Predictive Cost Model for Building Works.

A number of uncompleted and abandoned building projects are attributable to overall bad projects management. Determination of accurate cost of building projects is a huge factor in successful project management. This work is to ensure that accurate cost is determined and accurate as much as possible. Artificial neural network was used in this work to generate a cost predicting model. Neural network is a human brain simulated system having similar characteristic with human brain. This study entails using the strengths of neural network such as back-propagation effects, consistent output, less margin error, stable output and good processing speed, to develop a stable predictive cost models for building works. Data on building projects' cost parameters were grouped into work packets and fed into Back elimination neural network with levenberg-marqua set at 1000 epoch, to train the data and model generation. The model generated was cross- validated with step-wise regression technique, and re-sampling method was applied to establish the model's degree of stability. This model has relative average efficiency of 0.763 and coefficient of performance of 1.311 and average mean square error (M.S.E) of 0.01136, the MSE is an index used to measure when well fitted output is obtained to avoid output over fitting. In addition to the model generated, project cost influence matrix, risk-probability matrix and cost expectancy limit were formulated in this research work to enhance the models' validity and stability. It is hoped that a stable model will lead to a stable cost, firmly established to ensure adequate funding for project delivery.

Dedication

The initialization of the concepts presented in this thesis originated from the Almighty God, the custodian of knowledge, idea and wisdom. Therefore the work is dedicated to God the father, the son and the Holy Spirit. I also dedicate the work to my earthly father, Alhadjhi Mohammad-Ahmad A. Amusan and mother Mrs. Shilat Mohammad-Ahmad for their investment and labor on my life right from birth and their understanding when the great salvation call was answered.

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Certification

This Thesis entitled: Neural Network Based Cost Predictive Model for Building Works, by Amusan Lekan Murtala, meets the regulation governing the award of the degree of Doctor of Philosophy, of Covenant University, and is approved for its contribution to knowledge and literary presentation.

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CHAPTER ONE

INTRODUCTION

1.1 Background to the Research

A number of uncompleted and abandoned projects are attributable to overall bad projects management of which poor forecasting approach is a factor. Poor cost forecasting approach often leads to underestimation and inadequate fund which often culminates into project abandonment. Project abandonment because of cost overrun arising from poor cost forecasting approach, is an interesting phenomenon locally as well as globally.

The awareness of this phenomenon has resulted in various stakeholders in the built environment being aware of the importance of accurate project cost right from conceptual stage to the entire life cycle of the building projects. The awareness of working with accurate cost has thus created a trend among various clients including private, corporate, as well as public clients (government), that prudency in resources allocation is a great necessity for successful execution of project works (Mosaku and Kuroshi, 2008; Hegazy *et al.*, 1993, Murtaza and Fisher, 1994; Moselhi *et al.*, 1994; Jain *et al.*, 2002). Thus in a bid to have an appreciation of what the project cost should be, clients resort to request for cost implications of various aspect of the project for purpose of planning, also to have better appreciation of the magnitude of project cost and environmental cost implication of the project as well as impact of the projects financial implication on client's and other stakeholders' decisions. This development led to the advent of forecasting project cost so as to generate project cost information which reveals what the value of a project cost could be in future (Jain *et al.,* 2002; Williams (1994; Kuroshi *et al.,* 2007).

However, in providing project cost information, cost estimator often resorts to using traditional approach. Recent developments on the other hand had proven the fact that traditional approach, which uses historical information do not tend to capture the details of project cost components, as well as intervening variables that influence the cost magnitude. Without gainsaying, once the process is faulty, the result cannot be anything less than an incomplete account of project's cost and cost overrun.

Also, there are certain suspected factors (client type on a project, builders liability, Industry related factors, external factors, projects related issues and organizational factors) that can influence project cost in addition to the cost determination strategy adapted, to the extent of instigating cost overrun on project work, that should be reviewed, if issue of project cost determination would be appraised holistically.

There are different types of client obtainable in construction project works. They include public clients, private clients and corporate clients. Public clients refer to Government, including local and civil government, who has capacity to contract jobs out, having been empowered by the law of the land. Private clients on the other hand refer to an individual with financial capability to build and hire the professional that could get the work accomplished. Such financial base could be sourced through personal savings, fund sourcing organizations (e.g. Breton-wood institutions, including loan and overdraft from mortgage banks. Corporate clients are those clients that are not an individual but a collection of people, organizations, who have come together to pursue a common goals, with such association guided by an article of agreement, business mission statement as well as a memorandum of agreement (Kumaraswamy *et al.,* 2005).

Clients could be liable to having contributory effect to project cost overrun. They could also be culpable because of their inability to release funds on time for project. So also, clients can decide to execute project based on priority (funding only project with highest priority). Prioritization of projects however could be because of the order of importance attached to the concerned projects by the clients in the light of its social as well as economical importance; which can lead to client's contribution to cost overrun on sites. The prejudice of the client, negotiation ability and as well as extent of client's knowledge about construction could also affect the cost incurred on a project work (Kousky *et al.,* 2005; Kiang *et al.*, 2004)

Also, Builders' project in-experience vis-a-vis bad site management practice could also be responsible for project cost overrun. Builders should have well-articulated clients' initial brief, identified projects' bottle necks that could result in resources wastage, as well as establishing long term, short term and medium term planning program. This would help in ensuring up-to-date monitoring of project progress in order to prevent project cost overrun (Kiang *et al.,* 2004; Nargundkar and Priestly, 2004).

Project related issues such as project characteristics are also among the suspected factors that could be responsible for project cost overrun. These include contract variations, site conditions force- majeure, architect- client- team related issues, construction methods, supervision skill and capability, accidents and personnel. Project types and the procurement systems engaged could be used to describe project characteristics (Ogunlana *et al.,* 1996; Kousky *et al.*, 2005).

Project types could be private accommodation, office development, religions buildings, educational facilities, finance houses, industrial and social facilities. Procurement system that could be used in project execution includes direct labor; labor only method, design and build, traditional methods among others. The choice of procurement system often largely determines the extent of gain or loss incurable on a project. Therefore, the structure of a procurement system should be such that would prevent incurring unnecessary cost on site, thus, procurement system with slackened cost control strategy could lead project client to debt (Hegazy, 2006; Hu *et al.,* 2004.

Furthermore, contract variation is another factor worth considering. The relationship between initial budgeted project cost and final project completion cost follows law of inverse proportion. The higher the amount of variations incurred the lower the initial budgeted cost to actual final construction cost. So also, the prevailing site conditions can be the type that could warrant incurring an extra cost in form of remedial work or unbudgeted special provision of services or equipment; this has the potential of altering the cost of completion as initially programmed especially when it is not planned (Ogunlana *et al.*, 1996; Kousky *et al.*, 2005).

There is tendency to expend more on a project as a result of wrong construction methods as well as poor supervision skills. These can lead to call for opening up of section of work for inspection on which instruction could be passed authorizing a rework. This could results into incurring an extra cost. Situation could arise, that accident would occur either naturally, which is often refer to as “force majeure or act of God” or man-made, any of such incidents, like earthquakes, ground subsidence can lead to expending money beyond budgeted limit (Hegazy 2006). In the same vein, organizational factors are other group of factors that impacts cost, amongst which are firms characteristics, size of firms to engage the project works, evidence of past performance that testifies of capability to engage new projects, personnel skills, Health and safety, and magnitudes of companies overhead (John *et al.,* 2001; Jamshid 2005).

Industry related factor can also influence cost, this is about standards and permits obtainable on site, vis-a vis industrial regulations and standards. Certain permits needs to be procured before the commencement of project work, such as stacking permits-which confers on the holder the right to pool together material resources needed for successful execution of project works on site. Other types of permits are: reinforcement permit, formwork permit, scaffolding permit, safety and health permit, excavation permit and work permit. However, there is tendency for progressive review of charges attached to these permits, since they are subject to review as a result of changing economical parameters like inflations that determines their fixtures. These elements of instability in their costs can cause cost overrun, this is possible if there is review of one or many of the permits before the completion of the work (Al Tabatabai *et al.,* 2006; Anderson *et al.,* 1993). Finally, other factors that are extraneous to the project environment regarded as external factors, could also contribute to cost overrun; these factors are branded as external factors; some of the factors includes: economic environment, macro and microenvironment (standard regulations), political environment, social environment and technological environment (Bendert 2003;Bhoka and Ogunlana 1994).

Against this background, this research work has developed a model that could be used in project cost forecasting, taking into consideration certain variables, aimed at ensuring timely prediction of project costs, and serve as an early warning system. The cost elements used in the model development were stabilized with Artificial Neural network, and then used as model's weight (developed model), while the input parameters (cost elements) were derived from completed project works data, rather than pro-rata cost.

1.2 Statement of the Research Problem

Most firms, corporate organizations as well as individual clients cannot ignore the responsibility of project cost issues that concern them. Among the project cost issues, is completing project work at specified cost. In order to achieve this, an advanced cost determination framework is required for a system that would enable the cost to be determined before the commencement of the project work; and would ensure continuous monitoring of project expenditure against benchmarked limit of expenditure. Therefore, the development of advanced cost determination frameworks, for purpose of cost prediction as well as implementation of such an advanced system are therefore important issues in project work costs predicting. One of the decisive elements in project cost predicting system is the setting of measurement objectives and targets. There is therefore a corresponding need to develop good project management programme to ensure that the objectives and target set are achieved and the tool to measure them is adequate (Behlin 2001, Chester, 1993).

Recent developments on improved ways of determining project cost, have led to criticisms that traditional cost determination framework which focuses on the measurement and estimating of project cost using historical information often provides an incomplete account of a project' cost (Ogunlana *et al.,* 1996; Kousky *et al.,* 2005) David and Seah, 2004). Project cost using historical cost which are pro-rate based, does not report the variations and interplay of economic variables that impact cost. This makes it difficult to obtain accurate project cost through prediction of what the future value of such project cost should be. So also, research outputs in the past had shown that parametric model estimation such as regression method has variation error greater than 7% between expected output and derived output, while Expert system such as Neural networks gives prediction variation errors within range of 3%

to 4% (David and Seah, 2004; Dissanayaka *et al.*, 2007; Moore *et al.*, 1999). Information relating to interplay of variations and economic variables are not always captured using historical approach, and any prediction that is based on this might not be accurate. Therefore, developing a robust model that can incorporate economic and environmental parameters that is capable of generating an accurate project cost is important (Ogunlana *et al.*, 1996; Kousky *et al.*, 2005 Dissanayaka *et al.*, 2007; Moore *et al.*, 1999).

To achieve this, the following were determined: the extent of application of cost models in use by cost expert with a view to establishing their suitability and identifying parameters (cost centers) that can be used as input data in Neural network-based model that would be generated. Also, the extent to which the cost centers influences project cost was ascertained, and interoperability of factors that could influence variation of total expended cost and initially budgeted cost of a building projects, factoring cost center influence on project cost and development of cost impact matrix for the developed model, and formulating impact matrix of risk probability for cost components of building projects used in cost prediction model development.

1.3 Research Questions

The research work attempted providing answers to the following questions:

(i) To what extent is the interoperability of input parameters that will produce a stabilized neural network-based cost predicting model and what is the extent of application of cost model in project cost prediction?

(ii) How feasible is the development of a stabilized neural network-based model that could be used in project cost prediction at different stages of building work?

(iii) Is the development of a system that can provide projects cost early warning system feasible?

(iv) Is it possible to factor influence of cost center component on project cost and develop cost impact on project costs?

(v) How feasible is the formulation of influence, cost expectancy limit and impact matrix of risk probability for cost components of building projects types used in cost prediction model development?

1.4 Aim and Objectives of the Research Work

The aim of this research is to develop a cost predictive model based on Artificial Neural Network, which could be used for project cost prediction at early and latter stage of building works with minimum variation error. The objectives of this study are to:-

(i) identify parameters (cost centers) that can be used as input data and their interoperability with total construction cost in neural network based model formation, also to evaluate the practice and application of cost models in use by cost experts with a view to establishing their suitability and extent of use.

(ii) develop neural networks' cost optimization variables' stabilized models that could be used in predicting project costs at initial, as work progresses and latter stages of construction works.

(iii) make available, a system that can provide projects cost early warning system in order to prevent project cost overrun or underestimation.

(iv) factorize cost center influence on project cost and developing cost impact matrix for the developed model.

(v) formulate cost expectancy limit and impact matrix of risk probability for cost components of building projects used in cost prediction model development.

1.5 Significance of the Study

The variable nature of project costs could be attributed to different factors: clients induced factors, project environment; industry related factors, organization factors, as well as project related factors. The combination of one or many of these factors has the potential of determining the nature of end value of a project cost. So also, the magnitude of cost overrun experience on a project could also be dependent on the clients type, project type, procurement system, economic variables (macro and micro variable), as well as variations instigated on account of the design team. There is tendency for one or more of these parameters to affect the projects configuration (in terms of project cost elements). To be able to appreciate the impact of these parameters on the magnitude of the project cost elements the relationship between the mentioned parameters and the budgeted cost as well as final construction cost of a project should be appraised holistically. Expending more than initial budgeted cost on a project work is subjective in nature. The variation could be as a result of project's client, project type, project location, economic variables, or variations instigated on account of project team's personal interest. These variables need to be appraised, to provide right solution to preventing project cost variation on project sites.

Furthermore, it is possible for clearly defined relationship to exist among the variables in terms of margin of valued variations. The cross examination of variations among the data enabled this to be achieved. It was determined through discovering pattern or direction of the speculated relationship. However, in modeling, there is a need to adopt the best modeling approach, which could be applied to model the parameters, and opinion differs on absolute data modeling approach. There are different schools of thought as far as issue of selecting an appropriate modeling approach is concerned in cost prediction, some of the school of thoughts include: The traditional and conventional approach. A school of thought believes that traditional approach to cost modeling does not always capture the details of costs; it gives poor representation of costs. The reason lies in their inability in modeling costs the way they are incurred (Seeley 1996 and Raftery 1993). Traditional models relies on historic data as input in generating cost, this greatly impedes their suitability for present day cost modeling (Seeley, 1996; Raftrey, 1993; Skitmore and Ng, 2003). Models such as superficial, unit rate, and approximate quantities were the most popular amongst cost experts, which were examples of traditional models. They rely strictly on historical cost data in generating cost output (Seeley, 1996; Skitmore and Ng, 2003; Ogunsemi and Fasorabanku, 2000).

Inability of cost advisers in using correct approach in cost advising however, could lead to clients being unable to obtain value-for-money on their investments. On the other hand, this was amongst the reasons advanced for cost overrun and construction cost escalation in Nigeria. For instance, Boussabaine and Cheernahm (1997); Mosaku and Kuroshi, (2008); Flood and Kartam (1994a) submitted that cost overrun and construction cost escalation could occur at pre-contract and feasibility study stages of construction works. However, by feeding the relevant basic and easily accessible data into a typical cost model, a stable output in the form of cost estimate could be generated (Odusami and Olusanya, 2000; Ogunsemi and Jagboro, 2006; Oyediran,2001).

In the light of the antecedents, many cost researchers have suggested that present methods that relates to traditional approach in cost determination do not guarantee a consistent estimate, which is capable of being used in forecasting the future trend of such estimate. Traditional approach lacks capacity for studying data trend; therefore could not be absolutely relied upon in cost estimating and prediction (Boussabaine and Cheernahn, 1997; Flood and Kartam, 1994; Meijer, 2000a; Williams, 1994). Overreliance on historic cost data will undoubtedly lead to erroneous conclusion as far as issue of project cost determination and predicting is concerned (Ogunsemi and Jagboro 2006; Boussabaine, 1997). It is therefore against this background, that this research work developed a cost-forecasting model, based on the impact generated on the project cost elements by the cost optimization variables. The cost elements having been stabilized with artificial neural network formed the model's weight, with input parameters based on data from live project works, rather than historical-pro-rata data.

1.6 Summary of Research Methodology

This research work utilized the content analysis technique, which is a research technique for making replicable and valid inference from data contained in data-source documents from which data is to be extracted, for model development. The study used both primary and secondary data in eliciting the required information needed for this research. The secondary data was obtained from the bill of quantities of completed projects; the cost parameters extracted from the document were standardized by adjusting with price index, price index incorporates an uncertainty buffer that neutralizes negative effects of economic variables that can cause uncertainty in cost output, inflation factor and corruption escalator factor.

1.7 Research Tools

The basic tools in this research work are project cost document (Bill of quantities) and Oral interview to obtain the final project completion cost.

1.8 Method of Data Analysis

The following tasks were carried out in this section: The quantitative data were analyzed with descriptive statistics (univariate analysis), using means, frequencies, percentages, and proportions. Cross tabulation and test of association were used to determine existing relationship among model and result was presented in tables and charts. The strength and direction of the relationship between the model parameters was also analyzed using content analysis as well as the bi-variate and multivariate analysis with the aid of Pearson product moment correlation.

1.9 Research Design

This research work used Survey design style. So also, information that pertains to project cost parameters such as project type, project location, initial budgeted construction cost, completion cost, average floor area, total floor area, average storey height, total building height, and number of storey above ground level were collected through Bill of quantities and Oral interview of project cost experts of selected completed building project works.

1.10 Research Data Sets

This research work used two sets of data; first group of data was collected for model development, while the second group of data was used in models' validation. The data consist of project cost centers. The construction cost of building elements here, often refer to cost parameters or cost centers. Model parameters used consist of cost centers extracted from the Bill of quantities of building projects completed within the last 4years. However, the extracted costs were adjusted with construction price index, inflation factor and corruption escalator factor in order to generate an optimized value.

1.11 Research Population

The population constituent was categorized along the line of storey height and building project types. The Population frame of 500 public and private building projects, reinforced concrete and in-situ concrete structures was used

1.12 Sample and Sampling Technique

This study used probability sampling technique, while 440 samples were selected through random-sampling method.

1.13 Sampling Frame

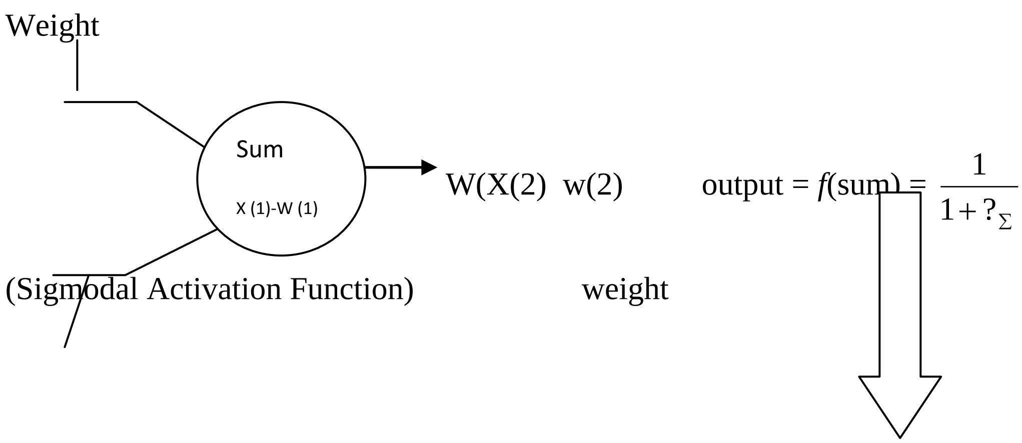
The sampling frame was divided into two; sampling frame for model development and sampling frame for model validation. The Bills of quantities of completed building works was classified as sample obtainable, in sampling frame for model development. Meanwhile, samples obtained here were used in model development and validation.

1.14 Sample Size

Data was categorized into two sets in order to have equal representation of various elements of samples in this research work. First category of data was used for model development via Artificial Neural Networks. The second category of data however was used in model generation and validation. As a result of peculiar nature of task to be carried out here, a total of 500 samples were used in this case, this was further divided into two halves, 200 samples out of 350 samples were used for model development while the other half (150) samples were also used for model validation.

1.15 Proposed Neural Network Based Building Cost Model.

Models were generated for predicting cost of building works (office and residential buildings) using Artificial Neural Networks. The choice of Neural network as an inter-phase in the generation of model predicting parameters lies in its good attributes such as; little margin error in computation, good data processing speed, and capacity for large data input. Two techniques, Genetic algorithm and Back-propagation training were used to determine the optimum neural network models. The resulting optimum model data were analyzed with Microsoft Excel to produce some visual effect with the aid of radar diagram and composite bars and in a user-friendly program to predict the outcome of new cases when presented with cost optimization variables.



$$\frac{e^{xi}}{\sum_{j-1}^{c} e^{xj}} \quad Ct = X_1W_1 \; + X_2W_2 ....X_{n-1}W_{n-1}$$

$$C_t = \sum {}_{ce} CW_1$$

Fig 1. Sigmoid Activation Function

1.16 Scope of Study

The model to be generated is limited to cost prediction of Building works. To be able to cover the axis of work above, this study achieved two distinct tasks: studying models currently in use to have proper appreciation of state of knowledge and to identify gap and bridging the gap as well as developing a neural network based model. The location of the research work was building project sites in South Western and Federal Capital Territory in Federal Republic of Nigeria.

The research work was restricted to developing a cost prediction tool, this was carried out with the aid of artificial/neural network generated output; the output data was used as parameter for the input modem or neuron of the model that was developed. The data of completed building projects of 1 to 4 years were used to formulate an input data. This method is regarded as right, since recent information about the building was captured and the econometric variables that could impacts the building cost were properly factored into the data for processing. Residential and office building projects completed within the period that fell between pre and post-economic meltdown period were used, along the line of reinforced concrete, In-situ concrete structures for this research work; this was to ensure effective capture of variables as it relates to various building types.

a. Current State of Cost Models in Use.

This research work studied the state of art in models application in building works, establishing their suitability, ascertain the extent to which the cost centers influences project cost and study of factors that could influence variation of total completion cost from initially budgeted cost of a building project.

b. Model Development using Identified Cost Parameters.

Information on project cost parameters was obtained from construction firms, contractors and clients (individual, private, corporate and public). The development of the model is predicated on use of information on project design cost parameters contained in design documents; these variables are those that are exclusively relevant to the project design and configuration. Cost parameter variables such as floor area, wall area, roof area, wall-to-wall height ratio substructures including cost of various elements and other variables. The samples were divided into two forms; the samples that were used for data training with the aid of Neural network till a stable pattern was obtained and in model development while the second set of samples were used to test the model's stability and robustness.

Project clients, cost advisers and construction professionals were sourced from construction sites in South western, Northern and Southern part of the Federal Republic of Nigeria, to give the equal representation of locations within the geo-political entity. Project's client is adjudged as one of the right sources of information, mainly for influential role he plays in providing design configuration information during design stage, and construction professionals are in right position to supply project related information at post design stage of construction works. These places are notable with largest concentration of development projects in Nigeria (Bamisile, 2004; Olalokun, 1987).

1.17 Definition of Terms

(i) **Abstraction (Mental Model)**: Mental models are models that are ill-structured representation of reality that cannot be felt or touched physically. That is, they lack physical or symbolic configuration. These type of models involve high level of creative imagination, they are unclear image of complex objects that have not been finalized. Summarily, abstract or mental models require high level of abstraction or creative ability.

(ii) **Boltzman Machine**: The Boltzmann machine can be thought of as a noisy Hopfield network. Invented by Geoff Hinton and Terry Sejnowski in 1985, the Boltzmann machine is important because it is one of the first neural networks to demonstrate learning of latent variables (hidden units). Boltzmann machine learning was at first slow to simulate, but the contrastive divergence algorithm of Geoff Hinton (2000) allows models such as Boltzmann machines and products of experts to be trained much faster.

(iii) **Committee of Machine (Come)**: A committee of machine (CoM) is a collection of different neural networks that together “vote” on a given example (Davies, 1994a). This generally gives a much better result compared to other neural network models. In fact, in many cases, starting with the same architecture and training but using different initial random weight gives vastly different networks. A CoM tends to stabilize the result.

The CoM is similar to the general machine learning bagging method, except that the necessary variety of machine in the committee is obtained by training from different random starting weights rather than training on different randomly selected subsets of the training data.

(iv) **Cost Parameters**: Cost parameters are the items in design documents upon which financial decision is usually based.

(iv) **Data Validation**: The output generated need to be validated, in order to test the output against established performance criteria and record the test performance. The information could be used in remolding, restructuring and demodulation. Once the stability of the generated output had been confirmed, the forecast result could be treated as model that could later be developed and abstracted for further use.

(v) **Data Training**: In this research, the two terms "training" and "learning" are used interchangeably. Training (or learning) is the process by which the weights and biases are initialized randomly. It deals with splitting the samples prior to feeding them to the networks. These also include the algorithm used for minimizing the system error, and criteria for stopping training.

(vi) **Estimates**: This refers to financial judgment made on design based on figure, texts, for purpose of construction works.

(vii) **Forecasting**: Forecasting and prediction are often used interchangeably; forecasting can be defined as the process of predicting future events. It may mean projecting into the future through examining past experiences or combination of a quantitative model and manager's good judgment

(ix) **Feed Forward Neural Machine**: The feed forward neural was the first and arguably simplest type of artificial neural network devised. In this network, the information moves in only one direction, forward, from the input nodes, through the hidden nodes (if any) and to the output nodes. There are no cycles or loops in the network.

(x) **Heuristics Model**: Heuristic model, according to Ashworth (1994) could be described as search procedures, which intelligently move from one solution point to another with the goal of improving on the value of the model objective. When no further improvement can be achieved, the best attained solution is the approximate solution to the model.

(xii) **Intrinsic Factors**: These factors are regarded as those that have direct influence on the building costs. They are features related. Here, reference is to these types of building features: height, building size, foundation depth, types of foundation used, storey height, roof pitch, building shape and host of others, building features such as these influences costs.

(Xiii) **Local Minima**: Is the presence of more than one valley in the error surface that yields a potential problem, i.e. the error function is at a local minimum rather than at the global minimum. Given a specific data set, the probability with which a local minimum exist goes down rapidly as the number of weights in the network increase. It is very likely to eliminate the existence of local minima for a network of a certain size by adding more hidden nodes.

(xiv) **Noise**: Includes inaccuracies because the independent variables do not contain all the information needed to determine the dependent variable, other factors that are not included in the model may play an important role. In other words, noise is not an inherent randomness or absence of causality in the world, rather, it is the effect of missing (or inaccuracies) the information about the world.

(xv) **Mapping**: This error occurs when mapping function does not have the same form as the target function.

(xvi) **Model**: A model can be described as simplified representation of complex reality.

Vermande *et al.,* (2000) describes a model as system that use simple inexpensive object to represent complex or uncertain situations. The system that makes use of this is termed modeling. To this end therefore, modeling is the process of converting complex real life problem situation to simple representation of the problem situation (See also Adedayo *et al.*, 2006)

(xvii) **Neural Networks**: ANNs are computational devices constructed from a large number of parallel processing devices. Individually, the neurons perform trivial functions, but collectively, they are capable of solving very complicated problems. In other words, they are capable of learning from example, can infer solutions to problems beyond those to which they are exposed during training. They can provide meaningful answers even when the data to be processed include errors or are incomplete. They can process information extremely rapidly (Gagarin *et al,* 1999).

(xvi) **Process Based Data**: In process- based approach, components of Building are systematically arranged against a pre-established configuration. The building components measurements are extracted for use, this therefore provides a uniform point of reference, and thus, the way building components are configured tends to dictate the order to follow during the process of their cost determination. The uniform configuration pattern therefore enables easy replication of various components and the corresponding determination of their various costs. The data generated through this approach is process based data.

(xvii) **Primary Data**: Primary data is a subdivision under data types; it refers to category of data obtained from direct source, such as data from interview, field survey e.t.c

(xviii) **Resources**: This refers to the items required in executing construction works such as plants, equipment, machines, money and work force.

(xix) **Sample Size**: Sample size is the magnitude of samples that is to be used in carrying out research works.

(xx) **Secondary Data**: These are data other than primary data often collected from collated sources. Such data is obtainable from collated sources which are usually in retrieval form such as Journals, Magazine, Textbooks, Periodical, and Gazette among others.

CHAPTER TWO

OVERVIEW OF CONSTRUCTION COST OVERRUN, FORECASTING MODELS AND NEURAL NETWORKS.

2.1 Introduction

This chapter provides a review of relevant literature on concept of cost as it relates to building works. It provides insight into factors that cause cost overrun in building works, relationship among cost overrun factors, physical and monetary impacts of the factors on projects' budgeted costs. Also, Neural network cost optimization model, that would be used in predicting project costs, practice and application of cost models in use by cost experts, and the cost parameters that can be used as input data in Neural Network based cost model are discussed.

2.2 Cost Overrun Factors in Building Works

Ogunsemi and Jagboro (2006) examined Time-cost modeling for building projects in Nigeria. They attributed the overrun to wrong cost estimation method adopted at the early stage of the building projects. The study was carried out by using the cost data of 87 completed building projects. Data of such projects within the period between 1991 and 2000 were used. The data were obtained from six major cities of Southwestern Nigeria: Lagos, Akure, Ibadan, Abeokuta, Ado-ekiti and Oshogbo. These are regarded as areas with largest concentration of building projects in Nigeria. As part of the work, the study identified the reason for cost overrun on building projects as wrong use of cost estimation method at early stage of the building projects. The study concluded with developing a time-cost model for building projects that is a step ahead of Bromilows models previously in use in determining project duration that would help in avoiding cost overrun. The study identified project cost related factors as the major source of project cost overrun. However, other factors that have potential to induce cost overrun such as: external related factors, industry related factors, organizational factors, as well as client type on a project work, were not part of the scope of the work, which this study reviewed. Moreover, the study stated that the model developed was very suitable, in predicting building projects' cost at early stage of work. So also 87 samples were used to generate the model, however, in this research work, 500 samples were used in model generation and validation to enhance its stability.

Koushki *et al.,* (2004) studied delays and cost increase in the construction of private projects in Kuwait, using a personal interview survey of 450 randomly selected private residential project owned and developed in 27 representative districts in metropolitan Kuwait. The study in conclusion, identified the major factor contributing to the sampled projects' time and cost overrun as composed of three main parts: insufficient time allocated to project design phase, material related problems and owners' financial constraints as the three factors contributing to cost overrun. However, the scope of the study did not cover other factors that have potential to induce cost overrun such as: external related factors, industry related factors, organizational factors, as well as client type on a project work, this study attempted at filling the identified gap with over viewing of the factors.

Similarly, Ogunlana *et al.,* (1996) studied construction delay in fast growing economy: comparing Thailand with other economies. The study researched into causes of cost overrun, using Thailand project as a case study of a developing economy. The study involved appraisal of cost overrun survey as experienced in the construction of 400 high-rise building projects in Bangkok, Thailand. The researchers discovered that projects were rarely finished on time and within allocated budget, 85 out of 140 questionnaires were used in collating responses from project team members of selected projects. The outcome of the questionnaire analysis indicates that factors that accounts for cost overrun in developing world can be categorized into three major groups: inadequacy of resource supplies, client and consultant shortcomings, and contractors' incompetence.

The study noted that one of the most serious problems the Nigeria construction industry was faced with is the project cost overrun, with attendant consequence of completing projects at sums higher than the initial sum. The study concluded by stating that resource supply problems were by far the most acute problems of the Thai Construction industry, which is reflective of problem common with developing countries including Nigeria.

However, scope of the research work did not include other issues that can influence project cost adversely, such as: project related issues, organizational related issues, project economic variables; industry related issues, as well as external factors. Such issues need to be examined and investigated if the factors that produces cost overrun will be appraised from a holistic perspective.

2.3 Cost Overrun Factors Relationships

In this section factors that instigates cost overrun on sites were studied with respect to their interrelationship, drawing strength from submissions of different authors. Elinwa *et al.*, (2006) studied time-cost overrun in building projects, executed in Nigeria, using seventy-two (72) questionnaires distributed among building construction professionals of up to 20 years in public or private sector as consultants and contractors. They categorized projects used for the study, into large, small size, corporate bodies and private developers. Twenty- three factors were identified through the questionnaires and this formed basis for the discussions on factors that may lead to overrun in cost on projects. Among the three important factors identified, mode of financing was ranked first, followed by underestimation of project cost while improper planning was ranked third. However, the research focus did not cover drawing correlation among the factors and the extent of their cost implications.

In another related study, Koushki *et al.*, (2005) examined delay and cost increases in construction of private residences in the state of Kuwait. According to the study, 450 private housing projects were systematically and randomly selected from among projects located in 27 metropolitan districts. The sampled districts were selected to represent various geographical locations, land use, socio- economic setting, cultural value, and population density of households in Kuwait. The study engaged a person – survey of owners of these sampled residential projects using a trained graduate and two senior civil engineering students. The selected samples of dwelling used were found to possess common characteristics: either had just been completed or were at the state of receiving finished touches (e.g. finishing works).

Among the factors adduced as responsible for cost overrun is underestimation of project cost, followed by contractors' in-experience, financial constraints, materials' price fluctuation, change orders and weather. It was stated that, a significant percentage of the sampled residential projects (33%) required additional (over the contracted amount) construction budgets to complete, and that, increase in construction cost for 37% of the sampled projects was KD 3000 (US $9, 900), while 28%, needed more than KD 15,000 (US $49, 500) of additional capitals to be completed. Builders liability as regards aspects of underestimation was ranked first as overrun factor with attendant cost implication of KD 20, 000. Also, materials price, contributed KD 10, 200 while financial constraints ranked third with financial implication of KD 10,000.

In conclusion, the paper recommended that; adequate and available source of finance should be ensured; preconstruction planning of project tasks and resources available should be carried out before project commencement; allocating sufficient fund for project and selection of competent contractor to handle the project work. The reviewed papers, presented an excellent view of the scenario as occurred in Middle

East and the extent of cost overrun on their projects. So also, the paper presented situation of building projects cost overrun as it relates to Kuwait context, it dwelt extensively on appraising the factors responsible while drawing correlation among the factors and the extent of their cost implications. To this end, this research work carried out among other things, factoring cost center influence on project cost and developing cost impact matrix for the developed model, as well as formulating impact matrix of risk probability for cost components of building projects used in cost prediction model development.

2.4 Project Cost Predicting Optimization Models In Use

A system representing building project can be configured in a format that incorporates systems' elements with potentials that can influence the nature of an end value generated from such a system. The elements can be formulated as input data (parameters), such as project cost items. These parameters can be configured in a format that is usable in generating acceptable output using a series of such input data. Such parameters that could be used are cost of building elements, project cost items and other variables that have cost implication on project work. The embodiment of this type of system is referred to as cost optimization models. These models can be traditional or non-traditional optimization model.

2.5 Review of Previous Applications of Non-traditional Models (Neural Networks)

Neural network is categorized as a non-traditional system that can be used in solving diverse form of problem in various field of endeavor. Previous researches have proven the fact that it has been successfully used in economic related fields in providing solution in situations of complex mathematical computation. It can be used in data classification and processing, data trend analysis, and forecasting. This section contains the review of previous application of neural network to built environment problem. Artificial neural network can be applied in providing solution to complex problems such as cost estimation. They are inspired from the biological structure of the human brain, which acquires knowledge through a learning process.

Neural networks are usually constructed by arranging several units in a number of layers. The output of a single layer provides the input of a subsequent layer and the strength of the output is determined by the connecting weights between the processing units of two adjacent layers. Neural networks have the ability to learn from examples in order to detect by themselves the relationships that link inputs to outputs. Artificial neural network are used in solving problems, where numerical solutions are hard to obtain. Several researchers have used neural networks as a tool for estimating costs at the earlier stage of project development. Summary of their research work is contained in the following presentation:

Ayed (1998) studied Parametric Cost Estimating of Highway Project using Neural Network, the purpose of the research is to provide an effective cost data management for highway projects in New Foundland, United Kingdom. The study utilized the actual construction cost of 85 highway projects constructed in New Foundland. Also the study designed parametric cost estimating system for the projects in a modular architecture with several components. Back propagation was used as an optimum method in training to predict the outcome of new cases. According to the study the research work has led to development of a complete system for parametric estimation of highway projects cost in New Foundland. Moreover, through the model developed, the effect of cost related parameters on the total cost of construction projects through its sensitivity analysis was determined. However, the scope of the study did not include building projects; it was limited solely to road construction projects while the preliminary test carried out on the extent of applicability of the model indicated that, the model can only be used at preliminary stage of work. This therefore limits the application to preliminary design stage, where the acceptable level of accuracy is within 20% range.

Therefore, this work used data of completed building projects in Nigeria since the location base of the research under review is Europe; the costs were adjusted with construction price index, to incorporate certain cost differential parameters. Furthermore, the reviewed work utilized data of 85 completed Highway projects, while this study used data from 500 sampled building projects for an enhanced precision. Genetic algorithm and multilayered perceptron with back elimination was used as the neural network interface for the model developments while the resulting model was coded on spreadsheet, radar diagram was used to create visualization effect and to predict outcome of new cases.

In another related study, Copeland and Proud-foot (2004) investigated application of Neural network in solving actual cost problems in construction project. With reference to the outcome of the research, Feed forward Neural system was found to have the greatest r-value and followed in regression order by Radial Basis Function (RBF), Kohonen Self Organizaing Network (KSO), Recurrent Network, and simple recurrent network. The scope of the study did not include using the output in formulating model it was about using the output generated to select the best method with accurate output of which feed forward neural system was found to have the best output. This was based-on output accuracy with greatest r-square value. Construction costs of 105 different construction projects in Netherland that are not location dependent were used. However, in this research work, sample size of 500, was used for model development. So also, genetic algorithm as well as feed forward neural system was used as interface, in model development.

So also, Williams (2005) researched into application of Neural Network in predicting construction cost indexes. The work was centered on estimating the changes in cost indexes using better approach, other than those used in the past. Construction costs of 250 projects were used, with prime lending rate for the month, and the year, used as input data into the neural network system. Exponential smoothing and linear regression were used as module for comparison of output generated. The research concluded with a statement on the reliability of the output, that neural network produced a good prediction for changes in cost index. This is indicative of the fact that variables affecting the construction cost indexes other than those used in the research need to be identified. However since the area of coverage of the study did not include modeling, this research work generated cost predictive model that can be used in building works. So also, samples from 250 projects were used for the research work, while this study deployed 500 samples for model's reliability.

Creese and Li (2005), studied cost estimating of Timber bridges using neural networks. The study deployed neural network and the output was simulated with output from regression analysis in order to determine which approach has least mean square error (r-square values). The study used cost parameters of the timber bridge such as volume of the web, volume of the decks, wooden flange and bridge weight as neural network input data. The study with neural network indicated that, the r-square values using neural network system were greater than when regression analysis was used. So also, according to the researchers' submission, in estimating cost of timber bridges, the models with 3 – input variables gave the least error; and Neural network systems give little variance to the actual cost from expected cost. Neural network however decreases in margin error as input variable increases, the large the sample, better the accuracy; to this end therefore sample of 500 magnitudes was used in the research under review. Expectation of this research work in this regard is that, there is assurance of the fact that the variance of actual construction cost from the initially budgeted cost will be negligible since larger sample was used.

Similarly, Gaza and Rouhana (1995), carried out a study on neural network versus parameter based application using neural network systems, in carbon steel pipes cost estimating. One hundred and ten (110) samples of carbon steel pipes were used for the study, with cost parameters such as pipe diameter, elbow and flange rating, fed into the system: the system generated cost/100fts as output. So also, the same parameters were used as input in regression analysis, using multiple regressions. The outputs from both systems were compared in order to conveniently draw correlation among the outputs. Creese and Li (2005) and Williams (2005), towed the line of submission of this study; in stating that mean square error generated using neural network system was less than mean square error obtained from multiple regression approach. The study concluded with stating that the neural network system is more accurate than the parameter based application. The study area of coverage excluded model development as well as studying relationship among the input variables which this study achieved. This study used cost parameters of completed building works as neural network input data and model development.

Mckim (2005a) worked on neural network application to Cost engineering. Neural network was utilized in estimating actual capacity of pumps, with a view to establishing the practicality of using neural network system, in determining the actual capacity of pumps. The study demonstrated the effect of the quality of historical data on the accuracy of output data generated from neural network system. The pump flow and head pump were used as input data into neural network system. The study according to the researcher adopted best – fit equation method, exponent scale method and best-fit exponent method as comparison module in data processing. According to the study, the r-square value from neural network was found to be greater than those of other form of estimating models. The study generated the actual capacity of the pump using historical data, from 100 projects, however, the study commented on the quality of output generated, as having been influenced by the quality of available historical data. For the purpose of this research work, data of completed building projects after adjusted with current price index was used as input parameters, since historical data has proven not to be reliable as a result of certain intervening parameters that it cannot measure. A model was developed with 350 samples as input data into neural network system.

Mckim (2005b) worked on application neural networks in identification/estimating of risk. The study used neural network to predict percentage change of the final cost from the rough estimated costs as an index of risk measurement. 150-sampled construction projects were used for the study, with parameters such as final costs, project size and estimated costs used as neural network system input data. The study obtained percentage change in cost of the actual estimated cost to final cost and submitted that it can be used as a construction project' risk indicator. The study further stated that, the mean variance obtained from neural network results was less than variance of mean overrun cost; and that neural network technique produces good result only in case of rough estimation. The study recommends this approach when risk is to be determined at early stage of construction project. The reviewed study scope did not include cost prediction of building works, it centered on risk measurement as well not on producing a model for cost prediction. To this end therefore, in this study, a model that can be used in building cost predicting was generated which can be used at early, middle and latter stages of building works.

Meijer (2009) utilized neural networks for circuit modeling. Neural network was adapted in device and circuit modeling. The study generated a semi –automatic modeling path that could be used for device and circuit modeling. So also, in another related study, Meijer (2009b) carried out a research work on the adaptation of generalized feed forward Networks; the study developed analogue modeling of continuous and dynamic non-linear multidimensional system for simulation. So also, the effect of using second order differential equations on feed forward networks was determined. The study identified among other things, the distribution of time steps that allows for smaller time steps during steep signal transaction in transaction feed forward networks. The study stated further, that, the use of second order differential equation for each neuron allows for efficient mapping to a general neural network formation. To this end, this research work developed a neural network based building project cost predicting model with genetic algorithm, using cost centers from building project document of completed works. The cost centers were adjusted with current price index. So also, a total sample of 500 magnitudes was used in this study for model development, validity and stability.

Hegazy and Ayed (1998) adopted a neural network approach to manage construction cost data and developed a parametric cost estimating for highway projects. Two alternative techniques, were used to train network's weight: simplex optimization (Excel solver function), and genetic algorithms, which is a flexible and adaptable model for estimating highways projects by using a spreadsheet simulation. Adeli *et al.,* (2008) formulated a regularization neural network to estimate highway construction cost and indicated that the models were very noisy and this results from many unpredictable factors related to human judgment, such as random market fluctuations, and weather conditions. They concluded that the model was successful in introducing a number of attributes to make it more reliable and predictable.

Also Gwang *et al.,* (2004) examined different methods of cost estimation models in the early stage of building construction projects such as multiple regression analysis and neural networks. The study submitted that neural networks performed best prediction accuracy. Murat *et al.,* (2004) developed a cost estimation model for building based on the structural system of future design process for the early design process. It was suggested that the model established a methodology that can provide an economical and rapid means of cost estimating for the structural system of future building design process. The study advocated that neural network is capable of reducing the uncertainties in estimating structural system of building, and that the accuracy of the model developed was 93% level.

Setyawati *et al.,* (2007) developed a neural network for cost estimation and suggested regression analysis with combined methods based on percentage errors for obtaining the appropriate linear regression which describe the artificial neural network models for cost estimating. Emsley *et al.,* (2007) suggested that procurement routes cannot be isolated from cost significant variables in a building project. Therefore, Al Tabtabai *et al.,* (2008) developed a neural network model that could be used to estimate the percentage increase in the cost of a typical highway project from a baseline reference estimate such as environmental and project specific factors. Their model generates a mean absolute percentage error of 8.1%. Shtub and Versano (1999) developed a system to estimate the cost of steel pipe bending that was a comparison between neural network and regression analysis, it was discovered that neural networks outperform linear regression analysis. Finally, Jamshid (2005) also examined cost estimation for highway projects by artificial neural network and argues that neural network could be an appropriate tool to help solve problems which comes from a number of uncertainties; further summary is scheduled in the next presentation.

Table 2.1 Neural Network (NNs) Model Input and Output with Validation model

Researchers	Study Area	NNs Inputs Variables	NNs Output Variables	Validation/Simulation Modules	Research Outcome	Further Note
Adeli and Wu (2008)	Regularization Neural Networks for construction cost estimation of Highways.	Costs of construction items.	Generated cost.	Neural Modules	Regularized model.	Variation between output and input is 9%
Al-Tabatabai et al (2008)	Preliminary Cost Estimation of Highway Construction using Neural Networks.	Preliminary Costs of road items	Final cost	Neural Modules.	Neural module that could be used to estimate the percentage increase in the cost of a typical highway project from baseline reference estimate was generated.	4.5% variation derived

Table 2 Continued						
Bouabaz et al(2008)	Cost estimation model Bridge repair based on artificial neural network.	Work packages derived from Bill of quantities of Bridge construction	System for estimating maintenance cost of Bridges.	None	The result indicated that Neural network provides high level of accuracy	None
Emsley et al (2007)	Application of a Neural network approach to estimation of Total cost.	Project cost variables that are procurement route specific.	Total cost	Linear regression model.	That Total cost of cost significant variables is directly related to procurement route adopted.	Percentage variation of 3.5% was obtained
Kline (2004)	A neural network approach for early cost estimation of structural systems of buildings		Estimated	An average cost estimation accuracy of 93% was achieved	Theapproach was shown to be capable of providing accurate estimates of building cost.	None

Table 2 continued						
Jamshid et al (2005)	Cost estimation for highway projects by artificial neural network.	Actual construction cost.	System for parametric estimation of Highway projects.	System for parametric estimation of Highway projects was generated.	The result indicated that artificial neural network could be an appropriate tool to help solve problems which comes from a number of uncertainties.	
Kline (2004)	Methods for Multi-step time series forecasting with Neural networks.	M-3 Competition quarterly data series	Output from three methods: iterative, joint and independent methods	Iterative methods, seasonality and trend-adjusted naïve forecast	The study suggested the use of all the methods as situation dictates.	None

Table 2 Continued						
Law and Pine (2004)	Tourism demand forecasting for the tourism industry: A neural network approach	Historical data on tourist arrival in Hong-kong from Japan,USA, UK and Taiwan	ANNs generated output	ANNs, Exponential smoothing, Regression analysis, Holt exponential smoothing and Moving average	It was found that ANNs and Single exponential smoothing forecasting models outperformed other models.	None

Table 2 continued.						
Li, et al (2004)	Forecasting short-term exchange rates: A recurrent Neural network approach	Daily quotes of foreign exchange rates	Output that can be used in forecasting exchange rates	None	The study demonstrated how to model markets behavior in situation of continuous movement in foreign exchange rates	None
Li, et al (2005)	Cost modeling of office building.	Elemental cost of project works	Output that can be used in cost modelling	None	The study demonstrated how to model cost of building work	None

Table 2 Continued

Meijer (2009)	Neural networks for Device and Circuit.	Extension of learning algorithm to include combination of time and domain application of model generator.	-Time. -Domain. None.		Semi automatic modeling path that could be used for circuit and device modeling.	None

Table 2 continued.

Hu *et al.*, (2004)	Predicting consumer situational choice with Neural networks	Samples of coded consumer opinion on modes of communicat ion (Telephone and Telegraph)	Coded output relating consumer choice situation to available services	None	The study shows how neural networks can be used to model posterior probabilities of consumer choice	None

Nargundkar *et al.*, (2004)	Assessment of evaluation methods for prediction and classifications of consumer risk in the credit industry	Data on car loan application	Output ratio for evaluation of predictive ability	Loss comparison index, linear discriminant analysis, Logistic analysis, K-S test and Classification rates	The study discovered that each modeling technique has its own strengths, and determination of the "best" depends upon the evaluation method utilized and the costs associated with misclassification
Hu *et al.*, (2004)	Predicting consumer situational choice with Neural networks	Samples of coded consumer opinion on modes of communication (Telephone and Telegraph)	Coded output relating consumer choice situation to available services	None	The study shows how neural networks can be used to model posterior probabilities of consumer choice

The area of departure between papers reviewed and this research work lies in the fact that, as good and exploratory as the identified approaches are, majority of them dealt with parametric estimating. However, no known research has been carried out in the aspect of Neural network application in predicting building construction cost in Nigeria, from holistic perspective. Parametric estimation method however used in the reviewed works relied on use of linear regression model. Few numbers of the papers that researched into neural network related issues only justified the feasibility of adapting neural networks to cost related problem in built environment especially in parametric estimation of Highway projects. There had been little recorded attempt to develop such model that could be used in cost forecasting of Building projects using Nigeria context. A missing link emerged from the review of previous application of neural networks, that little research has been carried out in the aspect of formulating a neural network based cost predictive model. Applications have been recorded in the aspect of using neural network in estimating the cost of Timber Bridge, as contained in the study carried out by Creese and Li (2005) and Gaza and Roughana (1995) who used neural network in estimating the cost of carbon steel pipes. Also, Williams (1994) used neural network in estimating the changes in cost indexes while Mc Kim (2005a) used it in estimating actual cost of pumps.

So also, McKim (2005b) deployed neural network in predicting the percentage change of final costs from estimated cost. Copeland and Proud foot (2004) used it in solving actual cost problems in construction project; and Meijer (2009) used neural network to produce a semi automatic modeling path that could be used for circuit and device modeling. In the applications, the few that had built environment related applications did not address the cost of building works as a whole, but the piecemeal determination of component cost of certain construction items.

Worth mention, however, is the work of Hegazy and Ayed (1998), the study adopted non-traditional estimating tool (Neural networks) to provide an effective cost data management for highway projects in New Found land. Genetic algorithm was used in generating the model, with reference to the concluding statement of the researchers, the model was recommended for use only at the initial stage of the construction projects where margin of acceptable variation errors, should be within 20% range. In the light of this therefore, this study used neural network as medium to generate a cost predicting model. The Neural network inputs used was based on cumulative cost of Average Floor Area, Total Floor Area, Storey Number, Total Building height and Average Storey Height of projects executed in Nigeria. On this premises therefore, the study generated a model that will be suitable in predicting cost of building works, at different stages of building construction work. Data from specific project type was used for the study (project types such as Office and Residential building projects). Data of completed projects from private and public building project category were used in model generation. The choice of Neural network as an inter-phase used in this study in generating model predicting parameters lies in little margin error in computation, good data processing speed, and capacity for large data input. Also, Genetic algorithm or Back-propagation training techniques were used to determine the optimum neural network model

2.6 Review of Previous Application of Traditional Models

Li, *et al*., (2004) studied cost modeling of office building in Hon Kong using an exploratory approach. The study used data from 87 historical, reinforced concrete and steel office building projects, the data collected was adjusted using construction price index, stepwise regression analysis was later conducted on the sampled data to produce a linear models. The outcome of the research indicated that percentage difference ranges from – 4.11 percent (underestimate) for reinforced concrete structure in Hongkong. However, the variability of percentage different for steel Buildings ranges from – 6.65 percent (6.65%) underestimate to overestimate. The study later concluded by stating that the regression model generated appear to be more accurate than traditional regression model. The scope of the study covered steel and reinforced concrete structure in Hongkong, the data used was also an historical base which will tend not to capture certain economic variables. Thus for the purpose of this research work, cost predicting model using Neural network system with variation error of less than 3% of the total construction cost over initially budgeted cost was investigated in this study.

Ogunsemi and Jagboro (2006), formulated Time-Cost model for building project in Nigeria. The study developed a model that relates Time and Cost together as a critical element in project completion in Nigeria. The model aimed at revalidating the previously developed Bromilow's time-cost model. the study used data from 87 completed building projects of private, public and other types selected from south western, northern and eastern part of Nigeria. The initial and final costs of the projects were used. All the costs were adjusted to year 2000 prices, using Building price indexes. The study developed non-piecewise-linear-regression-based model, this was compared in term of output to Bromilow's model and piecewise linear model with break point. The piecewise non-linear regression model with break point was found suitable in Time-cost relationship prediction. The T-test was conducted on the three categories of project used, the result also indicated that there was no significant difference between the observed and predicted duration for the projects. The predicted duration was almost the same in the three categories (private, public and all other types of projects). This research work did not adopt regression analysis in modeling; neural network was used, given its advantages over the regression model, in term of accuracy of output and minimum mean variance error. The regression model however was used in authenticating the validity of the developed Neural network based cost predictive model for Building that are similar to the above. The Buildings were residential and office buildings that are of reinforced concrete structure, and steel structures in nature.

Xiao and Proverbs (2002) studied the performance of contractors in Japan, the United Kingdom(UK) and the United State of America(USA) using a comparative evaluation of construction cost, and a new research protocol for comparing contractors performance internationally was developed. The study used a new research protocol that is regression based to determine the level of satisfaction of client as regards construction cost, cost certainty, contractors performance internationally and cost disparity between UK and USA and Japan. According to the study, three storey building, concrete-framed office-building were used as an hypothetical project, which were common to the three countries. Respondents (project managers or general contractor) were orally interviewed, while the research was implemented simultaneously in Japan, the UK and the USA. Analysis of variance (ANOVA) techniques, Kruscal Wallis test, statistical package for social sciences (S.P.S.S) software were used in determining cost performance, and unit price comparison, while Chi-square was used in analysis of budget overrun.

The outcome of the research work indicated that cost of construction in UK (converted by exchange rates) is much higher than in Japan and the USA and that contractor in the three countries displayed various differences in their cost performance. However, the research arc of coverage did not include modeling cost, but cost comparison for purpose of evaluation, and the regression model was used in the evaluation process. So also the outcome of the research is not intended to be used for cost prediction but evaluation. To this end therefore this research work generated a model for cost predicting in building works with larger samples of 500, greater than the sample size used in the work reviewed.

Vermande and Mulligen (2000) examined construction costs in the Netherlands in an international context. The study targeted determination of the accuracy of the basis of construction price data used by euro-stat in determining the countries construction cost. The study, used collection of 100 bills of quantities of building projects that span over of 10years, for analysis of Building price data from member states of Eurostat. According to the study, prices are based on a number of Bills of quantities of unit price that relate to each countries and operation. Geometric means are used by the study to end average weights. The study concluded by stating that, the Eurostat data appeared to deviate substantially from a range of the other independent comparisons for the five analyzed countries (Netherlands, Belgium, UK, France and Germany).

So also, that, construction price data used by Eurostat are not very accurate and that international to express and explain construction cost differences between countries. The study finally submitted that the Netherlands has the lowest building costs compared to the four surrounding countries; Belgium, France and Germany. In this reviewed work Geometric mean was used to determine average weights, the weights were used to interpret data and not modeling since the scope of the work did not include data modeling, in this research work cost model was developed from 500 samples.

Furthermore, Farah (2005) formulated Building information model software to support construction and design. The study build a warehouse project using two Building information model (BIM) tools, Autodesk Revit, and Graph soft Archi CAD. The two BIM feature were compared, in term of ease of use and database structure. The study later explored the possibilities of integrating the developed models with other software used by the estimating discipline. The study concluded with recommending the models for use at programming stage of a project since the implementation of the model will aid design quality and promote creativity. The model developed in the review is three dimensional model and is not aimed at cost predicting but design-based. To this end therefore, this research work generated a cost predicting model for building works.

Oyediran (2001) investigated movement of construction prices and macro-economic variables in the Nigerian construction industry. The study simulated the construction price variables movement in Algerian construction industry with Nigerian context, and studied as well the econometric variables that accompanied it. This attempt according to the research was to seek empirical understanding of which of the macro-economic variables affects price movement. The study deployed survey design or expo-facto design, or casual comparative design. In the work, 200 selected construction prices and economic data were obtained from both primary and secondary sources. The study relied heavily on quantitative data, which was available in historical form, from respective sources. Visual trend analysis was conducted on the summarized data with aid of E-view package. According to the study, both basic prices and unit rates have responded in similar manners to the impact of macro -economic variables. The study finally submitted that, there is high degree of correlation between construction prices and macroeconomic variables judging from the incremental pattern of the movement of the variables over time.

In this research work, the influence of the macro -economic variable such as inflation, price disparity was taken into consideration while adjusting the construction cost for modeling by adjusting with current price index that reflects typical Nigerian construction context. The adjusted cost parameters was later fed into the Neural network system to generate the much expected neural network Based cost predicting model for Building works as this study has proposed.

2.7 General Review and Theoretical Framework on Cost Modelling and Application of Artificial Neural Networks

Construction industry is a prime mover of any nation's growth. It has domestic representative fraction in a nation's domestic product. It contributed up to 5% of the annual domestic product and it is about one-third of total fixed capital investment of Nigeria (Olalokun, 1987). Notwithstanding, the Nigeria construction industry is presently faced with problem of resource management in the form of injudicious allocation of finances to capital projects and injudicious utilization of scarce financial resources at government and private level. There is therefore need to adapt effective strategic planning in the area of financial allocation to project works as only panacea to the problem (Mosaku, 2007; Kolo, 2004; Moore *et al.,* 1999). One of the strategic planning in ensuring effective allocation of resources is to cost work items properly and have thorough review of cost items and cost implication before commencement of project works, this would help in budgeting adequately for project works, thereby preventing negative project vices such as cost underestimation and cost overrun. However, Ogunsemi and Jagboro (2006); Gagarin *et al.*, (1999); Flanagan *et al.*, (1997) and Olalokun (1987) opined that one of the most serious problems the Nigeria construction industry is faced with, is the project cost overrun, with attendant consequence of completing projects at sums higher than their initial contract sum. Therefore working with realistic project estimate is necessary at the outset of a project work, which would eliminates uncertainty, and as well provide a platform for project success. (Dissanayaka *et al.*, 2007)

Furthermore, the importance of having good project cost control or management cannot be overemphasized. Irrespective of the project scope, scale and magnitude, construction cost need to be monitored to prevent overrun and for anticipated profit to be realized. To this end therefore, cost management of project work is important for an effective project cost management so as to obtain client satisfaction on cost, as well as value for money on investment in the project. (Kerzner, 2005; Harris *et al.*, 2005); advocates adoption of good Cost Control policies, this implies good cost management strategies, which include: cost estimating, project accounting, project cash flow, company cash flow, direct labour costing, overhead rate costing, others such as penalties, incentives and profit sharing. Cost Control is a sub system of the cost management and control system (MCCS) rather than a complete control system per se. However, Ogunsemi and Jagboro (2006); Ferry *et al.*, (1999), opined that great care has to be exercised in not mistaking failure of a cost control system to accurately describe the true status of a project as meant failed cost control system, because any cost controlling system is as good as original plan against which performance is going to be measured. Thus, the designing of an organization or project work must take into cognizance good cost control system as well. The purpose then, of project cost management system is to establish policies, procedures and techniques that can be used in the day-to-day monitoring of projects. In the light of the above, the following should be elicited by the system: Picture of work progress, relationship between cost and schedule performance, identification of potential problems and their sources, demonstration of the timeliness, laudableness and validity of set milestones. Also, a cost control system according to Harris; *et al.,* (2005) should enable a manager to observe current cost levels, compare them with a planned cost and institute corrective action to keep cost within acceptance bounds, Kerzner (2005); Ashworth (1994) supported this assertion by recommending manager/planner in order to monitor cost effectively, should categorised project budget into two standards: (a) performance result standards and (b) process standards. Performance result standards refer to quantitative measurements and this includes such items as quality of work, quantity of work and cost of work as well as time-to-complete.

A process standard on the other hand is qualitative in nature. This includes personnel, functional and physical factors relationship, therefore, Pilcher (1992); Bendert (2003) submitted that the systems should be able to measure resource consumed, (this will enable record of resources consumed to be kept for policy and planning purposes), measure status and accomplishment; compare measurement to projections and standards and provide basis for diagnose and preplanning (see fig 2.1). As a means of providing basis for diagnose and preplanning for effective project cost performance, the factors that interplay to have positive or negative effects on project cost performance needs to be studied. Therefore, the investigation of these factors to be able to diagnose those factors that impact project cost performance will be a major preoccupation of this research work**.**

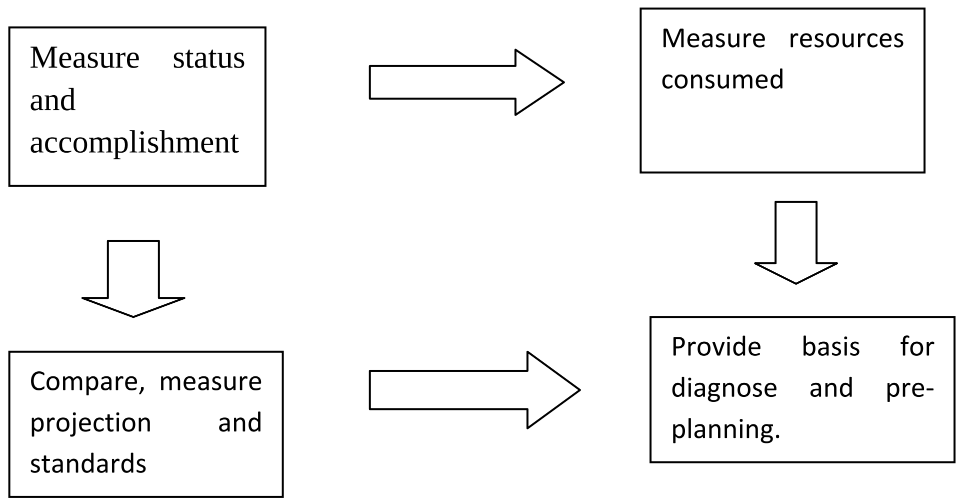


Figure 2.1: Cost Management Framework

To this end therefore, a sytem representing the building project could be configured incorporating elements that have potential of influencing nature of an end-value generated from such system as input data, such as projects cost items. This parameters could be configured in a format that could be used in generating acceptable output using a series of such input data; could be those parameters that determines cost at different stages of construction works, including the conception stage and construction stage; such system is referred to as a Model. In context of building work, data at conception stage, middle stage and final stage can be used as an input data to model the magnitude of cost at the stages (Seeley 1996). Peculiarity of Data at these stages lies in the fact that Data at the design stage is more quantity and specification related, while those at construction stage is subjective in nature, since it tends to be process related, it depends on construction methodology adopted. Most model nowadays produce output in objective terms such as total capital cost, cost per square meter of floor area, floor to height area, total built space (Seeley, 1996; Dissanayaka *et al.*, 2007). The models are however subjected to degree of errors, data output variance because of certain details that the models were not designed to capture. Parameters such as price variations and time factors cannot be incorporated accurately by some of the models, such as regression models, this tends to limit the extent of such model's application as a cost prediction tool.

However, in cost prediction, for accuracy of data output a cost prediction tool should have capacity for processing large data with precision. Processing speed is another aspect that is essential, a cost predictor should have good processing speed, the processing time should be short and effective data modulation capacity (Carpenter and Bethelemy, 1994). Effective data modulation capacity is the ability of a cost predictor to be able to modulate data as well as sorting to eliminate redundancy with low variation error (Skitmore and Ng, 2003; Marzouk *et al.,* 2008). Variation error should be minimal; however, the variation error in the series of output should be within specific range. Al-Tabatabai *et al.*, (2006), Davis and Seah (2004), specified $\leq 3\%$ and $\geq 5\%$ respectively. However, the previous models, three generations of cost modeling, are short of some of these attributes required of a good prediction tools (Raftrey, 1993). First generation models (1950s-1960s) are based on procedural approach in form of elemental cost planning. This is on abstracting time, quantity and quality of data collected from cost analysis of past projects (Kolo, 2004; Dissanayaka *et al.,* 2007; Skitmore and Ng, 2003). The intensive use of regression models begun in mid 1970s and this characterized second-generation models.

The third generation models, however, evolved around early 1980s, that utilizes Monte carlo techniques in carrying out probabilistic estimates. With this models however, problem of accounting for uncertainty and imprecision was reduced (Ashworth, 1988; Davis and Seah, 2004; Kolo 2004). Given the antecedents, cost models should aim at providing a general accurate representation of the whole cost variables contained in a building design (Mawdesley *et al.*, 1993; Seeley, 1996). Thus future generation models should be able to predict precisely magnitude of building cost, good processing speed, data training, and low degree of variation error among others. Non-statistical tools model fits into this context, these tools are unlike other models, can adapt spontaneously to changes in internal or external information that flows through the system. Neural networks are one of those tools. This is an expert system that is based on concept of biological neuron system, interwoven into a network that behaves like human biological neuron system, characterized with large input and data output, data training capability, minimum data- margin error. Data training capability involves training the system with a set of data to establish a definite pattern, and then adapt. They are particularly effective in solving complex estimating problems where relationship between the variables cannot be expressed by a single mathematical relationship (Hegazy, 2006). These attribute can be used in cost modeling and forecasting during building cost determination process.

The origin of cost determination practice, could be traced to eighteenth century (Smith 1993). During this period, measures were put into place, in measuring and valuing building costs, through employing measurers, after it has been designed and executed. During this era, measurement and cost determination are post-construction in nature. This operation encouraged strive and contention among tradesmen who sometimes feel short-changed or cheated since there is tendency on part of client to be overburdened as a result of emerging project costs and resort to style of short changing the contractors. The groups of tradesmen were later brought together under a main contractor; the main contractor system later became operational in the nine-teenth century. This introduced price competition before the actual construction commence, contrary to the previous era. This development upset the existing system of post project cost determination and this required the measurers to possess a special skill in order to undertake the task, this brought about the skill of pre-measuring, taking off of quantities from the drawings before construction started, and assembling them in a bill of quantities to provide a rational basis for competition. This, however lead to the advent of quantity surveying profession where work is priced and measured before execution but after design.

Considering the enormity of data to contend with, there is a need to evolve a better and fast approach, in order to find the approximation of various quantities, this eventually lead to the development of approximate quantities techniques. The development enables easy forecast of project's probable tender figure, although the basis of computation often left much to be desired (Ashworth, 1994). During preparation of construction cost, the use of cost planning techniques and the method of cost analysis on which they depend would facilitate determination of probable cost accurately, early in the design process, and sometimes even before. Gradojevic *et al.*, (2000) defined cost planning, as a process of pre-costing which culminates in representing the total picture of anticipated cost, in a manner that provides explicit concise and clear statement of the issues. So also, it isolates the course of action and their relative costs to provide a guide in decision-making. Cost has to be controlled effectively at design stage in order to prevent cost overlapping of various elements. The early system as mentioned, could be referred to as traditional approach, this later gave birth to more advance practice. These constitute the pattern of thoughts then. To this end, there is a need to examine various school of thoughts in cost preparation.

2.8 Perspectives in Building Construction Cost Preparation

There are different schools of thoughts or perspectives as regards issue of building cost. Prominent among them are the process approach (Synthetic approach) and traditional approach.

2.8.1 Traditional Approach: In traditional approach, there is general view that cost is more quantity and specification related, during the latter stages of design process. So also, that, cost generated during the early stage of design process can be usefully related to function and design. The degree of reliability here is then subject to function and design. This view is supported in Ashworth (1994) as reason behind civil engineering costs being rarely published because of its limited value. The fact lies in process of approach of arriving at the cost that is not often stated. Alternate view is systematic determination of various costs through an established process. This is termed process approach or synthetic approach.

2.8.2 Process Approach (Synthetic Approach): Components of Building are systematically arranged against a pre-established configuration. The building components measurement s are extracted for use, this therefore provides a uniform point of reference, thus, the way building components are configured tends to dictate the order to follow during the process of their cost determination. The uniform configuration pattern therefore enables easy replication of various components and the corresponding determination of their various costs. The uniform configuration also enables ease, in the ways that the construction operation of various building components would be carried out. With this, method of carrying out construction of individual components, plants and equipment, as well as methodology selected by the contractor, could be determined.

This phenomenon leads to evolution of Builder's estimate. Builder's estimates are often quantity related and process determined. The builder has prerogative of choice of construction methods and as such holds the ace as far as the quality of builder's projects estimate is concerned. The builder's estimate tends to be accurate since it would be based on extractions form project documents in his possession using process approach. Process approach follows the general view point according to Ashworth (1994) that building costs are quantity related and the quantity could be determine based on application of an established method.

2.9 Convergence of the Perspectives

From the standpoint of the two perspectives (traditional and process or synthetic), both perspectives have a common base. The costs generated from them originated from design concepts. To arrive at a cost standpoint, the measurer must work with design concept as contained in design documents and its accompanied specifications. The builder estimate rely much on the synthesized construction methodology from the design documents, which would be latter transformed into symbolic logic that would generate costs. This is adjudged more reliable, since it follows the projects system of configuration systematically, so that every detail contained in the design is captured. Critical examination of the two perspectives (traditional and process or synthetic), reveals the fact that, their data are often used as back-up information during construction cost determination, in arriving at a definite cost of an item. However, any cost data that would be reliable should have been generated through synthetic or process approach.

2.10 Characteristic of Cost Data

The following attributes are peculiar to construction cost data: They are required at various level of sophistication in construction. Cost data are required at inception stage of construction design process (to provide clients with cost idea on proposed project). Also,they are required at various stages of construction operation to produce cost data based on construction costs determinants; these are variable associated with the construction design concepts.

2.11 Reliability of Cost Data

Data reliability often depends on source from which data originated from, or data generation approach used. Cost data could be accessed through two major methods. Personally generated cost data and procured- published cost information. Personally generated cost data are those that are generated by the owner through applying relevant data generation skill. Cost information could be procured externally, through magazine, cost bulleting, cost periodicals and the likes. It contains predetermined parameters as contained in the documents of common pricing methods. Such parameters are contained in standard method of measurement (SMM8) or builder's quantities. The question then is how reliable are the published cost data?

The compilers of published cost data do not claim that the information is accurate. They are right in stating that the prices quoted are just a guide. However, it seems the only exception is the builder-merchants' price list. These at times are often presented alongside with disclaimer that the prices are subject to change; however, accuracy is a desired quality in an effective cost data Ashworth (1994), that the suitability of a cost data lays in the extent of their accuracy and consistency. Accuracy refers to the ability of cost data instruments to be able to measure what it had been designed to measure with closeness to the actual value. Consistency however refers to how often this accuracy can be relied upon. Having highlighted the importance of process-approach-generated data and advantages over other types, certain parameters that determine the usefulness need to be considered as well.

2.12 Usefulness of Process - Approach-Generated-Data [Determinants]

From the previous submissions, it has been established that process approach i.e. synthetic approach generated data are often prefer by contractors or builders, since it provides the privilege of using self generated inputs. Ferry *et al.,* (1999) affirmed this assertion by submitting that, variables that influences or have potential of influencing the cost input parameters could be adequately controlled. The ability to influence such factors is responsible for the good attributes of this system. To this end however, the determinants of usefulness of process approach generated data can be summarized as follow:

a. Evolution of data from familiar source

b. Provision of detailed breakdown of structured information

c. Geographical location specifics

d. Short processing and retrieval time

e. Absolute control of structured classification and processed data.

a. **Evolution of data from familiar source:** the data should be from a project whose background is familiar. So also problems associated with the project such as location, market conditions, complexity, would be better appreciated, these influences cost.

b. **Provision of detailed breakdown of structured information**: further breakdown of structured information should be available, should it be required, for instance when dealing with issues that relates to elemental (cost analysis) detail information on elemental components should be supplied. From the foregoing, the usefulness of using process approach in generating cost data on projects have been stated; this and other variables determines effective building or construction cost determination.

2.13 Towards Effective Building Cost Determination

It was generally believed before times, that building construction or construction costs are often influenced only by size and quality attribute of a project. That the magnitude of the project and the quality standard envisioned would determine what the building construction cost would be. However, in recent times, it is a known fact, that construction costs of a particular design solution are influenced by many factors. To this end therefore factors that impacts building construction costs i.e. factors that needs to be considered for effective building cost determination can be categorized into two main groups.

a. Extrinsic factors: (Environmental related factors).

b. Intrinsic factors: (Building features related factors).

(a) Intrinsic Factors: These factors are regarded as those that have direct influence on the building costs. They are features related. Here, reference is being made to these types of building features: height, building size, foundation depth, types of foundation used, storey height, roof pitch, building shape and host of others, building features such as these influences costs, Skitmore and Ng (2003) supported this view by stating that, these are features within the building form and configuration. So also the critical analyses of these in term of their financial implications, constitutes costs and are developed into cost centers. They are to be taken into consideration while preparing Bill of quantities or preparing project's estimate. Variations in these features from one building type to another, would lead to varieties in the cost obtainable of building types, particularly, when those variables are differently configured.

(i) Storey Height: Excessive storey heights do have the effect of directly increasing the cost of building. The higher the storey heights the more the cost implication of such development. (Skitmore and Ng, 2003; Ashworth, 1994). Buildings with storey heights will cost more per square meter of floor area than comparable accommodation with lower storey heights, such types of building often results in higher wall-to-floor ratios (Ashworth, 1994).

(ii) **Building Size:** Building size is one of the major factors to be considered in generating Building cost. Target buildings have lower unit costs than small-sized projects with equivalent status, attributes and specifications. An individual dwelling unit on a plot of land costs more to build than a similar dwelling unit that may be part of a large housing estate. This fact was buttressed by Dissanayaka and Kumaraswamy (2007), in that smaller factory costs more per unit than their larger counterparts. This was further illustrated by comparing the design time of smaller projects, which is often longer and the cumulative effects that often results in high design cost. Larger projects can be more efficiently managed and be completed in a disproportionate amount of time. So also a more intensive use of plants and a better capability of obtaining discounts on material's prices, arising from bulk purchase, favor larger-sized projects.

(iii) **Building Height:** the construction costs of tall buildings are greater than those of low-rise buildings, offering a similar amount of accommodation. Some of the reasons responsible, for multi-storey structures being more expensive, than low-rise buildings are as follows: Higher cost of providing certain building elements, such as foundation necessity for a structural frame, and stringent constructional requirements for staircases. Also, The need for provision of vertical transportation system, such as lifts and cranes, material storage problems, delays in waiting for construction to 'set' and the increased amounts payable to operatives and safety requirements.

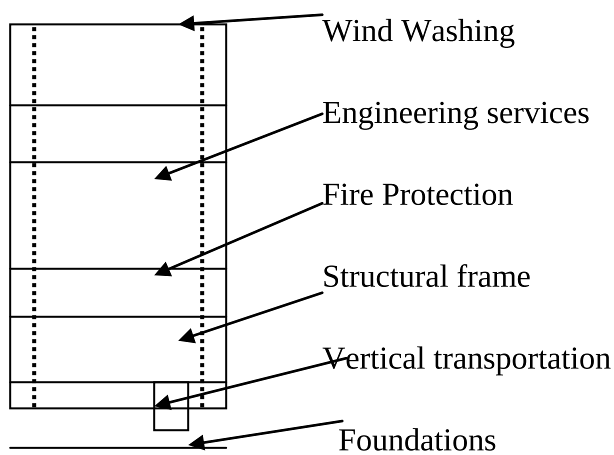


Fig 2.2 High Rise Engineering Components

Source: (Kezner, 2005)

Cost components of building in relation to building heights, can be divided into four (4) categories, for illustration see Fig 2. They are: costs that falls as the number of storey increase (e.g. roofs, foundations), those costs that increases as number of storey increases (e.g. life installations), costs that are unaffected by height (e.g. floor finishes, internal doors) and cost that fall initially and then rise as the number of storey increases e.g. exterior enclosure).

Costs that fall as the number of storey increase includes costs of roof and foundation.

(i)Roof: For medium to large spans, a satisfactory pitched roof is likely to be rather cheaper than flat roof of comparable quality. This is due to the simplicity of spanning large areas with roof trusses rather than deep beams. The greater the pitch of a roof the more cost incurred on such roof system.

(ii)Foundations: Type of structures to be erected, would determine the foundations type to be used in supporting the structure. Pile foundations are expensive than ordinary strip foundations, raft is less expensive compare to pile foundations and expensive than ordinary strips. Therefore, the choice of foundation should be carefully made during building design and configuration. This and other factor's cumulative effect, can to an extent influence building costs.

(b) **Extrinsic Factors:** These factors relate to the project environments. They are external to the project but to an extent play determining role in building cost determination. Material price fluctuation is among critical determinants of the project cost, the more the material costs, higher will building cost be and vice versa. Therefore, this can be generally stated, that price of material is directly proportional to building cost (Raftery, 1993). Furthermore, it is possible to decide the cost of a proposed project based on certain parameters. This could be grouped into systematic forms that contain the cost elements of the proposed project. These systematic forms are referred to as cost models and are used for forecasting. The present poor state of determining building cost has necessitated evolution of better and faster means of cost determination. The great expectation is that cost models are just some of the methods that may provide the long expected results. It was stated by Ashworth

(1988) that the use of model has highly subjective procedures, and it allows little use of experience, once the appropriate model has been constructed supported this view. The previous method in use, engages laborious and tedious mathematical approach, meanwhile experience has show that mathematical approach had little chance of success in effective cost determination. In the light of this, a model would assist those that are responsible for forecasting and predicting building cost and provide opportunity to increase their performance.

2.14 Building Cost Determination: Forecasting Model Approach

One of the problems of site productivity in Nigeria is resources wastage. This problem has entrenched itself in construction industry, to an extent, that seen material/resources being wasted in sites has somehow became a common thing. However, panacea to resources wastage problem is making good cost estimate and appropriate cost forecast. Adedayo *et al.,* (2006) that managers do make forecast, in a bid to arrive at suitable work cost estimate of some key business variables supported this view. This is necessary in order to know what will happen in the future, in face of uncertainty. It was also asserted that, making good estimates through consideration of present and future variables would go a long way in ensuring near perfect cost estimate of building works. Through this however, cost could be pre-known and this can help in forestalling site resources wastage.

2.15 Forecasting

Forecasting and prediction are often used interchangeably; forecasting can be defined as the process of predicting future events. It may mean projecting into the future through examining experiences or combination of a quantitative model and manager's good judgment (Adedayo *et al.*, 2006). Forecasting can however be classified into different forms.

2.16 Classification of Forecasting System

The major classifications are often based on future time scale, they are short - scale forecast, medium scale forecast and long-scale forecast.

In short-scale forecast, forecast operation is design to cover short period, this often peculiar to a particular operation planning. The time scale for this type is often less than one year. Medium-Scale Forecast refers to a forecasting method which is based on short time range/scale that spans from one year to three year. This is useful in building production management, planning, cash budgeting and analysis of business activity (Henricson *et al.,* 2003); Adedayo *et al.*, 2006).

Long-Scale Forecast on the other hand is the type that often projects into several years. Top management of an organization uses this method in resource planning, development of new products, expansion policy and developments.

2.17 Determinants of a Good Forecast

There are certain determinants of a good forecast system according to Moore (1999); Ferry *et al.,* (1999); Kummaraswamy *et al.,* (2005); Raftrey *et al.,* (1993). They are as follows:- **Simplicity:** It should be easily understood i.e. simple to decode and understand. **Accuracy:** It should be accurate. **Precision:**

It should be able to measure with minimal error margin. **Timeliness:** The period specified for the forecast should be sufficient to effect desired change. **Reliability:** The result generated should be reliable and should produce consistent output; which should be valid overtime. **Cost Effectiveness:** It should be achievable with minimum cost with great value for money invested. However, the most desirable features of a good forecast system should be accuracy and ability to product result at minimal error. There are certain parameters that need to be considered as regards accuracy of a good forecast system.

2.18 Parameters for Good Forecast System's Accuracy

The parameters that affects or influence forecast accuracy are as follows; data quality, data quantity, technological change, forecast time-scale, instability and elasticity of demand (Kumaraswamy *et al.*, 2005);Adedayo *et al.*, 2006;Ferry *et al.*, 1999 and Vermande *et al.*, 1998).

i) **Qualitative Aspect of Data:** The quality of the data would determine the nature of the output that would be generated. The data should be carefully prepared before processing. The data should be current, free of ambiguity and complete.

ii) **Forecast Time-Scale:** The accuracy of a forecast depends on the length of the time-scale of forecast. The longer the time-scale, less the accuracy of the forecast. This implies that some variable's interplay could interfere with forecast accuracy before the maturity date of such forecast, if longer than necessary.

iii) **Quantitative Aspect of Data:** The more the quantity of data imputed, the more accurate the forecast would be.

iv) **Instability:** Unforeseen/events have potential of interfering with forecast result that leads to unstable output or result. Thus, a forecast could not be stable in presence of unforeseen events. The above parameters however, plays important role in selecting the right forecast methods. To this end however, various approaches to forecasting need to be considered.

2.19 Forecasting Methods

There are two approaches to forecasting;

i) Qualitative forecast methods and

ii) Quantitative forecast methods

i) **Qualitative Methods:** This makes use of past data of buildings, to make forecast or predict future cost. So also historical data, and data generated through practice, could also be used for forecast. When such data as past data, historical data and practice-generated data are used, it is referred to as qualitative method. Examples of qualitative methods are

a) Naive methods and

b) Moving average

ii) **Quantitative Methods:** Quantitative methods involve forecasting using intuition, emotion, personal experience and value system. Any of the above can be used for forecasting, but combination of the two is usually well efficient (Wagner, 2001; Stephenson, 2005 and Williams, 2005). Delphi method, sales force composite, and jury of executive opinion (panel consensus) and consumer surveys, are examples of quantitative forecast method. Considering the attributes of the methods of forecast, thorough understanding of their working mechanism needs to be achieved through appraising steps involved, for proper judgment. To this end therefore, the steps involved in forecasting would be considered.

2.20 Mechanism of Data Forecasting

The steps involved in forecasting system are as follows:-

i) Aim definition
ii) Item selection
iii) Statement of time-scale
iv) Selection of forecasting techniques
v) Data gathering
vi) Forecasting configuration
vii) Result/output validation
viii) Result implementation

i) **Aim Definition:** The aim of the forecast should be clearly defined. This would provide achievable goals and enable easy achievement of such.

ii) **Forecast Item Selection:** The sample of data to be used in the forecast should be carefully selected, refined of all errors and complete in all regard.

iii) **Statement of Time-Scale:** The time-scale must be indicated, whether short-scale, medium-scale or long-term-scale forecast scale.

iv) **Selection of Forecasting Technique:** Statistical model(s) like exponential smoothing, moving averages and regression analysis, and most recently artificial neural networks could be used to analyze the obtained data.

v) **Data Gathering:** Data needed for the forecast must be gathered and analyzed. Appropriate information collection system must be employed here. Structured questionnaire, interview, past historical data and the like, can be used in data extraction. If the data are too much, they can further be refined using factor extraction and factor rotation method.

vi) **Forecast Configuration:** the forecast system must be set up and protection mechanism installed. The techniques earlier selected would then be used and output model generated.

vii) **Result Validation and Implementation:** the output generated need to be validated, in order to test the output against established performance criteria and record the test performance. The information could be used in remolding, restructuring and remodulation. Once the stability of the generated output has been confirmed, the forecast result could be treated as model that could later be developed and abstracted for further use. The generated output using the process above is termed forecast model. A model can be described as simplified representation of complex reality Vermande *et al.*, (1998) describes a model as system that use simple inexpensive object to represent complex or uncertain situations. The system that makes use of this is termed modeling.

To this end therefore, modeling can be described as the process whereby a complex real life problem situation is converted into simple representation of the problem situation (see also Adedayo *et al.*, 2006). For the sake of expediency and cost, it is therefore, necessary to construct models that represent the real situation in another form, or to a smaller scale, so that realistic appraisal of building can be made.

2.21 Building Cost Modeling

Building cost modeling may be defined as the symbolic representation of a building system, expressing the content of that system in terms of factors that influence its cost. In other words, building cost model attempts to represent the significant cost items of building or component in a form that will allow easy analysis and forecasting or prediction of cost (Ferry *et al.*, 2000). Such model must allow for the evaluation of changes in certain parameters, such as design variables, construction methods, timing of events and others Then, how can models be categorized for better appraisal and understanding.

2.22 Models Categorization

Models can be classified into two broad categories.

a) Product-based cost model

b) Process-based cost model

a. **Product-based cost model:** This type models the finished products (see also Moore et al., 1996 and Ferry, 1999). These types of models takes no account of configuration or details of design of the building but is based on certain building parameters. Such parameters are as follow:

i) The floor area of the proposed projects (gross or net).

ii) The volume of the proposed project

iii) Some user's parameters, such as number of pupil places for a school or number of bed for hospital.

b) **Process-based cost model:** This is the type of model that deals with construction items process of formation. This is adjudged the most accurate of the models. It is often argued that it is process that actually generates costs; however, the cost cannot be generated until the form of building has been conceptualized. With this, process approach could not be best approach to be adopted at early design stage, since little information would be available for analysis. This view was supported by Moore (1999) that attempt to model construction process at too early stage can result in over-riding of the design process in order to arrive at bricks-and-mortar solution before the user criteria have been properly worked out.

Process -based cost models, can further be classified into sub-types, within the context of probability model and deterministic model or combination of the two.

i. **Probability Models:** These models recognize the fact that, some variables can be uncertain and can therefore only be estimated. This type of model uses probability theory. Majority of models falls into this category
j. **Deterministic Model:** this type of model assumes that values can be attributed to all variables. It also assumes that the variables can be determined or predicted exactly.

To this end however, the other types of models can be subdivided into three groups, under the previously listed major classifications of models. They are as follows:

a) Classification based on structure
b) Model classification based on abstraction

However, for the purpose of this study, model classification based on abstraction shall be considered.

Model classification based on abstraction

Models can be classified based on source of extraction or abstraction. They can be classified based on their degree of abstraction (Adedayo, 2006). There are three groups under this:

i) Abstraction or metal models (High abstraction).
ii) Physical models (Low abstraction)
iii) Symbolic models (Moderate abstraction).

i) **Abstraction or Mental Models:** Mental models are models that are ill-structured representation of reality, that cannot be feel or touch physically. That is, they lack physical or symbolic configuration. These types of models involved high level of creative imagination; they are unclear image of complex objects that have not been finalized. Summarily, abstract or mental models require high level of abstraction or creative ability.

ii) **Physical Models:** Physical models bear semblance with the real objects. They are usually a prototype of the real objects, or posses characteristic that reflects the features or function of the real objects.

There are two types of physical models

a) Iconic Models

b) Analogue models

Iconic Models: Iconic Models are used to represent real features of an object. Scaling system is often used in the feature representation. The scale could be upward or downwards. They could also be presented in modular form (using system of dimension grids), three dimension forms, like model card to two dimensional models like sketches, photography's and paintings. The aim of iconic model developments is to physically represent client needs and requirements, e.g. architectural building models, model airplane, model train, car and so on and so forth. The scale used in iconic model is to convey design ideas to clients for feedback.

b) **Analogue models:** Analogue models are like physical models but they may not look exactly like the reality. They aim at performing basic functions instead of emphasizing and communicating ideas about appearances. They may or may not look like the real thing. Examples are flow diagrams, maps, circuit diagrams, building plans organization plans (See also Adedayo, 2006; Ashworth, 1994).

iii) **Symbolic Models:** These types of models represent ideas using numbers, notations, mathematical formulas, musical notation. e.t.c. they have lower level of abstraction when compared with mental models.

There are two types of symbolic models; namely:

a) Mathematical models.

b) Verbal models

a) Mathematical models: these models are also symbolic in nature. These models use symbols to express or simplified relationship between variables of complex problem

e.g. $y = mx + c$

Where y stands for dependent variable.

c stands for intercept on y-axis

x represents dependent variables

m is the slope of the graphical relationship

This is an example of mathematical model

These types of models find application in operation research, decision analysis, production management, complex computation problems, optics, material allocation, construction programming, electrical engineering, naval architecture and shipbuilding. The list is in exhaustive.

b) **Verbal models:** These models are referred to as written form of mental models of ideas. Examples are: poems, plays, stories, theories, television adverts of products. The models utilized tools of figurative expression, beautiful painting of scenario to appeal to people or customers sense of reasoning.

2.23 Models Usefulness

Raftrey *et al.*, (1993) and Ashworth (1998) submitted that the development of cost models and their wider application to aspects of construction pricing has proved its usefulness in the following aspects:

i. Emergence of better-informed decision.
ii. Speedy provision of cost information.
iii. Early production of suitable cost information at an early stage within the design process.
iv. Production of more reliable information, which tends to introduce greater confidence into decision-making process. For a model to be useful in producing such advantages listed above, there are certain criteria that cost models should take into consideration, the following are such criteria as presented by Raftery *et al.*, (1993) and Ashworth (1998).

i. The model should allow for continuous updating, by incorporating new data that become available.
ii. There should be adequate data; the data requirement for the model should be freely available in the appropriate form and quantity.
iii. The model should precisely and adequately represents what it is attempting to predict.

iv. The entire process of modeling should be done quickly, cheaply and efficiently.

v. The model should be capable of evolving to suit the needs of the changing situation that is prevalent in the construction industry. The above criteria however are the guiding principles in the choice of best method/approach in cost modeling

2.24 Cost Modelling Approach and Methods in Building Works.

There are different approaches in modeling construction cost. (Mawdesley *et al.*, 1997; Ashworth, 1994) presented the following approaches /methods that could be used in modeling cost in construction works:

a. Empirical methods.

b. Regression analysis.

c. Simulation.

d. Heuristics.

e. Expert system.

A. Empirical Models

These types of model are based on

(1) Observation

(2) Experiment

(3) Intuition.

These employ the common-sense method of understanding, application and presentation. They have been used and developed on basis of ‘right feeling’. Bill of quantity for example is an empirical model. The physical appearance of building and the methods used for construction have been modeled in terms of description and dimensions. This process has been refined continually to obtain realistic relationship between cost and quantity.

Raftery *et al.,* (1993), illustrate this fact further, by asserting the tendency, to unusually think of bill of quantities and costs in the context of algebraic terms, that it is easy transition to see quantities and costs in these terms. For example, the Price of concrete in a column can be obtained from the expression: P = H x W x D x R.

Where H=Height on Plan W=Width on Plan. D=Thickness of Concrete. R=Measured rate for Concrete in cubic meters in this Location. P=Price of the Column.

The empirical approach thus suggests that there could be different prices for the Concrete, thus concrete are classified into different categories. Advantage of this lies in the following:

a. Ease of understanding and
b. It can be related easily quickly to the construction project.

Below is possible mode of derivation of empirical models using model of building process:

Formulate the problem → Collection of data → . Analysis of Data → Model building → Optimum Model → Evaluation of Model → Testing → Application.

Figure 2.3 Model of Building Process.

Source: (Ashworth, 1994).

B. Regression Analysis

Regression analysis is a technique that finds a formula or mathematical models that best describe data collected. This is often used in situation whereby the relationship between variables is not unique. It is a simple mathematical technique, which tends to quantify relationship between two variables. Geoffrey Trimble (Dr.) at Loughborough University of Technology developed this method. Several researches were carried out there to verify the practicalities of its use. According to Raftrey *et al.,* (1993), Regression analysis was considered appropriate based on the following assumptions: The proposed method is a compromise between detailed classification and total cost. It uses a limited number of cost codes to capture feedback. It involves traditional ways of developing classification system and attempt to record cost against it. An alternative method of estimating is to apply regression analysis to complete projects. This method could be suitable for certain clients who are responsible for constructing similar projects e.g. hospital boards.

Regression analysis involves plotting 'line of best bit' across the scatter diagram. This is derived by the 'method of least square' that is, the line drawn in such a way that the sum of the squares of the vertical distances from the plotted points to the line would be a minimum.

The equations are written as follows:

$$\mathbf{y} = \mathbf{ax} + \mathbf{c} \qquad \text{.......eq.1}$$

where **y** = dependent variable

a = slope / gradient **x** or **n** = independent variable **c** or **b** = intercept

or alternatively

$$y = an + b\sum x \qquad \text{.......eq.2}$$

$$xy = a\sum x + b\sum x^2 \qquad \text{..........eq.3}$$

C. Simulation

A simulation model seeks to duplicate the behavior of system under investigation by studying interactions among its components. The output of simulation is often presented in form of measures that reflect its performance. Simulation originated because of the following:

i. Desire to avoid direct experimentation where it is possible. Direct experimentation could be costly to set up and manage.

ii Simulation is subject to experimental error as other mathematical techniques are. This means that they must be treated as a statistical experiment and any interference regarding the performance must be subject to the test of statistical analysis.

iii. Simulation experiment can be conducted completely on a computer. Complex mathematic functions that are normally difficult to analyze are represented with much greater flexibility. Simulation can however be time consuming particularly when the models are being optimized. The general method that could be used in solving these problems is referred to as Monte-Carlo techniques and is based on general idea of using sampling to estimate the desired result.

The method involves the description of an item after being drawn through probability distribution. Simulation cannot however be successful without the use of computers due to vast array of data being processed. In simulation models, sampling from any probability distribution is based on the use of random numbers. The sequence of such numbers can be found in mathematical tables or random numbers generator.

Applications of simulation according to Raftery (1993); Brandon (1987) and Roger (1992) in the fields of project cost management are as follows:

i. Construction estimating, particularly in tender bidding and cost forecast.

ii Life cycle costing of properties with variableness in data such as life of materials and components, maintenance periods, interest rate and building life.

iii Construction planning as a result of risk and uncertainty associated with project management.

D. Heuristic

The Heuristic model solution rely on intuitive or empirical rules that have potential to determine an improve solution relative to the current one. In heuristic model, there are usually set of objectives to attain, thus there are search procedures which could be established and which would be moving from one solution point to another.

Therefore, heuristic model, according to Ashworth (1994) could be described as search procedures, which intelligently move from one solution point to another with the goal of improving on the value of the model objective. When no further improvement can be achieved, the best-attained solution is the approximate solution to the model. In machine intelligence development, a heuristic is a rule that dictates the course of action depending on the state of current information available at a particular period.

E. Expert Systems

Expert systems are computers that behave like experts. The output of this kind of system is subjective; it depends on information input into it in order to generate output. It picks already made brainwork of someone with knowledge of the solution to the problem by carefully utilizing the programmer rules of thumb in generating desired results. Such expert system is Artificial Neural Networks (ANNs), which utilizes set of rules in predicting or forecasting an output. The system is subjective since there is opportunity of training the system in order to produce a desired trend, pattern and output, the input parameters are subject to change depending on information available or being processed. The output generated therefore can be used for cost planning and management.

Cost planning however are influenced by arrays of factors, according to MacCaffer *et al.,* (2000); this would be considered from design stage and construction stage perspectives, can only be effective when an efficient cost model is used which is of design based. However, the choice of cost model depends on the type of cost the model is designed to measure and arrays of factors. Some of these factors affects cost determination parameters during design and construction stage.

2.25 Factors Influencing Cost of Building Work

Factors influencing cost of building works were presented using project stages (design and construction stages) as guiding parameters.

a. **Design stage:** Some of the factors that impact cost of a building work during design stage are clients requirements, design maintenance relationship and design variables

b. **Construction stage:** some of the likely factors influencing cost of a building work during construction, Site conditions, contact conditions, construction methods, techniques, And Unpredictable Items.

2.26 Factors Influencing Cost of Building Work During Design Stage

At design stage, the cost of all building works is affected by factors that result in satisfaction of owner/user requirements. They are classified under the following headings: Requirements and design variables (Brandon, 1987) and Raftery, 1993).

1. Requirements

There are five categories under this: functional, technical, aesthetics, and design/users, and maintenance requirements:

a) Functional requirements

The specific purpose of any building must be served by the components provided therein. The unique need for the users must be accounted for. Even in similar designs. For instance, a nursery school design will have a simple layout. It will most likely be a single storey building to eliminate the risk of accidents and its classrooms will be designed to accommodate elementary learning processes for the age groups. The furniture can also be specially designed to suit sizes of pupils at this age. A technical school design on the other hand will be more complex because varying studies at complex levels will take place. High cost of land may imply multi storey structure with steps or lifts. Also, laboratories and elaborate workshops will be provided.

b) Technical requirements

This involves compliance with technical legislation and standard such as building regulations, manufacturer's instructions or British standards in the design of structural element design such as beans, columns, walls, floors, etc. specific loads determine minimum sizes of these members for various materials. e.g. timber, concrete, steel etc Factory processes may determine room length or plan layout. Processes or activities too influence size or volume of space. Specialist equipment in building like operating theatres, postmortem room, bidets, urinals all affect room size and shape.

c) Aesthetic requirements

These are specific requirements of the client concerning quality of finish, color and final appearance of building. Choice of color and textures, bricks bond patterns, colored mortar in a row of shops where the respective owners have tastes, the fitting of each shop may be left to respective shopkeeper and just the shell may be constructed. The aforementioned considerations namely functional, aesthetics and technical are all inter related and in satisfying them all, design and construction should incur the most economic utilization of all production techniques.

d) Design/user requirements

These vary tremendously and depend upon who the actual user of the building will be, whether the user for his use or as an investment to be leased out is building it. Variation in these is reflected in layout and quality of material used. In the former, more care is taken in the choice of materials and quality of finishes but for the latter, emphasis will most likely be place on functionality of space and highly durable materials.

e) Owner requirements

Owners' requirement includes good value for money, building with pleasing appearance, comfortable interior conditions and long working life with minimum maintenance.

f) User Requirements

A user requirement varies with different types of buildings, and taste or class of users. So also, users often desire provision of reasonably priced building with functional rather than elaborate finishes giving a good working life in relation to cost.

(i).Domestic use: Aims at providing modern amenities at realistic rents. Tenant always wants efficient services with respect to maintenance and repairs.

(ii).Office use: User rents building in relation to usable floor area hence should enclose maximum possible floor area within external walls. Internal walls are usually made of lightweight demountable partitions. This gives minimum reduction in floor area and a building readily adaptable to change later. School, hospitals, other public buildings, functional spaces, and hard wearing surface which can easily be kept clean with minimum effort. Fixtures and fittings must be as 'rugged' as possible.

(g).Maintenance requirements

Relationships between capital cost and future running and maintenance costs are seldom given adequate consideration. Design revisions are sometimes made during construction that from long-term point of view could be described as false economy. Careful consideration should thus be made when changing a building design to reduce cost as such change may have far-reaching financial implications.

II. Design Variables

The cost implications of design variables are by no means exhaustive; however, the following shall be discussed.

a. Structural form. e.g. load bearing brick work entails high labor content, and slow rate of erection. Excessively high brick wall, requires thickening of base hence has effects upon usable floor area. So also in designing Aluminum and timber frames, they are limited to 2-3storey buildings. However, the following factors influence the choice of frame in design:

- Load to be carried and desired span of building spaces.
- Speed of erection e.g. precast and steel frames may but loaded immediately but in situ needs time for curing and setting
- Fire resistance i.e. may necessitate encasement of frame e.g. steel
- In concrete work, the cost of formwork shoots up cost.

b. Plan shape

c. Size.

d. Height.

e. Communication/circulation space.

f. Prefabrication.

2.27 Factors Influencing Cost of Building Work During Construction Stage

The following worth considering in determining cost of building works at construction stage. Site conditions (Location of the site, access and traffic control, size of the site. ground conditions and organization of the site and contract conditions).

These and other factors need to be considered in model generation .So also these factors could be controlled through choosing best cost predicting approach using appropriate building cost predicting models. These factors would be considered while formulating input-parameters for the neural network to be used for data -training in this study. However, there is a need to review the previous applications of neural network in solving diverse humanity problems. Construction or building costs extraction tool is one of important items a contractor can have in achieving project success. This however is needed in obtaining accurate project costs reports (Browen, 2000). Numerous constructions's estimating software is available for contractors use, but it programmed much of guesswork out of creating an estimate. It offers a single application that handles all the calculations and data. So therefore, a good construction estimate program will take the dimensions of a site, as well as types of materials to be used, in order to generate relatively accurate accounting of the materials costs involved. In the light of this, tools that will eliminate this deficiency need to be developed. Construction cost data collected from past projects may be used to support estimating at different stages of a project life cycle, this is termed historical data (Ayed, 1998). The usable historical data at this level pertains to characteristics of past projects e.g. location, size, complexity. Neural network is one of such models that use non-traditional estimating tool to provide an effective cost data management for project works.

2.28 Artificial Neural Networks (ANNs).

Artificial neural network is mathematical model patterned after the order of human central nervous system operation. Human brain is believed to have composed of several interconnected neurons and dendrites with neural canal as center of signal coordination. An artificial neural network composed of interconnected group of neurons and uses this approach in information processing. ANNs can also be described as a non-statistical tool which can be used to simulate and replicate complex relationship between input and output so as to establish a definite data pattern. It was described by Ayed (1998) as an effective tool for complex estimating problems in a case where relationship between the variables cannot be established by a single mathematical formula and proposition. To really understand the concept of Neural network there is a need to study artificial neural network as researchers had described it.

2.29 Understanding the Nature of Artificial Neural Networks

Artificial neural network could be regarded as a simulate of complex reality of human biological neurons. Human biological neuron transmits millions of information within a fraction of nanosecond speed of light. It was described as a system of living cells that processes and transmits information at speed of light receiving multiple inputs from other interconnected neurons through systems of dendrites pathways (Lippman, 1988; Chester,1993; Klimasauskas, 1993; Madesker *et al.*,1993 and Karunasekera, 1992). Similarly, it was stated in Hawley *et al.*, (1993);Medesker *et al.*, (1993) Chao and Skiebnieswsky (1994) that ANNs exhibits a great deal of human brain's characteristics, such as learning from experience, data mining, mapping and generalization of input variation pattern in order to synthesis a new solution order,it was further stated that ANNs is capable of inferring solution from a set of data and used the result to judge new set of data being that has not been used on the system. Research output has confirmed the fact that ANNs was capable of providing a meaningful answers even in a situation whereby data to be processed contain errors or incomplete (Gagarin *et al.,* 1994; Forsyth, 1992). The versatile nature of ANNs accounted for various applications in hardware that simulates, act or thinks intelligently such application in robotics, nanotechnology (Forsth, 1992; Adeli, 1996 and Smith, 1993).

2.30 Defining an Artificial Neural Networks (ANN)

Artificial neural network can be found with different nomenclatures. It was defined by Lippman (1988) and Adeli and Wu (2008) as model that composed of arrangement of linear and non-linear mathematical related elements, often parallel in operation, configuration and pattern which symbolizes its likely link with biological related matter. Similarly, Nelson (1989) describes ANNs as a parallel information distribution structure consisting of elements that have attribute of local memory and can perform logical inferential operation and information processing. ANNs was described as information processing system whose configuration and architectural skeletal structures are inspired by structure of human biological systems and operates with internal control mechanism based on self adjustment of the internal parameters (Nielson, 1989; Adeli, 2008; Arciszewski and Ziarko, 1992).

In the same vein, Klimasauskas (1993) referred to it as an information processing technology, inspired by studies of human brain and nervous systems, composed of neurons and group of neurons arranged in layers. Flood and Kartam (1994a) and Salchenberger *et al.*, (1993) defined ANNs as an arranged system of neurons that can process information rapidly and transfer readily between computing systems. Finally, Gagarin *et al.*, (1994) and Paulson (1995) submitted that ANNs could be described as an Alternative Information Software Technology which presents information in nodal form and expresses the relationship between them as links. Weights and layers are often used in network training topology and configuration (Tan *et al.*, 1996).

2.31 Parameters for Consideration in Neural Networks ANNs Application

There are certain parameters that should be considered when deploying Artificial neural networks (ANNs). It was stated in the previous review that ANNs learns from an observed data set and then masters the trend for further generalization, however, there are principles that guides obtaining consistent, correct and valid output from the network whenever its being applied, some of them include: choice of appropriate logic architecture, data robustness, and choice of an appropriate learning algorithm (Caldwell, 1995a).

i. Selection of an Appropriate Learning Algorithm: One of the determinants of good and valid result in ANNs computational operation is getting the choice of learning algorithm right from outset, once an appropriate learning algorithm is selected there is bound to be valid and correct output. It is important therefore to solve the problem of data-learning algorithm compatibility before other computational processes.

ii. Data Robustness: Using a carefully screened and robust data is also important for good and quality output. Correct selection of cost function and learning algorithm often guarantee valid and good output.

iii. Choice of Model: The type of model to be used will be determined by the problem to be solved and data representation.

2.32 Literary and Life Situation Applications of Neural Networks (ANNs)

Literary applications used in this context refer to the collection of submissions as advocated by researchers in the field of artificial neural networks applications. The applications under consideration therefore include application of ANNs in identifying and correcting wrong spelling, extraction of detail from accounting related packages, biometrics, structural design, pile-fault diagnosis, detailing of structural damage in building. Also it includes group decision making, remote sensing, road maintenance, stock and bond prediction, bi linear moment rotation, bankruptcy prediction, thrift failure, bond rating prediction and determination of effectiveness of construction firms among many others.

In line with the above therefore, Chen and Wang (1990) used artificial neural network in text semantic application such as wrong spelling identification and analysis of handwritten text fault among others, Wang and Tsai (2007) used ANNs to provide solution to personnel transportation, Yeh *et al.,* (1990) configured a knowledge based expert system with back propagation networks. Kiretooh (1995) deployed Back propagation network to generate diagnostic approach in webometrics. Berry and Trigueroisis (1993) applied ANNs in cost accounting reporting and also applied ANNs in structural system fault identification. Furthermore, Tseng *et al.*, (1990) used Hopefield network to provide solution to job transportation and allocation problem. Murtaza and Fisher (1994) provided empirical framework for an application that could be used in decision making problems. Similarly, Kamarthi *et al.,* (1992) advocated the use of two layered back propagation technique for formwork selection considering technical parameters like flange size, width, slenderness ratio and buckling factors.

Soemardi (1996) solve group decision making with two fuzzy neural networks and provided criteria for critical success factors in decision making. Karunasekera (1992) worked on remote sensing for mineral exploration with ANNs and provided framework for soil layer characteristics typical of every mineral soil layers while Anderson (1993) provided characteristic for bi-linear moment rotation in steel structures. Furthermore, Neural network was used in financial decision making by Hawley *et al.,* (1993) while Kimoto *et al.,* (1993) carried out modular networking stock prediction.

However, there are a few applications on construction productivity, such as contained in the research carried out by Williams (1994) where back propagation technique was used for predicting change in construction index, Salchenberger *et al.,* (1993), Wu and Lim (1993) and Hegazy and Moselhi (1993).

2.33 Real Life Applications of Artificial Neural Networks (ANNs).

There are a few applications of neural network in the aspect of real-life application. The list includes function approximation, data classification, data processing, system identification, game playing, webo-metrics, vehicle tracking, pattern recognition face and hands identification and tracking, sequence recognition, process control and decision making.

(a) Data processing: Neural network was used to carry out data flittering, clustering and separation and compression by Mawdesley *et al.,* (1993) and Vaziri (1996)

(b) Data Classification: Data classification, pattern recognition novelty detection and sequential decision-making are carried out with the aid of neural network by Elazouni *et al.,* (1997), Chua *et al.,* (1997) and Li (1996)

(c) Function approximation: Vaziri (1996) and Gagarin *et al.,* (1994) utilized ANN's in function approximation and time series prediction and system modeling.

(d) Classical application: some other application areas include process control, decision making, face tracking, pattern recognition, game playing, and sequence recognition by Wu and Lim (1993), Davies (1994b), Fletcher (1993) and Gradojevic (2000).

2.34 Neural Networks Classification

There had been several attempts at classifying neural network by researchers. ANN's was categorized as feed forward neural network by Davies (1994b), Anderson *et al.*, (1993) called it radial basis network and self organizing network, recurrent networks and simple recurrent network. Also, Gradojevic (2000) Chester (1993), Smith (1993), Rosenbalt (1950), Adeli (1992), Chau *et al.*, (1994), Salchenberger *et al.*, (1993); Baker (1993) and Kahkonen and Pallas (1993) categorized it as Echo State Network , Long short term memory Network Stochastic Neural Network, Boltzman machine, Association Neural Network, Dynamic Neural Networks, Cascading Neural networks, Neuron-fuzzy networks and Cascading neural networks. Summary of the description is as follows:

(a) Cascading neural networks: Cascade network are the type that begins with a minimal network and then trains automatically to add hidden units.
(b) Neuron – fuzzy networks: A neuron-fuzzy network is a new system of an artificial neural network. It contains several layers that simulate fuzzy logic.
(c) Feed forward Neural Network: This is adjudged as the simplest type of artificial neural network. It contains hidden nodes and input nodes.
(d) Dynamic Neural Networks: this border about non-linear or multivariate behavior and transient phenomena.
(e) Self organizing network: Self organizing networks learn to map points in an input space to points at output space (Baker, 1993)
(f) Recurrent network: Recurrent network propagate data from processing stage to input stage (Adeli 1992) and Salceberger *et al.*, (1993)
(g) Echo state Network: Echo state Network is a reamed neural network with few hidden layers (Weitz, 1994; McCann, 1994; Zhang *et al.*, 1998).

2.35 Modeling Approaches in Artificial Neural Network.

As a result of dynamic nature of artificial neural network, there are different methods of using neural network in modeling, Elauzonni *et al.,* (1997), Adeli (1992) and Smith (1993) advocated five (5) method of modeling topology, the steps include; data acquisition, analysis and problem representation, selecting model architecture, network training, network testing and validation.

(a). Data Acquisition: The first stage in network modeling is selecting a suitable data (variable). The data must be separated into dependent and independent variables, which will be more useful for network (Wu and Lim, 1993), Yeh *et al.,* (1993).

(b). Problem representation: Problem to be modeled must be adequately represented since the mode of representation of the problem has great effect on network training. The problem can be presented in variables. Smith (1993) submitted that there are two types of variables that can be used to represent problem, class variables and quantitative variables. Variable can be cut up and represented with nodes. Yet *et al.,* (1993) suggested the representation of variables with binary numbers such as from 0 to 1, -1 to 1.

(c). Model architecture: Selecting right architectural configuration at modeling phase is essential. Suitable model configuration should be selected with appropriate layers and nodes. Input and output nodes should be carefully selected. It has been proved through researches that model with more hidden layers and nodes often produces better output, and ANN's network with more internal nodal and layer configuration yields better output (Karunasekera 1993, Lippman, 1987), William (1994), Roger and Lamash (1992). However when developing model architecture, care should be taken to prevent problem of over fitting of the network by limiting the number of hidden layers and nodes.

(e) Model weight determination and configuration:

Weights are referred to by the Medesker *et al.,* (1993), Khan *et al.,* (1993) as the strength that connects network inputs to another. The weights are described as mathematical value of initial entering data. They are often assigned to network before commencement of data processing; the weights are often used to update the network.

(f) Networks Learning Rate and Momentum:

Learning rate refers to the parameter selected before the data training, this regulates the network's processing speed. Learning rate is often represent by lambder η_1 is the constant proportionality that provides access to the frequency at which the weights can be changed. There are two types of learning rate and momentum; a high learning momentum and low learning rate momentum. High learning momentum when set on a network, increases the speed at which the network maps the input to output. Low learning rate on the other hand enables the system to learn at a very slow pace (Khan *et al.,* 1993; Anderson, 1993).

(g) Model Training

Training the model after configuration and weight selection is as important as validation process. The model must be exposed to selected variables (input and output parameters) in order to study the pattern of variation among the parameters. The training stage allows for modification weights error so as to ensure current answer from the network. ANN's learns from its mistakes at this stage (Klimasauskas, 1993, Medeskers, 1993). There are basically two methods of training in ANN's application. These are supervised learning method and unsupervised learning method. Supervised Learning requires two input vectors, target vector and input vector a target vector is often refers to as training pairs (Smith 1993).

Second learning method is referred to as a system that does not require target vector as compared to supervised learning technique. It doesn't require comparison. Output is often generated straight from input.

(h) Parameters for Network Training:

Several researchers attempted at presenting their view about what should be training benchmark parameters, which will serve as milestones to stopping network training, Carpenter and Bethelemy (1994) stated that there are two common parameters that could be used to terminate network training; the training cycles (epoch) and desired output. Khan *et al.,* (1993); Vaziri (1996) suggested 20,000 to 100,000 training cycles for a typical training session.

(i) Sample

Sample in this context refers to number of data used as inputs and output samples are often used as inputs and output in model configuration, training and validation.

(j) Configuration and training sample

Samples are often used from the whole sample population for purpose of network building and training, such samples are referred to as training samples; it helps to evolve suitable algorithm. This sample required at this stage is often huge; Carpenter and Barthelemy (1994) stated that neural network requires large samples for network training. In line with this, Klimasauskas (1993), Yeh *et al.,* (1993), Medesker *et al.,* (1993) recommended that sample strength should always be multiply with factor of five (5) during training while Bahram (2005) suggested factor of ten (10) for model output stability and validation

(j).Network Testing and validation sample.

The resultant model should be tested after construction, there are special set of samples used for this purpose, and they are termed, testing samples. The tests set are fed into the trained network as input. The resultant output then can be mapped with desired output and predicted variable is calculated to determine output fitness and error. The error generated is compared with the benchmarked error threshold, if it is within permissible range the model can be accepted as valid. (Kimoto 1993, Flood and Kartam ,1994a and 1994b). However, test set should be a reflection of the original samples used in model configuration and training, this according to Klimasauskas (1993); Kimoto (1993) will ensure accurate and consistent outputs. This approach was used in this research work, by splitting the entire samples in to configuration set, training set and model validation set to ensure holistic cost prediction.

Summary of Literature

The reviewed literatures have positioned this research work in the light of previous contribution by different researchers in the area of cost modeling, estimation and prediction. The chapter provides an insight into factors that instigates cost overrun, their interrelationship and impact on project cost, drawing strength from submissions of Ogunsemi and Jagboro (2006); Kouski *et al.*,(2004) and Ogunlana *et al.*, (1996) among others. Furthermore, the review was carried out with focus on traditional and non-traditional cost modeling system. Non-traditional model covers regression based models while neural network was used as an example of non-traditional models.

Also, in modeling the choice of input and mode of output desired are important, therefore a background was provided for different input modes used in output generation, this is to justify the mode of input used to generate output in this study. A background was provided for the review with study of traditional models with reference to regression-based Time-cost model of Ogunsemi and Jagboro (2006), exploratory regression analysis developed by Li *et al.*, (2004), regression-based new research protocol by Xiao and proverb (2002) and Building Information Model of Farah (2005) among others. Finally, an exploratory approach of neural network application was conducted with reference to definition of artificial neural network (ANN) consideration parameters in ANN deployment, literary and life applications in ANN, neural network application with reference to model architecture, learning rate momentum, model training, sample selection, model development, testing and validation.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

The methodology adopted in the analysis of various data and their interpretation was duly presented in this section. Tasks carried out include selection of project categories, formulation of project cost goals with respective building cost indicators, and assigning cost weight through various costs centers. In addition, the study deployed ranking and other decision-making tools that considered multiple performance measures for individual project cost, in analyzing the relationships among labor/project size, materials and projects multi-attribute (project-characteristics). Also, appropriate analytical tool was used in analyzing macro variables such as construction cost, gross floor area, and number of storey and micro factors that can influence project cost. However, multi attribute characteristics of project works were studied within the context of cost data of completed residential building projects (private projects including office and residential accommodation projects) completed within the last three years.

3.2 Research Design

Survey design was used in this research work. This involved random sampling of project bill of quantities, designed to capture project cost parameters or characteristics information such as: project type, location, and final construction cost, average floor area, total floor area, average storey height, total building height, number of storey above the ground and number of basement. These were adjusted using construction price index.

3.3 Population of Study

There are diverse ways by which population frame can be chosen for purpose of research works. Population constituents can be categorized along the line of client types, the type of building projects, procurement type adopted as well as projects' cost range. Type of client in the parlance of this study refers to any of the following individual clients: individual speculative developers, corporate organization (manufacturing), corporate organization (banks and finance institutions), corporate organization (IT), clubs, societies, religions organization, local government and state government, federal (parastatals, international government organization and non-government organizations. Project is described in this context as one that can be procured through direct labor approach, design and build; labour only method and traditional method. So also, in term of project cost (initial budget cost), cost range can be set in this regard to distinguish one project from the other, ranges like less than 50 million naira, 50 million to 100 million naira.

Building types can also be categorized along the line of client type in population classification. Building can be residential in nature, office, religious, academic, recreational facilities, health facilities and special buildings. Against this background therefore, the population constituents for the purpose of this research work was categorized along the line of clients and building project types. The population frame for the study included public and private building projects that were used for office and residential purpose and are reinforced concrete and in-situ concrete structure in nature. The projects used are those completed within the last (1) to (5) years in Lagos State, Ogun State, and Federal Capital Territory. The initial cost (Bill of quantities value) and As-built cost (final cost), extracted from project documents of these building projects were used; cost centers on them were used as modeling parameters for the Neural network-based model that was generated.

3.4 Scope of Work

The research work was restricted to developing a cost prediction tool, this was carried out with the aid of artificial/neural network generated output; the output data was used as parameter for the input modem or neuron of the model that was developed. The data of completed building projects of 1 to 4 years were used to formulate an input data. This method is adjudged right, since recent information about the building was captured and the econometric variables that can impacts the building cost were properly factored into the data for processing. Residential and office building projects completed within the period that falls between pre and post-economic meltdown period were used, along the line of reinforced concrete, In-situ concrete structures for this research work; this is to ensure effective capture of variables as it relates to various building types.

3.5 Sample and Sampling Technique

Probability sampling technique was used in this research work while random sampling method was deployed in sample selection for model development. The samples for this work were categorized into two: The first category is sample for data training for designing a suitable network algorithm, while the second category is sample for model validation.

3.6 Sampling Frame

The sampling frame composed of residential accommodation and office building projects that were completed within the past five (5) years. Sampling frame of 500 was used for the work from which samples were drawn at random. Creese and Li (2005), Adedayo (2001) provided a base for line of thought in sampling frame determination. They advocated selection of sampling frame in the following order: sampling frame: 100 = Poor, 200 = Fair, 300 = Good, 500 = Very Good, 1000 or more = Excellent. Thus for validation consistency and adequacy sampling frame of 500 was used in this context.

3.7 Determining Sample Size for Research Work

A wide range of recommendations regarding sample size in analysis have been made, these are usually stated in terms of either the minimum sample size (N) for a particular analysis or the minimum ratio of N to the number of variables, P, that is, the number of survey items being subjected to analysis (Mac Kim *et al.,* 1996). Gouda (2007) recommends five subjects per item, with a minimum of 100 subjects, regardless of the number of items. Guilford (1954) argued that N should be at least 200 while Cartel (2008) recommended three to six subjects per item, with a minimum of 250. Creese and Li (2005) provided the following guidance in determining the adequacy of sample size: 100 = Poor, 200 = Fair, 300 = Good, 500 = Very Good, 1000 or more = Excellent (refer to Adetayo 2001 in Appendix 19 for further detail).

3.8 Sample Size

Sample size selected for different types of building is presented in this section. It contains detail about residential accommodation and office facilities used for the study.

3.9 Residential Accommodation

Samples were selected in this section and the breakdown of sample selection with respect to each project types is presented in the following sub-sections while detail order of sample selection is contained in Table 3.1.

3.10 3&4-bedroom Flats on 3 Floors

Bill of quantities specifying initial cost and final project cost of residential works totaling two hundred and twenty (220) samples out of five hundred (500) population frame was used in model generation and network training for concrete-framed residential structures, three (3) storey structure, initiated and completed within year 2006 and 2009; the network was preset for data modulation and accepted 42% (92 samples) as data to be used in building network algorithm while the remaining 58% (128 samples) was used for network testing and output cross validation; network testing exemplars from the network context were 132 samples while cross validation exemplars were 92 samples.

In network generation for sampled office projects, one hundred (100) samples, of project initiated and completed between year 2006 and 2009, were used in network modeling and training. Thirty-six percent (36%) which translate to forty-three (43) nodal equivalent of network's Test exemplars and fourteen percent (14%)of training data was fed into the neural network system, which is 16% of cross validation exemplars (16 samples) for network stabilization and cross-validation, to determine performance of the generated algorithm when new set of data are introduced.

3.11 Four-bedroom Duplex

Seventy (100) samples of four-bedroom duplex initiated and completed within 2006-2009 were used in network generation and training.

3.12 Apartment (1/2-bedroom Bungalow)

Samples from completed One (1)-bedroom apartment totaled seventy (70) samples were used in generating network algorithm for the dataset.

3.13 Office Building

One-hundred (100) samples of Office building initiated and completed within 2006-2009 were used in network generation and training. To this end, a total sample of 390 magnitudes of 500 samples collected were used, some were rejected based on their inconsistent nature. It is important to note that in determining sample size, the size of a sample to be taken depends on the basic characteristics of the population, the type of information required, cost, personnel, and time involved (Adetayo, 2001).

Also, calculating the degree of accuracy required in the result beforehand is necessary. This refers to the level of significance specifying the degree of certainty, which the sample design will measure, within the tolerance of the true value (Norusis, 2004; Adetayo, 2001). However, the larger the size of the sample the greater its precision or reliability. This implies, an increase in precision can only be achieved by using large sample size while maintaining confidence, or increasing confidence as well as precision. In all cases large samples is needed (Norusis, 2004; Azoff, 1994). Therefore for the purpose of this work that involve neural network large data is needed for better accuracy.

Neural networks which was used in developing the cost model, has best prediction output relative to parametric estimation when trained with vast array of inputs data. Thus for the purpose of this research work, 500 units of samples is estimated as necessary for better output generation. Three-hundred and ninety (390) units were used in model generation and validation with neural network back propagation effect on the samples amplifying it to larger samples; the remaining samples were randomly selected for cross validation of generated model.

3.14 Research Location

This research work was carried out on some construction sites in south western part of Federal Republic of Nigeria and Federal capital Territory Abuja. The data for the study were obtained from major cities of south western Nigeria and specifically Ogun State, and Lagos State, due to their closeness and these places are notable with largest conglomeration of building projects in Nigeria.

Table 3.1: Geographical Spread of Sampled Projects

Project Location	3/4 - bedroom Unit	4-bedroom Duplex	Office	2-bedroom Bungalow	Period
Lagos State	110	35	35	40	1998-2010
Ogun State	60	40	40	15	1998-2010
Federal Capital Territory(FCT)	50	25	25	25	1998-2010
Total	220	100	100	70	

Source: 2010 Survey

The sampled data covered a suitable geographical spread in order to provide basis for sampling of robust data. A total number of two-hundred and twenty (220) samples were selected in 3/4-bedroom category, with one-hundred and ten (110) from Lagos State, sixty (60) from Ogun State and fifty (50) from Federal Capital Territory; all these samples covered year 1998 to 2010. Also, hundred (100) samples of 4-bedroom duplex were used. Forty (40) were obtained from Ogun State, thirty-five (35) from Lagos State and twenty-five (25) from Federal Capital Territory. Moreover, one-hundred (100) samples of office building were sampled and used, thirty five (35) samples were taken from Lagos State, while Forty (40), twenty-five (25) samples were taken from Ogun State and Federal Capital Territory respectively. Finally, a total number of seventy(70) samples were taken under the category of 2-bedroom bungalow project executed at three locations and distributed in the following order: twenty-five from FCT (25), fifteen (15) out of Ogun State while forty (40) was selected among those executed in Lagos State.

3.15 Data Collection Instruments

The data collection method involved the use of the following:

a. Major Source of Data: Bill of quantities of projects, Project specification, Initial and completion cost of selected building project.

b. Secondary Source of Data: Journals, Cost indices, Building price gazettes, Cost data, and Cost annuals.

c. Review of current developments in cost estimation and neural network that relates to the research modules.

CHAPTER FOUR

DATA ANALYSIS, PRESENTATION AND DEVELOPMENT OF COST FORECASTING SOFTWARE ALGORITHM,

4.1 Introduction

In this Chapter, procedure involved in the development of software for project cost forecasting through synthesization of suitable process algorithm is presented, also the data selected for the model development and validation including the synthesization process involved in cost units determination were presented. Cost data used in this work was extracted from the residential, and office projects, with their unique characteristics detailed out, such as the year of completion, project's unique features, elemental cost breakdown, initial budgeted cost, final completion cost, and economic variables (inflation factor and corruption escalator factor).

Cross tabulation of the parameters used in the analysis was conducted with a view to finding pattern of relationship that exist among the selected projects parameters such as variation among cost centers, parameters mapping, percentage variation, and project variables pattern correlation. So also, systematic analysis of technique and procedure adopted in the use of neural network in processing the data to build a suitable network algorithm for each of the project types were highlighted. The outcome of the optimum cost value obtained from the generated neural algorithm was tabulated and presented accordingly under each project types.

4.2 Parameters for Data Adjustment (Inflation Index and Corruption Escalator)

Inflation can be defined as a persistent increase in the level of consumer prices or a persistent decline in the purchasing power of money. In other words, it is the situation when commodities are getting more expensive.

4.3 Inflation Cause and Effect

Inflation is often caused by an increase in available currency and credit beyond the proportion of available good and services. It could therefore be inferred that people describes inflation by the effect that is experienced on the environment, when they see prices in their local stores going up. When people go to the building materials store, and see ever higher prices, they know how inflation affects them. But when they are feeling more philosophical, they might reason that if all wages and prices increased at the same rate, it would all balance out in the end. This is possible from theoretical point of consideration, but lack realistic application, prices of various items all increase at different rates, this tends to create imbalance on social benefit enjoyed by people. However, during inflation, there should be cost adjustment in term of administering a buffer stimulus in the form of cost of living allowance “COLA”, this should be an adjustment made to compensate for the increase in prices due to inflation.

Realistically, the effects of cost adjustment will not be felt early because consumer must have already been paying the higher prices for the material for a year before the income is adjusted. However, there are other good effects of inflation. One side of inflation often appreciated by the consumer is the fact that they can pay off their debts at lower cost compared to the time of lending and borrowing. The reason lies in the fact that it takes fewer hours of work to pay back the lender. Assurance of loan repayment often encourage lenders to lend, once he is unsure of certainty of repayment, the loan will be given out at high rate of charge or none, and as lending interest rate increases, economy grindstone a halt, it could therefore be inferred that the good side of inflation is bad for the economy in the long run.

4.4 Analysis of Inflation Growth Rate Since 1913

Inflation rate often grows faster like compound interest. The buildup of inflation rate growth that has accounted for the Average annual inflation rate since 1913 is “only” 3.42%, for better illustration, something that cost ₦1.00 in 1913 would cost ₦21.71 presently (₦1 + ₦ 20.71 inflation). In other words, consumer had been cheated of 95.24 out of every dollar. The actual inflation, (2000% inflation occurred since 1940), the actual figure has been 4.11% with the 1940’s, the 1970’s and the1980’s having 5.63%, 7.09% and 5.33% average annual inflation respectively. Those decades were especially hard economically for people trying to make ends meets while material prices increased and wages did not rise up (Turner, 2010). The above information on inflation growth rate was obtained through inclusion of other data such as consumer price index (CPI) and Building cost index among others.

4.5 Consumer Price Index

Consumer Price index describes the pattern of consumer goods price variation over a particular period of time. This is one of the data often used in inflation rate calculation. The Bureau of Statistics is the custodian and originator of consumer price index. The source data is often procured from the federal office of statistics and marketing boards. Consumer good prices have been studied overtime before reaching conclusion on the published data. Similarly, prices of building materials together with the variation are often compiled and indexed using selected year as base year. However, the Bureau of labor statistics often “embargoes” the release of consumer price index inflation data (CPIID) in other words they keep it secret until a specified date so that no one will have undue advantage by getting the consumer price information early, the information compiled for the previous month is often released at a particular date in a subsequent month. This is illustrated in Table 4.1

Table 4.1: Consumer Price Index Released Schedule

Reference month	**Consumer Price Index Release Date**
January, 2010	February 19, 2010
February, 2010	March 18, 2010
March, 2010	April 14, 2010
April, 2010	May 19, 2010
May, 2010	June 17, 2010
June, 2010	July 16, 2010
July, 2010	August13, 2010
August, 2010	September 17, 2010
September, 2010	October 15, 2010
October, 2010	November 17, 2010
November, 2010	December 17, 2010
December, 2010	Yet to be released

Source: Turner Building Index For 2010

4.6 Building Cost Index

The economic environment has created constrained demand in the construction market. This has created a downward pressure on construction costs thus created a competitive environment. The restrained market has made it difficult for manufacturers and suppliers to increase their prices, upward trend of a certain commodity prices notwithstanding (Turner, 2010). Prevailing factor of construction procurement value of a building is compounded and presented in a schedule referred to as building cost index schedule as presented in Tables 4.2, 4.3 and 4.4.

Table 4.2: Building Cost Index

Quarter	Index	D%
3rd quarter 2010	798	0.00
2nd quarter 2010	798	- 0.13
1st quarter 2010	799	- 0.50
4th quarter 2009	803	-2.07

Source: Turner Building Index 20

Table 4.3: 1998-2009 Index Figure

Year	Average Index	D %
2009	832	-8.4
2008	908	6.3
2007	854	7.7
2006	793	10.6
2005	717	9.5
2004	655	5.4
2003	621	0.3
2002	619	1.0
2001	613	0.3
2000	595	1.0
1999	570	3.8
1998	549	4.6
1997	525	4,0

Source: Turner Building Index 2010

Turner building cost index is determined by the following factors considered on a nationwide basis: Labour rates and productivity, material prices and the competitive condition of the market place.

4.7 Annual Current Inflation Rate (Inflation Rate in Percent for Jan 2000-Present)

Inflation data presented in this work was obtained from inflation .com, a group for research in micro and macro economic variables in United States. The inflation data presented was based on government's index, and that of the group calculated to two decimal places. Two data sources were considered for adoption in this work, the government from National Bureau of statistics index and inflation data from inflation.com, data from the latter was found to have consistent transition intervals, it showed the inflation figure rising steadily rather than being stationary, as compared to government's data. January and February, 2005 is an example, government statistics had the months as having inflation rate of 3%. In January, 2005, inflation.com data indicated the month as having inflation rate of 2.97% and February, 2005, as 3.01%, there was a slight increase instead of flat rate for the two months. This has a tendency of making one to have the believe that inflation rose 0.1% during that period, while in the real sense of it, there was increase from 2.16% to 2.32% or a 0.16% increase, which practically is more than 0.1% (National Bureau of Statistics 2010).

4.8 Current Inflation Schedule (in percentage)

The Current annual inflation rate is presented in Table 4.4.

Table 4.4: Current Inflation Detail (in percentages)

Year	Jan	Feb	Mar	April	May	June	July	Aug	Sep	Oct	Nov	Dec	Ave
2010	11.3	11.4	13.1	12.4	10.2	10.5	12.4	11.5	11.4	11.4	11.4	11.4	11.40
2009	13	12.4	12.8	12.4	12.8	13.3	12.10	13.8	12.9	13	12.4	12.2	12.4
2008	4.28	4.03	3.98	3.94	4.18	5.02	5.60	5.37	4.94	3.66	1.07	0.09	3.85
2007	2.08	2.42	3.78	2.57	2.69	2.69	2.36	1.97	2.76	3.54	4.31	4.08	2.85
2006	3.99	3.60	3.36	3.55	4.17	4.32	4.15	3.82	2.06	1.31	1.97	2.54	3.24
2005	2.97	3.01	3.15	3.51	2.80	2.53	3.17	3.64	4.69	4.35	3.46	3.42	3.39
2004	1.93	1.69	1.74	2.29	3.05	3.27	2.99	2.65	2.54	3.19	3.52	3.26	2.68
2003	2.605	2.98	3.02	2.22	2.06	2.11	2.11	2.16	2.32	2.04	1.77	1.88	2.27
2002	1.14	1.14%	1.48	1.64	1.18	1.07	1.46	1.80	1.51	2.03	2.20	2.38	1.59
2001	3.73	3.53	2.92	3.27	3.62	3.25	2.72	2.72	2.65	2.13	1.90	1.55	2.83
2000	2.74	3.22	3.76	3.07	3.19	3.73	3.66	3.41	3.45	3.45	3.45	3.39	3.38

Source: National Bureau of Statistics 2010.

4.9 Inflation Rate Determination Technique

The formula for calculating the inflation rate using the Consumer Price Index is relatively simple. Bureau of labor statistics (BLS) conducts commodities price survey and use the outcome to generate the current consumer price index (CPI). If the index consists of one item and that item cost $1.00 in 1984. The bureau of labor statistics published the index in 1984 at 100, if today that same item costs $1.65 the index would stand at 165.0

By considering the examples above, it would be discovered that the index increased (from 100 to 165(. To calculate how much it has increased, the second number (165) has to be subtracted with first number (100), the resultant value will be 65. Therefore it could be inferred that since 1984, price has increased, by 65 points. Having derived the magnitude of price movement, it need be compared to the starting price (100). This is done by dividing the increase by first price or 85/100. The result is (0.85), this number is still not very useful, so we convert it into a percent, to be able to do this, we multiply by 100 and add a percentage (%) symbol, and therefore the result is an 85% increase in price in 1984.

4.10 Derivation System for Initial Project Unit Rates

Cost production system in construction industry is a unique system, unlike other industries where production activities usually take place under stable conditions and in a stable environment, production system in construction industry however, is often expose to unstable environmental and economic parameters. This sometimes account for unstable nature of construction works' costs. It is therefore important to consider those extraneous factors that affect construction cost such as cost derivation technique that takes construction methodology into consideration, in addition to environmental and economic parameters. The choice of cost derivation technique adopted in the cost generation is of importance, and could to a large extent influence the correctness of the cost figure generated.

Against this background, the cost derivation technique that incorporates construction methodology for the work in generating the cost unit rate of item of work should be carefully selected to avoid wrong result. Builders cost derivation approach popularly referred to as "Builders estimate,'' is one of the best cost derivation strategy that a contractor can use, this is due to the fact that the construction methodology that is to be used in project execution would be used in deriving the cost centers and unit rate of cost items.

4.11 Building Unit Rate for Item of Work.

A few examples of technique of building basic unit rate for item of work adopting builder estimate approach are examined below, please note that rates, price and units used in this presentation are those of pre-economic melt-down period (2008/2009), being among base year of the projects used in this context. Also, system of building rates for items such as Excavation work, Earthwork, Concrete work and Block work are selected for illustration.

4.12 Earth-Work Support: This is measured and priced in square meter (sq. m) to the actual face of excavation, which may require support, a times, the contractor may choose not to price this in view of the fact that the ground is stable enough. However if he decide to price the item, but does not carry it out on site, he is still entitled to the amount in the in the bill because it is a risk item. Some of the factors to be considered in providing cost of earthwork support during excavation work are as follow:

(a) The nature of the ground and a depth of excavation

(b) The type of excavation crack, pit basement

(c) The number of cost of materials to be used

(d) The period of the year in which excavation is carried out.

(e) The no of times the materials can be reused. Cubic meter of timber is gotten by length × cross section

e.g.$\frac{(20 \times 100 \times 3000)}{(1000)^3}\ m^3$

4.13 Methods of Pricing

(a) Prepare a suitable design of the earthwork support

(b) Consider the cost of supporting a given length or area of trench, basement or pit.

(c) Calculate of cost of timber required and divide by of assumed number of uses.

(d) Calculate the labour cost of fixing and stringing the timber to the length or areas under consideration.

(e) Add the material and labour cost together and reduce the total cost to a rate per meter square (m^2). There are 2 types of estimating technique in basic item price determination

1. Synthetic Approach = Analyzing the items bit by bit

2. Analytic Approach – Analyzing the whole area and reduce it to a unit

Builder estimation approach was used to derive the cost of the following items of work:

1. Hardcore filling 2. Excavation 3. Earthwork support 4. Hardcore 5. Concrete work 6. Block work 7. Roofing.

4.15 Hard-Core Filling

Materials used for this are usually bought by volume and since it consolidates after compaction an average of 20% must be added to cover consolidation. Average output of barrowing and filling hardcore are as follow: Barrowing and filling bulk hardcore over 250mm thick, 1.2m^3/hr. ditto not exceeding 250mm thick 0.8m^3/hr. compacting vibrating roller is 0.4hr/m^2 10tonne roller, 0.2hr/m^2

For further illustration there is a need to calculate the unit rate of the following bill item to validate the adoption of builders estimate:

a). Excavation in reduced level not exceeding 0.25 m maximum depth per cubic metre

b). Excavate trenches to receive foundation over 0.3 m wide starting at reduced level not exceeding 200 m maximum depth /m^3

c). Earthwork support to faces of excavation not exceeding 2m between opposite faces maximum depth not exceeding 150 mm/m^2

d). Hardcore filling in bed 250 mm thick deposited and compacted in layers not exceeding. 150 mm/m^2.

e). Remove surplus excavation materials from site /m^3

Please note that Unit rate is made up of Material cost, Labour cost, Plant cost and Overhead cost

Unit Rate

Material cost, Labour cost, Plant cost, overheat profit

= Rate/m^3

Recall item 1: Excavation (Excavation in reduced level not exceeding 0.25m maximum depth per cubic metre)

Material Cost Nil(no material is to be purchased)

-Labour cost [output × Rate] ₦35/hr.

3. hr/m^3 @ ₦ 35/hr $\frac{3.25hr}{m^3} \times \frac{₦35}{hr}$ = ₦113.75/m^3

-plant cost nil

	113.75
Add profit and over head 20%	22.75
	₦136.50 Rate/m^3

Analytical Estimating

Another method is by considering the whole volume of work and check the amount that will be needed in excavating or carrying out the work.

Assume 250m^3 @ ₦28, 000 for the Volume

Volume (250$m^{3)}$ =	28000
Add 20%	5600
	33600 ÷ 250 = ₦ 134.4/m^3

Recall item 3: Earthwork (Earthwork support to faces of excavation not exceeding 2m between opposite faces maximum depth not exceeding 150mm/$m^{2)}$

Assume a length of 50m

Material cost

Poling board

2/51/1.00

0.10

0.05

$0.51m^3$

Walling board

$^{2}/_{50.00}$

0.10

0.05

$0.51m^3$

Struts

675

Less 2/100

200

475

51/0.48

0.05

0.05

$0.0612m^3$ $1.07m^3$

Assuming we are using special wood

2inches × 4inches × 12feet = N150

12ft = 3.6m

$\frac{150}{0.05 \times 0.10 \times 3.6}$ 2 inch = 50mm

4 inch = 100mm

= ₦ 8333.33/m^3
1.07m^3 @ 8333.33
= ₦ 8916.67

Add 10% waste 891.67_
9808.34

All nail
1kg @ ₦ 70   70.00__
9878.34
Assume 10 uses
Cost/use = $\frac{9878.34}{10}$

= ₦ 987.83

Labour

30hr/m^3@ N50/hr = ₦1500

₦ 1500/m^3 × 1.07m^3

= ₦ 1605
987.83
1605.00
₦ 2592.83

Length of a timber = 3.6m

Total area	= 50 × 1.0 × 2	=	100m^2
	100m^2	=	2592.83
	1m^2	=	$\frac{2592.83}{100}$
		=	25.93
Add profit + overhead 20%			5.19
Rate/m^2		=	₦ 31.12

4.15 Hard Core

Hardcore (250mm thick)
A tipper long = ₦3500 = 3.8m^3
1m^3 = $\frac{3500}{3.8}$
= ₦921.05/m^3

$0.250m^3$ = 230.26

Add 25% of compaction – 20% and waste – 5%

= 57.57

₦ 287.83/m^2

Labour for spreading assume $0.75m^3$/hr @ ₦ 35/hr

$\frac{35 \times 0.25}{0.75}$ = $46.67/m^3 \times 0.25$

= ₦$11.67/m^2$

Compacting

Assume $50m^2$/hr @ 100/hr of rollers to roll twice

$\frac{hr}{50m} \times \frac{100}{hr}$ = ₦ $2/m^2$

= ₦ 4

Total = 287.83

11.67

₦ 303.50

Add profit overhead 20%

60.70

₦ 364.20/m^2

4.16 Concrete Work

There are different types of concrete commonly used on sites; a few of them are listed below.

1. In- situ concrete in m^3
2. Precast – concrete
3. Prestressed concrete
4. Composite Concrete ------- in-situ and precast

Recall

(1) In-situ- concrete: This type of concrete can be (a) Site mixed and (b) Ready mixed.

(a) Read mixed: The following should be put into consideration

1. Material proportion (mixed/strength)

2. Addition of waste
3. Adding profit and overhead

(b) Site mixed: The following should as well be considered in estimating cost of site mixed concrete.

1. Cost of material	1:3:6 38mm aggregate
2. Cost of mixing	1:2:4 19mm aggregate
3. Cost of placing	

c. Concrete cost determination:

Cost of mixing (1:2:4)

a. Cement $1m^3 = 1400kg$ = 28bags for 50kg @ ₦400

b. Fine aggregate $2m^3$(Smallest $3.8m^3$) $\frac{2800}{3.8} \times 4 = 1473.68$

c. Coarse aggregate 4 m^3 $\frac{9500}{3.8} \times 4 = 10{,}000$

Machine mixing and labour

Assume 400/day machine $\frac{400}{16m^3}$ $/_{day} \rightarrow$ ₦250.00

Labour 5 hr/m^3

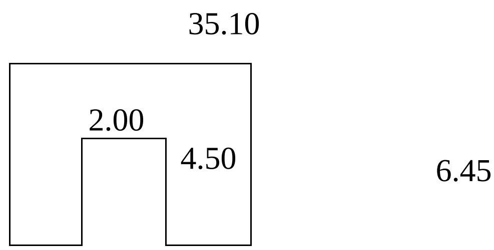
Head man 1 no.	₦ 500
Roller 1 no.	₦ 400
Wheelers 2 no.	₦ 350
Spreader 1 no.	₦ 400
Total	₦ 2000
	₦ $16m^3$

Add 25% for profit and overhead	₦ 125.00
	₦ 4909.74
	₦ 1227.44
	₦ $6137.18/m^3$

$1(28 \times 40\%) \div 7 =$ 5.6bag of cement/m of work concrete

$2(2m^2 \times 40\%) \div 7 = 0.4m^3$ of sand/m^3 of work concrete

$4(4m^2 \times 40\%) \div 7 = 0.8m^3$ of granite/ditto.



35.10
6.45
<u>0.15</u>
<u>33.96</u>

Total no. of cement = 33×5.6
= 184.8
= 185bags

D.dt 4.50
2.00
<u>0.15</u>
<u>1.35</u> <u>32.61</u>
$33m^3$

Total for sand = 33 × 0.4
= $13.2m^3$

For granite = $26.4m^3$

Since 1 long load of sand = $3.8m^3$ = $\frac{13.2}{3.8} = 3.5\ loads$

1 lorry load for granite = 3.2 = $\frac{26.4}{3.8} = 7\ loads$

Using the same method as above ditto for 1:1:2, 1:1½:3, 1:3:6, 1:4:8.

C. Reinforcement :
Bar – kg from Tonne
Fabric – m or m^2

For reinforcement bar, the following items should be provided for total cost to be achieved:

A. Cost material/tone = 30,000

B. Transportation/unloading = 2,000

C. Tying wire (10kg/tone)a roll about 3000, a roll =25kg $\frac{10\times3000}{25}$ = 7,200

D. Spaces biscuits = 1000

E. Waste 5% = 1,500

F. Labour 60hr @ n 50/hr = 3000

= 38, 700

Add for Profit and Overhead 25%
= ₦ 9,675

₦48, 375/tonne

1kg = $\frac{48,375}{1000}$
= ₦ 48.38

Mild steel / length = 9m
High tensile/length = 12m

Things that are wrong with reinforcement bar produced in Nigeria

1. Length
2. Diameter
3. Strength
4. Quantity

Conversion of length to kg
$10.00616d^2$
Where d = diameter of reinforcement.

d. Fabric Reinforcement
Check the width and length

- 10 blocks/m^2

A roll of Fabric reinforcement $= 2.1\times 4.8 = 10.08$
In a roll can cover $10m^2$ for ₦ 2000 = using the sign above

$1m^2 = \frac{2000}{10.08} =$ ₦198.40

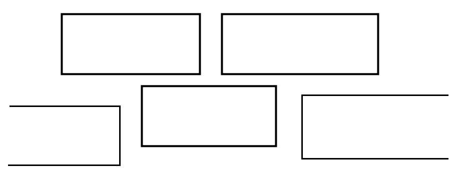
And for T- side lap add 10%, also add 15% for waste and lap = 29.76
Labour

$0.1hr/m^2$ at	6.00
	234.16
Add 25% O × P =	58.54
Rate/m^2	₦ 292.70

d. Form work

G. To slab beam, and column

4.17 Blockwork



About 10 blocks/m^2
For 1:6 1 bag cement to 12 head pairs of sand

a. Material cost

10 blks @ N 35	=	350.00
$0.032m^3/m^2$ @ 3179.47	=	101.74
		451.74
Add 5% for waste		22.59
		₦ 474.33

b. Labour cost

Assume 2 mason and 1 labourer 160 blks/day is $16m^2$

1 mason ₦ 400 1 labourer 200	
2 mason + 1labourer	= ₦ 1000
Pate/m^2 = $\frac{100}{16}$	= 62.50
	536.83

Add 25% for profit/overhead 134.21
Rate/m^2 = ₦ 671.04

4.18 Project Types

The projects selected for the purpose of suitable neural network algorithm generation are residential buildings and office building; they are as detailed below:

4.19 Residential Accommodation: These projects are residential projects that range from 1 and 2 Bedroom bungalows, which is often refer to as low cost housing system; 3 floors reinforced concrete structures, 3- bedroom flats, and 4-bedroom duplex.

4.20 Office Building: The type of office structures selected in this regard is those that are of reinforced concrete frame structures.

4.21 Residential Building: Data of obtained from 220 sampled residential building projects of 3 and 4- bedroom units composition on 4-floors, initiated and completed within the pre-economic meltdown and post economic meltdown were used in this context. Table 4.5 illustrates the summary of Bill of quantities' values and As-built value of the projects spanning 2006 to 2009.

Table 4.5: Summary of Projects Costs (B.o.q Value and As-Built Cost) 3 &4-bedroom Units, 3 Floors

Period: 2006-2009

Cost Centers	BOQ Value (₦)	As-built Value (₦)	Target Cost (₦)
Project 1-220	141,765,000	143,561,000	1,316,000

2006-2009	to 496,193,000	to 520,300,000	to 32,000,000

Source: 2010 Survey

Tables 4.5 and 4.6 present summary of sampled projects bill of quantities, specifying the bill of quantities (initial contract value), as-built cost value and cost variation. The variation recorded ranges from 0% to 53%. The analysis of the cost breakdown revealed nine (9) projects of the 7,220 selected projects as having no variation, the as actual amount budgeted as initial cost was spent in completing the project this constitute 4.01% of the projects initiated and completed within year 2006 and 2009 .

For this type of building work the highest initial cost recorded for project executed in 2009 is ₦520,300,000 while the lowest initial cost recorded for the same year is ₦ 464,024,000 , for the seventy (70) selected projects in this category. The highest initial cost of projects initiated and completed in 2008 is ₦385, 405,000 with the least completion cost of ₦227, 651,000. So also seventy selected projects among those executed in 2006 have highest initial contract cost of ₦141, 765,300 with ₦132, 227,000 lowest initial costs. The detail breakdown of cost is presented in Appendix i.

Table 4.6: Cross Tabulation of Project Cost Variables (in millions of Naira)

Period	Highest Initial Contract Sum	Highest As-Built Sum	Lowest Initial Contract Sum	Lowest As-Built Sum	Highest Variation	Lowest Variation
2009	496,193,000	520,300,000	464,024,000	472,000,000	24,107,000	7,976,000
2008	385,405,000	392,364,000	227,651,000	250,000,000	6,959,000	6,416,000
2007	189,234,000	195,650,000	41,765,000	143,561,000	7,835,000	1,796,000

2006	141,765,000	43,561,000	130,219,000	145,236,000	15,017,000	4,386,000

Source: 2010 Survey

From Table 4.6 above the lowest cost was recorded in pre-economic meltdown period with lowest variation of ₦1,796,000 to ₦6, 416,000 highest cost variations. Projects with highest cost variation were discovered to have been executed in economic meltdown period, 2008 and 2009, with highest cost variation of ₦ 24, 07,000 and lowest cost variation of ₦7, 976,000 respectively.

Table 4.7: Project Costs Adjustment Parameters (3-bedroom on 3 Floors)

Parameters used in cost data modification are presented in Table 4.7.

Cost Centers	As-built Value (₦)	Inflat.Adj Factor(%)	Corru.Esca.Factor(%)
Project 1-200 2006-2009	141,765,000 to 496,193,000	0.10(10.0)	0.0114(1.140)

Source: 2010 Survey

In Tables 4.7 and 4.8 projects cost variables and the factors used to adjust the cost are presented; the economic variables such as inflation index and corruption escalator factor were used. The factors are incorporated into the As-built cost of the project, 0.10 percent inflation index as obtained from National Bureau of Statistics compared with Turner inflation adjuster was used, which specified 10.00 % as constant inflation index factor as at the time of this composition (September, 2010).

LEGEND:

VAL == Value BOQ == Bill of Quantity

AS BLT == As Built Cost INF FACT == Inflation Factor

CRPT FACT == Corruption Factor

Table 4.8: Project Cost and Adjustment Parameters for 3-bedroom Units on 3-floors

2010 to December 2010.

Cost Centers	BOQ Value(₦)	As-built Cost(₦)	Inflat.Adjus.Cos(₦)	Corrupt.Escalator.Adjust Cost(₦)
Project 1-200	141,765,000	143,561,000	496,595	4,356,100
2006-2009	to	to	to	to
	496,193,000	520,300,000	5,931,420	520,350,000

Source: 2010 Survey

Table 4.8 presents the breakdown of 200 residential building projects spanning the pre-economic meltdown period and post meltdown period, with adjustment parameters over period of 4 months, September. As built cost with factors used to adjust it into the present value state is presented in Table 4.7, the adjusted value was later used to generate suitable neural network systems for the expected model. The detail breakdown of cost is presented in Appendix II.

4.22: Two/Four Bedroom Bungalow Cost Detail

Summary of 2 and 4- bedroom Bungalow contract sum and completion sum with magnitude of variation is presented in Table 4.9.

Table 4.9: Summary of Adjusted Projects B.O.Q Value and As-built Cost

Cost center	Boq Cost(₦)	As-built cost(₦)	Cost variation(₦)	Percentage variation
Project 1-70	2,100,000 to 4,010,850	2,850,000 to 9,201,000	4,500,000 to 5,032,380	7 to 154
2007-2009				

Source: 2010 Survey Legends: Prjt= Projects BOQ=Bill of quantity Var = Variation

Tables 4.9 and 4.10 present summary of sampled bill of quantities detailing the structure of initial contract sum and as-built cost of the executed projects with variation that range from ₦202, 680,000 to ₦5,490,000. Breakdown analysis of table 4.9 revealed seventy (70) projects as being used for the analysis, the highest variation was recorded among the projects executed in 2009 while the lowest variation was experience among the projects of 2007.

It was discovered that the margin between the initial contract sum and as-built cost of the project with highest variation was high compared to those of 2007 projects. The reason suspected as responsible for this could not be farther than recently experienced economic meltdown and other extraneous factors that are adjudged as internal and external to the project. Also, the highest percentage variation as obtained from the analysis is 154% and occurred among 2009 projects, with initial contract sum of ₦ 2,510,000 and as-built cost of ₦ 6,371,000 yielding ₦ 3,861,000 variation; this qualifies the project to be ranked as the project with highest variation figure. However, it should be noted that nineteen (19) of the seventy (70) projects sampled experienced variation higher than 100%, with highest occurring in 2009. The lowest project cost was experienced among 2007 projects, with ₦ 2, 910,320 initial contract sums to ₦ 3, 113,000 as-built costs

Table 4.10: Cross Tabulation of Projects Cost Variables (in million of naira)

Period	Highest intl cont sum	Highest as-blt cost	Lowest init cont sum	Lowest as-blt cost	Highest variation	Lowest variation
2009	4,010,850	9,201,000	2,100,000	4,286,350	5,032,380	1,111,397
2007	4,001,000	9,000,000	2,100,000	2,850,000	4,500,000	202,680

Source: 2010 Survey

From Table 4.10 above, the lowest cost was recorded in pre-economic meltdown period with variation of ₦202, 680 to ₦1,111,397 highest cost variations. Projects with highest cost variation were executed in year 2009 with highest cost variation of ₦5,032,380 and ₦1, 111,397 lowest cost variations respectively. The detailed breakdown of cost is presented in Appendix iii.

Table 4.11: Factor-Adjusted Project Costs for 2-bedroom bungalow.

Cost centers	As-built cost(₦)	Inflation Factor	Corruption Escalator Factor

Project 1-70 2007-2009	2,850,000 to 9,201,000	0.10	0.0114

Source: 2010 Survey

Parameters used in project costs adjustment ,inflation factor and corruption escalator are as presented in Table 4.11.The resultant effect of the factored-in parameters on the As-built cost of the project is also indicated in the table. With reference to Table 4.11 above, combine factor of 0.0114 was factored into the as-built value of the sampled projects (10% inflation index and 1.14 % corruption escalator). The resultant value was used as data for neural network system modeling. The detail breakdown of cost is presented in Appendix iv.

4.23 4 -bedroom Duplex Cost Details

Summary of Bill of quantities and As-built cost value of the completed four bedroom accommodation projects is presented in Table 4.12.

Table 4.12: Summary of Adjusted Projects B.O.Q Value and As-Built Cost 4- bedroom Duplex Year 2006 – 2009

Cost centers	Boq Initial Value cost (₦)	As-built cost(₦)	Cost Variation(₦)	Percentage Variation (%)
Projects 1-100	8,000,000 to 19,223,000	8,500,000 to 38,250,000	2,042,000 to 20,150,000	0 to 54

Source 2010 Field Survey

Tables 4.12 and 4.13 presents summary of sampled Bills of quantity detailing the structure of initial contract sum and as-built cost of the executed projects with variation that range from ₦ 20,1500,000 to ₦14,653,000. Breakdown analysis of Table 4.11 revealed seventy (100) projects as being used for the analysis, the highest variation was recorded among the projects executed in 2009 while the lowest variation was experience among the projects of 2007. See Appendix v for cost breakdown.

It was discovered that the margin between the initial contract sum and as-built cost of the project with highest variation is high compared to those of 2007 projects. The reason suspected as responsible for this could not be farther than recently experienced economic meltdown and price increase.

Table 4.13: Cross Tabulation of Project Cost Variables (million of naira)

Period	Highest Initial contract sum	Highest as-built cost	Lowest init cont sum	Lowest as-blt	Highest variation	Lowest variation	Variation Range
2009	19,223,000	38,250,000	15,000,151	20,650,000	20,150,000	4,289,916	15,860,084
2008	16,044,130	30,763,000	11,300,000	12,214,000	14,753,000	6,083,000	8,670,000
2007	14,289,000	26,363,000	10,101,000	11,785,000	21,368,000	2,042,000	9,583,000
2006	13,000,000	24,000,000	8,000,000	8,500,000	9,422,000	2,435,000	6,987,000

Source : 2010 Field Survey

Considering Table 4.13, highest initial contract sum is recorded in year 2009, with ₦ 19, 223,000 and with lowest initial contract sum found among 2006 projects. Also highest as-built sum is recorded in year 2009 to the tune of ₦ 38, 250,000 and lowest in 2006 with ₦ 24, 000,000. Likewise, highest variation range was recorded in 2009 with magnitude of ₦ 20, 150,000 and lowest in 2006 with ₦ 9, 422,000. However, highest variation range is discovered among project executed in 2009 with ₦ 15, 860, 000.

Table 4.14: Project Cost Adjustment Parameters for 4-bedroom Duplex

Cost center	BOQ Values (₦)	As-built Value (₦)	Inflation factor (%)	Corruption Escalator (%)
Project 1-100	8,000,000	8,500,000	0.0114	0.10
2006-2009	to	to		
	19,223,000	32,250,000		

Source 2010 Field Survey

Source: 2010 Survey Legend: TTL---Total Adj ---- Adjusted Infadj—Inflation Adjusted Val--Value

The data obtained from the sampled projects need to be modified before being fed into the neural system for processing, in this context therefore, the extracted data was adjusted with inflation index and corruption escalator factors as applicable to different project types modified. Refer to Appendix vi for cost detail. The costs and the parameter-treated outcome are presented in the Table above.

Table 4.15: Adjusted Project Cost Data 4-bedroom Duplex Period: 2006-2009

Cost centers	BOQ Value(₦)	As-built Value(₦)	Inflation Adjusted Value(₦)	Corruption Escalator Adjusted Value
Project 1-100	8,000,000	8,500,000	0.10	0.0114
2006-2009	to 19,223,000	to 38,250,000		

Source: 2010 Field Survey Legend: Ttl---Total,

The as-built cost value that would be used as input value for the neural system in network modeling was adjusted with inflation factor of 1.14% and 10% corruption escalator for data modification. The outcome is presented in the table above. The detail breakdown of cost is presented in Appendix vii.

4.24: 2-bedroom Bungalow

Project cost detail of the selected 2-bedroom bungalow selected for the work is presented in Table 4.16.

Table 4.16: Summary of Projects Boq Value and As-Built Cost [2-bedroom Bungalow]

Cost centers	BOQ Initial value(₦)	As-built Cost Value(₦)	Cost variation(₦)	Percentage Variation (%)
Project 1-70	2,100,000	2,850,000	1,100,000	7
2007-2009	to	to	to	to

	4,500,000	9,201,000	5,190,000	154

Source: 2010 Field Survey

Table 4.17: Cross Tabulation of Project Cost Variables [2-bedroom Bungalow][in millions of naira]

Period	Highest Initial Cont Sum	Highest As-Built Sum	Lowest Initial Cont Sum	Lowest As-Built Sum	Highest Variation	Lowest Variation
2009	4,500,000	9,201,000	2,100,000	4,236,000	5,190,000	1,100,000
2007	4,385,000	9,000,000	2,316,286	2,850,000	4,500,000	202,680

Source: 2010 Field Survey

Careful observation of Tables 4.18 and 4.17 above revealed that the highest initial contract sum occurred among 2009 projects with a unit awarded at ₦ 4,500,000 while it was ₦ 4,385,000 in 2007. Also, highest variation margin experienced among year 2009 projects with variation magnitude of ₦ 1,100,000 and lowest variation margin among 2007 projects. Summarily, in combine form, the highest variation experienced among year 2009 and 2007 projects is ₦1,100,000 with lowest variation margin of ₦ 202,680. Refer to Appendix viii for detail.

Table 4.18: Summary of Adjustment Parameters 2-bedroom Bungalow

Cost centers	BOQ Value(₦)	As-built Value(₦)	Inflation Adjusted Value	Corruption Escalator Adjusted Value
Project 1-70	2,100,000 to 4,500,000	2,850,000 to 9,201,000	0.10	0.014
2007-2009				

Source: 2010 Survey

Legend: Adj Val ---- Adjusted Value CombFact ---- Combined factor, Infl – Inflation Val -- Value

Table 4.18 above presents the outcome of adjusting the as-built cost of seventy residential building projects which falls between 2006 and 2009 with inflation index and corruption escalator. Highest cost of ₦ 9, 137,931 is obtained after adjustment, from Project initial construction cost of ₦ 4, 001,000 and as-built cost value of ₦ 8, 222,000. Also, lowest cost in the range of ₦ 2,710,000 bill of quantities value and ₦ 2,950,000 as-built cost. The detail breakdown of cost is presented in Appendix ix.

Table 4.19: Summary of Factor Adjusted Project Cost [2-bedroom Bungalow]

Cost centers	BOQ Value(₦)	As-built Value (₦)	Inflation Adjusted Value(₦)	Corruption Escalator Adjusted Value(₦)
Project 1-70	2,100,000 to 4,500,000	2,850,000 to 38,250,000	32,490,000 to 104,891,000	285,000 to 920,100
2007-2009				

Source: 2010 Survey Legend: Adj Val ---- Adjusted Value CombFact ---- Combined factor, Infl – Inflation Val – Value.

4.25 Office Accommodation

In the table below the cost detail of one-hundred selected office projects were highlighted. Magnitude of projects cost variation is stated as well for cross comparison of different projects involved.

Table 4.20: Summary of Adjusted B.o.q Value and As-Built Cost of Office Projects

Period: 2006-2009

Cost centers	BOQ Initial value (₦)	As-built Cost Value (₦)	Cost variation (₦)	Percentage Variation (%)
Project 1-100 2006-2009	111,320,500 to 297,323,000	102,720,000 to 478,737,280	1,500,000 to 125,512,000	9 to 135

Legend: BOQ --- Bill of quantity Inflatn Adj Fact ----- Inflation Adjusted Factors Corruptn Esc Fact ----- corruption escalator Factors   Perctg ------ Percentage Infladjval ------Inflation adjusted Value   PrcVal ----- Predicted Value.

Summary of bill of quantities value (initial cost) and as-built value of the 100 selected office projects is contained in Table 4.20. In Table 4.20, the highest initial contract sum obtainable is ₦297, 317,000 while the lowest initial project cost found is ₦111, 320,000. Also, the highest completion cost (As-built) sum recorded is ₦309, 873,000 and with ₦102,720,000 lowest value. With these figures, this yield 93% cost variation at upper boundary and 0% variation lower boundary between the initial project cost and as-built cost. Detail of parameter used to adjust project cost is presented in the table above, 10% inflation index being the current index and stable over a period of 6 months to the period of data analysis and 1.14% corruption escalator factor were used to modified the project cost before processing. See Appendix xi and xii for detail.

Table 4.21: Cross Tabulation of Project Cost Variables of Office Accommodation [in millions of Naira]

Period	Highest Initial Cont Sum	Highest As-Built Sum	Lowest Initial Cont Sum	Lowest As-Built Sum	Highest Variation	Lowest Variation
2009	296,571,798	478,737,280	141,138,227	155,238,227	5,190,000	1,100,000
2007	276,896,223	282,873,000	116,353,000	120,325,000	4,500,000	202,680

Source: 2010 Field Survey

Table 4.22: Variable Adjusted Project Costs for Office Project

Cost centers	BOQ Initial value(₦)	As-built Cost Value(₦)	Inflation Adjusted cost(₦)	Corruption Escalator Factored Cost (₦)
Project 1-100 2006-2009	111,320,500 to 297,323,000	102,720,000 to 478,737,280	1,171,008 to 5,457,605	10,272,000 to 47,873,728

Source 2010 Field Survey

LEGEND: BOQ --- Bill of quantity Inflatn Adj Fact ----- Inflation Adjusted Factors
Corruptn Esc Fact ----- corruption escalator Factors Perctg ------ Percentage
Infladjval ------Inflation adjusted Value PrcVal ----- Predicted Value.

Inflation index and corruption escalator factors were used to modify the 100 selected office projects, initiated and completed within 2006 and 2009. The result is as presented in the Tables 4.21 and 4.22. It would be recalled that certain parameters were factored into the initial and final completion cost of project cost in Table 4.21; the resultant cost effect of the factors is presented in Table 4.21 above. After adjustment, the highest as-built cost then became ₦484, 673,622 and with ₦103, 993,728 lowest. The highest occurred among projects executed in 2009, while the lowest cost falls among projects completed in 2007. This as well followed similar trend observed among project executed in 2009 as being caught up with inflation effect and those of 2007 overlapped into pre-economic melt-down period. Refer to Appendix 13 and 14 for detail breakdown of project costs.

CHAPTER FIVE

BUILDING, TESTING AND VALIDATION OF THE MODEL ALGORITHM

5.1 Synthesization Procedure

Procedure used in this context consists of model configuration and selection of suitable network algorithm.

5.2 Synthesization Procedure for Suitable Neural Network System for Model Configuration for the Building Types.

Synthesization process of the neural network generated output for the building types used in this research work involved three stages; training stage, cross validation stage and model testing stage.

5.3 Training Stage

Data training was carried out after the data had been adjusted with inflation index and corruption escalator with aid of a multilayer perceptron neural network model. Multilayer perceptron (MLPs) are layered feed forward network typically trained with static back propagation. Browse button was used to select an input file, which a selected neural builder scanned, the presented columns were tagged as “input,” “desired,” “symbol,” “annotate,” or “skip.” However, in prediction mode, “desired” tags are often replaced with “predict tag”. The data in the predict mode was used as both inputs and desired responses for the network with input delayed by “Delta samples.” Two inputs were used for the training, Bill of quantity values (initial cost) and As-built cost values, detail of the input and input selected for the building types are summarized as follow:

Table 5.1: Data Schedule for Training Testing and Validation

Data read from existing file	Office Building	3&4-bdrm,4Flrs	4- bdrm Duplx	1- bdrm Bunglw
Percentage of Training data for Cross validation	14	14	14	14
Percentage of data for Model testing	36	20	36	36
Cross validation exemplars	16	92	16	16
Test exemplars	43	132	43	43
Multilayer perceptron input	4	2	4	4
-ditto- Output processing elements	2	1	2	2
-ditto-Exemplars	62	437	62	62
Hidden layer	1	1	1	1

Source: 2010 Field Survey

220 samples were used for network testing and validation. Cross validation of generated output was carried out after the data training.

5.4 Cross Validation and Testing of Data

Cross validation and testing dataset were selected; the data was extracted from the existing training data. Cross validation is essential for stopping the network training, due to the fact that it monitors the error on an independent set of data, and stops the training when the errors begin to increase. This is considered to be a point of best generalization, the result obtained was used to generalize output for other values obtained as predicted value. The generated output was then compared with the desired output to determine their suitability. Using result of 3&4- bedroom units as example, a total of 192 samples which constitutes 14% of the file data was used for cross validation, while 132 samples (20%) were used for the test, with132 testing exemplars and 92 validation exemplars.

5.5 Multilayer Perception Inputs

Multilayer perceptron processing elements (PE'S) used had two (2) inputs and one (1) output, with the aid of back propagation effect the system generated four hundred and thirty-seven (437) exemplars, with one(1) hidden layer.

5.6 Hidden Layer [Input and Output Layer]

For the 3&4-bedroom units, Hidden layer contains detail about data processing parameters, twenty-two (22) processing elements were selected for data training. TanhAxon was selected as transfer nodes with Levenbeg Marqua or momentum set at step size 1 and network momentum set at 0.7; this is further illustrated in Table 5.2.

Table 5.2: Hidden Layers

Input Layer		Output layer	
Processing Element:	22	Processing element	1
Transfer:	TanhAxon	Transfer	TanhAxon

Learning Rule: LevenbergMarqua	Learning Rule: Levenberg Marqua
Momentum Step size: 1.0000 Momentum 0.7000	Momentum Step size 0.100 Momentum 0.7000

Source: Neuro Tool Box 2010

5.7 Supervised Learning Control

However, the training phase for the system in order to learn the data pattern has to be supervised; therefore parameters were set to stop the data training within the threshold of least error, after prescribed iterations. To this end, the parameters used are specified in Table 5.2.

Table 5.3: Supervised Learning Control Parameters

Maximum Epoch	1000		
Termination	Threshold		
MSE			
Minimum	Training set		
Incremental	Validation set		
Increase			Load Best on Test
Weight update	Online	Batch	

Source Neuro Tool Box 2010

Maximum of 1000 training epoch was specified for the systems iteration, the error change box contain the parameters such as mean square error (MSE) and iteration number. The mean square error was used as a training termination milieu for the network. The data was then used to build a suitable system for the data training.

5.8 Modeling Stage: Network building (probationary configuration for data training). Parameters for a suitable probationary network for data training configuration were further set, such as the mean through which input data, desired output, output data, and error, would be displayed. Also the display formats for performance matrix such as confusion matrix, active performance and cross validation window were specified before network building button was activated.

Table 5.4: System Configuration Parameters

Input--- [Training Dataset] Output---- Data writer [Training set and Cross validation set]
Desired Data writer[Training set and Cross validation set]
Performance Measure
Classification
General Confusion matrix ROC [Training set and Cross validation set]
Help ⇨ ⇦ Close Build

Source: Neuro Tool Box 2010

5.9 Model Validation Stage

Table 5.5: Active Cross validation performance

Parameters	3/4-brm	Office	4-brdplx	1-brbngl
MSE	0.00003	0.000037	0.0000282	0.000115
NMSE	280961.2	346521.81	264105.33	1030198.1
r	0.80432	0.9860	0.8567	0.93465

MSE-----------Mean square error
NMSE--------Normal mean square error r -----------Regression Value

Table 5.6: Cross validation Performance

Parameters	3&4-brm	Office	4-brdlx	1-brmbng
MSE	0.0074	0.032	0.0062	0.0089
NMSE	0.9992	0.098	0.0190	0.0273
r	0.0276	0.950	0.023	0.0193

NMSE----- Normal Mean Square Error MSE------Mean square error
r -------------Regression Value

5.10 Model Testing

Testing wizard was used for the data testing. It provides an easy way to produce the network output for the chosen dataset once the training phase is completed.

Table 13 Parameter for Model Testing

With selection of the parameters in Table 5.4, and Finish button clicked, the Testing wizard has thus finished collection of necessary information. The training dataset was then tested, the network output and desired output was also included for further comparison, and the neural network generated value is presented in Tables 5.5 to 5.6.

5.11 Neural Network Synthesized Output

In this section the neural network generated output from the developed algorithm is presented, the neural output for 1-bedroom apartment,4-bedroom duplex units, reinforced-concrete office units and 3&4-bedroom units (4-floors apartment). Initial contract cost and completion cost (As-built cost) were included for ease of comparison.

Table 5.7: Presentation of Neural Network Generated Output (2&3-bedroom Unit, 4-floors]

Cost Centers	BOQ Initial value (₦)	As-built Cost(₦)	Neural Output (₦)
Project 1-200	141,765,000 to 496,193,000	43,561,000 to 520,300,000	473,840,312 to 475,504,943
2006-2009			

Source: 2010 Survey

The neural network generated output of 220 sampled projects cost adjusted with inflation and corruption index is presented in Table 5.7. The detail breakdown of cost is presented in Appendix xiv.

Table 5.8: Neural Network Output for Office Project

Cost Centers	BOQ Initial value (₦)	As-built Cost(₦)	Neural Output (₦)
Project 1-200 2006-2009	113,320,000 to 297,317,000	102,720,000 to 309,873,000	310,324,221 to 478,307,495

Source: 2010 Neural Analysis

The neural network generated output of 100 sampled projects cost adjusted with inflation and corruption index is presented in Table 5.8. The detail breakdown of cost is presented in Appendix xv.

Table 5.9: Neural Network Output for 4- bedroom Duplex Project

Cost Centers	BOQ Initial value (₦)	As-built Cost(₦)	Neural Output (₦)
Project 1-200 2006-2009	19,223,000 to 8,000,000	38,250,000 to 8,850,000	42,955,610 to 9,446,000

Source: 2010 Neural Analysis

Table 5.10: Neural Network Output for 2-bedroom Bungalow Project

Cost Centers	BOQ Initial value (₦)	As-built Cost(₦)	Neural Output (₦)
Project 1-200 2006-2009	2,100,000 to 4,500,000	2,850,000 to 9,201,000	3,513,914 to 9,813,217

Source: 2010 Neural Analysis

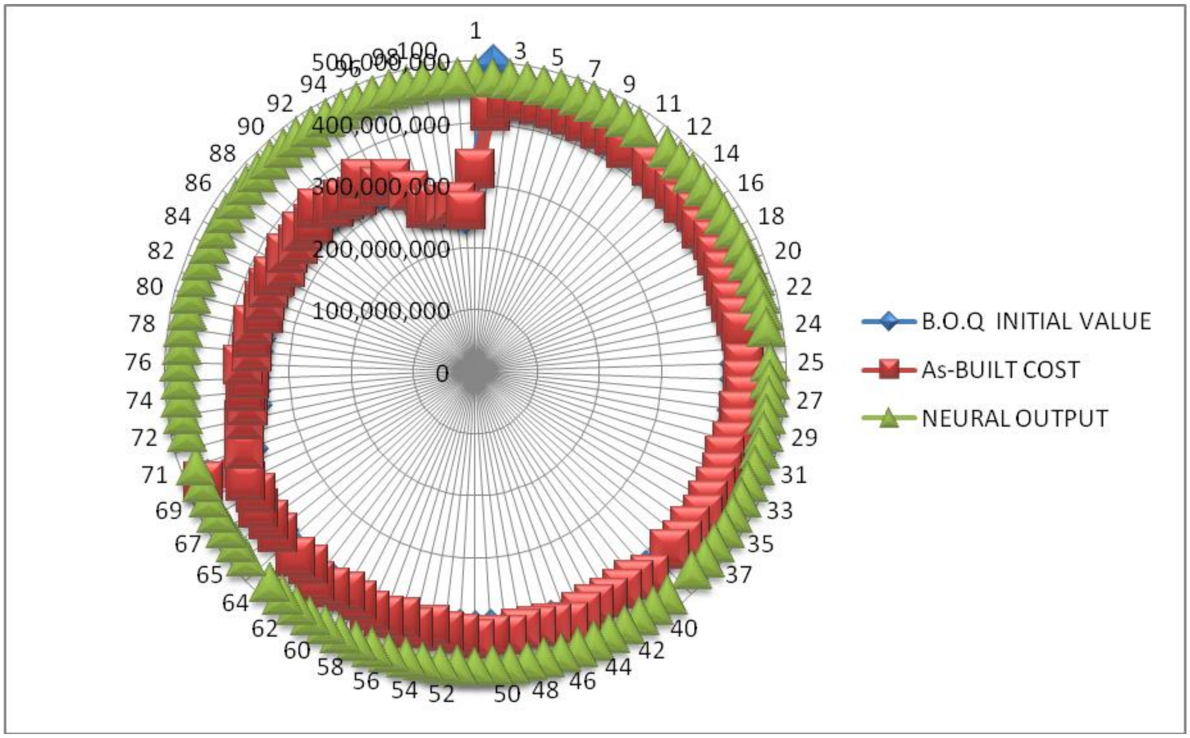
The neural network generated output of 200 sampled projects cost adjusted with inflation and corruption index is presented in Table 5.10. The detail breakdown of cost is presented in Appendix xvi.

5.12 Study of Distribution Pattern of As-Built Cost and Neural Network Output of Selected Projects.

Visual illustration of the distribution pattern of output data as compared to the as-built cost for better appreciation of the nature of relationship of costs with the economic condition of period under consideration is presented in this section. Radial diagram and bar chart were used in this context.

5.13 Visualization of Input and Neural Output Pattern for 2/3–bedroom on 3 Floors Project

Three millieu were used to represent cost package in this context, Bill of quantity-initial value,As-built cost and Neural output.



Source: 2010 Field Survey

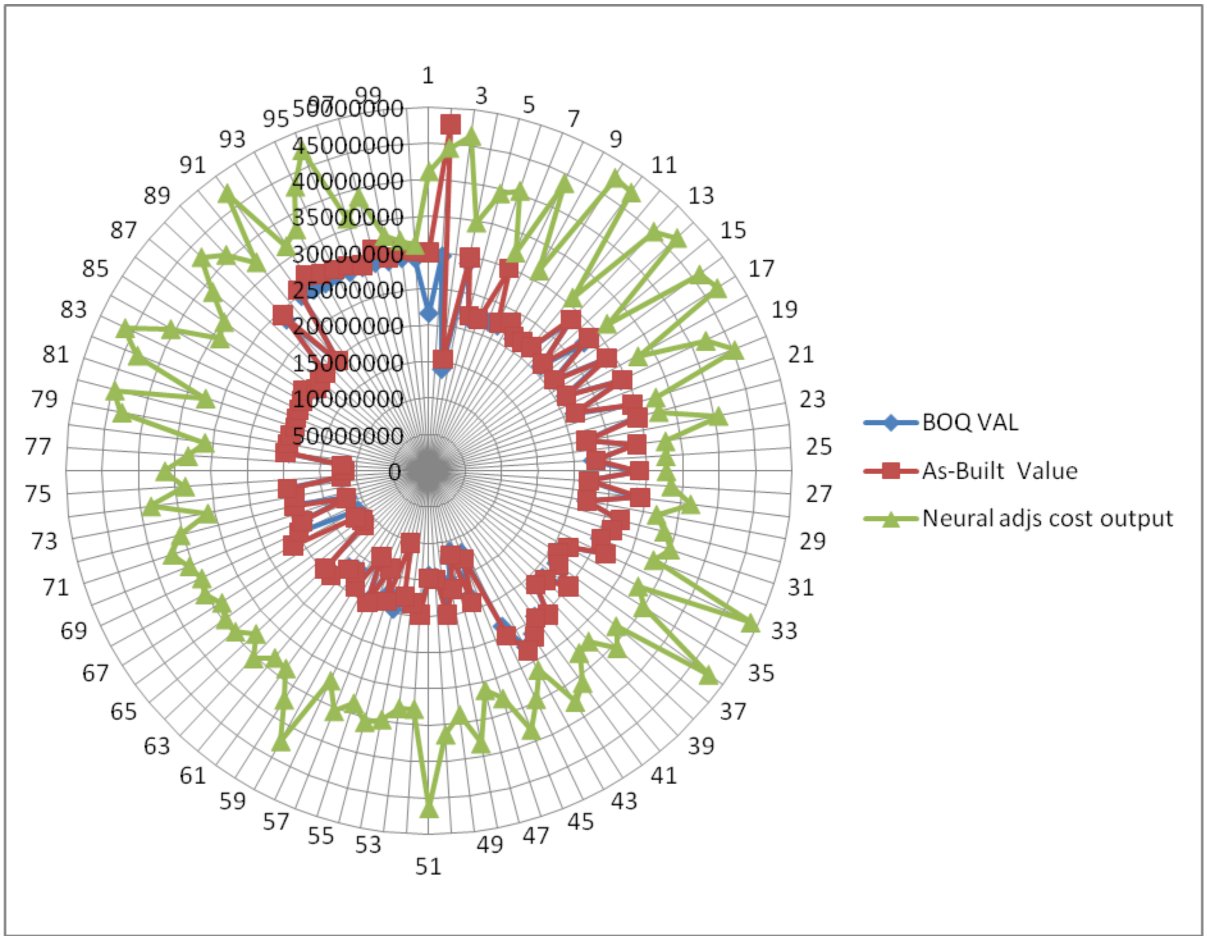
Fig. 5.1: Radar Diagram Visualization of Input and Neural Output Pattern for 2/3 –bedroom on 3 -floors project

Legend: BOQ----- Bill of quantity. NNOTPT ----- Neural Network Output

Distribution pattern of the cost for one-hundred 2&3-bedroom on 3 floors, residential building projects, is presented in Figure 5.1 with the aid of compact-radar diagram. As-built cost value overlapped the initial value of the projects (BOQ value), from project one (1) to seventy-four (74) where a noticeable divergence occurred. These cost divergence was recorded among projects executed during the economic meltdown period. Also**,** there is significant difference between the As-built cost and neural network predicted output, this is attributed to trend mastering of the neural system used to develop the model's skeletal structure, which tend to generalize magnitude of variation order along the matrix of group data. This often occurs once the data trend has been mastered by neural network. This variation generalization accounts for the cycles which neural output formed around the concentric cycles, representing the As-built cost and BOQ value of the projects under consideration.

5.14 Visualization of Input and Neural Output Pattern for Office Accommodation

Input and output pattern of cost data of office accommodation used in model generation is presented in Fig. 5.2:



Source: 2010 Field Survey

Legend: BOQ----- Bill of quantity. NNOTPT ----- Neural Network Output

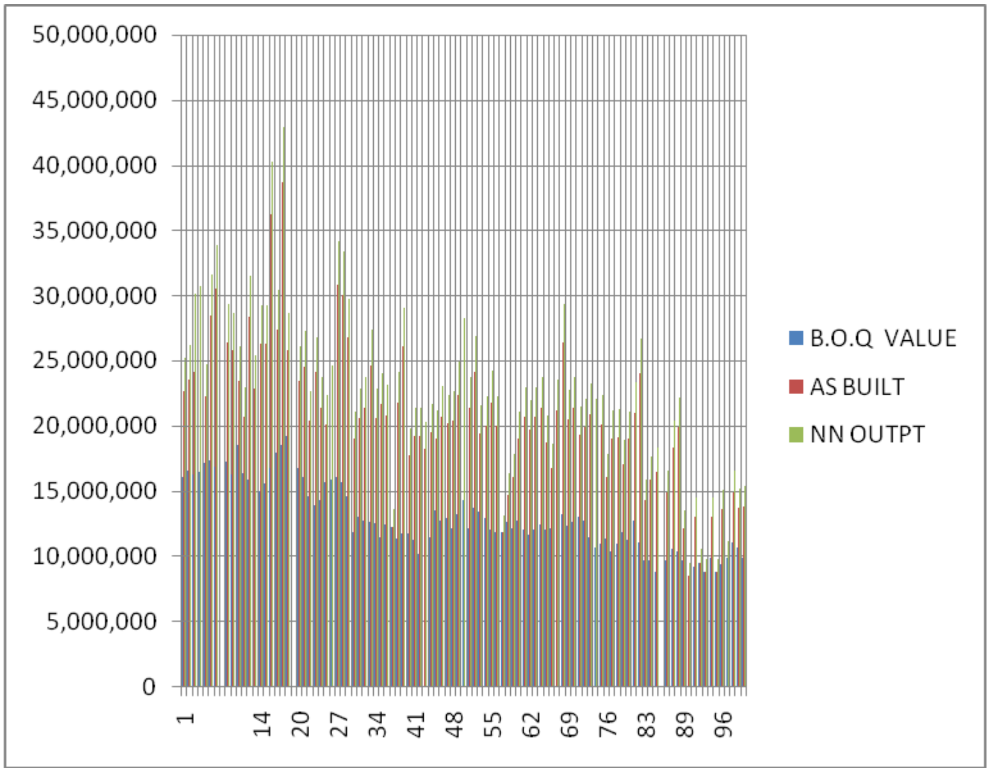
Fig. 5.2: Radar Diagrammatic Visualization of Input and Neural Output for Office Accommodation

Fig. 5.2 illustrates distribution pattern of the As-built cost, BOQ value and neural network predicted cost on a stretched-line radar diagram. As-built cost value overlapped the initial value of the projects (BOQ value), this occurred from project one (1) to twenty-nine (29), where a noticeable variation occurred. Significance difference was noticed between As-built cost and neural network predicted project cost. The projects were discovered to have been completed during the economic meltdown period, this tend to tow the line of occurrence as observed in the case of 2/3 bedroom projects presented in Table 5.2. Reason suggested as responsible for this is data variation margin generalization by the neural network system used in data training for fitness so as to obtain an optimum and stabilized value.

The period in consideration for purpose of prediction in this context is 7 months from base reference period (November 2010), at prevailing inflation rate index of 10% and adopted corruption escalator factor of (1.14%) percent. This is however subject to change since the prevailing economic factor at the time of any cost prediction has to be taken into consideration.

5.15 Visualization of Input and Neural Output Pattern for 4-bedrooms Duplex

Input and output pattern of cost data of 4-bedroom Duplex used in model generation is presented in Fig. 7:



Source: 2010 Field Survey

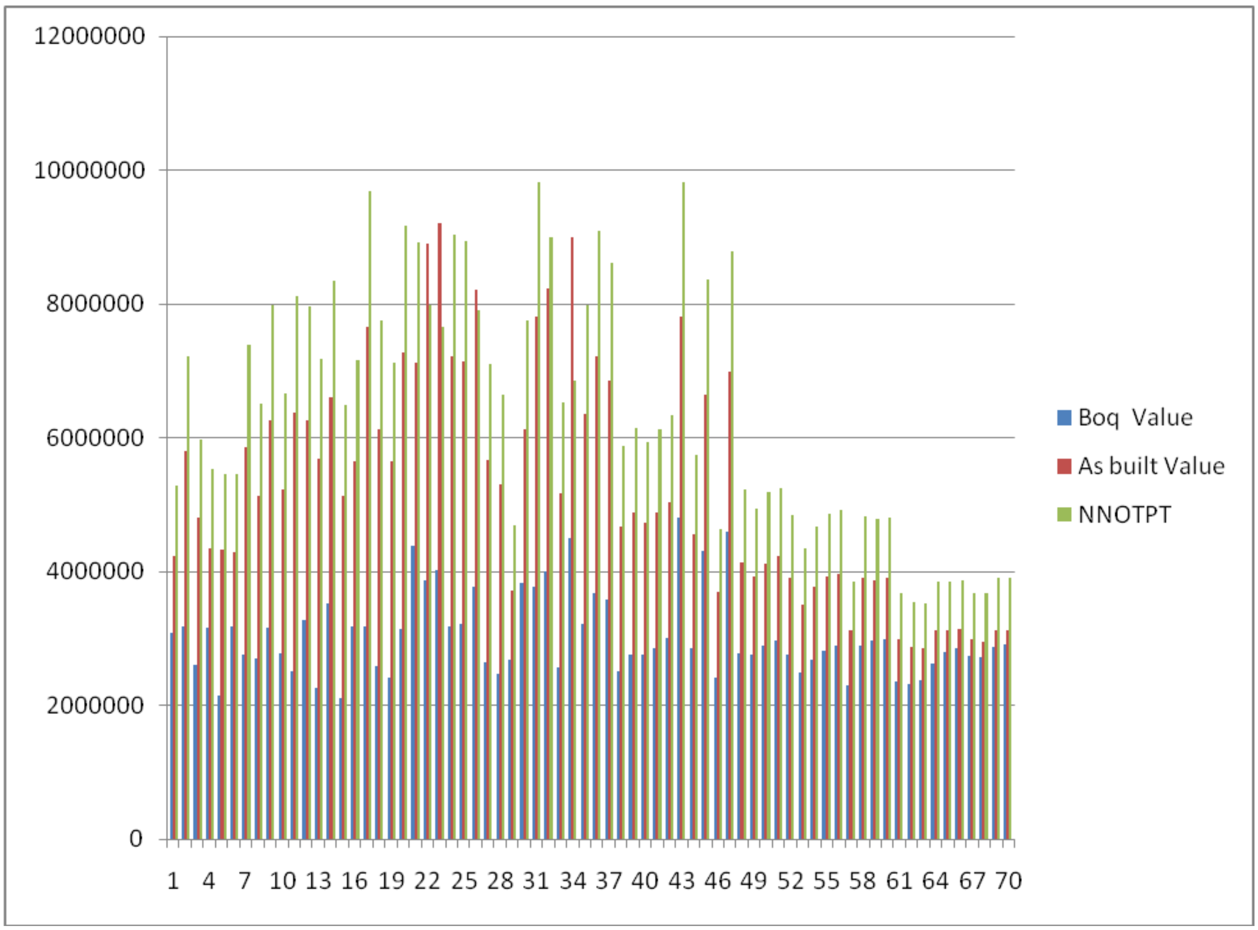
Legend: BOQ----- Bill of quantity. NNOTPT ----- Neural Network Output

Fig. 5.3: Bar- Visualization of Input and Neural Output for 4-bedrooms Duplex

Cost distribution pattern of the three cost envelopes (the neural network predicted cost, as-built cost and bill of quantity value) is presented in Fig. 5.3. Highest neural network predicted cost was recorded within the cost range ₦12 million and ₦42 million. The range falls among projects completed between 2008 and 2009. Lowest as-built cost is ₦14 million during pre-economic meltdown and ₦26 million during post economic meltdown period. The base reference period used for prediction in this context is 7 months and with November 2010 as base month. Also, inflation index of 10% and corruption escalator factor of (1.14%) was used. This is however subject to change since the prevailing economic factor at the time of any cost prediction has to be taken into consideration.

5.16 Visualization of Input and Neural Input Pattern of 2-bedrooms Bungalow

Distribution pattern of input and output cost data of 4-bedroom Duplex used in model generation is presented in Fig. 5.4:



Source: 2010 Survey Legend: BOQ-- Bill of quantity. NNOTPT-- Neural Network Output

Fig. 5.4: Bar- Visualization of Input and Neural Input of 2-bedroom Bungalows

Component bar chart is used in presenting the panoramic view of the cost distribution pattern of the three cost envelopes (the neural network predicted cost, as-built cost and bill of quantity value), is presented in Table 5.4 above. Highest neural network predicted cost was recorded within the cost range ₦9.4 million and ₦3.5 million. The range falls among projects completed between 2008 and 2009. Lowest as-built cost is N14 million during pre-economic meltdown and ₦26 million during post economic melt-down period. The base reference period used for prediction in this context is 7 months and with November, 2010 as base month. Also, inflation index of 10% and corruption escalator factor of (1.14%) was used. This is however subject to change since the prevailing economic factor at the time of any cost prediction has to be taken into consideration.

5.17 Calibration of Neural Network Cost Output [Range Setting]

Table: 5.11 Range Setting

Building Types	Highest As-Built Cost(₦)	Specified Cost Range(₦)	
		Highest(₦)	Lowest(₦)
Office Bldg,Reinf,Frm,2flrs	472,737,280	478,307,495	310,324,221
3&4-bdrm Bunglw,4-floors	443,800,620	475,509,943	473,840,312
4-bdrm Duplex	38,650,000	50,687,620	10,391,590
1-bdrm Bunglw	9,201,000	11,524,692	3,515,914

Bldg-building, Reinf—reinforcement,Bunglw—bungalow, Bdrm—bedroom, Frm—Frame Flr—floor.

5.18 Models' Algorithm Processing Modules and Data Ports

The proposed application consists of four (4) command modules and six (6) data ports. The four main command modules include; data optimization module, applications input module and fitness evaluation module and process booting and termination module.

5.19 The Main Command Module

i. Selection Criteria Evaluation Module

This module carries out optimization process by searching for optimal solutions among available sets of alternatives. Multilayer perceptron with genetic algorithms and back-elimination are used in this context because these algorithms are formulated independent of objective function. This module performs the optimization process utilizing Multilayer perceptron (MLP's). Solution alternatives which are coded, as individuals undergo cycles of variation and selection in order to be steadily improved, so that optimal or near optimal solutions are eventually found. This makes optimization system algorithm an attractive tool for solving multi-objective optimization problems, where different Pareto-optimal solutions are sought.

In the presence of multi and conflicting objectives a set of optimal solutions, instead of one optimal solution, are usually obtained, therefore, multi-optimal solutions often exist since there is no one solution that can be considered as optimal for multiple conflicting objectives (Hegazy, 2006; Mazouk et al, 2008). Multilayer perceptron (MLPs) are layered feed forward networks typically trained with static back propagation and suitable for application in such situation of multi-conflicting objective selection, thus the need for its adoption in this context.

These networks have found their way into countless applications requiring static pattern classification (Lam *et al.,* 2005). Their main advantage is that they are easy to use, and that they can approximate any input/output map. The key disadvantages are that they train slowly, and require lots of training data (typically three times more training samples than network weights). Multilayered perceptron (MLP's) have been used as powerful tools for optimization based on heuristic search techniques following random sampling (Marzouk *et al.,* 2008, Zein *et al.*, 2006, Marzouk and Moselhi 2004). A flowchart that depicts the developed algorithm is shown in Fig 5.4 under Section 5.1.0.8

ii. Data Modulation Evaluation Module (Fitness Module)

Data modulation module calculates the cost and picks an optimization value for project types within a range of values and economic index such as prevailing inflation index and corruption escalator. The module is designed to measure the influence of building project types and economic optimization parameters via 'what if' analysis. It takes into account the dynamic nature of the building types and the economic parameters. The fitness evaluation module utilizes Microsoft Office Excel spreadsheet to estimate projects' cost and building project as-built cost with incorporated economic parameters. On the other hand, a sub-module, named Project type-Mod, was developed to calculate the cost of projects. It accounts for four main categories by calculating their cost individually. Project type-Mod application consists of four components: Office units, 3&4-bedrooms units, 4-bedroom duplex and 1-bedroom bungalow.

iii. Application Input Module

Application modules consist of two sub-modules: Project data module and optimization parameter module. Project data sub module is linked to Excel spreadsheet and Project type_Mod sub-modules in Fitness evaluation module. Project data sub-module contains the economic optimization parameter; inflation rate index (I.R.I), corruption escalator factor (C.E.F) and the project data (initial cost and as-built cost)

iv.Booting and Termination Command Module:

The fourth module is process booting and termination module. The initialization process for the algorithm, looping and termination takes place in this module. Application input data selection is based on the harmonization of data at six data port of the module.

5.20 Data Port & Cost Center Harmonization Factor

I. Data Ports

In respect of expected versatility of the developed model, creating a database for the module is highly essential; the database which contains detail from data ports is linked to the cost optimization module for interoperability. To this end, there are seven (7) data ports in this module, detail is as follow:

Data Port Alpha &----------------------------3/4-bedrooms

Data Port Beta (β) ----------------------------Office Units

Data Port Gamma (γ) ------------------------4-bedroom Duplex

Data Port Roger (R)------------------------1-bedroom Bungalow

Data Port Phil (Infladex) --------------------Current Inflation Index

Data Port Omega (Corrupt. Escal) ----------Corruption Escalator Factor

Cost Fitness Data Port -----------------------Cost Expectancy Limit Value

ii. Cost Center Harmonization Factors

Table 5.12: Data Port Alpha[A]

S/N	Data Source	Base Cost[₦]	Derived Cost[₦]	Multiplier Factor
∞1	4-bedroom 1-floors	478,307,495.00	157,841473.35	0.33
∞2	4-bedroom 2-floors	478,307,495.00	320,466,021.65	0.67
∞3	4-bedroom, 3-floors	478,307,495.00	478,307,495.00	1.00
∞4	4-bedroom, 4-floors	478,307,495.00	637,743,326.67	1.33
∞5	3-bedroom, 1-floor	179,365,310.20	59,788,436.50	0.50
∞6	3-bedroom, 2-floors	269,047,966.00	179,365,310.70	0.67
∞7	3-bedroom, 3-floors	358,730,621.30	269,047,966	0.75
∞8	3-bedroom, 4-floors	358,730,621.30	358,730,621.30	1.00

Source: 2011 Survey

Table 5.13: Data Port Beta [B] Office Units, 3-floors Reinforced

S/N	Data Source	Base Cost[₦]	Derived Cost[₦]	Multiplier Factors
B1	1- floor Reinforced	475,509,943	156,918,281	0.33
B2	2 -floors Reinforced	475,509,943	317,006,29	0.67
β3	3 -floors Reinforced	475,509,943	475,509,943	1.00

Source : 2010 Survey

Table 5.14: Data Port Gamma[Γ] 4-bedroom Duplex

S/N	Data Source	Cost[₦]	Derived Cost[₦]	Multiplier Factor
γ4	2-bedroom Duplex	50,687,620	12,671,905	0.25
γ3	2-bedroom Duplex	50,687,620	25,343,810	0.5
γ2	3-bedroom Duplex	50,687,620	38,015,715	0.75

γ 1	4- bedroom Duplex	50,687,620	50,687,620	1.0

Source 2010 Field survey Legend: bunglw-bungalow bdrm - bedroom

Table 5.15: Data Port Roger (R): 1 Bedroom Bungalow

	Data Source	**Base Cost[₦]**	**Derived Cost [₦]**	**Multiplier Factor**
R1	2-bedroom Bungalow	11,524,692	11,524,620	1.00
R2	2-bedroom Bungalow	11,524,692	23,49,384	2.0
R3	3-bedroom Bungalow	11,524,692	34,574,076	3.0
R4	4- bedroom Bungalow	11,524,692	46,098,768	4.0

Source: 2010 Field Survey

Table 5.16: Cost Fitness Data Port (CFDP)

S/N	Data Port Code	Project Type	Cost ₦(000)
I	CFDP1	3/4-bedroom Units	464,024,000-473,840,312
II	CFDP2	4 -bedroom Duplex Units	13,214,000-16,044,130
III	CFDP3	2- bedroom Bungalow	5,000,000-3,515,914
IV	CFDP4	Office Units	472,737,280 - 366,324,221

Source: 2010 Field Survey

Table 5.17: Data Port Phile (Infladex): Current Inflation Index

Period	OCT 2010	NOV 2010	DEC 2010	JAN 2011
Index	10.0	10.0	10.0	10.0

Source : 2010 Field Survey

Inflation index in this port is 10 % this is however subjected to prevailing economic condition as at the time of prediction.

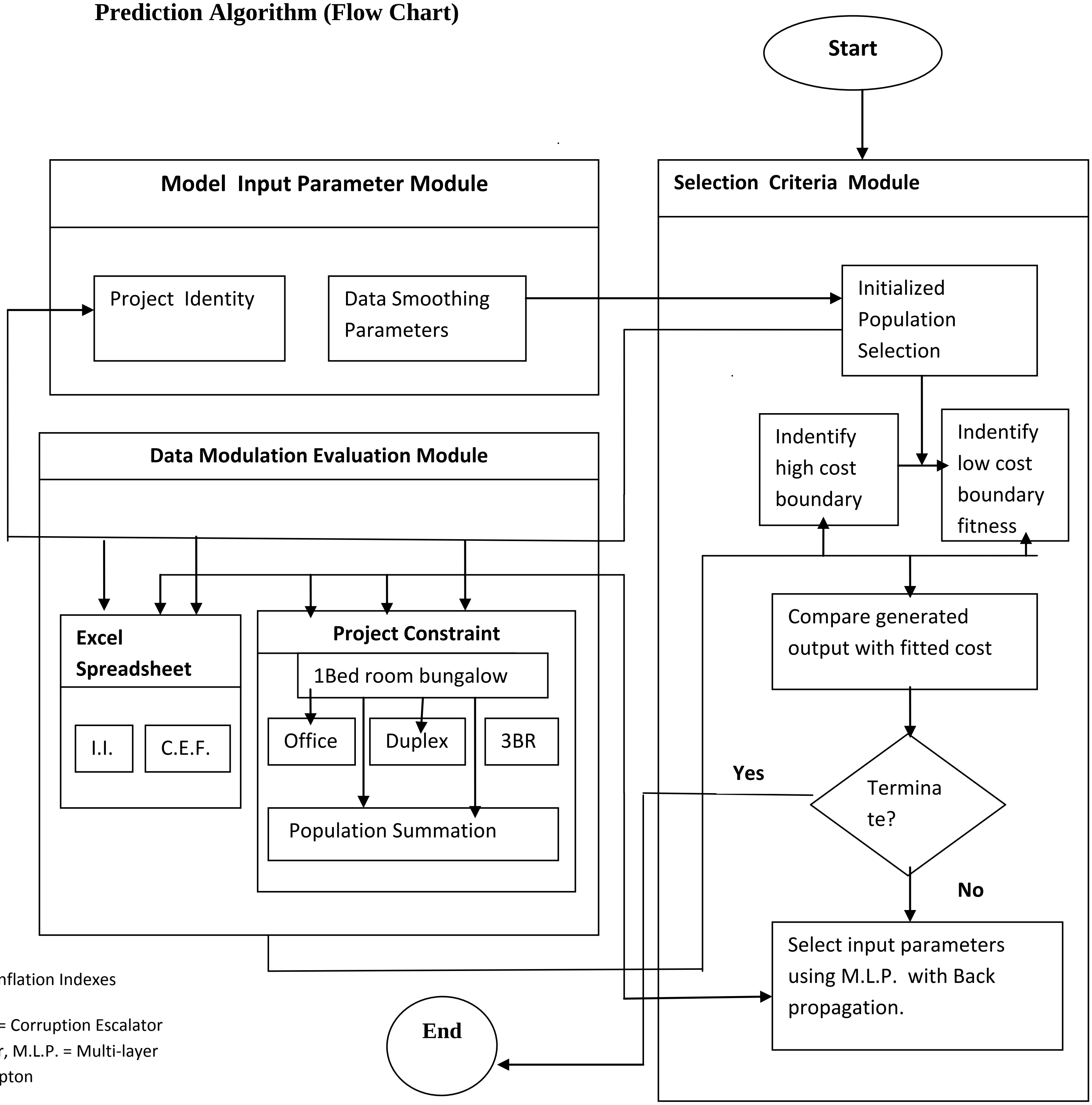
Table 5.18: Data Port Omega (Ω) Corruption Escalator

Variables	Percentage (%)	Index
Corruption Factor	1.14	0.014

Source: 2010 Field Survey

Project exigency factor (corruption escalator) in this context could be as high as 5% however corruption escalator factor of 1.14% was used being the derived economic index that impacts the project..

5.21 Flowcharting of Models Computational Algorithm: Cost Variable Prediction Algorithm (Flow Chart)



I.I. = Inflation Indexes

C.E.F = Corruption Escalator Factor, M.L.P. = Multi-layer Percepton

Fig 5.5 Cost Variable Prediction Algorithm (Flowchart)

5.22 Command and Execution Order of Developed Algorithm

The command and execution of orders flows in sequential order through the algorithm. The optimization module plays active role here, command and execution takes place in this module. Command is issue and accomplish in the following sequence.

Step1: Initialization of generation (selection of cost input)

Step 2: Calculations of objective functions' values

Step 3: Finding upper and lower boundary cost range

Step 4: Determining the best optimized cost against benchmarked cost limit

Step 5: Fitness assignment

Task : Using developed algorithm, predict the prevailing construction cost of a reinforced concrete frame office building, 3-floors high, and 3&4-bedroom units, 4-floors high, with inflation rate over period of 6 months being 10%, and at 1.14% corruption escalator factor.

Step I Command Establish Population

Execution As-built cost of Office building and 3&4-bedroom units. Highest cost: ₦ 478,307,495, Lowes cost: ₦ 310,324,221(Office)

Highest cost: ₦ 478,307,495 (3&4-bedroom)

Lowest cost: ₦310,324,221 (3&4-bedroom)

Step II Command Identify cost boundary, assign fitness and calculate sharing fitness (factor I.I.F and C.E.F into the costs). Add 1.14% prevailing inflation index and corruption escalator factor into the extracted costs. 1.14% inflation and 10% corruption escalator have been constant for period of 6 months.

Execution As-built cost of Office building (0.1114) [₦478,307,495] = ₦531, 590,950 [Highest cost] As-built cost of Office building (0.1114)[₦310, 324,221 = ₦344,894,339.20

[Lowest cost] As-built cost of 3&4-bedroom units Building. (0.1114)[₦475, 509,943] =₦528, 481,750.7[Highest cost]

As-built cost of 3&4-bedroom units building (0.1114)[₦473, 840,312 = ₦526, 626,123 [Lowest cost]

Step III Command Determining upper and lower cost boundaries.

Execution The upper boundary and lower solutions for cost of

the two types of building for the next 6month at prevailing economic and environmental conditions are: Office building [₦531, 590,950] Office building [₦344, 894,339.20]

3&4-bedroom units, 4 floors [₦528, 481,750.7:
3&4- bedroom units, 4 floors [₦526, 626,123]

Step iv: Command Determining the best optimized cost against benchmarked cost limit for the analysis.

Execution The values picked as the as-built value adjusted and used as the data for neural processing were already non-dominant values. Therefore the specify values to be budgeted when executing the project types are: a. Office building [₦531, 590,950 to ₦344,894,339.20]. This cost range could be budgeted for the reinforced concrete office building over a period of 6 months at 10%inflation and 1.14% corruption escalator and other prevailing economic conditions.

b. 3&4-bedroom units, 4 floors [₦528, 481, 75 6 to ₦526, 626,123]

Step V : **Command** Assign data fitness

Execution If non-dominant value emerge, return to step I of the algorithm and run through to step 5, however on identifying the non dominant values, adopt as the predicted cost range for the building types.

5.23 Performance Evaluation of Developed Model

The working system of the algorithm is associated with constraints; the minimization of such constraints determines its effectiveness in variables measurement and prediction. The mean square error and regression value is often used as parameter to measure algorithms' validity at cross validation stage. However, mean square error and regression value produced at cross validation stage were recorded while building an algorithm for expected model development, summary of other parameters used to determine the generated model algorithm effectiveness is in Table 5.19.

Table 5.19 Properties of Generated Model

Building types	Mean square error(MSE)	Regression value (r)	Output value[₦]	Input value [₦]	Relative Efficiency (%)	Coefficient of Performance
3&4-bedroom units	0.0074	0.028	478,307,495	472,737,280	0.988	1.012
Office building	0.0320	0.950	475,509,943	443,800,620	0.929	1.077
4-bedroom duplex	0.0062	0.023	50,687,620	38,650,000	0.688	1.454
1-bedroom bungalow	0.0089	0.0193	11,524,692	9,201,000	0.747	1.339

MSE-----------Mean square error
NMSE--------Normal mean square error
r -------------Regression value

MSE-----------Mean square error
NMSE--------Normal mean square error
r -------------Regression value

Performance characteristics of the developed model is presented in Table 5.19, the efficiency is highest in processing data of 4-bedroom complex with average relative efficiency of 0.988 is recorded with average coefficient of performance of 1.012 for all the cases considered.

Table 5.20: Algorithm Logic Code Sheet

Projects	**Base cost**	**Ham fact**	**Prdt**	**Cusmtn**	**Corr esc(%)**	**Asblt-cst**	**Cusmtn**	**Infl.ind**	**Cusmtn**	**Sumtn**	**Predval**	**Output**
3b001	Bs1		(b1*c1)	(b1+d1)	1.14	asb1	(e1*f1)	0.01	(b1*i1)	(e1+h1+j1)	1.15	(L2*k2)/L2
3b002	Bs2	1	(b2*c2)	(b2+d2)	1.14	asb2	(e2*f2)	0.01	(b2*i2)	(e2+h2+j2)	2.15	(L3*k3)/L3
3b003	Bs3	0.75	(b3*c3)	(b3+d3)	1.14	asb3	(e3*f3)	0.01	(b3*i3)	(e3+h3+j3)	1.9	(L4*k4)/L4
3b004	Bs4	0.5	(b4*c4)	(b4+d4)	1.14	asb4	(e4*f4)	0.01	(b4*i4)	(e4+h4+j4)	1.65	(L5*k5)/L5
3b005	Bs5	0.25	(b5*c5)	(b5+d5)	1.14	asb5	(e5*f5)	0.01	(b5*i5)	(e5+h5+j5)	1.4	(L6*k6)/L6
3b006	Bs6	0.75	(b6*c6)	(b6+d6)	1.14	asb6	(e6*f6)	0.01	(b6*i6)	(e6+h6+j6)	1.9	(L7*k7)/L7
3b007	Bs7		(b7*c7)	(b7+d7)	1.14	asb7	(e7*f7)	0.01	(b7*i7)	(e7+h7+j7)	1.15	(L8*k8)/L8
3b008	Bs8	0.75	(b8*c8)	(b8+d8)	1.14	asb8	(e8*f8)	0.01	(b8*i8)	(e8+h8+j8)	1.9	(L9*k9)/L9
3b009	Bs9	0.67	(b9*c9)	(b9+d9)	1.14	asb9	(e9*f9)	0.01	(b9*i9)	(e9+h9+j9)	1.82	(L10*k10)/L10
3b010	Bs10	0.5	(b10*c10)	(b10+d10)	1.14	asb10	(e10*f10)	0.01	(b10*i10)	(e10+h10+j10)	1.65	(L11*k11)/

												L11
Dp001r	Bs11	**1**	(b11*c11)	(b11+d11)	1.14	asb11	(e11*f11)	0.01	(b11*i11)	(e11+h11 +j11)	2.15	
Dp002	Bs12	0.75	(b12*c12)	(b12+d12)	1.14	asb12	(e12*f12)	0.01	(b12*i12)	(e12+h12 +j12)	1.9	(L14* k14)/ L14
Dp003	Bs13	0.5	(b13*c13)	(b13+d13)	1.14	asb13	(e13*f13)	0.01	(b13*i13)	(e13+h13 +j13)	1.65	(L15* k15)/ L15
Dp004	Bs14		(b14*c14)	(b14+d14)	1.14	asb14	(e14*f14)	0.01	(b14*i14)	(e14+h14 +j14)	1.15	(L16* k16)/ L16
Dp005	Bs15	0.25	(b15*c15)	(b15+d15)	1.14	asb15	(e15*f15)	0.01	(b15*i15)	(e15+h15 +j15)	1.4	(L17* k17)/ L17
Of001	Bs16		(b16*c16)	(b16+d16)	1.14	asb16	(e16*f16)	0.01	(b16*i16)	(e16+h16 +j16)	1.15	(L18* k18)/ L18

Source: 2011 survey

LEGEND: Hamfact ----- Harmonization Factor Prdt ------- Product Cusmtn ----- Cost Summation Infladex ------ Inflation Index Asbltcst ------ As-built Cost Corrptesc ----- Corruption Escalator factor Pred val ----- Predicted value 3b001 – 010 ---- 3 Bedroom Units.

Adaptable code sheet, in which the required elements and function as relevant to the prediction objective stated in this research work is contained is in Table 5.2. Function parameters were assigned coded cells, loaded with pre-calculated values. The command and execution modules which are presented in Sections 5.21 and 5.22 of this work contains the logic route through which appropriate command is selected through the flow chart in order to select input and expected output generation. With the incorporation of the code sheet into a programme, and relevant cost and economic cost parameters supplied, the model is capable of generating predicted cost value for twenty-one different projects.

5.24 Tentative Algorithm Logic Programme

This section contains the statements of semantic algorithm representing the command and execution sequence of the system. The logic code sheet provide summary link to the six(6) data ports presented earlier, this logic route has been tested mechanically and was used to generate output described under Section 5.22, captioned command and execution order of developed algorithm.

PS00001Start

PS00002 Optm project cost? Yes? go to EAVDP1 then Select! No? go to (00007)

PS00003 2/3-bdrm? Yes? then select initializing optm cost (N) No? go to (00007)

PS00004 2-bdmbung? Yes? then select initializing optm cost (N) No? go to (00007)

PS00005 3-bdrm duplx? Yes? then select initializing optm cost (N) No? go to (00007)

PS00006 Office bldg? Yes? then select initializing optm cost (N) No? go to (00007)

PS00007 adjst inicost? Infladex? Corrptesc?Yes? go to CHIDΦ, No? go to (000012)

PS00008 adjst 3/4-bdrm? Yes? then select CHDPα, No? go to (PS00012)

PS00009 adjst 4 -bdrm? 4 floors? Yes? then select CHIDPα ii, No? go to (PS00030)

PS00010 adjst 4 -bdrm? 3 floors? Yes? then select CHIDPα iii, No? go to (PS00030)

PS00011 adjst 4 -bdrm? 2 floors? Yes? then select CHIDPα iv, No? go to (PS00030)

PS00012 adjst 3- bdrm? 4 floors? Yes? then select CHIDPα v, No? go to (PS00030)

PS00013 adjst 3- bdrm? 3 floors? Yes? then select CHIDPα vi, No? go to (PS00030)

PS00014 adjst 3 -bdrm? 2 floors? Yes? then select CHIDPα vii, No? go to (PS00030)

PS00015 adjst 3 -bdrm? 1 floor? Yes? then select CHIDPα viii, No? go to (PS00030)

PS00016adjst X-no bdrm duplx? Yes? then select CHDPγ No? go to (PS00030)

PS00017 adjst 4 -bdrm duplx? Yes? then select CHDPγ i, No? go to (PS00030)

PS00018 adjst 3 -bdrm duplx? Yes? then select CHDPγ ii, No? go to (PS00030)

PS00019 adjst 2 -bdrm duplx? Yes? then select CHDPγ iii, No? go to (PS00030)

PS00020 adjst 1-bdrm duplx? Yes? then select CHDPγ iv, No? go to (PS00030)

PS00021 adjst X-no reinf-offc? Yes? then select CHDPβ No? go to (PS00030)

PS00022 adjst X-no reinf-offc? 3 flrs? Yes? then select CHDPβi No? go to (PS00030)

PS00023 adjst X-no reinf-offc? 2 flrs? Yes? then select CHDPβi No? go to (PS00030)

PS00024 adjst X-no reinf-offc? 1 flr? Yes? then select CHDPβi No? go to (PS00030)

PS00025 adjst X-no bdrm bungl? X- bedroom? Yes? then select CHDPγ No? go to (PS00030)

PS00026 adjst X-no bdrm bungl? 1 bedroom? Yes? then select CHDPγ No? go to (PS00030)

PS00027 adjst X-no bdrm bungl? 2 bedrooms? Yes? then select CHDPγ No? go to (PS00030)

PS00028 adjst X-no bdrm bungl? 3bedroom? Yes? then select CHDPγ No? go to (PS00030)

PS00029 adjst X-no bdrm bungl? 4 bedrooms? Yes? then select CHDPγ No? go to (PS00030)

PS00030 adjst modified cost? with forecstperd? Yes? then select CHDPprd No? go to (PS00032)

PS00031 check modified cost? for fitness? Yes? then select CFDP No? go to (PS00032)

PS000032 cost fit? 3/4-bdrm? Yes? then select CFDP No? go to (ps00038)

PS000033 3/4-cost fit? bdrm? Yes? then select CFDPii No? go to (ps00038)

PS00034 cost fit? 2 -bdrm bungl? Yes? then select CHIDPiii No? go to (00038)

PS00035 cost fit? 4 -bdrm dplx? Yes? then select CHIDPiv No? go to (000038)

PS00036 cost fit? offc? Yes? then select CHIDPv No? go to (00038)

PS000037 cost fit? bdrm bungl? Yes? then select CHIDP 1 No? go to (ps00012)

PS000038 EXTRACT COST (PREDICTED COST) OK? Go to (PS000040)

PS000040 STOP

Legend: EAVDP----Estimated Adjusted Value Data Port

CHD ------- Cost Harmonization Data Port

CFDP ----- Cost Fitness Data Port

CFHDP-----------Cost Factors Harmonization Data Port.

5.25 Adaptability of Developed Model to Construction Stages Cost Prediction

Adaptability of developed model to cost prediction at different stages of building project is presented in this section, using content analysis technique. Projects bill of quantities structured in elemental format were used for this purpose. The adaptability lies in factoring of elemental components, elemental rating and cost component risk matrix as peculiar to each of projects.

5.26 Content Analysis of Projects Bill of Quantities

4 -bedroom Duplex Bill of Quantities

Table 5.21: 4-bedroom Duplex Bill of Quantities

S/N	Project Particular	Element	Cost[₦]	Total Project Cost[₦]	Relative Percent
A	4-bedroom Duplex				
ELT1		Substructure	2,216,550	16,043,868	13.816
ELT2		Frame & Walls	3,101,070	16,043,868	19.329
ELT3		Stair Cases	246,115	16,043,868	1.534
ELT4		Upper Floor	1,376,520	16,043,868	8.580
ELT5		Roofs	1,169,990	16,043,868	7.293
ELT6		Windows	871,840	16,043,868	5.434
ELT7		Doors	877,640	16,043,868	5.470
ELT8		Finishing Works	2,466,800	16,043,868	15.375
ELT10		Fittings	283,000	16,043,868	1.764

ELT11		Services	1,136,350	16,043,868	7.083
ELT12		Soil Drainage	334,000	16,043,868	2.082
ELT13		Preliminaries	700,000	16,043,868	4.363
ELT14		Contingencies	500,000	16,043,868	3.117
ELT15		Value Added Tax (5%)	763,993.75	16,043,868	4.762

Bill of quantities of 4- bedroom duplex is presented in Table 5.21, containing elements, total cost and relative percent. From Table 5.21 Substructure (22.87 %) has the highest percentage; Finishing works has the next highest percentage (21.77%); Frame and walls (13.015 %) and Roofs has 10.253% cost composition relative to total cost of the project. Windows has 4.434 %; Preliminaries (4.283%); Doors (4.667 %); Soil and drainage (2.347%), Contingencies (2.313%), while the least is Fittings (2.54 %).

Table 5.22: 2 & 3-bedroom Bungalow Bill of Quantity

S/N	Project Particular	Element	Cost[₦]	Total Project Cost[₦]	Relative Percent
B.	2 or 3-bedroom Bungalow				
ELT1		Substructure	2,669,340	11,674,519.50	22.865
ELT2		Frame & Walls	1,519,415	11,674,519.50	13.015
ELT3		Roofs	1,197,000	11,674,519.50	10.253
ELT4		Windows	517,650	11,674,519.50	4.434
ELT5		Doors	544,500	11,674,519.50	4.664
ELT6		Finishing	2,541,535	11,674,519.50	21.770
ELT7		Fittings	298,800	11,674,519.50	2.560
ELT8		Services	786,350	11,674,519.50	6.736
ELT10		Soil Drainage	274,000	11,674,519.50	2.347
ELT11		Preliminaries	500,000	11,674,519.50	4.283
ELT12		Contingencies	270,000	11,674,519.50	2.313
ELT13		Value Added Tax (5%)	555,929.50	11,674,519.50	4.762

Source 2011 Field Survey

From Table 5.22 Substructure (22.87 %) has the highest percentage; Finishing works has the next highest percentage (21.77%); Frame and walls (13.015 %) and Roofs have 10.253% cost composition relative to total cost of the project. Windows has 4.434 %; Preliminaries (4.283%); Doors (4.667 %); Soil and drainage (2.347%), Contingencies (2.313%), while the least is Fittings (2.54 %).

Table 5.23: 1- bedroom Apartment Bill of Quantities

S/N	Project Particular	Element	Cost[₦]	Total Project Cost[₦]	Relative Percent
C.	1-bedroom Apartment				
ELT1		Substructure	600,920	3,174,953.25	18.925
ELT2		Frame & Walls	370,000	3,174,953.25	11.654
ELT3		Roofs	441,720	3,174,953.25	13.913
ELT4		Windows	166,500	3,174,953.25	5.244
ELT5		Doors	165,650	3,174,953.25	5.217
ELT6		Finishing	643,725	3,174,953.25	20.278
ELT7		Services	177,250	3,174,953.25	5.583
ELT8		Soil Drainage	213,000	3,174,953.25	6.709
ELT10		Preliminaries	145,000	3,174,953.25	4.567
ELT11		Contingencies	100,000	3,174,953.25	3.150
ELT12		Value Added Tax (5%)	151,188.25	3,174,953.25	4.762

Source: 2010 Field Survey

From Table 5.23 Finishing works has the highest percentage (20.278%); Substructure (22.87 %) has the next highest percentage; Roofs has 13.913% Frame and walls has11.654 % cost composition relative to total cost of the project. Windows has 5.244 %; Preliminaries (4.283%); Doors (5.217 %); Soil and drainage (2.347%), Contingencies (3.153%), while the least is Contingencies which has 2.54 %**.**

Table 5.24: 3/4 - bedroom Reinforced Framed Structure Bill of Quantities

Cost centers of the bill of quantities of 3 / 4- bedroom reinforced concrete frame structure is presented in Table 5.24 for content analysis.

S/N	Project Particular	Element	Cost[₦]	Total Project Cost[₦]	Relative Percent
D.	3/4 -bedroom Reinforced Framed Structure 4 Floors 24 Units				
ELT1		Substructure	26,145,000	321240000	8.139
ELT2		Concrete Frame	112,124,000	321240000	34.904
ELT3		Over site Concrete	7,555,000	321240000	2.352
ELT4		Ceiling	4,163,000	321240000	1.296
ELT5		Roofs	12,133,000	321240000	3.777
ELT6		Block work	39,181,000	321240000	12.197
ELT7		Doors/Windows	19,173,000	321240000	5.969
ELT8		Plastering	12,123,000	321240000	3.774
ELT10		Wall Tilling	12,361,000	321240000	3.848
ELT11		Floor Tilling	11,123,000	321240000	3.463
ELT12		Painting	13,700,000	321240000	4.265
ELT13		Services	23,131,000	321240000	7.201
ELT14		Drainage and Landscaping	19,767,000	321240000	6.154
ELT15		Contingencies	7,764,350	321240000	2.417
ELT16		Preliminaries	23,872,000	321240000	7.431
ELT17		Value Added Tax (5%)	408,650	321240000	0.127

Source 2011 Survey

From Table 5.24 Concrete frame work has the highest percentage (34.94%); Finishing has the next highest percentage with 15.35%; Block work (12.197%); Substructure (8.139 %); Services (7.201%); Drainage (6.154%). Roofs have 3.77%, Drainage and landscape (6.154 %) cost composition relative to total cost of the project. Window and Doors has 5.96 %; Preliminaries (7.43%), while the least Value Added Tax (0.127%) and Contingencies which has 2.417 %.

Table 5.25: Factoring Elemental Cost Centers Influence on Project Cost

S/N C.	Elements	Cost Rating On Scale (1) To Ten (10)			
		4-bedroom Duplex	2/3 -bedroom Bungalow	1-bedroom Apartment	3&4-bedroom, 4 Floors
ELT1	Substructure	10^{+4}	10^{+12}	10^{+19}	8
ELT2	Frame & Walls	10^{+9}	10^{+3}	10^{+2}	10^{+25}
ELT3	Stair Cases	2	---	---	3
ELT4	Upper Floor	9	---	---	4
ELT5	Roofs	7	10	10^{+4}	4
ELT6	Windows	5	4	5	5
ELT7	Doors	6	5	5	5
ELT8	Finishing	10^{+4}	10^{+12}	10^{+10}	10^{+5}
ELT10	Fittings	2	3	---	6
ELT11	Services	7	7	6	7
ELT12	Soil Drainage	2	2	7	6
ELT13	Preliminaries	4	4	5	7
ELT14	Contingencies	3	2	3	3
ELT15	Value Added Tax (5%)	5	5	5	1

Source 2011 Field Survey

In this section, influence of cost center on project cost was quantified, this was carried out through quantitative analysis of cost component of sampled projects bill of quantities that were used in the model development. The elemental cost component was used for this purpose and is presented in the table below. In Table 5.25, influence of the elements' cost on total project cost was factored on rating scale one (1) to ten (10) using percentage cost composition as base reference point. Cost of substructure for 4-bedroom Duplex, 2/3-bedroom bungalow, Frame and walls were rated high on scale 10^{+} high relative to base cost, for all building types. Finishing is ranked high on scale 10^{+} 4-bedroom Duplex, 1-bedroom apartment, 3/4–bedroom on 3 floors-24 Units and 2/3-bedroom bungalow, this indicates that the influence of this is high on the project final cost. The implication of this is that a great deal of resource is at stake on this particular element, careful management of this cost center can determine to a very large extent the overall success of the project work. Value added Tax, Contingencies, Preliminaries, Soil drainage; Fittings were rated low on scale 4 down to However, this does not mean they are the least in term of importance, they as well has contributory effect on the total project cost. This however satisfied objective i which borders on identifying parameters that could be used as input data in neural network –based model. Ideally, one would have been tempted to select those cost centers with high rating and high risk index as the core parameters and prorate the remaining elements; danger in this option lies in imbalance prediction that could arise as the consequence.

Furthermore, incorporating all the elements cost in model formulation is highly recommended, since this could always guarantee an holistic cost prediction whenever such model is being used as demonstrated in this study. This study engaged all cost centers in model development; this is believed to ensure provision of a model that is valid in holistic cost prediction whenever used. It is against this background that the model developed is adjudged to be capable of being deployed at various stages of construction works using the probability and risk matrix generated bearing in mind fixing predicted cost within the cost expectancy limit generated.

Table 5. 26: Cost and Risk Impact Prediction Probability Matrix

		4 -bedroom Duplex	2&3-bedroom Bungalow	1-bedroom Apartment	3 /4-bedroom, 24 Units 4 Floors
PROBABILITY	EXTREME 9-20	14(1.4Sub) 15(1.5Finish) 19(1.9Frame) 7(0.7Serv) 9(0.9Uppflr) 7(0.7Roof)	13(1.3Sub) 13(1.3Frame) 10(1.0Roof) 12(1.2Finish)	20(2.0) Finishing) 19(1.9 Substruct) 12(1.2 Frame) ------ ------- 14(1.4Roof)	20^{+} (2.0) Frame 15(1.5 Finishing)
	HIGH 6-8	5(0.5Wind) 6(0.6 Doors)	7(0.7Services)	6(0.6Services) 7(0.7Soildrg)	8(0.8 Sub) 6(0.6 Fittings) 6(0.6 Soildrhg)) 7(0.7 Services) 7(0.7 Services)
	MEDIUM 3-5	3(0.3 Contig) 4(0.4 Prelm) 3(0.3 Contg)	3(0.3 Fittings) 5(0.5 VAT) 4(0.4 Wind) 5(0.5 Doors) 4(0.4 Prelim)	5(0.5 Window) 5(0.5 Prelim) 3(0.3 Doors) 5(0.5 Soildrg) 5(0.5 VAT)	3(0.3 Staircs) 4(0.4 Upperflr) 4(0.4 Upperflr) 5(0.5 Windw) 5(0.5 Doors) 3(0.3 Contig)
	LOW 0-2	2(0.2 Stair) 2(0.2 Soildrg) 2(0.2 Fittgs)	2(0.2SoilDrain) 2(0.2Conting)		
		1	2	3	4

IMPACT/CONSEQUENCE Source 2011 Survey

Having identified the range of risks, the next step is to quantify the probability of the risk occurrence and the likely effect or consequence on the project and the amount at stake. Risk impact quantification in cost prediction as presented in Table 5.26 is primarily concerned with determining what areas of risk warrant response and where resources are limited, a risk priority will identify the areas of risk that should be addressed first. The risk matrix developed for each project types with degree of risk liability of cost centers is presented in Table 5.26.

5. 27 Derivation of Model Cost Expectancy Limit Using Three-Cost Probabilistic Model Approach

Expected cost of project in lieu of the need to establish cost bench mark so as to have cost limits which will guide as boundary in cost prediction is presented in this section. In this context, optimistic cost, most likely cost and projected costs were used. This is patterned after the three-time probabilistic estimating technique. It has been established through research submissions, that, there is linear relationship between the project cost and time spent on a project. To this end, models relating cost and time together had been developed, for instance, Ogunsemi and Jagboro (2006) developed Time-Cost model which was adjudged as a step ahead of earlier developed Brommillow model in term of predictive ability. Marzouk and Moselhi (2006), Kumaraswammy *et al.*, (2005), Koushki *et al.*, (2005) developed Time-Cost Model which also has predictive ability. It was on this premise, that, Three-cost Estimating Model (TCEM) was adapted in synthesizing projected cost and modeling cost expectancy limit as was presented in Table 5.27 in this research work.

Table 5.27: Three- Cost Probabilistic Estimating (TCEM) Cost Schedule

S/N	Project Particular	Optimistic Cost[₦]	Most Likely Cost[₦]	Projected Cost[₦]
A	4 -bedroom Duplex	16,044,130	13,214,000	10,391,590
B	2&3- bedroom Bungalow	4,385,000	9,000,000	13,000,000
C	1- bedroom Apartment	4,385,000	6,000,000	9,201,000

D	3 /4 -bedroom, 24 Units 4 floors	464,024,000	473,840,312	475,509,943
D	Office Accommodation	472,737,280	310,324,221	478,307,495

Source: 2011 Survey

Table 5.27 contains the three-cost probabilistic estimating cost schedule, cost component of optimistic cost, most likely cost and projected cost of building projects within the category of residential and office accommodation. Three costs probabilistic estimating was carried out on the most likely cost, optimistic and pessimistic cost of sampled project work, so as to determine cost region in which expected cost of the projects would lie. In order to achieve this feat, formulating a contingency schedule is highly essential. To this end a suitable contingency table was formulated, containing calculated optimistic cost, most likely cost pessimistic cost with a view to finding cost expectancy limit for the developed model.

Table 5.28: Expected Cost Contingency Schedule

S/N	Optimistic Cost(O)₦	Most Likely Cost(M)₦	Pessimistic Cost(P)₦	Expected Cost (O+4+M+P /6)₦	Expected Cost Region[₦]
4-bedroom Duplex	16,044,130	13,214,000	10,391,590	13,215,287	13,214,000
2&3-bedroom Bungalow	4,385,000	9,000,000	13,000,000	8,897,500	9,000,000
1-bedroom Apartment	3,515,914	5,000,000	11,524,692	5,840,101	5,000,000
3 /4 -bedroom, 24 Units 4 Floors	464,024,000	473,840,312	475,509,943	472,482,532	473,840,312

Office Accommodation	472,737,280	310,324,221	478,307,495	366,318,646	366,324,221

Source 2011 Field Survey

The generated three costs needed to develop cost expectancy limit which could serve as guide for the model developed is presented in Table 5.28. Table 5.28 contains the cost component of optimistic cost, most likely cost and projected cost of building projects within the category of residential and office accommodation. Three costs probabilistic estimating was carried out on the most likely cost, optimistic and pessimistic cost of project work, so as to determine cost region in which expected cost of the projects will lie. Careful observation of the contingency table revealed the closeness between the expected cost and most likely cost.

Most likely cost generated for 4 bedroom duplex is ₦13,214,000 which has the same value as calculated expected cost with exception of pessimistic cost which is ₦ 9,000,000, this leaves the expectancy cost limit within the threshold of ₦13,214,000. Also, most-likely cost for 2&3-bedroom bungalow is ₦9,000,000. Optimistic cost is ₦4,385,000; pessimistic cost is ₦13,000,000 while expected cost is ₦8,897,500. As regard 1-bedroom apartment, most-likely cost is ₦5,000,000; expected cost is ₦5,840,101 optimistic cost is ₦3,515,914 while expected cost limit is ₦5,000,000. In practice, one would estimate the predicted cost around the most-likely cost. The optimistic cost would be slightly shorter, if everything went better than planned, while the pessimistic cost would be extended if everything went worse than planned such as in the case of late delivery, machine breakdown and other factors. Moreover, in this context cost prediction was ranged around the region of expected cost, and this has been incorporated into cost data fitness module of developed algorithm. In the light of this development, cost expectancy limit for purpose of determining cost fitness when the model is being used for prediction is presented in the Table 5.29.

Table 5.29: Cost Expectancy Limit for Cost Prediction

S/N	Project Detail	Upper Limit Cost[₦]	Lower Limit Cost[₦]	Comment
I	4- bedroom Duplex	16,044,130	13,214,000	Range
II	2&3 -bedroom Bungalow	9,000,000	4,385,000	Range
III	2 -bedroom Apartment	5,000,000	3,515,914	Range
IV	3 /4 -bedroom, 24 Units on 4 floors	473,840,312	464,024,000	Range
V	Office Accommodation	472,737,280	366,324,221	Range

Source 2011 Field Survey

The cost expectancy limit for different categories of project is presented in table 5.29. From the analysis, the benchmarked limit for the project types is as follow: ₦13,214,000 lower limit to ₦16,044,130 upper limit for 4- bedroom units; ₦4,385,000lower cost limit to ₦9,000,000 upper cost limit for a 2&3- bedroom bungalow; ₦3,515,914 lower to ₦5,000,000 upper cost limit for 2- bedroom apartment; ₦464,024,000 lower cost limit to ₦473,840,312 upper cost limit for 3/4- bedroom, 24 Units, with 4 floors and ₦366,324,221 lower to ₦472,737,280 upper limit for Office accommodation. This provides adjustment parameter for data fitness determination when the model is being used in cost prediction. The values are incorporated into the fitness evaluation module of the developed model for cost fitness determination.

Table 5.30: Cost Limit Component Validation

Elements and Statistical Parameters		4-bedroomduplex	2/3-bdrmbunglw	1-bdrm bung	3-bdrm,3-floors
4-bedrmdplx	Pearsons Corr.	1.00	-	-	-
	Sig.(2-tailed)	0.00	-	-	-
2/3-bedrmbung	Pearsons Corr.	0.787	1.00	-	-
	Sig.(2-Tailed)	0.001	0.000	-	-
1-bedrm bunglw	Pearsons Corr.	0.764	0.905	1.000	-
	Sig.(2-Tailed)	0.001	0.000	0.000	-
3-bdrm on 4flrs	Pearsons Corr.	0.791	0.586	0.485	1.000
	Sig.(2-Tailed)	0.001	0.028	0.079	0.000

Source 2010 Field Survey

Strong positive relationship exist between cost limit of 1-bedroom duplex and 2/3-bedroom bungalow with Pearson coefficient of 0.905, also there is very weak relationship with Pearsons correlation -coefficient of 0.45 that exist between the cost limit of 3-bedroom on four floors and 1-bedroom bungalow. However, averagely strong relationship is recorded as well in mapping 2/3- bedroom duplex with 4-bedroom duplex the analysis came up with Pearsons correlation coefficient of 0.787. Similarly, an average strong relationship occurred between 1-bedroom bungalow and 4-bedroom duplex;3 bedroom on 4-floors and 2/3-bedroom bungalow with Pearsons coefficient of 0.764 and 0.586 respectively.

Table 5.31 Acceptance of Projects Influence Factors and Cost expectancy Limit

Elements and Statistical Parameters		4-bedroomduplex	2/3-bdrmbunglw	1-bdrm bung	3-bdrm,3-floors
Substructure	Pearsons Corr.	0.735	0.626	0.245	0.990
	Sig.(2-tailed)	0.265	0.374	0.755	0.010
Frame walls	Pearsons Corr.	-0.073	-0.421	-0.297	-0.423
	Sig.(2-Tailed)	0.927	0.579	0.703	0.577
Staircases	Pearsons Corr.	-0.048	-0.327	-0.128	-0.494
	Sig.(2-Tailed)	0.952	0.673	0.872	0.560
Upper floor	Pearsons Corr.	0.219	0.329	0.668	0.358
	Sig.(2-Tailed)	0.781	0.671	0.332	0.642
Roofs	Pearsons Corr.	-0.355	-0.050	-0.166	-0.136
	Sig.(2-Tailed)	0.645	0.950	0.834	0.864
Windows	Pearsons Corr.	-0.735	-0.626	-0.245	-0.990
	Sig.(2-Tailed)	0.265	0.374	0.755	0.010
Doors	Pearsons Corr.	0.276	0.526	0.832	0.198
	Sig.(2-Tailed)	0.724	0.474	0.168	0.802
Finishings	Pearsons Corr.	0.095	0.127	-0.235	0.652
	Sig.(2-Tailed)	0.905	0.873	0.765	0.348
Fittings	Pearsons Corr.	0.191	-0.255	-0.317	-0.020
	Sig.(2-Tailed)	0.809	0.745	0.683	0.980
Services	Pearsons Corr.	0.827	0.576	0.539	0.418
	Sig.(2-Tailed)	0.173	0.424	0.461	0.582
Soildrainage	Pearsons Corr.	-0.926	-0.986	-0.922	-0.682
	Sig.(2-Tailed)	0.074	0.014	0.078	0.318
Preliminaries	Pearsons Corr.	-0.487	-0.815	-0.762	-0.544
	Sig.(2-Tailed)	0.513	0.165	0.238	0.456
Contingencies	Pearsons Corr.	-0.735	-0.626	-0.245	-0.990
	Sig.(2-Tailed)	0.265	0.374	0.755	0.010
Value Added Tax	Pearsons Corr.	0.184	0.576	0.539	0.374
	Sig.(2-Tailed)	0.816	0.424	0.461	0.626

Table 5.32: Cross Tabulation of Cost Influence Factors on Projects' Cost Parameter

Elements and Statistical Parameters	4-bedroomduplex	2/3-bdrmbunglw	1-bdrm bunglw	3-bdrm,on 3-floors
Chi-Square	2.714	1.714	4.000	1.429
Degree of Freedom	8	8	8	8
Asymptotic Significance	0.951	0.995	0.857	0.994

Source 2010 Field survey   Legend: bunglw-bungalow   bdrm - bedroom

The results of the Chi-square analysis carried out on project influence factors and cost limits are presented in Table 5.31. It indicates the acceptance of project influence factors and cost limit designed for the model. Cross tabulation of project elements with influence factors with a view to determining impact on different types of buildings is presented in Table 5.32. Negative correlations was recorded in Preliminaries, Contingencies, Soil drainage, Roofs, Windows, Stair cases and Frame walls for all categories of building types, while other components indicates strong and positive correlation with all the building types. This could be attributed to the variable nature of the elements relative to design and cost requirement of the building types.

Table 5.33 Early and Late Constructible Elements and Early Warning System Schedule

Project Parameter	Early Constructible Elements Cost(₦)	Latest Constructible Elements Cost(₦)	Entropy (Cost Movement) (₦)	Cost Entropy Status
4-bedroomduplex (₦)			0.063	Very Low
2/3-bedroom Bungalow (₦)	4,996,812	572,468	0.25	Low
1-bedroom Bungalow (₦)	99,860	81,810	0.049	Very Low
3-bedroom,3-Floors (₦)	11,494,237	7,107,068	0.11	Low
Cost Entropy Evaluation Scale	0.1-0.5 Low			
	0.005-0.09 Very Low			
	0.5-0.7 High			
	0.7- 1.0 Very High			

Table 5.34: Project Cost Early Warning Schedule with Initial and Econometric Cost

Elements and Statistical Parameters		4-Bedroomduplex (₦)	2/3-bdrmbunglw (₦)	1-bdrm bung (₦)	3-bdrm,3-floors (₦)
Substructure	Initial Cost (₦)	33,700,000	2,669,340	600,920	2,216,550
	Econometric Value(₦)	31,966,206	2,516,651	566,547	2,089,761
Frame walls	Initial Cost(₦)	112,124,000	-----	---	-----
	Econometric Value (₦)	105,710,395	-----	---	-----
Staircases	Initial Cost(₦)	-----	------	---	246,115
	Econometric Value(₦)	------	-------	---	232,038
Upper floor	Initial Cost(₦)	------	--------	----	1,376,500
	Econometric Value(₦)	-------	---------	-----	1,297,764
Roofs	Initial Cost(₦)	16,296,000	1,197,000	441,720	1,169,990
	Econometric Value(₦)	15,363,853	1,128,531	416,454	1,103,066
Blockwork	Initial cost(₦)	39,181,000	1,519,415	370,000	3,101,070
	Econometric Value(₦)	36,939,808	1,432,505	348,836	2,923,687
Windows	Initial Cost(₦)	18,068,286	517,650	166,650	871,840
	Econometric Value(₦)	488,041	488,041	157,118	821,971
Doors	Initial Cost(₦)	19,173,000	544,500	165,650	877,640
	Econometric Value(₦)	513,355	513,355	156,125	827,439
Finishings	Initial Cost (₦)	49,307,000	2,541,535	643,725	2,466,800
	Econometric Value(₦)		2,396,157	606,904	2,325,697
Fittings	Initial Cost(₦)	46,486,591	298,800	-------	283,000
	Econometric Value(₦)		281,709	-------	266,813
Services	Initial Cost(₦)	23,131,000	786,350	177,250	1,136,350
	Econometric Value(₦)	21,807,884	741,371	167,112	1,071,351
Soil drainage	Initial Cost (₦)	19,764,350	274,000	213,000	334,000
	Econometric Value(₦)	18,633,810	258,327	200,816	314,895
Preliminaries	Initial Cost(₦)	23,872,000	23,872,000	145,000	700,000

	Econometric Value(₦)	22,506,498	22,506,498	136,706	659,960
Contingencies	Initial Cost (₦)	7,764,350	270,000,000	100,000	500,000
	Econometric Value(₦)	7,320,222	254,556	94,280	471,400
Value Added Tax	Initial Cost (₦)	408,650	555,556	151,188	763,994
	Econometric Value(₦)	385,277	500,000,000	142,541	720,293
Total	Initial Cost(₦)	336,957,000	14,244,854	3,175,103	16,043,849
	Econometric Value(₦)	325,188,830	9,989,233	2,993,439	15,126,135

Source 2010 Field survey Legend: bunglw-bungalow bdrm – bedroom

Mechanism of providing an early warning system that helps in monitoring project cost is presented in Tables 5.33 and 5.34. An econometric-cost factor model was used to generate an output as basis of cost warning benchmark. Back-end loading system of Cattel, Kaka, and Bowen (2008) simplified unbalanced bidding model was modified and used in formulating the econometric model. $[\Sigma (1/1\text{-}r)^n]([C\lambda_{nj}[Q_j + Q_i][\gamma_{nj} fP_j - C^1)] + \lambda_{nj}[Q_j + Q_i][\gamma_{nj} fP_j - C^1)])$

The Back-end econometric model $[\Sigma [(1\text{-}r)^n]([C\lambda_{nj}[Q_j$ ___incorporates duration'n'and often used for factoring elements that has potential of being constructed later as the project progresses. In other to accommodate other elements schedule to be executed later in the project, an econometric factor λ_{nj} [$Q_j + Q_i$][$\gamma_{njnj} fP_j - C^1$)]) need to be added. This factor incorporates inflation factor/index, and period in consideration together with variation factor anticipated.

Legend: rj --- monthly discount rate n --- month number C^1--actual increase in cost of items. λ_{nj} --- proportion of elements Q_j; Q_i ---- bill cost of iitem i, j γ_{nj} --- adjustment for escalation fP_j----Haylet Factor(0.85) C^1 ---- unit cost of item j

Back-end loading is a system that compensates a builder for loss due to inflationary effect. It rewards a builder for increase in his expenses. This is possible in a contract that incorporates cost escalation payment in terms of cost adjustment provision (Cattel *et al.,* 2008). The concept is to allow contractor and builder to be compensated for cost incurred during inflation. It affords builder opportunity to neither make gain or loss during inflation but that the risk they would have borne is passed to the client or project developer. In practice it is not possible for the builders' actual cost to be known since it is usually confidential, however gross item price of contractor is often used. The actual escalation on gross item price could then be used to factor the margin of inflation increment. This is a wide practice in South Africa according to Cattel *et al.,* (2008),where escalation calculation is done in term of "Haylet Factor'', the Haylet Contract Price Adjustment provision. The factor allows for incorporation of non-adjustable element of 15% (0.85). This implies that a builder's cost is 85% of any items price.

The simple way back-end loading can be carried out is for a builder to load items billed to occur late in the contract high, this will give impression that the costs are high therefore attracts high escalation this will tend to allow the builder to monitor closely the price variation on the project. In the context of generating an early system function from the developed model, a modified form of the back-end loading was generated for the model, with projects elements grouped into cost centers. The items were grouped into escalation work group to enable close monitoring of inflation on the items. The escalation work centers were categorized into early constructible and late constructible elements as contain in Table 5.34 for close monitoring of price change on account of inflation and other economic factors. This allows for cost escalation prediction on each item in the respective group therefore keep abreast of price movement.

CHAPTER SIX

SUMMARY, FINDINGS, CONCLUSION AND RECOMMENDATION

6.1 Introduction

In the previous Chapter an attempt was made to review some of the factors that instigate cost overrun on construction projects. Factors such as organization related variables, client induced variables, and project related variables among others were reviewed. The most striking one is project related variables under which poor cost determination approach was identified. Extensive review was carried out to be able to situate position of forecasting approach in this context.

However, it was discovered that there are a number of benefits that could be derived in using expert system in prediction, such as ability to capture data trend, accommodating intervening variables such as economic and environmental parameters that impacts cost. The forecasting paradigm must then as a matter of necessity shift in the direction of expert system prediction. To this end therefore, the study has used neural network to develop a model that could be used to predict the cost of building works both at initial stage and as the project progresses. It is hoped that the implementation of recommendations included in this chapter will achieve practical results and help in further research and finding realistic solution to problem of cost prediction in construction industry.

There is often need for cost information provision on project works for purpose of project monitoring. Researchers had attempted developing model for cost estimating using regression models while few attempts had been recorded in the past of neural network application in building cost prediction in this part of the world. Neural network-based predictive cost model was therefore developed in this study. The aim of the research work is to develop a cost predictive model suitable for building works cost prediction. The objectives of the study are as follows:

i. Evaluation of practice and application of models in use by cost expert and identification of cos centers that could be used as model input parameters.

ii. To develop neural networks cost optimized stabilized model that could serve as an early warning system.

iii Make available, a system that can provide projects cost early warning system in order to prevent project cost overrun or underestimation.

iv. Factoring cost center influence on project cost component and projects cost expectancy limit

v. Formulation of impact matrix of risk probability for building components.

6.2 Evaluation of Practice and Application of Cost models and model input and output

The first objective of this study is evaluation of practice and application of models in use by cost expert with a view to establishing the suitability of the methods. It was discovered that most of the available applications were based on cost estimation using regression analysis and expert systems, some of them that are expert system-based are applications in the area of civil structural works, such as roads, dams, steel girders, bridges, pipe flow, weather prediction, marketing, bankruptcy prediction, risk prediction while few are on actual construction . This objective was satisfied with results of the applications presented in Table 1.0. Some of the sampled works among other works include that of Adeli and Wu (2008) and Jashmid *et al.*, (2005) who used regularization network in highway cost estimation, Al-Tabatabai et al., (2008) carried out preliminary cost estimation of highway project, Ayed (1998) worked on parametric cost estimation of highway project using Neural networks, Bouabaz *et al.*, (2008), Copeland and Proud foot (2004), Gaza and Rouhana (1995) used Neural network in carbon steel cost estimating, Gwang-Hee *et al.,* (2004) utilized neural network in model comparison, Gouda *et al.,* (2007) applied neural network in modeling thermal exchange in building space while Hue *et al.*, (2004) deployed neural networks in predicting consumer situational choice.

Some of the few works that are built environment related were mostly on cost property estimation, for instance, Jamshid *et al.,* (2005), Mc Kim (2005a), Mc Kim (2005b), Setyawati *et al.,* (2007), Shtub and Versano (1999), Thawornwong and Enke (2004) and Zhang (2004) among others used Neural network in cost estimation. It is against this background, that this research work developed an artificial neural network-based cost predictive model with back elimination method and with model's cost expectancy limit which could be used in holistic building cost prediction. This research work therefore used artificial neural network with back elimination and levenberg marqua as a base for the predictive cost model developed.

6.3 Identification of Model Input Parameters.

In modeling selection of input and output parameters is important therefore the second part of objective 1 of this work. There are different schools of thought as far as parametric and expert system modeling is concerned. Some believed that using sectionalized portion of project data was good therefore elemental approach was used in some cases, for instance Bouabas *et al.,* (2008) used building elements in model estimation, Creese and Li (1995), Gaza and Rouhana (1995), Zhang (2004) used energy rate from house hold utilities with the aid of neural network for time series forecasting among others as presented in Table 1. Therefore for the purpose of this work, content analysis and trial and error method were used in analyzing the content of the bill of quantities for proper grouping. The elements in the bills were formed into work group packages by grouping together elements with similar description or methodology. The initial and final costs of the sampled residential and industrial projects considering the various work packages were used. The costs were adjusted with inflation factor and corruption escalator factor before being fed into the network. This is to ensure holistic cost prediction whenever the model is being used.

6.4 Developing Neural Network-Based Building Projects Prediction Model.

The third objective is model generation using neural networks. Different neural networks model were selected for trial, such as genetic algorithm, back propagation technique with delta rule and multilayer perceptron with back-elimination, strap with Levenberg Marqua at 1000 training cycles. Multilayer perceptron was found to yield least mean square error and high coefficient of performance of 1.311. Therefore multilayered perceptron was used in training the data for model construction. Flow diagram of developed model data processing algorithm containing four application modules were developed for the model linked with seven data ports. The four processing modules includes; selection criteria module, model input parameter module, data modulation evaluation module and process looping vis-a-vis termination module, detail of this can be found in Sections 5.20 and 5.21.

The four modules contains seven data ports, the ports include; cost center harmonization data port(data port alpha for 3/4 bedroom cost detail); data port beta (office units); data port gamma (4 bedroom duplex); data port roger(1 bedroom bungalow cost detail); data port phile (current inflation index); data port omega (corruption escalator factor) and cost fitness data port (cost expectancy limit value) presented in Section 5.21 The ports are contained in a algorithm logic coded sheet presented in Table 5.20 with each cells connected with a tentative interlinked logic programme command presented in Section 5.24. The properties of the model are presented in Table 5.19 of this presentation.

6.5 Developing A System That Can Provide Projects Cost Early Warning System.

The fourth objective is developing a model that can provide early warning function on project works. Mechanism of providing an early warning system that helps in monitoring project cost is presented in Tables 5.33 and 5.34. An econometric-cost factor model was used to generate an output as basis of cost warning benchmark.

Back-end loading system of Cattel, Kaka, and Bowen (2008) simplified unbalanced bidding model was modified and used in formulating the econometric model. $[\Sigma (1/1-r)^n]([C\lambda_{nj} [Q_j + Q_i][\gamma_{nj}fP_j – C^1)] + \lambda_{nj} [Q_j + Q_i][\gamma_{nj}fP_j – C^1)])$

The Back-end econometric model $[\Sigma [(1-r)^n] ([C\lambda_{nj} [Q_j$ ______incorporates duration'n'and often used for factoring elements that has potential of being constructed later as the project progresses. In other to accommodate other elements schedule to be executed later in the project, an econometric factor $\lambda_{nj} [Q_j + Q_i][\gamma_{njnj}fP_j – C^1)])$ need to be added. This factor incorporates inflation factor/index, and period in consideration together with variation factor anticipated.

Legend: rj --- monthly discount rate n --- month number C^1--actual increase in cost of items. λ_{nj} --- proportion of elements Q_j; Q_i ---- bill cost of iitem i, j γ_{nj} --- adjustment for escalation fPj----Haylet Factor(0.85) C^{1} ---- unit cost of item j

Back-end loading is a system that compensates a builder for loss due to inflationary effect. It rewards a builder for increase in his expenses. This is possible in a contract that incorporates cost escalation payment in terms of cost adjustment provision (Cattel *et al.*, 2008). The concept is to allow contractor and builder to be compensated for cost incurred during inflation. In the context of generating an early system function from the developed model, a modified form of the back-end loading was generated for the model, with projects elements grouped into cost centers. The items were grouped into escalation work group to enable close monitoring of inflation on the items. The escalation work centers were categorized into early constructible and late constructible elements as contain in Table 5.34 for close monitoring of price change on account of inflation and other economic factors. This allows for cost escalation prediction on each item in the respective group therefore keep abreast of price movement.

6.6 Factorization of Cost Center Influence on Project Cost.

The fifth objective is projecting cost center influence limit for the model. Influence of the elements' cost on total project cost was factored on rating scale one (1) to ten (10) using percentage cost composition as base reference point. This is presented in Tables 5.21 to 5.25. Cost of substructure for 4-bedroom Duplex, 2/3-bedroom bungalow, Frame and walls are rated high on scale 10^{+} high relative to base cost, for all building types. Finishing is ranked high on scale 10^{+} for 4-bedroom Duplex, 2-bedroom apartment, 3/4- bedroom- on 3 floors-24 Units and 2/3- bedroom Bungalow, this indicate that the influence of this is high on the project final cost. This implies that a great deal of resource is at stake on this particular element, careful management of this cost center can determine to a very large extent the overall success of the project work. Value added Tax, Contingencies, Preliminaries, Soil drainage; Fittings are rated low on scale 4 down to 1.

6.7 Risk Probability Impact Matrix Formulation and Cost Expectancy Limit for Building Components.

The sixth objective is the formulation of risk probability impact matrix and cost expectancy limit for the developed model. Cost expectancy limit for different categories of project is presented in Table 5.29. From the analysis, the benchmarked limit for the project types is as follow: ₦13,214,000 lower limit to ₦16,044,130 upper limit for 4-bedroom units; ₦4,385,000lower cost limit to ₦ 9,000,000 upper cost limit for a 2&3- bedroom bungalow; ₦3,515,914 lower to ₦ 5,000,000 upper cost limit for 2-bedroom apartment; ₦ 464,024,000 lower cost limit to ₦ 473,840,312 upper cost limit for 3/4-bedroom,24 Units, with 3 floors and ₦ 366,324,221 lower to ₦ 472,737,280 upper limit for Office accommodation. This detail designed provides adjustment parameter for data fitness determination when the model is being used for cost prediction. The values are incorporated into the fitness evaluation module of the developed model for cost fitness determination.

6.8 Summary of Findings:

The research work has made an attempt at providing a conventional means of forecasting project cost. To this end therefore a predictive cost model is developed with a base in artificial neural network. However, findings during the course of the research work are summarized below:

(i) Less than 5% of the total projects sampled did not experienced cost variation with majority having variation of up to 150% over initial project cost.

(ii) It was discovered that difference exists in the cost obtainable during pre-economic meltdown and post economic meltdown. The initial cost of project initiated during pre-economic meltdown period is less as compared to those caught up with economic meltdown. This has made predicted cost of high variation when compared to cost obtainable during pre-economic meltdown period.

(iii) The efficiency of the model developed is found to be reasonably high, with relative average efficiency of 0.763 and coefficient of performance of 1.311. This is adjudged good.

(iv) It was discovered that programmer has freedom to control error of performance of the model at training stage, the training phase was under strict control and the optimum error at optimum value of the output was selected. This model has an average mean square error (M.S.E) of 0.01136, the MSE is an index used to measure when well fitted output is obtained to avoid output over fitting. The margin of error is therefore very low. The lower the MSE value the better the accuracy of the model.

(v). It was discovered that most of the application of neural network to costing are in the area of cost estimating and little effort is recorded in the aspect of using neural network in holistic building cost prediction. This research work has therefore developed a model that could be used in cost valuation at different stages of construction work. However, the model developed in this study is capable of being deployed at various stages of building works and has capability to accommodate other projects' extraneous variables to the extent of predicting new outcome. This fact has been validated at cross validation stage of the model development recorded in Chapter Five of this work.

(vi). Among the facts discovered is possibility of grouping project cost centers into cost-work-packages in order to reduce data noise, over-fitting and volume. The data used to train the network was partitioned along the initial cost (tender sum), and final cost (as-built cost) dichotomy. This helps eliminate data redundancy, data over-fitting and data output error.

(vii) A definite pattern of project cost data formation emerged, it was discovered that, some vital elements among project cost centers contained in the projects' bill of quantity, with high cost magnitude falls between the range of 25% to 30% of total project cost and the remaining 70% that are considered as non-vital elements constitute 70%. However, for holistic cost output prediction, this study combined those that falls within 25- 30 % and those that constitute 70% into the cost work packages of initial project cost and as-built cost used in model formation. This ensures holistic prediction of project cost whenever the model is being used for prediction.

(viii). Finally, an average prediction variation of 12.94% was recorded between the input value and output value generated by the model, 11.14 % of the 12.94% is suspected as being constituted by the adjustment parameters used on the project cost and 1.78% contributed by attrition within the neural network system used in model generation, thereby process induced. This should be noted to have been a clear departure from previous research outputs which however are cost estimation based, that had variation margin higher than that obtained in this research work. Adeli and Wu (2008) obtained 9% variation error when used neural network in cost estimation of Timber bridges in Newfoundland, Al-Tabatabai *et al.,* (2008) also used neural network in preliminary estimation of percentage increase in the cost of typical highway project from baseline reference estimate and generated 4.5% variation while Emsley *et al.,* (2007) carried out research on modeling relationship between project cost variation and execution route and end up with 3.5% variation. Against these antecedents therefore, the variation margin of 1.798% obtained in the context of cost prediction between the input cost and output cost, presented in this research, is considered low and within tolerance limit.

6.9 Recommendation

As a follow-up to the conclusion drawn from the outcome of this study, the following issues are recommended for implementation.

i. **Adoption of expert based forecasting system:** An iterative model has been developed in this model, through which cost of building can be predicted. The output of this research work (model) should be supported so as to translate into cost prediction software that will become a house-hold item in the hands of construction work practitioners

ii. **Cost advisers to adopt the model:** Cost advisers often renders cost advice to clients, and in advising, process through which judgments are passed on the project cost implication matters, because if the process is faulty, end result will not be anything less than erroneous conclusion and project cost fallacy. Therefore, a forecasting system that will incorporate multi-variables to generate pareto optimal solutions in the face of multi-conflicting objectives, a type that this research output has provided is needed. This will help forestall cost underestimation and overestimation.

iii. **Establishment of database:** Data base for different projects should be established and this will further enhance and consolidate knowledge and research base in construction cost management.

6.10 Suggestion for Further Studies

i. Data management system for different projects: One of the major challenges encountered during the course of this research work is getting project cost data for research work. Therefore it will worth a while if research can be centered on formulating data base for various categories of projects both for academic and industrial use.

ii. Modeling projects cost disparity: Research can be carried out in the area of neural network modeling of cost disparity among projects delivered through different procurement system in Nigeria.

6.11 Contribution to Knowledge

The study generated Neural network based - cost optimization variables stabilized model that is capable of being used to predict Building project cost at different stages of building works. This is a step ahead of Traditional approach which lack capability to accommodate these variables and can only be used at final stage of construction work.

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Appendix i: Summary of Projects Costs (Boq Value and As-Built Cost) 3 &4-bedroom Units, 3 Floors Period: 2006-2009

Cost Centers		B.O.Q Initial Value	As-Built Cost	Target Cost(B-A)
Project 1-70	1	496,193,000	520,300,000	24,107,000
Residential	2	464,024,000	472,000,000	7,976,000
Building	3	440,879,000	441,500,672	621,672
2009	4	440,308,000	443,500,620	3,192,620
	5	439,851,113	442,900,000	3,048,887
	6	439,153,000	442,160,333	3,007,333
	7	438,943,000	440,900,000	1,957,000
	8	437,506,121	439,506,121	2,000,000
	9	437,114,000	439,300,000	2,186,000
	10	433,535,000	442,375,000	8,840,000
	11	433,210,000	433,436,000	226,000
	12	432,701,000	435,953,000	3,252,000
	13	431,067,000	431,067,100	100
	14	430,648,000	433,936,500	3,288,500
	15	429,860,000	430,820,000	960,000
	16	429,361,000	439,361,000	10,000,000
	17	429,231,000	430,238,000	1,007,000
	18	428,670,000	438,338,146	9,668,146
	19	428,474,000	432,453,000	3,979,000
	20	426,882,000	430,800,000	3,918,000
	21	426,814,000	426,814,000	0
	22	426,722,000	426,722,248	248
	23	426,696,000	428,673,500	1,977,500
	24	425,850,600	432,790,000	6,939,400
	25	425,492,000	432,400,000	6,908,000
	26	425,492,000	430,300,000	4,808,000
	27	425,392,313	435,698,725	10,306,412
	28	425,292,000	428,350,000	3,058,000
	29	424,936,000	435,600,773	10,664,773
	30	424,808,000	429,600,800	4,792,800
	31	424,503,000	424,657,600	154,600

	32	424,370,000	428,860,000	4,490,000
	33	423,701,000	428,672,000	4,971,000
	34	422,919,920	428,633,000	5,713,080
	35	422,918,000	432,685,763	9,767,763
	36	422,596,321	425,800,000	3,203,679
	37	422,470,000	430,500,000	8,030,000
	38	422,449,000	424,500,124	2,051,124
	39	421,574,000	430,500,000	8,926,000
	40	421,384,000	421,384,000	0
	41	421,137,000	422,893,000	1,756,000
	42	421,062,500	422,720,520	1,658,020
	43	420,777,116	420,777,116	0
	44	419,738,222	422,850,000	3,111,778
	45	419,585,000	429,688,124	10,103,124
	46	419,403,144	423,614,268	4,211,124
	47	418,677,600	420,850,100	2,172,500
	48	418,377,600	420,138,000	1,760,400
	49	417,673,000	426,998,000	9,325,000
	50	416,596,321	425,600,000	9,003,679
	51	416,591,000	430,338,000	13,747,000
	52	416,268,000	422,665,000	6,397,000
	53	415,834,860	420,650,800	4,815,940
	54	414,846,000	414,846,000	0
	55	414,827,333	424,837,167	10,009,834
	56	414,581,000	414,581,000	0
	57	414,476,200	420,684,300	6,208,100
	58	413,380,000	420,000,000	6,620,000
	59	411,820,000	414,368,000	2,548,000
	60	410,453,000	410,453,000	0
	61	410,264,000	419,300,123	9,036,123
	62	410,013,000	425,300,000	15,287,000
	63	409,128,000	410,385,000	1,257,000
	64	408,413,000	416,413,000	8,000,000
	65	406,464,000	410,550,000	4,086,000
	66	406,364,000	408,676,850	2,312,850
	67	403,660,000	413,610,000	9,950,000
	68	403,647,000	403,647,000	0

	69	403,436,000	409,436,000	6,000,000
	70	385,405,000	392,364,000	6,959,000
Project 71-143	71	375,619,000	380,700,000	5,081,000
Residential	72	363,061,000	370,577,500	7,516,500
Building	73	362,715,000	370,876,000	8,161,000
2008	74	360,358,000	363,500,000	3,142,000
	75	357,952,500	373,866,000	15,913,500
	76	357,564,000	360,000,000	2,436,000
	77	355,575,000	362,316,000	6,741,000
	78	355,063,000	365,000,000	9,937,000
	79	352,628,590	352,628,590	0
	80	350,011,600	357,287,000	7,275,400
	81	349,274,800	358,850,200	9,575,400
	82	348,876,000	357,986,000	9,110,000
	83	348,851,000	348,851,000	0
	84	348,522,000	357,650,000	9,128,000
	85	348,030,000	350,533,800	2,503,800
	86	347,402,000	359,000,000	11,598,000
	87	345,467,000	353,000,000	7,533,000
	88	343,848,000	364,921,000	21,073,000
	89	341,228,000	349,800,000	8,572,000
	90	340,755,000	349,000,000	8,245,000
	91	333,965,000	340,125,000	6,160,000
	92	330,044,000	360,153,678	30,109,678
	93	328,005,000	335,000,000	6,995,000
	94	325,339,767	337,967,000	12,627,233
	95	320,169,000	325,689,000	5,520,000
	96	307,821,000	310,667,000	2,846,000
	97	272,573,000	274,000,000	1,427,000
	98	272,031,000	275,650,000	3,619,000
	99	268,125,500	272,333,000	4,207,500
	100	263,861,000	274,000,000	10,139,000
	101	253,449,000	260,000,000	6,551,000
	102	248,593,000	258,000,000	9,407,000
	103	248,039,000	252,100,000	4,061,000
	104	247,736,000	250,000,000	2,264,000

	105	247,449,000	250,000,000	2,551,000
	106	247,004,900	251,700,000	4,695,100
	107	246,558,600	266,358,000	19,799,400
	108	246,530,000	256,000,000	9,470,000
	109	246,102,000	256,000,000	9,898,000
	110	246,016,000	252,350,000	6,334,000
	111	245,522,000	250,000,000	4,478,000
	112	245,509,000	265,000,000	19,491,000
	113	245,401,000	245,801,000	400,000
	114	245,212,000	257,000,000	11,788,000
	115	244,534,000	249,320,000	4,786,000
	116	244,534,000	245,850,000	1,316,000
	117	243,727,000	251,300,000	7,573,000
	118	243,648,000	252,000,000	8,352,000
	119	243,065,000	260,534,890	17,469,890
	120	242,902,000	257,800,000	14,898,000
	121	242,409,000	247,332,000	4,923,000
	122	242,110,000	262,000,000	19,890,000
	123	241,642,000	251,350,000	9,708,000
	124	241,634,000	251,800,000	10,166,000
	125	241,519,000	248,000,000	6,481,000
	126	241,500,000	245,712,000	4,212,000
	127	240,551,000	247,876,000	7,325,000
	128	240,452,000	263,650,000	23,198,000
	129	240,427,000	248,221,000	7,794,000
	130	240,418,000	243,000,000	2,582,000
	131	240,031,000	247,800,000	7,769,000
	132	239,500,000	246,000,000	6,500,000
	133	239,229,000	245,700,000	6,471,000
	134	239,053,000	243,850,000	4,797,000
	135	239,020,000	242,000,000	2,980,000
	136	237,912,000	252,902,000	14,990,000
	137	237,912,000	239,850,000	1,938,000
	138	237,678,000	241,520,000	3,842,000
	139	236,024,000	239,500,000	3,476,000

	140	234,532,000	240,800,000	6,268,000
	141	233,765,000	241,600,000	7,835,000
Project142-192	142	231,799,100	236,800,000	5,000,900
Residential	143	227,651,000	250,000,000	22,349,000
Building	144	189,234,000	195,650,000	6,416,000
2007	155	185,000,000	210,000,000	25,000,000
	145	183,700,000	198,665,000	14,965,000
	146	180,233,000	210,560,000	30,327,000
	147	170,557,937	218,000,000	47,442,063
	148	169,500,000.00	175,500,000	6,000,000
	149	165,886,913	172,500,000	6,613,087
	150	165,443,000	173,765,000	8,322,000
	151	164,354,000	164,733,000	379,000
	152	163,237,000	195,000,000	31,763,000
	153	163,200,000	165,987,000	2,787,000
	154	161,500,440.00	190,000,000	28,499,560
	155	160,876,000	166,320,000	5,444,000
	156	159,754,000	163,400,000	3,646,000
	157	158,654,800	162,350,000	3,695,200
	158	158,567,000	165,800,000	7,233,000
	159	157,378,930	171,700,000	14,321,070
	160	157,300,839	166,136,000	8,835,161
	161	157,000,000	177,000,000	20,000,000
	162	155,600,000	159,650,000	4,050,000
	163	154,000,000	207,000,000	53,000,000
	164	152,667,000	169,750,000	17,083,000
	165	151,500,000	172,520,000	21,020,000
	166	150,825,000	180,926,000	30,101,000
	167	149,887,000	174,500,000	24,613,000
	168	149,000,000	178,510,000.00	29,510,000
	169	148,569,000	151,000,000	2,431,000
Projct250-270	170	148,128,000	178,210,000	30,082,000
Residential	171	147,985,000	151,135,000	3,150,000
Building	172	147,765,000	152,131,000	4,366,000

	173	147,650,000	158,000,000	10,350,000
	174	147,638,000	167,133,000	19,495,000
	175	147,500,000	153,359,870	5,859,870
	176	147,382,000	167,216,000	19,834,000
	177	147,336,813	149,000,000	1,663,187
	178	147,336,813	148,500,000	1,163,187
	179	146,356,000	172,000,000	25,644,000
	180	146,329,000	156,233,000	9,904,000
	181	146,300,943	153,800,000	7,499,057
	182	146,000,000	166,832,000	20,832,000
	183	145,892,000	168,225,000	22,333,000
	184	145,500,000	175,000,000	29,500,000
	185	144,886,913	155,230,000	10,343,087
	186	144,651,000	146,872,000	2,221,000
	187	143,031,000	159,113,000	16,082,000
	188	143,031,000	149,500,000	6,469,000
	189	142,500,000	154,750,000	12,250,000
	190	141,823,000	147,008,100	5,185,100
	191	141,765,000	143,561,000	1,796,000
Project 192-220	192	140,928,000	145,314,000	4,386,000
Residential	193	138,934,500	149,520,000	10,585,500
Building	194	135,672,000	165,500,000	29,828,000
2006	195	133,779,000	142,107,000	8,328,000
	196	133,765,000	138,324,166	4,559,166
	197	133,431,010	149,000,000	15,568,990
	198	132,706,000	143,888,000	11,182,000
	199	132,360,000	138,000,000	5,640,000
	200	132,227,000	152,000,000	19,773,000
	201	130,702,000	145,950,000	15,248,000
	202	130,219,000	145,236,000	15,017,000
	203	130,017,000	133,113,014	3,096,014
	204	129,532,000	145,000,000	15,468,000
	205	129,471,000	132,685,000	3,214,000
	206	129,272,000	138,200,000	8,928,000
	207	128,597,000	148,210,000	19,613,000
	208	128,590,000	139,250,000	10,660,000

	209	128,505,000	158,000,000	29,495,000
	210	128,064,000	138,000,000	9,936,000
	211	127,708,000	129,850,000	2,142,000
	212	127,025,000	135,228,177	8,203,177
	213	126,377,000	146,850,000	20,473,000
	214	125,998,000	154,000,000	28,002,000
	215	125,637,000	140,800,000	15,163,000
	216	125,628,000	128,214,136	2,586,136
	217	125,554,000	143,010,000	17,456,000
	218	124,738,000	144,650,000	19,912,000
	219	123,243,000	155243000.00	32,000,000
	220	121,092,000	139,000,000	17,908,000

Source: 2010 Survey

Appendix ii: Project Costs Adjustment Parameters (3-bedroom flats on 3 Floors)

		1	2	3	4
	Project	A	B	C	D
Cost Centers		As-Built Value	Corup Esc Adjval	Inf Fact Adjs Val	Comb Factors Adj Val
Project 1-70	1	325689000	0.0114	0.1	0.1114
Residential	2	234,150,000	0.0114	0.1	0.1114
Building	3	177000000	0.0114	0.1	0.1114
2009	4	360153678	0.0114	0.1	0.1114
	5	218000000	0.0114	0.1	0.1114
	6	155243000	0.0114	0.1	0.1114
	7	158000000	0.0114	0.1	0.1114
	8	154000000	0.0114	0.1	0.1114
	9	165500000	0.0114	0.1	0.1114
	10	178210000	0.0114	0.1	0.1114

	11	175000000	0.0114	0.1	0.1114
	12	180926000	0.0114	0.1	0.1114
	13	178510000	0.0114	0.1	0.1114
	14	195000000	0.0114	0.1	0.1114
	15	190000000	0.0114	0.1	0.1114
	16	172000000	0.0114	0.1	0.1114
	17	210560000	0.0114	0.1	0.1114
	18	174500000	0.0114	0.1	0.1114
	19	146850000	0.0114	0.1	0.1114
	20	144650000	0.0114	0.1	0.1114
Project 71-140	21	168225000	0.0114	0.1	0.1114
Residential	22	148210000	0.0114	0.1	0.1114
Building	23	152000000	0.0114	0.1	0.1114
2008	24	139000000	0.0114	0.1	0.1114
	25	166832000	0.0114	0.1	0.1114
	26	143010000	0.0114	0.1	0.1114
	27	172520000	0.0114	0.1	0.1114
	28	210000000	0.0114	0.1	0.1114
	29	167216000	0.0114	0.1	0.1114
	30	167133000	0.0114	0.1	0.1114
	31	140800000	0.0114	0.1	0.1114
	32	145000000	0.0114	0.1	0.1114
	33	149000000	0.0114	0.1	0.1114
	34	145950000	0.0114	0.1	0.1114
	35	145236000	0.0114	0.1	0.1114
	36	159113000	0.0114	0.1	0.1114
	37	169750000	0.0114	0.1	0.1114
	38	250000000	0.0114	0.1	0.1114
	39	263650000	0.0114	0.1	0.1114
	40	171700000	0.0114	0.1	0.1114
Project 141-190	41	154750000	0.0114	0.1	0.1114
Residential	42	143888000	0.0114	0.1	0.1114
Building	43	139250000	0.0114	0.1	0.1114
2007	44	262000000	0.0114	0.1	0.1114
	45	198665000	0.0114	0.1	0.1114

	46	266358000	0.0114	0.1	0.1114
	47	265000000	0.0114	0.1	0.1114
	48	138000000	0.0114	0.1	0.1114
	49	149520000	0.0114	0.1	0.1114
	50	260534890	0.0114	0.1	0.1114
	51	155230000	0.0114	0.1	0.1114
	52	158000000	0.0114	0.1	0.1114
	53	138200000	0.0114	0.1	0.1114
	54	156233000	0.0114	0.1	0.1114
	55	135228177	0.0114	0.1	0.1114
	56	252902000	0.0114	0.1	0.1114
	57	142107000	0.0114	0.1	0.1114
	58	257800000	0.0114	0.1	0.1114
	59	364921000	0.0114	0.1	0.1114
	60	166136000	0.0114	0.1	0.1114
Project 61-100	61	153800000	0.0114	0.1	0.1114
Residential	62	173765000	0.0114	0.1	0.1114
Building	63	257000000	0.0114	0.1	0.1114
2006	64	165800000	0.0114	0.1	0.1114
	65	149500000	0.0114	0.1	0.1114
	66	373866000	0.0114	0.1	0.1114
	67	138000000	0.0114	0.1	0.1114
	68	251800000	0.0114	0.1	0.1114
	69	256000000	0.0114	0.1	0.1114
	70	251350000	0.0114	0.1	0.1114
	71	172500000	0.0114	0.1	0.1114
	72	153359870	0.0114	0.1	0.1114
	73	337967000	0.0114	0.1	0.1114
	74	274000000	0.0114	0.1	0.1114
	75	256000000	0.0114	0.1	0.1114
	76	258000000	0.0114	0.1	0.1114
	77	147008100	0.0114	0.1	0.1114
	78	175500000	0.0114	0.1	0.1114
	79	720300000	0.0114	0.1	0.1114
	80	252000000	0.0114	0.1	0.1114
	81	138324166	0.0114	0.1	0.1114

	82	195650000	0.0114	0.1	0.1114
	83	166320000	0.0114	0.1	0.1114
	84	241600000	0.0114	0.1	0.1114
	85	359000000	0.0114	0.1	0.1114
	86	248221000	0.0114	0.1	0.1114
	87	247800000	0.0114	0.1	0.1114
	88	145314000	0.0114	0.1	0.1114
	89	251300000	0.0114	0.1	0.1114
	90	247876000	0.0114	0.1	0.1114
	91	525300000	0.0114	0.1	0.1114
	92	152131000	0.0114	0.1	0.1s114
	93	365000000	0.0114	0.1	0.1114
	94	358850200	0.0114	0.1	0.1114
	95	246000000	0.0114	0.1	0.1114
	96	245700000	0.0114	0.1	0.1114
	97	248000000	0.0114	0.1	0.1114
	98	240800000	0.0114	0.1	0.1114
	99	430338000	0.0114	0.1	0.1114
	100	357650000	0.0114	0.1	0.1114
Projct111-120	101	357986000	0.0114	0.1	0.1114
Residential	102	159650000	0.0114	0.1	0.1114
Building	103	260000000	0.0114	0.1	0.1114
2004	104	252350000	0.0114	0.1	0.1114
	105	349800000	0.0114	0.1	0.1114
	106	132685000	0.0114	0.1	0.1114
	107	349000000	0.0114	0.1	0.1114
	108	133113014	0.0114	0.1	0.1114
	109	162350000	0.0114	0.1	0.1114
	110	163400000	0.0114	0.1	0.1114
	111	370876000	0.0114	0.1	0.1114
	112	353000000	0.0114	0.1	0.1114
	113	236800000	0.0114	0.1	0.1114
	114	335000000	0.0114	0.1	0.1114
	115	151135000	0.0114	0.1	0.1114
	116	357287000	0.0114	0.1	0.1114
	117	370577500	0.0114	0.1	0.1114

	118	128214136	0.0114	0.1	0.1114
	119	435600773	0.0114	0.1	0.1114
	120	247332000	0.0114	0.1	0.1114
	121	243850000	0.0114	0.1	0.1114
	122	13610000	0.0114	0.1	0.1114
	123	435698725	0.0114	0.1	0.1114
	124	249320000	0.0114	0.1	0.1114
	125	429688124	0.0114	0.1	0.1114
	126	424837167	0.0114	0.1	0.1114
	127	251700000	0.0114	0.1	0.1114
	128	362316000	0.0114	0.1	0.1114
	129	439361000	0.0114	0.1	0.1114
	130	432685763	0.0114	0.1	0.1114
Projct 211-230	131	340125000	0.0114	0.1	0.1114
Residential	132	438338146	0.0114	0.1	0.1114
Building	133	250000000	0.0114	0.1	0.1114
2003	134	392364000	0.0114	0.1	0.1114
	135	426998000	0.0114	0.1	0.1114
	136	419300123	0.0114	0.1	0.1114
	137	245712000	0.0114	0.1	0.1114
	138	425600000	0.0114	0.1	0.1114
	139	472000000	0.0114	0.1	0.1114
	140	430500000	0.0114	0.1	0.1114
	141	165987000	0.0114	0.1	0.1114
	142	129850000	0.0114	0.1	0.1114
	143	442375000	0.0114	0.1	0.1114
	144	252100000	0.0114	0.1	0.1114
	155	151000000	0.0114	0.1	0.1114
	145	241520000	0.0114	0.1	0.1114
	146	416413000	0.0114	0.1	0.1114
	147	272333000	0.0114	0.1	0.1114
	148	430500000	0.0114	0.1	0.1114
	149	146872000	0.0114	0.1	0.1114
Projct231-250	150	239500000	0.0114	0.1	0.1114
Residential	151	380700000	0.0114	0.1	0.1114

Building	152	275650000	0.0114	0.1	0.1114
2002	153	432790000	0.0114	0.1	0.1114
	154	432400000	0.0114	0.1	0.1114
	155	420000000	0.0114	0.1	0.1114
	156	143561000	0.0114	0.1	0.1114
	157	242000000	0.0114	0.1	0.1114
	158	422665000	0.0114	0.1	0.1114
	159	420684300	0.0114	0.1	0.1114
	160	409436000	0.0114	0.1	0.1114
	161	149000000	0.0114	0.1	0.1114
	162	428633000	0.0114	0.1	0.1114
	163	243000000	0.0114	0.1	0.1114
	164	250000000	0.0114	0.1	0.1114
	165	428672000	0.0114	0.1	0.1114
	166	420650800	0.0114	0.1	0.1114
	167	310667000	0.0114	0.1	0.1114
	168	430300000	0.0114	0.1	0.1114
	169	250000000	0.0114	0.1	0.1114
Projct250-270	170	429600800	0.0114	0.1	0.1114
Residential	171	363500000	0.0114	0.1	0.1114
Building	172	428860000	0.0114	0.1	0.1114
	173	239850000	0.0114	0.1	0.1114
	174	423614268	0.0114	0.1	0.1114
	175	410550000	0.0114	0.1	0.1114
	176	148500000	0.0114	0.1	0.1114
	177	432453000	0.0114	0.1	0.1114
	178	430800000	0.0114	0.1	0.1114
	179	350533800	0.0114	0.1	0.1114
	180	360000000	0.0114	0.1	0.1114
	181	433936500	0.0114	0.1	0.1114
	182	425800000	0.0114	0.1	0.1114
	183	435953000	0.0114	0.1	0.1114
	184	422850000	0.0114	0.1	0.1114
	185	443500620	0.0114	0.1	0.1114
	186	428350000	0.0114	0.1	0.1114
	187	442900000	0.0114	0.1	0.1114

	188	442160333	0.0114	0.1	0.1114
Projt 270-290	189	245850000	0.0114	0.1	0.1114
Residential	190	274000000	0.0114	0.1	0.1114
Building	191	414368000	0.0114	0.1	0.1114
	192	408676850	0.0114	0.1	0.1114
	193	420850100	0.0114	0.1	0.1114
	194	439300000	0.0114	0.1	0.1114
	195	424500124	0.0114	0.1	0.1114
	196	428673500	0.0114	0.1	0.1114
	197	439506121	0.0114	0.1	0.1114
	198	440900000	0.0114	0.1	0.1114
	199	420138000	0.0114	0.1	0.1114
	200	422893000	0.0114	0.1	0.1114
	201	422720520	0.0114	0.1	0.1114
	202	410385000	0.0114	0.1	0.1114
	203	164733000	0.0114	0.1	0.1114
	204	430238000	0.0114	0.1	0.1114
	205	430820000	0.0114	0.1	0.1114
	206	245801000	0.0114	0.1	0.1114
	207	441500672	0.0114	0.1	0.1114
	208	433436000	0.0114	0.1	0.1114
	209	424657600	0.0114	0.1	0.1114
Projt 300-310	210	426722248	0.0114	0.1	0.1114
Residential	211	431067100	0.0114	0.1	0.1114
Building	212	426814000	0.0114	0.1	0.1114
	213	421384000	0.0114	0.1	0.1114
	214	420777116	0.0114	0.1	0.1114
	215	414846000	0.0114	0.1	0.1114

	216	414581000	0.0114	0.1	0.1114
	217	410453000	0.0114	0.1	0.1114
	218	403647000	0.0114	0.1	0.1114
	219	352628590	0.0114	0.1	0.1114
	220	348851000	0.0114	0.1	0.1114

Appendix iii: Cost and Adjustment Parameters for 3-bedroom Units on 3 Floors.

		Boq Cost	As-Blt Cost	Crptadj	Crptdjval	Inflact	Infltadjval	Combfact
Project 1-20	1	325,689,000	325,689,00	0.0114	3712854.	0.1	325689003	36281754.
Residential	2	207,000,000	207,000,00	0.0114	2359800	0.1	20700000	23059800.
Building	3	177,000,000	177,000,00	0.0114	2017800	0.1	17700000	19717800.
2009	4	360,153,678	360,153,67	0.0114	4105751.	0.1	36015367	40121119.
	5	218,000,000	218,000,00	0.0114	2485200	0.1	21800000	24285200.
	6	155243000.0	155243000.	0.0114	1769770.	0.1	15524300	17294070.
	7	158,000,000	158,000,00	0.0114	1801200	0.1	15800000	17601200.
	8	154,000,000	154,000,00	0.0114	1755600	0.1	15400000	17155600.
	9	165,500,000	165,500,00	0.0114	1886700	0.1	16550000	18436700.
	10	178,210,000	178,210,00	0.0114	2031594	0.1	17821000	19852594.
	11	175,000,000	175,000,00	0.0114	1995000	0.1	17500000	19495000.
	12	180,926,000	180,926,00	0.0114	2062556.	0.1	18092600	20155156.
	13	178,51 0,000	178,510),000	0.0114	2035014	0.1	17851000	19886014.
	14	195,000,000	195,000,00	0.0114	2223000	0.1	19500000	21723000.
	15	190,000,000	190,000,00	0.0114	2166000	0.1	19000000	21166000.
	16	172,000,000	172,000,00	0.0114	1960800	0.1	17200000	19160800.
	17	210,560,000	210,560,00	0.0114	2400384	0.1	21056000	23456384.

	18	174,500,000	174,500,000	0.0114	1989300	0.1	17450000	19439300.
	19	146,850,000	146,850,000	0.0114	1674090	0.1	14685000	16359090.
	20	144,650,000	144,650,000	0.0114	1649010	0.1	14465000	16114010.
Project 21-	21	168,225,000	168,225,000	0.0114	1917765	0.1	16822500	18740265.
Residential	22	148,210,000	148,210,000	0.0114	1689594	0.1	14821000	16510594.
Building	23	152,000,000	152,000,000	0.0114	1732800	0.1	15200000	16932800.
2008	24	139,000,000	139,000,000	0.0114	1584600	0.1	13900000	15484600.
	25	166,832,000	166,832,000	0.0114	1901884.	0.1	16683200	18585084.
	26	143,010,000	143,010,000	0.0114	1630314	0.1	14301000	15931314.
	27	172,520,000	172,520,000	0.0114	1966728	0.1	17252000	19218728.
	28	210,000,000	210,000,000	0.0114	2394000	0.1	21000000	23394000.
	29	167,216,000	167,216,000	0.0114	1906262.	0.1	16721600	18627862.
	30	167,133,000	167,133,000	0.0114	1905316.	0.1	16713300	18618616.
	31	140,800,000	140,800,000	0.0114	1605120	0.1	14080000	15685120.
	32	145,000,000	145,000,000	0.0114	1653000	0.1	14500000	16153000.
	33	149,000,000	149,000,000	0.0114	1698600	0.1	14900000	16598600.
	34	145,950,000	145,950,000	0.0114	1663830	0.1	14595000	164,786,00
	35	145,236,000	145,236,000	0.0114	1655690.	0.1	14523600	16179290.
	36	159,113,000	159,113,000	0.0114	1813888.	0.1	15911300	17725188.
	37	169,750,000	169,750,000	0.0114	1935150	0.1	16975000	18910150.

	38	250,000,000	250,000,000	0.0114	2850000	0.1	25000000	27850000.
	39	263,650,000	263,650,000	0.0114	3005610	0.1	26365000	29370610.
	40	171,700,000	171,700,000	0.0114	1957380	0.1	17170000	19127380.
Project 41-	41	154,750,000	154,750,000	0.0114	1764150	0.1	15475000	17239150.
Residential	42	143,888,000	143,888,000	0.0114	1640323.	0.1	14388800	16029123.
Building	43	139,250,000	139,250,000	0.0114	1587450	0.1	13925000	15512450.
2007	44	262,000,000	262,000,000	0.0114	2986800	0.1	26200000	29186800.
	45	198,665,000	198,665,000	0.0114	2264781	0.1	19866500	22131281.
	46	266,358,000	266,358,000	0.0114	3036481.	0.1	26635800	29672281.
	47	265,000,000	265,000,000	0.0114	3021000	0.1	26500000	29521000.
	48	138,000,000	138,000,000	0.0114	1573200	0.1	13800000	15373200.
	49	149,520,000	149,520,000	0.0114	1704528	0.1	14952000	16656528.
	50	260,534,890	260,534,890	0.0114	2970097.	0.1	26053489	29023586.
	51	155,230,000	155,230,000	0.0114	1769622	0.1	15523000	17292622.
	52	158,000,000	158,000,000	0.0114	1801200	0.1	15800000	17601200.
	53	138,200,000	138,200,000	0.0114	1575480	0.1	13820000	15395480.
	54	156,233,000	156,233,000	0.0114	1781056.	0.1	15623300	17404356.
	55	135,228,177	135,228,177	0.0114	1541601.	0.1	13522817.	15064419
	56	252,902,000	252,902,000	0.0114	2883082.	0.1	25290200	28173282.
	57	142,107,000	142,107,000	0.0114	1620019.	0.1	14210700	15830719.

	58	257,800,000	257,800,000	0.0114	2938920	0.1	25780000	28718920.
	59	364,921,000	364,921,000	0.0114	4160099.	0.1	36492100	40652199.
	60	166,136,000	166,136,000	0.0114	1893950.	0.1	16613600	18507550.
Project 61-	61	153,800,000	153,800,000	0.0114	1753320	0.1	15380000	17133320.
Residential	62	173,765,000	173,765,000	0.0114	1980921	0.1	17376500	19357421.
Building	63	257,000,000	257,000,000	0.0114	2929800	0.1	25700000	28629800.
2006	64	165,800,000	165,800,000	0.0114	1890120	0.1	16580000	18470120.
	65	149,500,000	149,500,000	0.0114	1704300	0.1	14950000	16654300.
	66	373,866,000	373,866,000	0.0114	4262072.	0.1	37386600	41648672.
	67	138,000,000	138,000,000	0.0114	1573200	0.1	13800000	15373200.
	68	251,800,000	251,800,000	0.0114	2870520	0.1	25180000	28050520.
	69	256,000,000	256,000,000	0.0114	2918400	0.1	25600000	28518400.
	70	251,350,000	251,350,000	0.0114	2865390	0.1	25135000	28000390.
	71	172,500,000	172,500,000	0.0114	1966500	0.1	17250000	19216500.
	72	153,359,870	153,359,870	0.0114	1748302.	0.1	15335987	17084289.
	73	337,967,000	337,967,000	0.0114	3852823.	0.1	33796700	37649523.
	74	274,000,000	274,000,000	0.0114	3123600	0.1	27400000	30523600.
	75	256,000,000	256,000,000	0.0114	2918400	0.1	25600000	28518400.
	76	258,000,000	258,000,000	0.0114	2941200	0.1	25800000	28741200.
	77	147,008,100	147,008,100	0.0114	1675892.	0.1	14700810	16376702.

	78	175,500,000	175,500,000	0.0114	2000700	0.1	17550000	19550700.
	79	720,300,000	720,300,000	0.0114	8211420	0.1	72030000	80241420.
	80	252,000,000	252,000,000	0.0114	2872800	0.1	25200000	28072800.
Project 81-	81	138,324,166	138,324,166	0.0114	1576895.	0.1	13832416.	15409312.
Residential	82	195,650,000	195,650,000	0.0114	2230410	0.1	19565000	21795410.
Building	83	166,320,000	166,320,000	0.0114	1896048	0.1	16632000	18528048.
2005	84	241,600,000	241,600,000	0.0114	2754240	0.1	24160000	26914240.
	85	359,000,000	359,000,000	0.0114	4092600	0.1	35900000	39992600.
	86	248,221,000	248,221,000	0.0114	2829719.	0.1	24822100	27651819.
	87	247,800,000	247,800,000	0.0114	2824920	0.1	24780000	27604920.
	88	145,314,000	145,314,000	0.0114	1656579.	0.1	14531400	16187979.
	89	251,300,000	251,300,000	0.0114	2864820	0.1	25130000	27994820.
	90	247,876,000	247,876,000	0.0114	2825786.	0.1	24787600	27613386.
	91	425,300,000	425,300,000	0.0114	4848420	0.1	42530000	47378420.
	92	152,131,000	152,131,000	0.0114	1734293.	0.1	15213100	16947393.
	93	365,000,000	365,000,000	0.0114	4161000	0.1	36500000	40661000.
	94	358,850,200	358,850,200	0.0114	4090892.	0.1	35885020	39975912.
	95	246,000,000	246,000,000	0.0114	2804400	0.1	24600000	
	96	245,700,000	245,700,000	0.0114	2800980	0.1	24570000	27370980.
	97	248,000,000	248,000,000	0.0114	2827200	0.1	24800000	27627200.
	98	240,800,000	240,800,000	0.0114	2745120	0.1	24080000	26825120.

	99	430,338,000	430,338,000	0.0114	4905853.	0.1	43033800	47939653.
	100	357,650,000	357,650,000	0.0114	4077210	0.1	35765000	39842210.
Projct111-	101	357,986,000	357,986,000	0.0114	4081040.	0.1	35798600	39879640.
Residential	102	159,650,000	159,650,000	0.0114	1820010	0.1	15965000	17785010.
Building	103	260,000,000	260,000,000	0.0114	2964000	0.1	26000000	28964000.
2004	104	252,350,000	252,350,000	0.0114	2876790	0.1	25235000	28111790.
	105	349,800,000	349,800,000	0.0114	3987720	0.1	34980000	38967720.
	106	132,685,000	132,685,000	0.0114	1512609	0.1	13268500	14781109.
	107	349,000,000	349,000,000	0.0114	3978600	0.1	34900000	38878600.
	108	133,113,014	133,113,014	0.0114	1517488.	0.1	13311301.	14828789.
	109	162,350,000	162,350,000	0.0114	1850790	0.1	16235000	18085790.
	110	163,400,000	163,400,000	0.0114	1862760	0.1	16340000	18202760.
	111	370,876,000	370,876,000	0.0114	4227986.	0.1	37087600	41315586.
	112	353,000,000	353,000,000	0.0114	4024200	0.1	35300000	39324200.
	113	236,800,000	236,800,000	0.0114	2699520	0.1	23680000	26379520.
	114	335,000,000	335,000,000	0.0114	3819000	0.1	33500000	37319000.
	115	151,135,000	151,135,000	0.0114	1722939	0.1	15113500	16836439.
	116	357,287,000	357,287,000	0.0114	4073071.	0.1	35728700	39801771.
	117	370,577,500	370,577,500	0.0114	4224583.	0.1	37057750	41282333.
	118	128,214,136	128,214,136	0.0114	1461641.	0.1	12821413.	14283054.

	119	435,600,773	435,600,773	0.0114	4965848.	0.1	43560077.	48525926.
	120	247,332,000	247,332,000	0.0114	2819584.	0.1	24733200	27552784.
	121	243,850,000	243,850,000	0.0114	2779890	0.1	24385000	27164890.
	122	413,610,000	413,610,000	0.0114	4715154	0.1	41361000	46076154.
	123	435,698,725	435,698,725	0.0114	4966965.	0.1	43569872.	48536838.
	124	249,320,000	249,320,000	0.0114	2842248	0.1	24932000	27774248.
	125	429,688,124	429,688,124	0.0114	4898444.	0.1	42968812.	47867257.
	126	424,837,167	424,837,167	0.0114	4843143.	0.1	42483716.	47326860.
	127	251,700,000	251,700,000	0.0114	2869380	0.1	25170000	28039380.
	128	362,316,000	362,316,000	0.0114	4130402.	0.1	36231600	40362002.
	129	439,361,000	439,361,000	0.0114	5008715.	0.1	43936100	48944815.
	130	432,685,763	432,685,763	0.0114	4932617.	0.1	43268576.	48201194.
Projct 211-	131	340,125,000	340,125,000	0.0114	3877425	0.1	34012500	37889925.
Residential	132	438,338,146	438,338,146	0.0114	4997054.	0.1	43833814.	48830869.
Building	133	250,000,000	250,000,000	0.0114	2850000	0.1	25000000	27850000.
2003	134	392,364,000	392,364,000	0.0114	4472949.	0.1	39236400	43709349.
	135	426,998,000	426,998,000	0.0114	4867777.	0.1	42699800	47567577.
	136	419,300,123	419,300,123	0.0114	4780021.	0.1	41930012.	46710033.
	137	245,712,000	245,712,000	0.0114	2801116.	0.1	24571200	27372316.

Source: 2010 Survey

Appendix iv: Summary of Adjusted Projects B.O.Q Value and As-built Cost

		1	2	3	
	Project	A	B	C	
Cost Centers		B.O.Q Initial Value	As-Built Cost	Cost Variation(B-A)	Percent Var
Project 1-26	1	3,085,100	4,236,000	1,150,900	36
Residential	2	3,171,800	5,800,000	2,628,200	83
Building	3	2,610,000	4,800,000	2,190,000	84
2009	4	3,165,000	4,350,000	1,185,000	37
	5	2,145,000	4,325,000	2,180,000	102
	6	3,174,953	4,286,350	1,111,397	35
	7	2,750,000	5,850,000	3,100,000	113
	8	2,700,850	5,121,000	2,420,150	90
	9	3,150,000	6,265,000	3,115,000	99
	10	2,766,000	5,223,000	2,457,000	89
	11	2,510,000	6,371,000	3,861,000	154
	12	3,268,000	6,250,000	2,982,000	91
	13	2,250,325	5,675,000	3,424,675	152
	14	3,520,000	6,600,000	3,080,000	88
	15	2,100,000	5,125,000	3,025,000	144
	16	3,173,000	5,652,000	2,479,000	78
	17	3,173,000	7,650,000	4,477,000	141
	18	2,580,315	6,131,000	3,550,685	138
	19	2,420,500	5,643,000	3,222,500	133
	20	3,143,000	7,266,000	4,123,000	131

	21	4,385,500	7,121,000	2,735,500	62
	22	3,867,620	8,900,000	5,032,380	72
	23	4,010,850	9,201,000	5,190,150	129
	24	3,172,771	7,213,000	4,040,229	127
	25	3,222,776	7,136,000	3,913,224	121
Project 26-70	26	3,767,000	8,208,000	4,441,000	118
Residential	27	2,646,000	5,670,000	3,024,000	114
Building	28	2,475,337	5,300,000	2,824,663	114
2007	29	2,680,286	3,720,000	1,039,714	39
	30	3,831,000	6,121,000	2,290,000	60
	31	3,763,000	7,800,000	4,037,000	107
	32	4,001,000	8,222,000	4,221,000	105
	33	2,560,500	5,172,000	2,611,500	102
	34	4,500,000	9,000,000	4,500,000	100
	35	3,216,000	6,350,000	3,134,000	97
	36	3,682,710	7,221,000	3,538,290	96
	37	3,580,000	6,850,000	3,270,000	91
	38	2,500,000	4,670,000	2,170,000	87
	39	2,760,000	4,885,000	2,125,000	77
	40	2,761,730	4,722,000	1,960,270	71
	41	2,855,210	4,873,000	2,017,790	71
	42	3,010,000	5,035,000	2,025,000	67
	43	4,800,000	7,800,000	3,000,000	63
	44	2,856,725	4,550,000	1,693,275	59
	45	4,300,000	6,650,000	2,350,000	55
	46	2,418,163	3,685,000	1,266,837	52
	47	4,600,000	6,985,000	2,385,000	52
	48	2,783,011	4,136,000	1,352,989	49
	49	2,746,500	3,926,000	1,179,500	35
	50	2,896,230	4,121,000	1,224,770	42
	51	2,975,610	4,227,000	1,251,390	42

	52	2,756,380	3,896,000	1,139,620	41
	53	2,480,500	3,500,000	1,019,500	41
	54	2,685,420	3,762,000	1,076,580	40
	55	2,811,143	3,922,000	1,110,857	40
	56	2,889,385	3,963,000	1,073,615	37
	57	2,300,121	3,113,000	812,879	35
	58	2,890,010	3,910,000	1,019,990	35
	59	2,962,500	3,872,000	909,500	31
	60	2,982,630	3,896,000	913,370	31
	61	2,350,000	2,985,000	635,000	27
	62	2,316,286	2,868,000	551,714	24
	63	2,370,135	2,850,000	479,865	20
	64	2,615,115	3,123,000	507,885	19
	65	2,796,610	3,126,000	329,390	12
	66	2,850,035	3,136,000	285,965	10
	67	2,735,000	2,986,000	251,000	
	68	2,710,000	2,950,000	240,000	9
	69	2,873,182	3,113,000	239,818	8
	70	2,910,320	3,113,000	202,680	7

Source: 2010 Survey Legends: Prjt= Projects BOQ=Bill of quantity Var = Variation

Appendix v: Factor-Adjusted Project Costs for 2-bedroom Bungalow.

Project Adjusted Cost Variables							
		1	2	3	4	5	6
	Project	A	B	C	D	E	F
Cost Centers		Boq Value	As Built Value	Inflatn Adj Fact	Corptn Escl Fact+Infl	Adjval	Adjttl
Project 1-20	1	3085100	4236000	0.0114	0.1114	471890.4	4707890
Residential	2	3171800	5800000	0.0114	0.1114	646120	6446120
Building	3	2610000	4800000	0.0114	0.1114	534720	5334720
2009	4	3165000	4350000	0.0114	0.1114	484590	4834590
	5	2145000	4325000	0.0114	0.1114	481805	4806805
	6	3174953	4286350	0.0114	0.1114	477499.39	4763849
	7	2750000	5850000	0.0114	0.1114	651690	6501690
	8	2700850	5121000	0.0114	0.1114	570479.4	5691479
	9	3150000	6265000	0.0114	0.1114	697921	6962921
	10	2766000	5223000	0.0114	0.1114	581842.2	5804842
	11	2510000	6371000	0.0114	0.1114	709729.4	7080729
	12	3268000	6250000	0.0114	0.1114	696250	6946250
	13	2250325	5675000	0.0114	0.1114	632195	6307195
	14	3520000	6600000	0.0114	0.1114	735240	7335240
	15	2100000	5125000	0.0114	0.1114	570925	5695925
	16	3173000	5652000	0.0114	0.1114	629632.8	6281633
	17	3173000	7650000	0.0114	0.1114	852210	8502210
	18	2580315	6131000	0.0114	0.1114	682993.4	6813993
	19	2420500	5643000	0.0114	0.1114	628630.2	6271630
	20	3143000	7266000	0.0114	0.1114	809432.4	8075432
Project 21-40	21	4385500	7121000	0.0114	0.1114	793279.4	7914279
Residential	22	3867620	8900000	0.0114	0.1114	991460	9891460
Building	23	4010850	9201000	0.0114	0.1114	1024991.4	10225991
2008	24	3172771	7213000	0.0114	0.1114	803528.2	8016528
	25	3222776	7136000	0.0114	0.1114	794950.4	7930950
	26	3767000	8208000	0.0114	0.1114	914371.2	9122371

	27	2646000	5670000	0.0114	0.1114	631638	6301638
	28	2475337	5300000	0.0114	0.1114	590420	5890420
	29	2680286	3720000	0.0114	0.1114	414408	4134408
	30	3831000	6121000	0.0114	0.1114	681879.4	6802879
	31	3763000	7800000	0.0114	0.1114	868920	8668920
	32	4001000	8222000	0.0114	0.1114	915930.8	9137931
	33	2560500	5172000	0.0114	0.1114	576160.8	5748161
	34	4500000	9000000	0.0114	0.1114	1002600	10002600
	35	3216000	6350000	0.0114	0.1114	707390	7057390
	36	3682710	7221000	0.0114	0.1114	804419.4	8025419
	37	3580000	6850000	0.0114	0.1114	763090	7613090
	38	2500000	4670000	0.0114	0.1114	520238	5190238
	39	2760000	4885000	0.0114	0.1114	544189	5429189
	40	2761730	4722000	0.0114	0.1114	526030.8	5248031
Project 41-60	41	2855210	4873000	0.0114	0.1114	542852.2	5415852
Residential	42	3010000	5035000	0.0114	0.1114	560899	5595899
Building	43	4800000	7800000	0.0114	0.1114	868920	8668920
2007	44	2856725	4550000	0.0114	0.1114	506870	5056870
	45	4300000	6650000	0.0114	0.1114	740810	7390810
	46	2418163	3685000	0.0114	0.1114	410509	4095509
	47	4600000	6985000	0.0114	0.1114	778129	7763129
	48	2783011	4136000	0.0114	0.1114	460750.4	4596750
	49	2746500	3926000	0.0114	0.1114	437356.4	4363356
	50	2896230	4121000	0.0114	0.1114	459079.4	4580079
	51	2975610	4227000	0.0114	0.1114	470887.8	4697888
	52	2756380	3896000	0.0114	0.1114	434014.4	4330014
	53	2480500	3500000	0.0114	0.1114	389900	3889900
	54	2685420	3762000	0.0114	0.1114	419086.8	4181087
	55	2811143	3922000	0.0114	0.1114	436910.8	4358911
	56	2889385	3963000	0.0114	0.1114	441478.2	4404478
	57	2300121	3113000	0.0114	0.1114	346788.2	3459788
	58	2890010	3910000	0.0114	0.1114	435574	4345574
	59	2962500	3872000	0.0114	0.1114	431340.8	4303341
	60	2982630	3896000	0.0114	0.1114	434014.4	4330014
Project 61-80	61	2350000	2985000	0.0114	0.1114	332529	3317529
Residential	62	2316286	2868000	0.0114	0.1114	319495.2	3187495

Building	63	2370135	2850000	0.0114	0.1114	317490	3167490
2006	64	2615115	3123000	0.0114	0.1114	347902.2	3470902
	65	2796610	3126000	0.0114	0.1114	348236.4	3474236
	66	2850035	3136000	0.0114	0.1114	349350.4	3485350
	67	2735000	2986000	0.0114	0.1114	332640.4	3318640
	68	2710000	2950000	0.0114	0.1114	328630	3278630
	69	2873182	3113000	0.0114	0.1114	346788.2	3459788
	70	2910320	3113000	0.0114	0.1114	346788.2	3459788

Source: 2010 Survey

Appendix vi: Summary of Adjusted Projects B.O.Q Value and As-Built Cost 4-bedroom Duplex - Year 2006 – 2009

		1	2	3	
	Project	A	B	C	
Cost Centers		B.O.Q Initial Value	As-Built Cost	Cost Vartn	Perctg
Project 1-41	1	16,043,869	22,676,000	6632131	29
Residential	2	16,500,603	23,565,000	7064397	30
Building	3	16,225,501	24,113,000	7887499	33
2009	4	16,400,521	27,654,000	11253479	41
	5	17,100,438	22,221,000	5120562	23
	6	17,300,113	28,450,000	11149887	39
	7	16,800,073	30,500,000	13699927	45
	8	17,220,134	26,350,000	9129866	35
	9	16,210,687	25,800,120	9589433	37
	10	18,500,936	23,450,000	4949064	21
	11	16,360,084	20,650,000	4289916	21
	12	15,850,172	28,335,000	12484828	44
	13	16,000,163	22,850,000	6849837	30
	14	15,000,151	26,321,000	11320849	43
	15	15,600,148	26,321,000	10720852	41
	16	16,725,133	36,225,000	19499867	54

	17	17,890,112	27,338,000	9447888	35
	18	18,500,000	38,650,000	20150000	52
	19	19,223,000	25,773,000	6550000	25
	20	16,720,000	23,443,000	6723000	26
	21	16,044,130	24,557,000	8512870	35
	22	14,550,000	20,335,000	5785000	28
	23	13,889,000	24,113,000	10224000	42
	24	14,270,000	21,327,000	7057000	33
	25	15,633,321	20,114,000	4480679	22
	26	15,850,000	22,136,000	6286000	28
	27	16,010,000	30,763,000	14753000	48
	28	15,680,000	30,035,000	14355000	48
	29	14,600,000	26,736,000	12136000	45
	30	11,850,000	18,950,000	7100000	37
	31	13,010,000	20,560,000	7550000	37
	32	12,687,000	21,335,000	8648000	41
	33	12,600,000	24,625,000	12025000	49
	34	12,460,000	20,567,000	8107000	39
	35	11,400,000	21,650,000	10250000	47
	36	12,385,000	20,775,000	8390000	40
	37	12,214,000	12,214,000	0	0
	38	11,300,000	21,736,000	10436000	48
	39	11,750,000	26,113,000	14363000	55
	40	11,680,000	17,763,000	6083000	34
Project 41-60	41	11,200,000	19,236,000	8036000	42
Residential	42	10,101,000	19,203,000	9102000	47
Building	43	10,850,000	18,222,000	7372000	40
2007	44	11,380,000	19,492,000	8112000	42
	45	13,450,000	19,000,000	5550000	29
	46	12,676,000	20,689,000	8013000	39
	47	12,889,000	20,137,000	7248000	36
	48	12,136,000	20,373,000	8237000	40
	49	13,176,000	22,381,000	9205000	41
	50	14,289,000	25,391,000	11102000	44
	51	12,100,000	21,320,000	9220000	43
	52	13,676,000	24,136,000	10460000	43

	53	13,413,000	19,428,000	6015000	31
	54	12,850,000	19,985,000	7135000	36
	55	11,967,000	21,768,000	9801000	45
	56	11,813,000	20,000,000	8187000	41
	57	11,785,000	11,785,000	0	42
	58	12,631,000	14,673,000	2042000	14
	59	12,101,000	16,014,000	3913000	24
	60	12,673,000	18,969,000	6296000	33
	61	11,972,000	20,673,000	8701000	36
	62	11,636,000	19,731,000	8095000	41
	63	11,974,000	20,671,000	8697000	42
	64	12,370,000	21,363,000	8993000	42
	65	11,970,000	18,678,000	6708000	36
	66	12,140,142	16,713,000	4572858	27
	67	13,101,000	21,132,000	8031000	38
	68	13,203,500	26,363,000	13159500	50
	69	12,350,600	20,465,100	8114500	40
	70	12,550,112	21,368,000	8817888	41
Project 71-100	71	13,000,000	19,324,000	6324000	33
Residential	72	12,654,000	19,866,000	7212000	36
Building	73	11,465,000	20,887,000	9422000	45
2006	74	10,665,000	19,876,000	9211000	46
	75	10,964,000	20,113,000	9149000	45
	76	11,335,878	16,000,000	4664122	29
	77	10,365,000	18,997,000	8632000	45
	78	10,887,000	19,118,000	8231000	43
	79	11,775,000	17,000,000	5225000	31
	80	11,225,000	18,978,000	7753000	41
	81	12,654,000	21,000,000	8346000	40
	82	10,996,000	24,000,000	13004000	54
	83	9,667,000	14,225,000	4558000	32
	84	9,654,000	15,876,000	6222000	39
	85	8,776,999	16,444,000	7667001	47
	86	9,654,000	14,879,000	5225000	35
	87	10,546,000	18,334,000	7788000	42
	88	10,321,000	19,887,000	9566000	48

	89	9,678,000	12,113,000	2435000	20
	90	8,000,000	8,500,000	500000	6
	91	9,118,987	13,000,000	3881013	30
	92	9,432,000	9,432,000	0	0
	93	8,768,000	8,768,000	0	0
	94	9,876,000	13,000,000	3124000	25
	95	8,772,000	8,772,000	0	0
	96	9,311,000	13,567,000	4256000	31
	97	9,845,000	9,995,000	150000	2
	98	11,000,000	14,876,000	3876000	26
	99	10,678,000	13,675,000	2997000	22
	100	9,867,000	13,778,000	3911000	28

Source: 2010 Survey

Source: 2010 Survey Legend: TTL---Total Adj ---- Adjusted Infadj—Inflation Adjusted Val-- Value

The data obtained from the sampled projects need to be modified before being fed into the neural system for processing, in this context therefore, the extracted data was adjusted with inflation index and corruption escalator factors as applicable to different project types modified.

Appendix vii: Adjusted Project Cost Data 4- bedroom Duplex

Period: 2006-2009

		1	2	3	4	5	6
	Project	A	B	C	D	E	F
Cost Centers		B.O.Q Value	As Built	Inf Adjst Value	Corrupt Esc Adjval	Comb Adjval	Ttl
Project 1-29	1	16,043,869	22,676,000	0.0114	0.1114	2,526,106	25,202,106
Residential	2	16,500,603	23,565,000	0.0114	0.1114	2,625,141	26,190,141
Building	3	16,225,501	24,113,000	0.0114	0.1114	2,686,188	26,799,188
2009	4	16,400,521	27,654,000	0.0114	0.1114	3,080,656	30,734,656

	5	17,100,438	22,221,000	0.0114	0.1114	2,475,419	24,696,419
	6	17,300,113	28,450,000	0.0114	0.1114	3,169,330	31,619,330
	7	16,800,073	30,500,000	0.0114	0.1114	3,397,700	33,897,700
	8	17,220,134	26,350,000	0.0114	0.1114	2,935,390	29,285,390
	9	16,210,687	25,800,120	0.0114	0.1114	2,874,133	28,674,253
	10	18,500,936	23,450,000	0.0114	0.1114	2,612,330	26,062,330
	11	16,360,084	20,650,000	0.0114	0.1114	2,300,410	22,950,410
	12	15,850,172	28,335,000	0.0114	0.1114	3,156,519	31,491,519
	13	16,000,163	22,850,000	0.0114	0.1114	2,545,490	25,395,490
	14	15,000,151	26,321,000	0.0114	0.1114	2,932,159	29,253,159
	15	15,600,148	26,321,000	0.0114	0.1114	2,932,159	29,253,159
	16	16,725,133	36,225,000	0.0114	0.1114	4,035,465	40,260,465
	17	17,890,112	27,338,000	0.0114	0.1114	3,045,453	30,383,453
	18	18,500,000	38,650,000	0.0114	0.1114	4,305,610	42,955,610
	19	19,223,000	25,773,000	0.0114	0.1114	2,871,112	
	20	16,720,000	23,443,000	0.0114	0.1114	2,611,550	26,054,550
	21	16,044,130	24,557,000	0.0114	0.1114	2,735,650	27,292,650
	22	14,550,000	20,335,000	0.0114	0.1114	2,265,319	22,600,319
	23	13,889,000	24,113,000	0.0114	0.1114	2,686,188	26,799,188
	24	14,270,000	21,327,000	0.0114	0.1114	2,375,828	23,702,828
	25	15,633,321	20,114,000	0.0114	0.1114	2,240,700	22,354,700
	26	15,850,000	22,136,000	0.0114	0.1114	2,465,950	24,601,950
	27	16,010,000	30,763,000	0.0114	0.1114	3,426,998	34,189,998
	28	15,680,000	30,035,000	0.0114	0.1114	3,345,899	33,380,899
	29	14,600,000	26,736,000	0.0114	0.1114	2,978,390	29,714,390
	30	11,850,000	18,950,000	0.0114	0.1114	2,111,030	21,061,030
	31	13,010,000	20,560,000	0.0114	0.1114	2,290,384	22,850,384
	32	12,687,000	21,335,000	0.0114	0.1114	2,376,719	23,711,719
	33	12,600,000	24,625,000	0.0114	0.1114	2,743,225	27,368,225
	34	12,460,000	20,567,000	0.0114	0.1114	2,291,164	22,858,164
	35	11,400,000	21,650,000	0.0114	0.1114	2,411,810	24,061,810
	36	12,385,000	20,775,000	0.0114	0.1114	2,314,335	23,089,335
	37	12,214,000	12,214,000	0.0114	0.1114	1,360,640	13,574,640
	38	11,300,000	21,736,000	0.0114	0.1114	2,421,390	24,157,390
	39	11,750,000	26,113,000	0.0114	0.1114	2,908,988	29,021,988
	40	11,680,000	17,763,000	0.0114	0.1114	1,978,798	19,741,798
Project 41-60	41	11,200,000	19,236,000	0.0114	0.1114	2,142,890	21,378,890
Residential	42	10,101,000	19,203,000	0.0114	0.1114	2,139,214	21,342,214
Building	43	10,850,000	18,222,000	0.0114	0.1114	2,029,931	20,251,931

2007	44	11,380,000	19,492,000	0.0114	0.1114	2,171,409	21,663,409
	45	13,450,000	19,000,000	0.0114	0.1114	2,116,600	21,116,600
	46	12,676,000	20,689,000	0.0114	0.1114	2,304,755	22,993,755
	47	12,889,000	20,137,000	0.0114	0.1114	2,243,262	22,380,262
	48	12,136,000	20,373,000	0.0114	0.1114	2,269,552	22,642,552
	49	13,176,000	22,381,000	0.0114	0.1114	2,493,243	24,874,243
	50	14,289,000	25,391,000	0.0114	0.1114	2,828,557	28,219,557
	51	12,100,000	21,320,000	0.0114	0.1114	2,375,048	23,695,048
	52	13,676,000	24,136,000	0.0114	0.1114	2,688,750	26,824,750
	53	13,413,000	19,428,000	0.0114	0.1114	2,164,279	21,592,279
	54	12,850,000	19,985,000	0.0114	0.1114	2,226,329	22,211,329
	55	11,967,000	21,768,000	0.0114	0.1114	2,424,955	24,192,955
	56	11,813,000	20,000,000	0.0114	0.1114	2,228,000	22,228,000
	57	11,785,000	11,785,000	0.0114	0.1114	1,312,849	13,097,849
	58	12,631,000	14,673,000	0.0114	0.1114	1,634,572	16,307,572
	59	12,101,000	16,014,000	0.0114	0.1114	1,783,960	17,797,960
	60	12,673,000	18,969,000	0.0114	0.1114	2,113,147	21,082,147
Project 61-80	61	11,972,000	20,673,000	0.0114	0.1114	2,302,972	22,975,972
Residential	62	11,636,000	19,731,000	0.0114	0.1114	2,198,033	21,929,033
Building	63	11,974,000	20,671,000	0.0114	0.1114	2,302,749	22,973,749
2006	64	12,370,000	21,363,000	0.0114	0.1114	2,379,838	23,742,838
	65	11,970,000	18,678,000	0.0114	0.1114	2,080,729	20,758,729
	66	12,140,142	16,713,000	0.0114	0.1114	1,861,828	18,574,828
	67	13,101,000	21,132,000	0.0114	0.1114	2,354,105	23,486,105
	68	13,203,500	26,363,000	0.0114	0.1114	2,936,838	29,299,838
	69	12,350,600	20,465,100	0.0114	0.1114	2,279,812	22,744,912
	70	12,550,112	21,368,000	0.0114	0.1114	2,380,395	23,748,395
	71	13,000,000	19,324,000	0.0114	0.1114	2,152,694	21,476,694
	72	12,654,000	19,866,000	0.0114	0.1114	2,213,072	22,079,072
	73	11,465,000	20,887,000	0.0114	0.1114	2,326,812	23,213,812
	74	10,665,000	19,876,000	0.0114	0.1114	2,214,186	22,090,186
	75	10,964,000	20,113,000	0.0114	0.1114	2,240,588	22,353,588
	76	11,335,878	16,000,000	0.0114	0.1114	1,782,400	17,782,400
	77	10,365,000	18,997,000	0.0114	0.1114	2,116,266	21,113,266
	78	10,887,000	19,118,000	0.0114	0.1114	2,129,745	21,247,745
	79	11,775,000	17,000,000	0.0114	0.1114	1,893,800	18,893,800
	80	11,225,000	18,978,000	0.0114	0.1114	2,114,149	21,092,149
Project 81-100	81	12,654,000	21,000,000	0.0114	0.1114	2,339,400	23,339,400
Residential	82	10,996,000	24,000,000	0.0114	0.1114	2,673,600	26,673,600
Building	83	9,667,000	14,225,000	0.0114	0.1114	1,584,665	15,809,665

2006	84	9,654,000	15,876,000	0.0114	0.1114	1,768,586	17,644,586
	85	8,776,999	16,444,000	0.0114	0.1114	1,831,862	18,275,862
	86	9,654,000	14,879,000	0.0114	0.1114	1,657,521	16,536,521
	87	10,546,000	18,334,000	0.0114	0.1114	2,042,408	20,376,408
	88	10,321,000	19,887,000	0.0114	0.1114	2,215,412	22,102,412
	89	9,678,000	12,113,000	0.0114	0.1114	1,349,388	13,462,388
	90	8,000,000	8,500,000	0.0114	0.1114	946,900	9,446,900
	91	9,118,987	13,000,000	0.0114	0.1114	1,448,200	14,448,200
	92	9,432,000	9,432,000	0.0114	0.1114	1,050,725	10,482,725
	93	8,768,000	8,768,000	0.0114	0.1114	976,755	9,744,755
	94	9,876,000	13,000,000	0.0114	0.1114	1,448,200	14,448,200
	95	8,772,000	8,772,000	0.0114	0.1114	977,201	9,749,201
	96	9,311,000	13,567,000	0.0114	0.1114	1,511,364	15,078,364
	97	9,845,000	9,995,000	0.0114	0.1114	1,113,443	11,108,443
	98	11,000,000	14,876,000	0.0114	0.1114	1,657,186	16,533,186
	99	10,678,000	13,675,000	0.0114	0.1114	1,523,395	15,198,395
	100	9,867,000	13,778,000	0.0114	0.1114	1,534,869	15,312,869

Source: 2010 Survey Legend: Ttl---Total,

Appendix viii: **Summary of Projects Boq Value and As-Built Cost for 2-bedroom Bungalow**

Year 2007 – 2009					
		1	2	3	
	Project	A	B	C	
Cost Centers		B.O.Q Initial Value (Nm	As-Built Cost (Nm)	Cost Variation(B-A) Nm	Percent Var (%)
Project 1-26	1	3,085,100	4,236,000	1,150,900	37
Residential	2	3,171,800	5,800,000	2,628,200	83
Building	3	2,610,000	4,800,000	2,190,000	84
2009	4	3,165,000	4,350,000	1,185,000	37
	5	2,145,000	4,325,000	2,180,000	102
	6	3,174,953	4,286,350	1,111,397	35
	7	2,750,000	5,850,000	3,100,000	113
	8	2,700,850	5,121,000	2,420,150	90

	9	3,150,000	6,265,000	3,115,000	99
	10	2,766,000	5,223,000	2,457,000	89
	11	2,510,000	6,371,000	3,861,000	154
	12	3,268,000	6,250,000	2,982,000	91
	13	2,250,325	5,675,000	3,424,675	152
	14	3,520,000	6,600,000	3,080,000	88
	15	2,100,000	5,125,000	3,025,000	144
	16	3,173,000	5,652,000	2,479,000	78
	17	3,173,000	7,650,000	4,477,000	141
	18	2,580,315	6,131,000	3,550,685	138
	19	2,420,500	5,643,000	3,222,500	133
	20	3,143,000	7,266,000	4,123,000	131
	21	4,385,500	7,121,000	2,735,500	62
	22	3,867,620	8,900,000	5,032,380	130
	23	4,010,850	9,201,000	5,190,150	129
	24	3,172,771	7,213,000	4,040,229	127
	25	3,222,776	7,136,000	3,913,224	121
Project 26-70	26	3,767,000	8,208,000	4,441,000	118
Residential	27	2,646,000	5,670,000	3,024,000	114
Building	28	2,475,337	5,300,000	2,824,663	114
2007	29	2,680,286	3,720,000	1,039,714	39
	32	4,001,000	8,222,000	4,221,000	105
	33	2,560,500	5,172,000	2,611,500	102
	34	4,500,000	9,000,000	4,500,000	100
	35	3,216,000	6,350,000	3,134,000	97
	36	3,682,710	7,221,000	3,538,290	96
	37	3,580,000	6,850,000	3,270,000	91
	38	2,500,000	4,670,000	2,170,000	87
	39	2,760,000	4,885,000	2,125,000	77
	40	2,761,730	4,722,000	1,960,270	71
	41	2,855,210	4,873,000	2,017,790	71
	42	3,010,000	5,035,000	2,025,000	90
	43	4,800,000	7,800,000	3,000,000	63
	44	2,856,725	4,550,000	1,693,275	59
	45	4,300,000	6,650,000	2,350,000	55
	46	2,418,163	3,685,000	1,266,837	52

	47	4,600,000	6,985,000	2,385,000	52	
	48	2,783,011	4,136,000	1,352,989	49	
	49	2,746,500	3,926,000	1,179,500	43	
	50	2,896,230	4,121,000	1,224,770	42	
	51	2,975,610	4,227,000	1,251,390	42	
	52	2,756,380	3,896,000	1,139,620	41	
	53	2,480,500	3,500,000	1,019,500	41	
	54	2,685,420	3,762,000	1,076,580	40	
	55	2,811,143	3,922,000	1,110,857	40	
	56	2,889,385	3,963,000	1,073,615	37	
	57	2,300,121	3,113,000	812,879	35	
	58	2,890,010	3,910,000	1,019,990	35	
	59	2,962,500	3,872,000	909,500	31	
	60	2,982,630	3,896,000	913,370	31	
	61	2,350,000	2,985,000	635,000	27	
	62	2,316,286	2,868,000	551,714	24	
	63	2,370,135	2,850,000	479,865	20	
	64	2,615,115	3,123,000	507,885	19	
	65	2,796,610	3,126,000	329,390	12	
	66	2,850,035	3,136,000	285,965	10	
	67	2,735,000	2,986,000	251,000	9	
	68	2,710,000	2,950,000	240,000	9	
	69	2,873,182	3,113,000	239,818	8	
	70	2,910,320	3,113,000	202,680	7	

Source: 2010 Survey

Appendix ix: Summary of Adjustment Parameters 2- bedroom Bungalow

Pject Adjusted Cost Variables		1	2	3	4	5	
	Project	A	B	C	D	E	
Cost Centers		Boq Value	As Built Value	Inflatn Adj Fact	Corptn Escl Fact+Infl	Adjval	Adjttl
Project 1-20	1	3085100	4236000	0.0114	0.1114	471890.4	4707890
Residential	2	3171800	5800000	0.0114	0.1114	646120	6446120
Building	3	2610000	4800000	0.0114	0.1114	534720	5334720
2009	4	3165000	4350000	0.0114	0.1114	484590	4834590
	5	2145000	4325000	0.0114	0.1114	481805	4806805
	6	3174953	4286350	0.0114	0.1114	477499.39	4763849
	7	2750000	5850000	0.0114	0.1114	651690	6501690
	8	2700850	5121000	0.0114	0.1114	570479.4	5691479
	9	3150000	6265000	0.0114	0.1114	697921	6962921
	10	2766000	5223000	0.0114	0.1114	581842.2	5804842
	11	2510000	6371000	0.0114	0.1114	709729.4	7080729
	12	3268000	6250000	0.0114	0.1114	696250	6946250
	13	2250325	5675000	0.0114	0.1114	632195	6307195
	14	3520000	6600000	0.0114	0.1114	735240	7335240
	15	2100000	5125000	0.0114	0.1114	570925	5695925
	16	3173000	5652000	0.0114	0.1114	629632.8	6281633
	17	3173000	7650000	0.0114	0.1114	852210	8502210
	18	2580315	6131000	0.0114	0.1114	682993.4	6813993
	19	2420500	5643000	0.0114	0.1114	628630.2	6271630
	20	3143000	7266000	0.0114	0.1114	809432.4	8075432
Project 21-40	21	4385500	7121000	0.0114	0.1114	793279.4	7914279
Residential	22	3867620	8900000	0.0114	0.1114	991460	9891460
Building	23	4010850	9201000	0.0114	0.1114	1024991.4	10225991
2008	24	3172771	7213000	0.0114	0.1114	803528.2	8016528
	25	3222776	7136000	0.0114	0.1114	794950.4	7930950
	26	3767000	8208000	0.0114	0.1114	914371.2	9122371
	27	2646000	5670000	0.0114	0.1114	631638	6301638
	28	2475337	5300000	0.0114	0.1114	590420	5890420

	29	2680286	3720000	0.0114	0.1114	414408	4134408
	30	3831000	6121000	0.0114	0.1114	681879.4	6802879
	31	3763000	7800000	0.0114	0.1114	868920	8668920
	32	4001000	8222000	0.0114	0.1114	915930.8	9137931
	33	2560500	5172000	0.0114	0.1114	576160.8	5748161
	34	4500000	9000000	0.0114	0.1114	1002600	10002600
	35	3216000	6350000	0.0114	0.1114	707390	7057390
	36	3682710	7221000	0.0114	0.1114	804419.4	8025419
	37	3580000	6850000	0.0114	0.1114	763090	7613090
	38	2500000	4670000	0.0114	0.1114	520238	5190238
	39	2760000	4885000	0.0114	0.1114	544189	5429189
	40	2761730	4722000	0.0114	0.1114	526030.8	5248031
Project 41-60	41	2855210	4873000	0.0114	0.1114	542852.2	5415852
Residential	42	3010000	5035000	0.0114	0.1114	560899	5595899
Building	43	4800000	7800000	0.0114	0.1114	868920	8668920
2007	44	2856725	4550000	0.0114	0.1114	506870	5056870
	45	4300000	6650000	0.0114	0.1114	740810	7390810
	46	2418163	3685000	0.0114	0.1114	410509	4095509
	47	4600000	6985000	0.0114	0.1114	778129	7763129
	48	2783011	4136000	0.0114	0.1114	460750.4	4596750
	49	2746500	3926000	0.0114	0.1114	437356.4	4363356
	50	2896230	4121000	0.0114	0.1114	459079.4	4580079
	51	2975610	4227000	0.0114	0.1114	470887.8	4697888
	52	2756380	3896000	0.0114	0.1114	434014.4	4330014
	53	2480500	3500000	0.0114	0.1114	389900	3889900
	54	2685420	3762000	0.0114	0.1114	419086.8	4181087
	55	2811143	3922000	0.0114	0.1114	436910.8	4358911
	56	2889385	3963000	0.0114	0.1114	441478.2	4404478
	57	2300121	3113000	0.0114	0.1114	346788.2	3459788
	58	2890010	3910000	0.0114	0.1114	435574	4345574
	59	2962500	3872000	0.0114	0.1114	431340.8	4303341
	60	2982630	3896000	0.0114	0.1114	434014.4	4330014
Project 61-80	61	2350000	2985000	0.0114	0.1114	332529	3317529
Residential	62	2316286	2868000	0.0114	0.1114	319495.2	3187495
Building	63	2370135	2850000	0.0114	0.1114	317490	3167490
2006	64	2615115	3123000	0.0114	0.1114	347902.2	3470902
	65	2796610	3126000	0.0114	0.1114	348236.4	3474236

	66	2850035	3136000	0.0114	0.1114	349350.4	3485350
	67	2735000	2986000	0.0114	0.1114	332640.4	3318640
	68	2710000	2950000	0.0114	0.1114	328630	3278630
	69	2873182	3113000	0.0114	0.1114	346788.2	3459788
	70	2910320	3113000	0.0114	0.1114	346788.2	3459788

Source: 2010 Survey

Appendix x: Summary of Factor Adjusted Project Cost [2-bedroom Bungalow]

Period: 2006-2009				
	1	2	3	4
Project	A	B	C	D
	Boq Value	As Built Value	Corptn Adj Fact	Corptn Escl Fact+Infl
1	3085100	4236000	0.0114	0.1114
2	3171800	5800000	0.0114	0.1114
3	2610000	4800000	0.0114	0.1114
4	3165000	4350000	0.0114	0.1114
5	2145000	4325000	0.0114	0.1114
6	3174953	4286350	0.0114	0.1114
7	2750000	5850000	0.0114	0.1114
8	2700850	5121000	0.0114	0.1114
9	3150000	6265000	0.0114	0.1114
10	2766000	5223000	0.0114	0.1114
11	2510000	6371000	0.0114	0.1114
12	3268000	6250000	0.0114	0.1114
13	2250325	5675000	0.0114	0.1114
14	3520000	6600000	0.0114	0.1114
15	2100000	5125000	0.0114	0.1114
16	3173000	5652000	0.0114	0.1114
17	3173000	7650000	0.0114	0.1114
18	2580315	6131000	0.0114	0.1114

19	2420500	5643000	0.0114	0.1114
20	3143000	7266000	0.0114	0.1114
21	4385500	7121000	0.0114	0.1114
22	3867620	8900000	0.0114	0.1114
23	4010850	9201000	0.0114	0.1114
24	3172771	7213000	0.0114	0.1114
25	3222776	7136000	0.0114	0.1114
26	3767000	8208000	0.0114	0.1114
27	2646000	5670000	0.0114	0.1114
28	2475337	5300000	0.0114	0.1114
29	2680286	3720000	0.0114	0.1114
30	3831000	6121000	0.0114	0.1114
31	3763000	7800000	0.0114	0.1114
32	4001000	8222000	0.0114	0.1114
33	2560500	5172000	0.0114	0.1114
34	4500000	9000000	0.0114	0.1114
35	3216000	6350000	0.0114	0.1114
36	3682710	7221000	0.0114	0.1114
37	3580000	6850000	0.0114	0.1114
38	2500000	4670000	0.0114	0.1114
39	2760000	4885000	0.0114	0.1114
40	2761730	4722000	0.0114	0.1114
41	2855210	4873000	0.0114	0.1114
42	3010000	5035000	0.0114	0.1114
43	4800000	7800000	0.0114	0.1114
44	2856725	4550000	0.0114	0.1114
45	4300000	6650000	0.0114	0.1114
46	2418163	3685000	0.0114	0.1114
47	4600000	6985000	0.0114	0.1114
48	2783011	4136000	0.0114	0.1114
49	2746500	3926000	0.0114	0.1114
50	2896230	4121000	0.0114	0.1114
51	2975610	4227000	0.0114	0.1114
52	2756380	3896000	0.0114	0.1114
53	2480500	3500000	0.0114	0.1114
54	2685420	3762000	0.0114	0.1114
55	2811143	3922000	0.0114	0.1114

56	2889385	3963000	0.0114	0.1114
57	2300121	3113000	0.0114	0.1114
58	2890010	3910000	0.0114	0.1114
59	2962500	3872000	0.0114	0.1114
60	2982630	3896000	0.0114	0.1114
61	2350000	2985000	0.0114	0.1114
62	2316286	2868000	0.0114	0.1114
63	2370135	2850000	0.0114	0.1114
64	2615115	3123000	0.0114	0.1114
65	2796610	3126000	0.0114	0.1114
66	2850035	3136000	0.0114	0.1114
67	2735000	2986000	0.0114	0.1114
68	2710000	2950000	0.0114	0.1114
69	2873182	3113000	0.0114	0.1114
70	2910320	3113000	0.0114	0.1114

Source: 2010 Survey

Legend: Adj Val ---- Adjusted Value CombFact ---- Combined factor, Infl – Inflation Val – Value.

Appendix xi: Summary of Adjusted Boq Value and As-Built Cost Of Office Projects Period : 2006-2009

		1	2	3	4
	Project	A	B	C	D
Cost Centers		Boq Val	As-Built Value	Coup Esc Adj Value	Inf Adj Factr
Project 1-20	1	217093854	300814387	0.0114	0.1
Residential	2	296571798	478737280	0.0114	0.1
Building	3	141138227	155238227	0.0114	0.1
2009	4	290928823	298956814	0.0114	0.1

	5	216996254	220856000	0.0114	0.1
	6	219887135	219887136	0.0114	0.1
	7	220768961	299672863	0.0114	0.1
	8	220768961	225138124	0.0114	0.1
	9	231136821	233268148	0.0114	0.1
	10	215783222	218112136	0.0114	0.1
	11	218444863	219000125	0.0114	0.1
	12	219564813	221136000	0.0114	0.1
	13	285763822	286144368	0.0114	0.1
	14	210703023	215231000	0.0114	0.1
	15	276813043	286144268	0.0114	0.1
	16	211973388	213142000	0.0114	0.1
	17	288764472	290166500	0.0114	0.1
	18	213671123	215850000	0.0114	0.1
	19	291773632	294650000	0.0114	0.1
	20	214685684	216720000	0.0114	0.1
Project 21-40	21	293886923	294986520	0.0114	0.1
Residential	22	294693872	296700622	0.0114	0.1
Building	23	219784963	220825120	0.0114	0.1
2008	24	286668982	288700000	0.0114	0.1
	25	225513614	230525000	0.0114	0.1
	26	288996713	289885120	0.0114	0.1
	27	218682814	220350000	0.0114	0.1
	28	287981813	293650000	0.0114	0.1
	29	219822673	221762000	0.0114	0.1
	30	271136048	271948000	0.0114	0.1
	31	263268149	265300122	0.0114	0.1
	32	252367136	255400000	0.0114	
	33	265318206	268350000	0.0114	0.1
	34	217429308	219500000	0.0114	0.1
	35	208318316	210450000	0.0114	0.1
	36	216276309	220650100	0.0114	0.1
	37	244187219	249321000	0.0114	0.1
	38	214163108	219271000	0.0114	0.1
	39	213241563	215321000	0.0114	0.1

	40	256569431	256569431	0.0114	0.1
Project 41-60	41	247432217	250311000	0.0114	0.1
Residential	42	265772861	270612000	0.0114	0.1
Building	43	276896223	282873000	0.0114	0.1
2007	44	236763222	250881000	0.0114	0.1
	45	121165813	130322000	0.0114	0.1
	46	181176721	190936000	0.0114	0.1
	47	114173623	120231000	0.0114	0.1
	48	155181013	165762000	0.0114	
	49	196366137	199613000	0.0114	0.1
	50	146673384	149850000	0.0114	0.1
	51	143863642	148112000	0.0114	0.1
	52	193683143	198363000	0.0114	0.1
	53	181764237	183700000	0.0114	0.1
	54	173813124	176822000	0.0114	0.1
	55	196621131	102720000	0.0114	0.1
	56	176510022	188620000	0.0114	0.1
	57	143431012	144500012	0.0114	0.1
	58	197321113	200125000	0.0114	0.1
	59	134211014	135650000	0.0114	0.1
	60	188673124	189631000	0.0114	0.1
	61	166561024	172621000	0.0114	0.1
	62	171655671	175600000	0.0114	0.1
	63	191513423	197812000	0.0114	0.1
	64	195854000	196889000	0.0114	0.1
	65	114652000	116500000	0.0114	0.1
	66	112350500	114450000	0.0114	0.1
	67	113850350	119910000	0.0114	0.1
	68	111320500	214326000	0.0114	0.1
	69	194633000	198652000	0.0114	0.1
	70	184912000	188650000	0.0114	0.1
Project 71-100	71	116353000	120325000	0.0114	0.1
Residential	72	190385500	192115000	0.0114	0.1
Building	73	186932600	188850000	0.0114	0.1
2006	74	195695600	196700000	0.0114	0.1

	75	116763500	121850000	0.0114	0.1
	76	114682000	116350000	0.0114	0.1
	77	118932000	120123000	0.0114	0.1
	78	193600500	200112000	0.0114	0.1
	79	196520500	198252000	0.0114	0.1
	80	194322500	197450000	0.0114	0.1
	81	193614890	194622000	0.0114	0.1
	82	194625385	196520000	0.0114	0.1
	83	195615123	198114500	0.0114	0.1
	84	197736500	199500000	0.0114	0.1
	85	196365000	206128000	0.0114	0.1
	86	187892500	192500000	0.0114	0.1
	87	193675000	195720000	0.0114	0.1
	88	196367000	196367000	0.0114	0.1
	89	285388000	295028000	0.0114	0.1
	90	196113000	196814000	0.0114	0.1
	91	297323000	308000000	0.0114	0.1
	92	295113000	318673000	0.0114	0.1
	93	294317000	309873000	0.0114	0.1
	94	296801000	306565000	0.0114	0.1
	95	293963000	303873000	0.0114	0.1
	96	294528000	298235000	0.0114	0.1
	97	295334000	314865000	0.0114	0.1
	98	293673000	299147500	0.0114	0.1
	99	294972000	306289000	0.0114	0.1
	100	292876000	302150000	0.0114	0.1

Legend: BOQ --- Bill of quantity Inflatn Adj Fact ----- Inflation Adjusted Factors Corruptn Esc Fact ----- corruption escalator Factors Perctg ------ Percentage Infladjval ------Inflation adjusted Value PrcVal ----- Predicted Value

Appendix xii: Variable Adjusted Project Costs for Office Project

		1	2	3	4	5
	Project	A	B	C	D	E
Cost Centers		Boq Val	As-Built Value	Inf Adjs Fac	Corup Esc Fac	Adj Val
Project 1-20	1	217,093,854	300,814,387	0.0114	3,730,098	304,544,485
Residential	2	296,571,798	478,737,280	0.0114	45,936,342	484,673,622
Building	3	141,138,227	155,238,227	0.0114	1,924,954	157,163,181
2009	4	290,928,823	298,956,814	0.0114	3,707,064	302,663,878
	5	216,996,254	220,856,000	0.0114	2,738,614	223,594,614
	6	219,887,135	219,887,136	0.0114	2,726,600	222,613,736
	7	220,768,961	299,672,863	0.0114	3,715,944	303,388,807
	8	220,768,961	225,138,124	0.0114	2,791,713	227,929,837
	9	231,136,821	233,268,148	0.0114	2,892,525	236,160,673
	10	215,783,222	218,112,136	0.0114	2,704,590	220,816,726
	11	218,444,863	219,000,125	0.0114	2,715,602	221,715,727
	12	219,564,813	221,136,000	0.0114	2,742,086	223,878,086
	13	285,763,822	286,144,368	0.0114	3,548,190	289,692,558
	14	210,703,023	215,231,000	0.0114	2,668,864	217,899,864
	15	276,813,043	286,144,268	0.0114	3,548,189	289,692,457
	16	211,973,388	213,142,000	0.0114	2,642,961	215,784,961
	17	288,764,472	290,166,500	0.0114	3,598,065	293,764,565
	18	213,671,123	215,850,000	0.0114	2,676,540	218,526,540
	19	291,773,632	294,650,000	0.0114	3,653,660	298,303,660
	20	214,685,684	216,720,000	0.0114	2,687,328	219,407,328
Project 21-40	21	293,886,923	294,986,520	0.0114	3,657,833	298,644,353
Residential	22	294,693,872	296,700,622	0.0114	3,679,088	300,379,710
Building	23	219,784,963	220,825,120	0.0114	2,738,231	223,563,351

2008	24	286,668,982	288,700,000	0.0114	3,579,880	292,279,880
	25	225,513,614	230,525,000	0.0114	2,858,510	233,383,510
	26	288,996,713	289,885,120	0.0114	3,594,575	293,479,695
	27	218,682,814	220,350,000	0.0114	2,732,340	223,082,340
	28	287,981,813	293,650,000	0.0114	3,641,260	297,291,260
	29	219,822,673	221,762,000	0.0114	2,749,849	224,511,849
	30	271,136,048	271,948,000	0.0114	3,372,155	275,320,155
	31	263,268,149	265,300,122	0.0114	3,289,722	268,589,844
	32	252,367,136	255,400,000	0.0114	3,166,960	258,566,960
	33	265,318,206	268,350,000	0.0114	3,327,540	271,677,540
	34	217,429,308	219,500,000	0.0114	2,721,800	222,221,800
	35	208,318,316	210,450,000	0.0114	2,609,580	213,059,580
	36	216,276,309	220,650,100	0.0114	2,736,061	223,386,161
	37	244,187,219	249,321,000	0.0114	3,091,580	252,412,580
	38	214,163,108	219,271,000	0.0114	2,718,960	221,989,960
	39	213,241,563	215,321,000	0.0114	2,669,980	217,990,980
	40	256,569,431	256,569,431	0.0114	3,181,461	259,750,892
Project 41-70	41	247,432,217	250,311,000	0.0114	3,103,856	253,414,856
Residential	42	265,772,861	270,612,000	0.0114	3,355,589	273,967,589
Building	43	276,896,223	282,873,000	0.0114	3,507,625	286,380,625
2007	44	236,763,222	250,881,000	0.0114	3,110,924	253,991,924
	45	121,165,813	130,322,000	0.0114	1,615,993	131,937,993
	46	181,176,721	190,936,000	0.0114	2,367,606	193,303,606
	47	114,173,623	120,231,000	0.0114	1,490,864	121,721,864
	48	155,181,013	165,762,000	0.0114	2,055,449	167,817,449
	49	196,366,137	199,613,000	0.0114	2,475,201	202,088,201
	50	146,673,384	149,850,000	0.0114	1,858,140	151,708,140
	51	143,863,642	148,112,000	0.0114	1,836,589	149,948,589
	52	193,683,143	198,363,000	0.0114	2,459,701	200,822,701
	53	181,764,237	183,700,000	0.0114	2,277,880	185,977,880
	54	173,813,124	176,822,000	0.0114	2,192,593	179,014,593
	55	196,621,131	102,720,000	0.0114	1,273,728	103,993,728
	56	176,510,022	188,620,000	0.0114	2,338,888	190,958,888
	57	143,431,012	144,500,012	0.0114	1,791,800	146,291,812

	58	197,321,113	200,125,000	0.0114	2,481,550	202,606,550
	59	134,211,014	135,650,000	0.0114	1,682,060	137,332,060
	60	188,673,124	189,631,000	0.0114	2,351,424	191,982,424
Project 71-1000	61	166,561,024	172,621,000	0.0114	2,140,500	174,761,500
Residential	62	171,655,671	175,600,000	0.0114	2,177,440	177,777,440
Building	63	191,513,423	197,812,000	0.0114	2,452,869	200,264,869
2006	64	195,854,000	196,889,000	0.0114	2,441,424	199,330,424
	65	114,652,000	116,500,000	0.0114	1,444,600	117,944,600
	66	112,350,500	114,450,000	0.0114	1,419,180	115,869,180
	67	113,850,350	119,910,000	0.0114	1,486,884	121,396,884
	68	111,320,500	214,326,000	0.0114	2,657,642	216,983,642
	69	194,633,000	198,652,000	0.0114	2,463,285	201,115,285
	70	184,912,000	188,650,000	0.0114	2,339,260	190,989,260
	71	116,353,000	120,325,000	0.0114	1,492,030	121,817,030
	72	190,385,500	192,115,000	0.0114	2,382,226	194,497,226
	73	186,932,600	188,850,000	0.0114	2,341,740	191,191,740
	74	195,695,600	196,700,000	0.0114	2,439,080	199,139,080
	75	116,763,500	121,850,000	0.0114	1,510,940	123,360,940
	76	114,682,000	116,350,000	0.0114	1,442,740	117,792,740
	77	118,932,000	120,123,000	0.0114	1,489,525	121,612,525
	78	193,600,500	200,112,000	0.0114	2,481,389	202,593,389
	79	196,520,500	198,252,000	0.0114	2,458,325	200,710,325
	80	194,322,500	197,450,000	0.0114	2,448,380	199,898,380
	81	193,614,890	194,622,000	0.0114	2,413,313	197,035,313
	82	194,625,385	196,520,000	0.0114	2,436,848	198,956,848
	83	195,615,123	198,114,500	0.0114	2,456,620	200,571,120
	84	197,736,500	199,500,000	0.0114	2,473,800	201,973,800
	85	196,365,000	206,128,000	0.0114	2,555,987	208,683,987
	86	187,892,500	192,500,000	0.0114	2,387,000	194,887,000
	87	193,675,000	195,720,000	0.0114	2,426,928	198,146,928
	88	196,367,000	196,367,000	0.0114	2,434,951	198,801,951
	89	285,388,000	295,028,000	0.0114	3,658,347	298,686,347

	90	196,113,000	196,814,000	0.0114	2,440,494	199,254,494
	91	297,323,000	308,000,000	0.0114	3,819,200	311,819,200
	92	295,113,000	318,673,000	0.0114	3,951,545	322,624,545
	93	294,317,000	309,873,000	0.0114	3,842,425	313,715,425
	94	296,801,000	306,565,000	0.0114	3,801,406	310,366,406
	95	293,963,000	303,873,000	0.0114	3,768,025	307,641,025
	96	294,528,000	298,235,000	0.0114	3,698,114	301,933,114
	97	295,334,000	314,865,000	0.0114	3,904,326	318,769,326
	98	293,673,000	299,147,500	0.0114	3,709,429	302,856,929
	99	294,972,000	306,289,000	0.0114	3,797,984	310,086,984
	100	292,876,000	302,150,000	0.0114	3,746,660	305,896,660

LEGEND: BOQ --- Bill of quantity Inflatn Adj Fact ----- Inflation Adjusted Factors Corruptn Esc Fact ----- corruption escalator Factors Perctg ------ Percentage Infladjval ------Inflation adjusted Value PrcVal ----- Predicted Value.

Appendix xiii: Presentation of Neural Network Generated Output (2&3-bedroom Unit, 4-floors]

		1	2	3
	Project	A	B	C
Cost Centers		B.O.Q Initial Value	As-Built Cost	Neural Output
Project 1-70	1	320,169,000	325,689,000	475,444,340
Residential	2	496,193,000	420,300,000	473,840,312
Building	3	440,879,000	441,500,672	473,840,312
2009	4	440,308,000	443,500,620	473,918,725
	5	439,851,113	442,900,000	473,840,313
	6	439,153,000	442,160,333	474,832,995
	7	438,943,000	440,900,000	473,840,313
	8	437,506,121	439,506,121	474,273,372
	9	437,114,000	439,300,000	474,740,316
	10	433,535,000	442,375,000	473,840,312
	11	433,210,000	433,436,000	473,840,313
	12	432,701,000	435,953,000	475,037,960
	13	431,067,000	431,067,100	473,840,312

	14	430,648,000	433,936,500	474,068,424
	15	429,860,000	430,820,000	473,840,312
	16	429,361,000	439,361,000	474,731,404
	17	429,231,000	430,238,000	473,840,312
	18	428,670,000	438,338,146	473,840,312
	19	428,474,000	432,453,000	475,310,661
	20	426,882,000	430,800,000	473,840,312
	21	426,814,000	426,814,000	475,310,660
	22	426,722,000	426,722,248	473,840,312
	23	426,696,000	428,673,500	474,262,679
	24	425,850,600	432,790,000	473,840,312
	25	425,492,000	432,400,000	474,731,404
	26	425,492,000	430,300,000	473,840,312
	27	425,392,313	435,698,725	474,474,761
	28	425,292,000	428,350,000	473,840,312
	29	424,936,000	435,600,773	474,255,550
	30	424,808,000	429,600,800	473,840,312
	31	424,503,000	424,657,600	475,421,169
	32	424,370,000	428,860,000	473,840,312
	33	423,701,000	428,672,000	474,512,188
	34	422,919,920	428,633,000	473,840,312
	35	422,918,000	432,685,763	475,155,595
	36	422,596,321	425,800,000	473,840,312
	37	422,470,000	430,500,000	475,430,083
	38	422,449,000	424,500,124	473,840,312
	39	421,574,000	430,500,000	474,904,286
	40	421,384,000	421,384,000	473,840,312
	41	421,137,000	422,893,000	474,244,857
	42	421,062,500	422,720,520	473,840,312
	43	420,777,116	420,777,116	474,004,267
	44	419,738,222	422,850,000	473,840,312
	45	419,585,000	429,688,124	473,840,312
	46	419,403,144	423,614,268	473,840,312
	47	418,677,600	420,850,100	473,840,312
	48	418,377,600	420,138,000	473,840,312

	49	417,673,000	426,998,000	474,827,643
	50	416,596,321	425,600,000	473,840,312
	51	416,591,000	430,338,000	474,731,404
	52	416,591,000	422,665,000	473,840,312
	53	415,834,860	420,650,800	473,840,312
	54	414,846,000	414,846,000	473,840,312
	55	414,827,333	424,837,167	473,840,312
	56	414,581,000	414,581,000	473,840,312
	57	414,476,200	420,684,300	473,840,312
	58	413,380,000	420,000,000	474,521,099
	59	411,820,000	414,368,000	474,977,362
	60	410,453,000	410,453,000	473,840,312
	61	410,264,000	419,300,123	474,788,437
	62	410,013,000	425,300,000	473,840,312
	63	409,128,000	410,385,000	474,608,429
	64	408,413,000	416,413,000	473,840,312
	65	406,464,000	410,550,000	475,091,430
	66	406,364,000	408,676,850	473,840,312
	67	403,660,000	413,610,000	474,230,312
	68	403,647,000	403,647,000	473,840,312
	69	403,436,000	409,436,000	474,230,600
	70	464,024,000	472,000,000	473,840,312
Project 71-143	71	385,405,000	392,364,000	473,895,558
Residential	72	375,619,000	380,700,000	473,840,312
Building	73	363,061,000	370,577,500	475,029,049
2008	74	362,715,000	370,876,000	475,029,049
	75	360,358,000	363,500,000	473,840,312
	76	357,952,500	373,866,000	475,029,049
	77	357,564,000	360,000,000	473,840,312
	78	355,575,000	362,316,000	475,000,531
	79	355,063,000	365,000,000	473,840,312
	80	352,628,590	352,628,590	474,645,856
	81	350,011,600	357,287,000	473,840,312

	82	349,274,800	358,850,200	474,513,970
	83	348,876,000	357,986,000	473,840,312
	84	348,851,000	348,851,000	474,513,700
	85	348,522,000	357,650,000	474,731,404
	86	348,030,000	350,533,800	473,840,312
	87	347,402,000	359,000,000	475,098,559
	88	345,467,000	353,000,000	473,840,312
	89	343,848,000	364,921,000	474,891,810
	90	341,228,000	349,800,000	473,840,312
	91	340,755,000	349,000,000	474,036,345
	92	333,965,000	340,125,000	473,840,312
	93	330,044,000	360,153,678	473,840,312
	94	328,005,000	335,000,000	473,840,312
	95	325,339,767	337,967,000	475,087,866
	96	307,821,000	310,667,000	473,803,123
	97	272,573,000	274,000,000	474,834,776
	98	272,031,000	275,650,000	473,840,312
	99	268,125,500	272,333,000	474,747,445
	100	263,861,000	274,000,000	473,840,312
	101	253,449,000	260,000,000	473,954,367
	102	248,593,000	258,000,000	473,849,312
	104	247,736,000	250,000,000	475,504,943
	105	247,449,000	250,000,000	473,840,312
	106	247,004,900	251,700,000	473,956,149
	107	246,558,600	266,358,000	473,840,312
	108	246,530,000	256,000,000	475,419,387
	109	246,102,000	256,000,000	473,840,312
	110	246,016,000	252,350,000	474,998,749
	111	245,522,000	250,000,000	473,840,312
	112	245,509,000	265,000,000	473,840,312
	113	245,401,000	245,801,000	473,525,056
	114	245,212,000	257,000,000	473,840,312
	115	244,534,000	249,320,000	474,426,641
	116	244,534,000	245,850,000	473,840,312
	117	243,727,000	251,300,000	473,884,864
	118	243,648,000	252,000,000	473,840,312

	119	243,065,000	260,534,890	475,465,729
	120	242,902,000	257,800,000	473,840,312
	121	242,409,000	247,332,000	473,840,312
	122	242,110,000	262,000,000	474,447,905
	123	241,642,000	251,350,000	473,840,312
	124	241,634,000	251,800,000	475,351,656
	125	241,519,000	248,000,000	473,840,312
	126	241,500,000	245,712,000	474,374,951
	127	240,551,000	247,876,000	473,840,312
	128	240,452,000	263,650,000	474,374,951
	129	240,427,000	248,221,000	473,803,122
	130	240,418,000	243,000,000	474,629,816
	131	240,031,000	247,800,000	473,840,312
	132	239,500,000	246,000,000	474,218,125
	133	239,229,000	245,700,000	473,840,312
	134	239,053,000	243,850,000	473,840,312
	135	239,020,000	242,000,000	474,850,817
	136	237,912,000	252,902,000	473,840,312
	137	237,912,000	239,850,000	473,995,354
	138	237,678,000	241,520,000	473,840,312
	139	236,024,000	239,500,000	475,465,729
	140	234,532,000	240,800,000	473,840,312
	141	233,765,000	241,600,000	475,447,904
Project142-192	142	231,799,100	236,800,000	473,840,312
2007	144	185,000,000	210,000,000	474,374,957
	145	183,700,000	198,665,000	473,803,123
	146	180,233,000	210,560,000	474,629,816
	147	170,557,937	218,000,000	473,840,312
	148	169,500,000	175,500,000	474,218125
	149	165,886,913	172,500,000	473,840,312
	150	165,443,000	173,765,000	473,840,312
	151	164,354,000	164,733,000	474,850,818
	152	163,237,000	195,000,000	473,850,312
	153	163,200,000	165,987,000	473,995,556

	154	161,500,440	190,000,000	473,840,312
	155	160,876,000	166,320,000	475,531,628
	156	159,754,000	163,400,000	473,840,312
	157	158,654,800	162,350,000	474,481,890
	158	158,567,000	165,800,000	473,840,312
	159	157,378,930	171,700,000	474,481,889
	160	157,300,839	166,136,000	473,840,312
	161	157,000,000	177,000,000	473,840,312
	162	155,600,000	159,650,000	474,970,232
	163	154,000,000	207,000,000	473,840,312
	164	152,667,000	169,750,000	474,022,089
	165	151,500,000	172,520,000	473,840,312
	166	150,825,000	180,926,000	473,840,312
	167	149,887,000	174,500,000	474,984,490
	168	149,000,000	178,510,000	473,840,312
	169	148,569,000	151,000,000	475,419,386
Projct250-270	170	148,128,000	178,210,000	473,840,312
Residential	171	147,985,000	151,135,000	474,426,641
Building	172	147,765,000	152,131,000	473,840,312
	173	147,650,000	158,000,000	473,884,864
	174	147,638,000	167,133,000	473,840,312
	175	147,500,000	153,359,870	475,465,729
	176	147,382,000	167,216,000	473,840,312
	177	147,336,813	149,000,000	473,840,312
	178	147,336,813	148,500,000	474,447,905
	179	146,356,000	172,000,000	473,840,312
	180	146,329,000	156,233,000	475,351,656
	181	146,300,943	153,800,000	473,840,312
	182	146,000,000	166,832,000	474,374,951
	183	145,892,000	168,225,000	473,840,312
	184	145,500,000	175,000,000	474,374,951
	185	144,886,913	155,230,000	473,803,122
	186	144,651,000	146,872,000	474,629,816
	187	143,031,000	159,113,000	473,840,312
	188	143,031,000	149,500,000	474,218,125

	189	142,500,000	154,750,000	473,840,312
	190	141,823,000	147,008,100	473,840,312
	191	141,765,000	143,561,000	474,850,817
Project 192-220	192	140,928,000	145,314,000	473,840,312
Residential	193	138,934,500	149,520,000	473,995,354
Building	194	135,672,000	165,500,000	473,840,312
2006	195	133,779,000	142,107,000	475,465,729
	196	133,765,000	138,324,166	473,840,312
	197	133,431,010	149,000,000	475,447,904
	198	132,706,000	143,888,000	473,840,312
	199	132,360,000	138,000,000	473,840,312
	200	132,227,000	152,000,000	474,426,641
	201	130,702,000	145,950,000	473,840,312
	202	130,219,000	145,236,000	473,884,864
	203	130,017,000	133,113,014	473,840,312
	204	129,532,000	145,000,000	475,465,729
	205	129,471,000	132,685,000	473,840,312
	206	129,272,000	138,200,000	473,840,312
	207	128,597,000	148,210,000	474,447,905
	208	128,590,000	139,250,000	473,840,312
	209	128,505,000	158,000,000	475,351,656
	210	128,064,000	138,000,000	473,840,312
	211	127,708,000	129,850,000	474,374,951
	212	127,025,000	135,228,177	473,840,312
	213	126,377,000	146,850,000	474,374,951
	214	125,998,000	154,000,000	473,803,122
	215	125,637,000	140,800,000	474,629,816
	216	125,628,000	128,214,136	473,840,312
	217	125,554,000	143,010,000	474,218,125
	218	124,738,000	144,650,000	473,840,312
	219	123,243,000	155243000.00	473,840,312
	220	121,092,000	139,000,000	474,850,817

Legend: BOQ --- Bill of quantity Inflatn Adj Fact ----- Inflation Adjusted Factors Corruptn Esc Fact ----- corrupt Perctg ------ Percentage Infladjval ------Inflation adjusted Value PrcVal ----- Predicted Value.

Appendix xiv: Neural Network Output for Office Project

		1	2	3
	Project	A	B	C
Cost Centers		Boq Value	As-Built Value	Neural Adjs Cost Output
Project 1-20	1	217093854	300814387	412,797,416
Residential	2	296571798	478737280	445,738,080
Building	3	141138227	155238227	465,329,444
2009	4	290928823	298956814	348,432,150
	5	216996254	220856000	394,547,922
	6	219887135	219887136	405,878,924
	7	220768961	299672863	323,622,889
	8	220768961	225138124	438,200,127
	9	231136821	233268148	315,232,642
	10	215783222	218112136	478,307,495
	11	218444863	219000125	474,091,263
	12	219564813	221136000	310,324,221
	13	285763822	286144368	452,405,229
	14	210703023	215231000	469,007,811
	15	276813043	286144268	318,401,000
	16	211973388	213142000	460,833,922
	17	288764472	290166500	470,407,364
	18	213671123	215850000	328,522,228
	19	291773632	294650000	421,535,709
	20	214685684	216720000	453,063,634
Project 21-40	21	293886923	294986520	328,522,229
Residential	22	294693872	296700622	327,022,716

Building	23	219784963	220825120	406,183,226
2008	24	286668982	288700000	328,522,228
	25	225513614	230525000	327,022,717
	26	288996713	289885120	327,169,021
	27	218682814	220350000	334,397,421
	28	287981813	293650000	363,394,497
	29	219822673	221762000	319,290,903
	30	271136048	271948000	334,397,421
	31	263268149	265300122	349,213,502
	32	252367136	255400000	332,733,494
	33	265318206	268350000	489,800,317
	34	217429308	219500000	328,978,338
	35	208318316	210450000	349,213,501
	36	216276309	220650100	476,226,435
	37	244187219	249321000	334,649,790
	38	214163108	219271000	355,642,781
	39	213241563	215321000	321,310,947
	40	256569431	256569431	324,530,258
Project 41-60	41	247432217	250311000	360,154,187
Residential	42	265772861	270612000	376,226,435
Building	43	276896223	282873000	311,936,852
2007	44	236763222	250881000	346,557,269
	45	121165813	130322000	382,975,632
	46	181176721	190936000	328,886,914
	47	114173623	120231000	311,150,165
	48	155181013	165762000	381,512,870
	49	196366137	199613000	337,825,361
	50	146673384	149850000	363,219,664
	51	143863642	148112000	464,007,879
	52	193683143	198363000	328,068,642
	53	181764237	183700000	328,801,434
	54	173813124	176822000	347,896,004
	55	196621131	102720000	356,423,068
	56	176510022	188620000	335,753,179
	57	143431012	144500012	355,334,464

	58	197321113	200125000	318,480,280
	59	134211014	135650000	424,170,703
	60	188673124	189631000	372,691,505
Project 61-80	61	166561024	172621000	335,630,830
Residential	62	171655671	175600000	333,436,973
Building	63	191513423	197812000	353,315,976
2006	64	195854000	196889000	327,079,612
	65	114652000	116500000	346,351,098
	66	112350500	114450000	346,726,152
	67	113850350	119910000	338,128,484
	68	111320500	214326000	352,415,583
	69	194633000	198652000	346,204,976
	70	184912000	188650000	355,059,439
	71	116353000	120325000	372,164,009
	72	190385500	192115000	353,603,686
	73	186932600	188850000	310,324,221
	74	195695600	196700000	386,277,203
	75	116763500	121850000	336,721,858
	76	114682000	116350000	364,076,524
	77	118932000	120123000	332,803,709
	78	193600500	200112000	311,370,481
	79	196520500	198252000	431,027,839
	80	194322500	197450000	447,049,149
Project 81-100	81	193614890	194622000	323,756,101
Residential	82	194625385	196520000	432,169,313
Building	83	195615123	198114500	462,908,029
2005	84	197736500	199500000	406,183,236
	85	196365000	206128000	341,487,833
	86	187892500	192500000	349,100,138
	87	193675000	195720000	386,792,640
	88	196367000	196367000	430,326,963
	89	285388000	295028000	408,639,619
	90	196113000	196814000	373,262,767
	91	297323000	308000000	473,306,111
	92	295113000	318673000	366,946,822

	93	294317000	309873000	379,844,315
	94	296801000	306565000	432,705,375
	95	293963000	303873000	475,122,295
	96	294528000	298235000	365,270,515
	97	295334000	314865000	389,930,314
	98	293673000	299147500	329,352,135
	99	294972000	306289000	320,167,100
	100	292876000	302150000	312,136,567

Source: 2010 Neural Analysis

Legend: BOQ --- Bill of quantity Inflatn Adj Fact ----- Inflation Adjusted Factors
Corruptn Esc Fact ----- corruption escalator Factors   Perctg ------ Percentage
Infladjval ------Inflation adjusted Value   PrcVal ----- Predicted Value.

Appendix xv: Neural Network Output For 4- bedroom Duplex Project

	B.O.Q Value	As- Built	Inf Adjst Value	Corptsca Adjval	Comb Adj Val	Total	Neural Outpt
1	16,043,869	22,676,000	0.0114	0.1114	2,526,106	25,202,106	25,202,107
2	16,500,603	23,565,000	0.0114	0.1114	2,625,141	26,190,141	26,190,141
3	16,225,501	24,113,000	0.0114	0.1114	2,686,188	26,799,188	30,149,087
4	16,400,521	27,654,000	0.0114	0.1114	3,080,656	30,734,656	30,734,656
5	17,100,438	22,221,000	0.0114	0.1114	2,475,419	24,696,419	24,696,420
6	17,300,113	28,450,000	0.0114	0.1114	3,169,330	31,619,330	31,619,330
7	16,800,073	30,500,000	0.0114	0.1114	3,397,700	33,897,700	33,897,700
8	17,220,134	26,350,000	0.0114	0.1114	2,935,390	29,285,390	29,285,390
9	16,210,687	25,800,120	0.0114	0.1114	2,874,133	28,674,253	28,674,253
10	18,500,936	23,450,000	0.0114	0.1114	2,612,330	26,062,330	26,062,330
11	16,360,084	20,650,000	0.0114	0.1114	2,300,410	22,950,410	22,950,410
12	15,850,172	28,335,000	0.0114	0.	3,156,519	31,491,519	31,491,519
13	16,000,163	22,850,000	0.0114	0.1114	2,545,490	25,395,490	25,395,490
14	15,000,151	26,321,000	0.0114	0.1114	2,932,159	29,253,159	29,253,160
15	15,600,148	26,321,000	0.0114	0.1114	2,932,159	29,253,159	29,253,160
16	16,725,133	36,225,000	0.0114	0.1114	4,035,465	40,260,465	40,260,465
17	17,890,112	27,338,000	0.0114	0.1114	3,045,453	30,383,453	30,383,453

18	18,500,000	38,650,000	0.0114	0.1114	4,305,610	42,955,610	42,955,610
19	19,223,000	25,773,000	0.0114	0.1114	2,871,112	28,644,112	28,644,112
20	16,720,000	23,443,000	0.0114	0.1114	2,611,550	26,054,550	26,054,550
21	16,044,130	24,557,000	0.0114	0.1114	2,735,650	27,292,650	27,292,650
22	14,550,000	20,335,000	0.0114	0.1114	2,265,319	22,600,319	22,600,319
23	13,889,000	24,113,000	0.0114	0.1114	2,686,188	26,799,188	26,799,188
24	14,270,000	21,327,000	0.0114	0.1114	2,375,828	23,702,828	23,702,828
25	15,633,321	20,114,000	0.0114	0.1114	2,240,700	22,354,700	22,354,700
26	15,850,000	22,136,000	0.0114	0.1114	2,465,950	24,601,950	24,601,951
27	16,010,000	30,763,000	0.0114	0.1114	3,426,998	34,189,998	34,189,998
28	15,680,000	30,035,000	0.0114	0.1114	3,345,899	33,380,899	33,380,899
29	14,600,000	26,736,000	0.0114	0.1114	2,978,390	29,714,390	29,714,391
30	11,850,000	18,950,000	0.0114	0.1114	2,111,030	21,061,030	21,061,030
31	13,010,000	20,560,000	0.0114	0.1114	2,290,384	22,850,384	22,850,384
32	12,687,000	21,335,000	0.0114	0.1114	2,376,719	23,711,719	23,711,719
33	12,600,000	24,625,000	0.0114	0.1114	2,743,225	27,368,225	27,368,225
34	12,460,000	20,567,000	0.0114	0.1114	2,291,164	22,858,164	22,858,164
35	11,400,000	21,650,000	0.0114	0.1114	2,411,810	24,061,810	24,061,810
36	12,385,000	20,775,000	0.0114	0.1114	2,314,335	23,089,335	23,089,335
37	12,214,000	12,214,000	0.0114	0.1114	1,360,640	13,574,640	13,574,640
38	11,300,000	21,736,000	0.0114	0.1114	2,421,390	24,157,390	24,157,391
39	11,750,000	26,113,000	0.0114	0.1114	2,908,988	29,021,988	29,021,988
40	11,680,000	17,763,000	0.0114	0.1114	1,978,798	19,741,798	19,741,798
41	11,200,000	19,236,000	0.0114	0.1114	2,142,890	21,378,890	21,378,891
42	10,101,000	19,203,000	0.0114	0.1114	2,139,214	21,342,214	21,342,214
43	10,850,000	18,222,000	0.0114	0.1114	2,029,931	20,251,931	20,251,931
44	11,380,000	19,492,000	0.0114	0.1114	2,171,409	21,663,409	21,663,409
45	13,450,000	19,000,000	0.0114	0.1114	2,116,600	21,116,600	21,116,600
46	12,676,000	20,689,000	0.0114	0.1114	2,304,755	22,993,755	22,993,755
47	12,889,000	20,137,000	0.0114	0.1114	2,243,262	22,380,262	22,380,262
48	12,136,000	20,373,000	0.0114	0.1114	2,269,552	22,642,552	22,642,552
49	13,176,000	22,381,000	0.0114	0.1114	2,493,243	24,874,243	24,874,244
50	14,289,000	25,391,000	0.0114	0.1114	2,828,557	28,219,557	28,219,558
51	12,100,000	21,320,000	0.0114	0.1114	2,375,048	23,695,048	23,695,048
52	13,676,000	24,136,000	0.0114	0.1114	2,688,750	26,824,750	26,824,751
53	13,413,000	19,428,000	0.0114	0.1114	2,164,279	21,592,279	21,592,279

54	12,850,000	19,985,000	0.0114	0.1114	2,226,329	22,211,329	22,211,329
55	11,967,000	21,768,000	0.0114	0.1114	2,424,955	24,192,955	24,192,955
56	11,813,000	20,000,000	0.0114	0.1114	2,228,000	22,228,000	22,228,000
57	11,785,000	11,785,000	0.0114	0.1114	1,312,849	13,097,849	13,097,849
58	12,631,000	14,673,000	0.0114	0.1114	1,634,572	16,307,572	16,307,572
59	12,101,000	16,014,000	0.0114	0.1114	1,783,960	17,797,960	17,797,960
60	12,673,000	18,969,000	0.0114	0.1114	2,113,147	21,082,147	21,082,147
61	11,972,000	20,673,000	0.0114	0.1114	2,302,972	22,975,972	22,975,972
62	11,636,000	19,731,000	0.0114	0.1114	2,198,033	21,929,033	21,929,034
63	11,974,000	20,671,000	0.0114	0.1114	2,302,749	22,973,749	22,973,750
64	12,370,000	21,363,000	0.0114	0.1114	2,379,838	23,742,838	23,742,838
65	11,970,000	18,678,000	0.0114	0.1114	2,080,729	20,758,729	20,758,729
66	12,140,142	16,713,000	0.0114	0.1114	1,861,828	18,574,828	18,574,828
67	13,101,000	21,132,000	0.0114	0.1114	2,354,105	23,486,105	23,486,105
68	13,203,500	26,363,000	0.0114	0.1114	2,936,838	29,299,838	29,299,838
69	12,350,600	20,465,100	0.0114	0.1114	2,279,812	22,744,912	22,744,912
70	12,550,112	21,368,000	0.0114	0.1114	2,380,395	23,748,395	23,748,395
71	13,000,000	19,324,000	0.0114	0.1114	2,152,694	21,476,694	21,476,694
72	12,654,000	19,866,000	0.0114	0.1114	2,213,072	22,079,072	22,079,073
73	11,465,000	20,887,000	0.0114	0.1114	2,326,812	23,213,812	23,213,812
74	10,665,000	19,876,000	0.0114	0.1114	2,214,186	22,090,186	22,090,187
75	10,964,000	20,113,000	0.0114	0.1114	2,240,588	22,353,588	22,353,588
76	11,335,878	16,000,000	0.0114	0.1114	1,782,400	17,782,400	17,782,400
77	10,365,000	18,997,000	0.0114	0.1114	2,116,266	21,113,266	21,113,266
78	10,887,000	19,118,000	0.0114	0.1114	2,129,745	21,247,745	21,247,745
79	11,775,000	17,000,000	0.0114	0.1114	1,893,800	18,893,800	18,893,800
80	11,225,000	18,978,000	0.0114	0.1114	2,114,149	21,092,149	21,092,149
81	12,654,000	21,000,000	0.0114	0.1114	2,339,400	23,339,400	23,339,400
82	10,996,000	24,000,000	0.0114	0.1114	2,673,600	26,673,600	26,673,600
83	9,667,000	14,225,000	0.0114	0.1114	1,584,665	15,809,665	15,809,665
84	9,654,000	15,876,000	0.0114	0.1114	1,768,586	17,644,586	17,644,587
85	8,776,999	16,444,000	0.0114	0.1114	1,831,862	18,275,862	18,275,862
86	9,654,000	14,879,000	0.0114	0.1114	1,657,521	16,536,521	16,536,521
87	10,546,000	18,334,000	0.0114	0.1114	2,042,408	20,376,408	20,376,408
88	10,321,000	19,887,000	0.0114	0.1114	2,215,412	22,102,412	22,102,412
89	9,678,000	12,113,000	0.0114	0.1114	1,349,388	13,462,388	13,462,388
90	8,000,000	8,500,000	0.0114	0.1114	946,900	9,446,900	9,446,900

91	9,118,987	13,000,000	0.0114	0.1114	1,448,200	14,448,200	14,448,200
92	9,432,000	9,432,000	0.0114	0.1114	1,050,725	10,482,725	10,482,725
93	8,768,000	8,768,000	0.0114	0.1114	976,755	9,744,755	9,744,755
94	9,876,000	13,000,000	0.0114	0.1114	1,448,200	14,448,200	14,448,200
95	8,772,000	8,772,000	0.0114	0.1114	977,201	9,749,201	9,749,201
96	9,311,000	13,567,000	0.0114	0.1114	1,511,364	15,078,364	15,078,364
97	9,845,000	9,995,000	0.0114	0.1114	1,113,443	11,108,443	11,108,443
98	11,000,000	14,876,000	0.0114	0.1114	1,657,186	16,533,186	16,533,187
99	10,678,000	13,675,000	0.0114	0.1114	1,523,395	15,198,395	15,198,395
100	9,867,000	13,778,000	0.0114	0.1114	1,534,869	15,312,869	15,312,869

Source: 2010 Neural Analysis

Legend: BOQ --- Bill of quantity Inflatn Adj Fact ----- Inflation Adjusted Factors
Corruptn Esc Fact ----- corruption escalator Factors Perctg ------ Percentage
Infladjval ------Inflation adjusted Value PrcVal ----- Predicted Value.

Appendix xvi: Neural Network Output for 2- bedroom Bungalow Project

Project	A	B	C	D	D	E	F	G
	Boq Value	As Built Value	Inflatn Adj Fact	Corptn Escl Fac	Perctg	Infladjval	Prcval	Nnotpt
1	3085100	4236000	0.0114	0.1114	0.149	4707890	564,947	5,272,837
2	3171800	5800000	0.0114	0.1114	0.145	6446120	773,534	7,219,654
3	2610000	4800000	0.0114	0.1114	0.145	5334720	640,166	5,974,886
4	3165000	4350000	0.0114	0.1114	0.145	4834590	701,016	5,535,606
5	2145000	4325000	0.0114	0.1114	0.135	4806805	648,919	5,455,724
6	3174953	4286350	0.0114	0.1114	0.145	4763849	690,758	5,454,607
7	2750000	5850000	0.0114	0.1114	0.137	6501690	890,732	7,392,422
8	2700850	5121000	0.0114	0.1114	0.145	5691479	825,264	6,516,743
9	3150000	6265000	0.0114	0.1114	0.145	6962921	1,009,624	7,972,545

10	2766000	5223000	0.0114	0.1114	0.149	5804842	864,921	6,669,763
11	2510000	6371000	0.0114	0.1114	0.145	7080729	1,026,706	8,107,435
12	3268000	6250000	0.0114	0.1114	0.145	6946250	1,007,206	7,953,456
13	2250325	5675000	0.0114	0.1114	0.138	6307195	870,393	7,177,588
14	3520000	6600000	0.0114	0.1114	0.138	7335240	1,012,263	8,347,503
15	2100000	5125000	0.0114	0.1114	0.138	5695925	786,038	6,481,963
16	3173000	5652000	0.0114	0.1114	0.138	6281633	866,865	7,148,498
17	3173000	7650000	0.0114	0.1114	0.138	8502210	1,173,305	9,675,515
18	2580315	6131000	0.0114	0.1114	0.138	6813993	940,331	7,754,324
19	2420500	5643000	0.0114	0.1114	0.134	6271630	840,398	7,112,028
20	3143000	7266000	0.0114	0.1114	0.133	8075432	1,098,259	9,173,691
21	4385500	7121000	0.0114	0.1114	0.132	7914279	1,005,113	8,919,392
22	3867620	8900000	0.0114	0.1114	0.138	9891460	1,256,215	7,987,634
23	4010850	9201000	0.0114	0.1114	0.132	10225991	1,298,701	7,654,136
24	3172771	7213000	0.0114	0.1114	0.132	8016528	1,018,099	9,034,627
23	3222776	7136000	0.0114	0.1114	0.138	7930950	1,007,231	8,938,181
26	3767000	8208000	0.0114	0.1114	0.135	9122371	1,158,541	7,897,221
27	2646000	5670000	0.0114	0.1114	0.135	6301638	800,308	7,101,946
28	2475337	5300000	0.0114	0.1114	0.135	5890420	748,083	6,638,503
29	2680286	3720000	0.0114	0.1114	0.132	4134408	545,742	4,680,150
30	3831000	6121000	0.0114	0.1114	0.138	6802879	938,797	7,741,676
31	3763000	7800000	0.0114	0.1114	0.132	8668920	1,144,297	9,813,217
32	4001000	8222000	0.0114	0.1114	0.132	9137931	1,206,207	8,987,321
33	2560500	5172000	0.0114	0.1114	0.135	5748161	776,002	6,524,163
34	4500000	9000000	0.0114	0.1114	0.132	10002600	1,320,343	6,852,132
35	3216000	6350000	0.0114	0.1114	0.132	7057390	931,575	7,988,965
36	3682710	7221000	0.0114	0.1114	0.132	8025419	1,059,355	9,084,774
37	3580000	6850000	0.0114	0.1114	0.132	7613090	1,004,928	8,618,018
38	2500000	4670000	0.0114	0.1114	0.132	5190238	685,111	5,875,349
39	2760000	4885000	0.0114	0.1114	0.132	5429189	716,653	6,145,842
40	2761730	4722000	0.0114	0.1114	0.132	5248031	692,740	5,940,771
41	2855210	4873000	0.0114	0.1114	0.132	5415852	714,892	6,130,744
42	3010000	5035000	0.0114	0.1114	0.132	5595899	738,659	6,334,558
43	4800000	7800000	0.0114	0.1114	0.132	8668920	1,144,297	9,813,217
44	2856725	4550000	0.0114	0.1114	0.136	5056870	687,734	5,744,604
45	4300000	6650000	0.0114	0.1114	0.132	7390810	975,587	8,366,397
46	2418163	3685000	0.0114	0.1114	0.132	4095509	540,607	4,636,116

47	4600000	6985000	0.0114	0.1114	0.132	7763129	1,024,733	8,787,862
48	2783011	4136000	0.0114	0.1114	0.137	4596750	629,755	5,226,505
49	2746500	3926000	0.0114	0.1114	0.132	4363356	575,963	4,939,319
50	2896230	4121000	0.0114	0.1114	0.132	4580079	604,570	5,184,649
51	2975610	4227000	0.0114	0.1114	0.132	4697888	549,653	5,247,541
52	2756380	3896000	0.0114	0.1114	0.132	4330014	506,612	4,836,626
53	2480500	3500000	0.0114	0.1114	0.123	3889900	455,118	4,345,018
54	2685420	3762000	0.0114	0.1114	0.11	4181087	489,187	4,670,274
55	2811143	3922000	0.0114	0.1114	0.11	4358911	509,993	4,868,904
56	2889385	3963000	0.0114	0.1114	0.11	4404478	515,324	4,919,802
57	2300121	3113000	0.0114	0.1114	0.11	3459788	380,577	3,840,365
58	2890010	3910000	0.0114	0.1114	0.11	4345574	478,013	4,823,587
59	2962500	3872000	0.0114	0.1114	0.11	4303341	473,368	4,776,709
60	2982630	3896000	0.0114	0.1114	0.11	4330014	476,302	4,806,316
61	2350000	2985000	0.0114	0.1114	0.11	3317529	364,928	3,682,457
62	2316286	2868000	0.0114	0.1114	0.11	3187495	350,624	3,538,119
63	2370135	2850000	0.0114	0.1114	0.11	3167490	348,424	3,515,914
64	2615115	3123000	0.0114	0.1114	0.11	3470902	381,799	3,852,701
65	2796610	3126000	0.0114	0.1114	0.11	3474236	382,166	3,856,402
66	2850035	3136000	0.0114	0.1114	0.11	3485350	383,389	3,868,739
67	2735000	2986000	0.0114	0.1114	0.11	3318640	365,050	3,683,690
68	2710000	2950000	0.0114	0.1114	0.123	3278630	403,271	3,681,901
69	2873182	3113000	0.0114	0.1114	0.127	3459788	439,393	3,899,181
70	2910320	3113000	0.0114	0.1114	0.127	3459788	439,393	3,899,181

Source: 2010 Neural Analysis

Legend: BOQ --- Bill of quantity Inflatn Adj Fact ----- Inflation Adjusted Factors
Corruptn Esc Fact ----- corruption escalator Factors   Perctg ------ Percentage
Infladjval ------Inflation adjusted Value   PrcVal ----- Predicted Value.

Appendix xvii: Building Cost Index Table

Quarter	Index	D%
3rd quarter 2010	798	0.00
2nd quarter 2010	798	- 0.13
1st quarter 2010	799	- 0.50
4th quarter 2009	803	-2.07

Appendix xviii: Summary of Building Cost Index 1997 -2009

Year	Average Index	D %	
2009	832	-8.4	
2008	908	6.3	
2007	854	7.7	
2006	793	10.6	
2005	717	9.5	
2004	655	5.4	
2003	621	0.3	
2002	619	1.0	
2001	613	0.3	
2000	595	1.0	
1999	570	3.8	
1998	549	4.6	
1997	525	4,0	

Appendix xix: Sample Size

Table for determining sample size from a given population.				
N	S		N	S
10	10		220	140
15	14		230	144
20	19		240	148
25	24		**250**	**152**
30	28		260	155
35	32		270	159
40	36		280	162
45	40		290	165
50	44		300	169
55	48		320	175
60	52		340	381
65	56		360	186
70	59		380	191
75	63		400	196
80	66		420	201
85	70		440	205

90	73		460	210
95	76		480	214
100	80		**500**	**217**
110	86		550	226
120	92		600	234
130	97		650	242
140	103		700	248
150	108		750	254
160	113		800	260
170	118		850	265
180	125		900	269
190	127		950	274
200	132		1000	278
210	136		1100	285

Source Adetayo 2005

Appendix xx: Inflation Data

InflationData.com

Your Place in Cyber Space for Inflation Data

- Inflation Charts and Data
    - Annual Inflation Rate Chart
    - Average Annual Inflation by Decade
    - Current Inflation Rate
    - Historical US Inflation Rates
    - Inflation Rate Calculator
    - Confederate Inflation (1861-1865)
-
- Consumer Price Index Data
    - Current CPI
    - Historical CPI

Page Summary Using our Inflation Calculator, you can calculate the inflation rate between any two dates from 1914 to the present. Quick Links

- Ho me
- Infl atio n

Inflation Rate Calculator

Your browser does not support inline frames currently configured not to display inline frai

Calculate the rate of price inflation between two dates.

Ranging from 1914- Present using the **Inflation Rate Calculator below**.

This calculator uses the Consumer Price Index published by the U.S. Bureau of Labor Statistics which is the most closely watched indicator for inflation in the U.S. It can be considered the "government's key inflation barometer".

Using the Inflation Rate Calculator will give you the **cumulative inflation** between two points in time.

CPI

Current Consumer Price Index (CPI-U) 218.439
Current Inflation Rate 1.14%
Released October 15, 2010 for September 2010 Provided by InflationData.com

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Please read the following instructions carefully. It does make a difference in understanding how the Inflation calculator works and ensuring that you get the right answer.

To start select the starting month and year and the ending month and year and then click the "Calculate Inflation Rate" button to see your inflation calculation.

Remember the data is a month old by the time it is released by the Bureau of Labor Statistics. CPI Index Release Dates

So depending on what time of month it is, you can only get data up through last month or even the previous month. (Early in the month you will have to go two months prior, late in the month it will be the previous month.

Once you hit the "Calculate Inflation Rate" Button the result will appear in an empty box in the bottom of the inflation calculator.

To compare the **cost of living in two cities** use this Cost of Living calculator

Note: This U.S. Inflation Rate Calculator gives you the percentage of increase in prices over a period. For example from January 2005 - January 2006 prices increased 3.99% therefore something that cost $1 in January 2005 would cost $1 +

information has been updated!

First name:

Last name:

Country:

Permanent Email:

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Dow	11283.10	-73.94
S&P 500	1213.54	-5.17
Nasdaq	2555.52	-23.26
ReutersCRB	310.35	-4.50
Crude Oil	86.02	-1.79
Natural Gas	4.086	-0.025
Gold	1386.45	-2.51
Silver	26.8556	-0.0044
Platinum	1705.5	-8.7
Palladium	684.00	-2.00
Euro	1.3715	+0.0100
Canadian$	1.0098	+0.0021
Yen	82.07	-0.36
Australian $	1.38360	+0.01360
British Pound	0.8502	+0.0036
Swiss Franc	1.33543	+0.00487
Chinese Yuan	6.6150	-0.0002

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(inflation rate) in January 2006. So in this case it would be $1+($1 x .0399)= $1.0399 or $1.04

Although this seems obvious for one year when the inflation rate gets larger (above 100%) it is not so intuitive.

From December 1957 through December 2007 the Inflation Rate Calculator will tell you that inflation was 639.56%.

If we plug the calculator results into the above formula we find that something that cost $1 in December 1957 would cost $1+ ($1 x 6.3956)=$7.40

Remember the result is in percent.

To calculate its decimal equivalent you need to move the decimal point two places to the left. So 639.56% = 6.3956 in decimals.

Inflation Rate Calculator

To Calculate the inflation rate for a whole year use	**Month**	**Year**

name.

Financial Trend Forecaster

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Today we have an analysis by Chris Vermeulen "The

Your Family Finances

Strategy vs. Tactics

the same month, *i.e.*, Jan. 2009 - Jan. 2010 gives a full year. Jan - Dec only gives 11 months.		
Start Date:	January	2010
(Do Not Choose Current Month) End Date:	September	2010
	Calculate Inflation Rate	
Inflation Calculator Results:		
Total inflation over the period from **January 2010** to **September 2010** is	0.81%	

Once you know the inflation rate from the calculator above, you might want to know

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Calculate how much it would cost after Inflation

Starting Amount
$

Rate of inflation
X

How much it would

$

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